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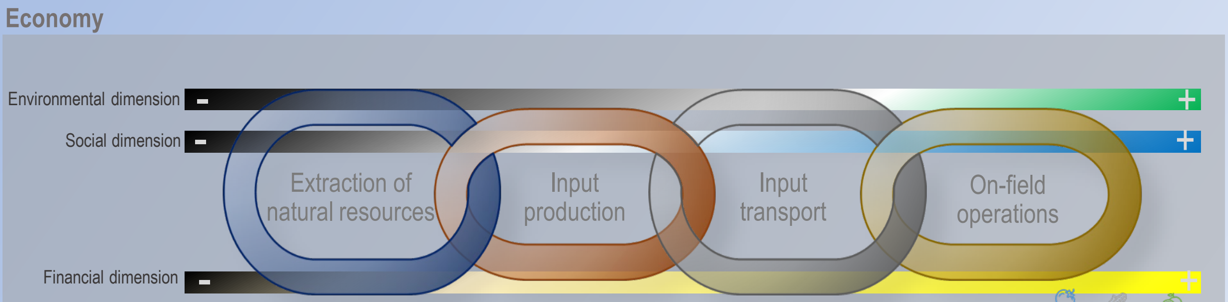

Developing indicators to assess agricultural sustainability. Application to the Spanish context

DOCTORAL THESIS

International PhD Mention

Presented by:

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February, 2024

UNIVERSITAT POLITÈCNICA DE VALENCIA

Departamento de Economía y Ciencias Sociales

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Abstract

Considering the importance of including quantitative measures in the decision-making process, this dissertation aims to develop indicators with which to assess the environmental and overall sustainability of current agricultural practices in Spain at a regional level. What is sought is the provision of data that work as a starting point from which to support the transition to sustainable agriculture while addressing critical methodological aspects in sustainability assessment. The main methodological choices of this thesis are attributional life cycle assessment, multicriteria techniques for developing of a composite sustainability indicator and using sources of average statistics. Besides providing quantitative information, this dissertation also explores key methodological issues regarding the quantitative assessment of agricultural sustainability. In particular, the results, focus on assessing the environmental and the overall sustainability. In section 2.1 of the results chapter, the environmental impacts of conventional and organic vineyards located in a relevant wine region in Spain (Utiel-Requena DOP) are assessed, delving into the influence of the modelling on-field emissions on the impact results. The environmental impacts of tomato and orange production in the main Spanish producing regions are assessed in section 2.2, where also an approach to estimate agricultural inventories from farm accountancy data is developed (section 2.3). The previous approach is adopted in section 2.4, to estimate the environmental impacts of the main crops grown in the Spanish regions. In addition, there is an exploration of a functional unit for a proper representation of the economic role of agriculture according to the target audience. In section 2.5, the overall sustainability of the same crops by developing a composite indicator is assessed, considering the weights assigned to the sustainability attributes and the trade-offs between them as key normative factors in the assessment of sustainability. Overall, the results show differential performances of Spanish agriculture depending on the crop type and region, water management, and farming system. These differences should be interpreted in the context of the primary data sources, modelling assumptions and the scope considered. In brief, it can be concluded that the quantitative evaluation of agricultural sustainability is a complex issue due to the ambiguity of the concept, the intensive use of data required and the highly sensitive nature of agriculture to agroecological aspects and market factors.

Resumen

Considerando la importancia que tiene en el proceso de toma de decisiones el disponer de datos, en esta tesis doctoral se desarrollan indicadores cuantitativos para monitorizar la sostenibilidad integral y ambiental de las prácticas agrícolas actuales en España. Se pretende proporcionar datos que sirvan como punto de partida para apoyar la transición hacia una agricultura sostenible y al mismo tiempo abordar aspectos metodológicos críticos en la evaluación de la sostenibilidad. Las principales opciones metodológicas que se abordan en esta tesis son la aplicación del análisis de ciclo de vida atribucional para la evaluación ambiental de la sostenibilidad agraria y el uso de técnicas multicriterio para desarrollar un indicador compuesto de sostenibilidad que permita evaluar la sostenibilidad agraria. Además, se usan datos estadísticos promedio para realizar las modelizaciones de los sistemas estudiados. En la sección 2.1 del capítulo de resultados se evalúan los impactos ambientales de viñedos convencionales y ecológicos representativos en una región vitivinícola relevante en España (DOP Utiel-Requena). En este caso de estudio se profundiza en la influencia que tiene la modelización de emisiones en campo en los resultados de impacto medioambiental. En la sección 2.2 se evalúan los impactos ambientales de la producción de tomate y naranja en las principales regiones productoras españolas. Además, en la sección 2.3 se desarrolla una propuesta metodológica para estimar los datos de actividad de las explotaciones agrarias a partir de datos contables. En la sección 2.4, la propuesta metodológica anterior se adapta y se aplica en la estimación de los impactos ambientales de cultivos relevantes en siete de las diecisiete comunidades autónomas españolas. También se explora la presentación de los impactos con base en una unidad funcional que represente adecuadamente el papel económico de la agricultura según el público objetivo. En la sección 2.5 se evalúa la sostenibilidad integral de las mismas explotaciones agrarias mediante el desarrollo de un indicador compuesto, destacando como factores de carácter normativo claves en la evaluación de la sostenibilidad las ponderaciones asignadas a los atributos individuales de sostenibilidad y la compensación entre ellos. En general, los resultados en sostenibilidad muestran comportamientos diferenciales de la agricultura española en función del tipo de cultivo y región, gestión del agua y sistema de cultivo. Estas diferencias deben interpretarse en el contexto de las fuentes de datos utilizadas, los supuestos tenidos en cuenta en las modelizaciones y el alcance de la investigación. En resumen, se puede concluir que la evaluación cuantitativa de la sostenibilidad agrícola es un asunto complejo debido a la ambigüedad del concepto, el uso intensivo de datos y la alta sensibilidad de la agricultura a aspectos agroecológicos y factores de mercado.

Resum

Considerant la importància que té en el procés de presa de decisions disposar de dades, en aquesta tesi doctoral es desenvolupen indicadors quantitatius per monitoritzar la sostenibilitat integral i ambiental de les pràctiques agrícoles actuals a Espanya. Es pretén proporcionar dades que funcionen com a punt de partida per donar suport a la transició cap a una agricultura sostenible i alhora abordar aspectes metodològics crítics en l'avaluació de la sostenibilitat. Les principals opcions metodològiques que aborda aquesta tesi són l'aplicació d'anàlisi de cicle de vida atribucional per a l'avaluació de la sostenibilitat ambiental agrària i l'ús de tècniques multicriteri per desenvolupar un indicador compost de sostenibilitat per avaluar la sostenibilitat agrària. A més, s'utilitzen dades mitjanes estadístiques per a realitzar les modelitzacions. A l'apartat 2.1 del capítol de resultats s'avaluen els impactes ambientals de vinyes convencionals i ecològiques representatives d'una regió vitivinícola rellevant a Espanya (DOP Utiel-Requena). En aquest cas d'estudi s'aprofundeix en la influència que té la modelització d'emissions en camp als resultats d'impacte mediambiental. A l'apartat 2.2 s'avaluen els impactes ambientals de la producció de tomaca i taronja a les principals regions productores espanyoles, on a més es desenvolupa una proposta metodològica per estimar les dades d'activitat de les explotacions agràries a partir de dades comptables (apartat 2.3). A la secció 2.4, la proposta metodològica anterior s'adapta i s'aplica a l'estimació dels impactes ambientals de cultius rellevants en set de les disset comunitats autònomes espanyoles. A més d'això, s'explora la presentació dels impactes sobre la base d'una unitat funcional que represente adequadament el paper econòmic de l'agricultura segons el públic objectiu. A l'apartat 2.5 s'avalua la sostenibilitat integral de les mateixes explotacions agràries mitjançant el desenvolupament d'un indicador compost, destacant com a factors claus de caràcter normatiu en l'avaluació de la sostenibilitat les ponderacions assignades als atributs individuals de sostenibilitat i la compensació entre ells. En general, els resultats de sostenibilitat mostren comportaments diferencials de l'agricultura espanyola en funció del tipus de cultiu i regió, gestió de l'aigua i sistema de cultiu. Aquestes diferències s'han d'interpretar en el context de les fonts de dades utilitzades, les assumpcions realitzades en les modelitzacions i l'abast de la investigació. En resum, es pot concloure que l'avaluació quantitativa de la sostenibilitat agrícola és un assumpte complex a causa de l'ambigüitat del concepte, de l'ús intensiu de dades i de l'elevada sensibilitat de l'agricultura a aspectes agroecològics i factors de mercat.

Acknowledgments

The motivations and support that made the development of this dissertation possible came from different sources. Firstly, I would like to acknowledge the institutions that provided financial support, namely the Universitat Politècnica de València, for funding a four-year research contract through Subprogram 1 (PAID-01-18), the ADSIDEO - COOPERACIÓN 2020 Program (AD2011), and the Erasmus+ program that provided the funds for a three months research stay at the Bioeconomy and Biosystems Economics Laboratory of the Technical University of Crete -TUC (Chania, Greece). Finally, I also wish to thank the Colombian Government for its funding through the program "Doctorado en el Exterior-885" of COLCIENCIAS.

I would also like to acknowledge the research group that has involved me during mi PhD. Specifically, the ASPA group that provided the space and material items and made me feel like a member of the family and Profs. Gabriela Clemente and Vicente Estruch, my formal supervisors, together with Profs. Neus Sanjuan and Javier Ribal (my informal supervisors) for their invaluable guidance, unwavering support, and exceptional mentorship throughout the course of this research. Their expertise, dedication, and constant encouragement have played a pivotal role in shaping the direction and success of this dissertation. I am truly fortunate to have had such knowledgeable and inspiring mentors by my side. I also wish to make special mention of Prof. Stelios Rozakis for his invaluable supervision and mentorship during my stay in TUC.

I would also like to extend my appreciation to the external examinators [Jacopo Bacenitti, Isabel Bardají Azcárate and Ian Vázquez Rowe] and the members of my thesis committee, [Jacopo Bacenetti, José María Garcia Alverez-Coque and Neus Escobar Lanzuela], for their insightful comments, constructive criticism, and valuable suggestions that greatly enhanced the quality of this work. Furthermore, I would like to thank the numerous research participants who generously contributed their time, expertise and knowledge to this study. Without their collaboration and participation, this research would not have been possible. I also want to highlight the support of different experts in my research: Dr. Nancy Peña and Dr. Assumpció Antón for the modelling and estimation of pesticide emissions in different farming systems, Dr. Diego Gómez and Dr. Rafael Laborda for the information on pesticide treatments of agri-food crops, Dr. Juan Manzano for the estimation of irrigation requirements in agriculture, and Dr. Jose David Prieto and Dr. Gentil Andrés Collazos for their support the statistics analysis of the results.

Last but not least, I greatly appreciate all the support from my family and friends, they have been my pillar, both in this process and in life itself.

Dedication

This doctoral thesis is dedicated to the cherished memory of my loving brothers Luis Fernando Sinisterra Solís and Arnold Royer Sinisterra Ordoñez. The transient nature of life and my decision to pursue my professional career limited any opportunity I might have had to enjoy their presence and madness. Though they are no longer with us, their influence and love continue to guide me every step of the way.

Preface

The starting point of this research was the personal and professional motivation to acquire objective information for the purposes of supporting the decision-making process related to sustainability issues. Therefore, this doctoral thesis focuses on providing quantitative indicators with which to assess the environmental and overall sustainability performance of Spanish agriculture.

It must also be considered that when applying attributional life cycle assessment and composite indicator techniques, different methodological challenges arise. In particular, aspects such as the definition of the functional unit, the estimation of activity data, and trade-off modelling are covered in the assessments. This dissertation gathers the results of the following articles published or under review in international peer-reviewed journals:

Section 2.1:

Sinisterra-Solís, N. K., Sanjuán, N., Estruch, V., & Clemente, G. (2020). Assessing the environmental impact of Spanish vineyards in Utiel-Requena PDO: the influence of farm management and on-field emission modelling. *Journal of environmental management*, *262*, 110325.

Section 2.2:

Sinisterra-Solís, N., Sanjuán, N., Ribal, J., Estruch, V., & Clemente, G. (2023). An approach to regionalise the life cycle inventories of Spanish agriculture: Monitoring the environmental impacts of orange and tomato crops. *Science of The Total Environment*, *856*, 158909.

Section 2.3:

Sinisterra-Solís, N. K., Sanjuán, N., Ribal, J., Estruch, V., & Clemente, G. (2023). Dataset to monitor regionalised environmental impacts of the main agricultural products in Spain. *Data in Brief*, 108883.

Section 2.4:

Sinisterra-Solís, N. K., Sanjuán, N., Ribal, J., Estruch, V., & Clemente, G. (2023). From farm accountancy data to environmental indicators: Assessing the environmental performance of Spanish agriculture at a regional level. *Science of The Total Environment*, 164937.

Section 2.5:

Sinisterra-Solís, N., Sanjuán, N., Ribal, J., Estruch, V., Clemente, G., & Rozakis, S. Developing a Composite Indicator Based on Decision-Makers' Preferences to Assess Agricultural Sustainability. *Available at SSRN 4542926*.

In addition, several participations in national and international conferences were developed during the pre-doctoral period. Two of them are directly related to the goals of this thesis:

Sinisterra-Solis, Nelson Kevin; Sanjuán Pellicer, Neus; Estruch-Guitart, Vicente; Clemente Polo, Gabriela (2019). ***How critical is the estimation of fertilizers and pesticide emissions in agricultural LCAs? A case study on vineyards of D.O. Utiel-Requena.*** EN *3rd International Congress of Chemical Engineering (ANQUE-ICCE-CIBIQ 2019)*. Santander, Spain: ANQUE. [oral comunication]

Sinisterra-Solis, Nelson Kevin; Sanjuán Pellicer, María Nieves; Estruch-Guitart, Vicente; Clemente Polo, Gabriela (2019). ***Evaluación Medioambiental Mediante Acv de Uva Bobal para Vinificación***. EN *X Congreso Nacional de Ciencia y Tecnología de los Alimentos (CyTA/CESIA 2019)*. León, Spain: Universidad de León. [poster]

The following contributions focus on the assessment of the sustainability of agricultural systems, and are, thus, indirectly related to the goals of this thesis.

Sinisterra-Solis, Nelson Kevin; Corona-Mariscal, Alejandro; Sanjuán Pellicer, Neus; Lilian A. Carrillo-Rodriguez; Elizabeth Aponte-Jaramillo; Margot Cajigas Romero; Clemente Polo, Gabriela (2022). ***Assessing the sustainability of coconut chain in Sanquianga region, Colombia.*** EN *13th International Conference on Life Cycle Assessment of Food (LCA Foods 2022)*. Lima, Perú. [oral comunication]

Castiñeira Ibáñez, Sergio; Rubio Michavila, Constanza; Tarrazó-Serrano, Daniel; Uris Martínez, Antonio; Sinisterra-Solis, Nelson Kevin; Clemente Polo, Gabriela (2022). ***Sostenibilidad ambiental y social mediante el uso de materiales reciclados para la implementación de pantallas acústicas abiertas.*** EN *IX Congreso I+D+i Campus de Alcoi. Creando sinergias*. (121 - 124). Alcoy, España: Compobell, S.L. [Poster/Oral presetation]

Sinisterra-Solis, Nelson Kevin; Clemente Polo, Gabriela; Rubio Michavila, Constanza; Fenollar, Octavio; Castiñeira Ibáñez, Sergio. (2022). *Futuritat: la vida dels materials*. Agora de la UPV [Exhibition]

Ribal, Javier; Fenollosa, M. Loreto; Sinisterra-Solis, Nelson Kevin; Sanjuán, Neus (2020). ***Organic and conventional citrus production. An eco-efficiency analysis.*** In *12th International Conference on Life Cycle Assessment of Food (LCA Food 2020)*. (494 - 499). Online: DIL [poster]

In addition, this dissertation has been funded by two research projects:

Clemente Polo, Gabriela (I.P.); Sinisterra-Solis, Nelson Kevin; Ribal, Javier; Jiménez Belenguer, Ana Isabel; Sanjuán Pellicer, Neus; Estruch-Guitart, Vicente ... Rubio Michavila, Constanza. *Evaluación de la sostenibilidad del establecimiento de una fábrica artesana de productos de coco en la subregión de Sanquianga (departamento de Nariño, Colombia)* (AD2011). (01/01/21 - 30/06/23). Investigación competitiva proyectos. UNIVERSIDAD POLITECNICA DE VALENCIA.

Clemente Polo, Gabriela (I.P.); Sinisterra-Solis, Nelson Kevin. *Desarrollo de indicadores para la intensificación sostenible de la agricultura.* (08/03/20 - 06/08/22). Financiación RRHH. UNIVERSIDAD POLITECNICA DE VALENCIA.

During my pre-doctoral period, I taught sixteen ECTs in subjects related to this thesis, thanks to the opportunity offered by the UPV to doctoral students. Moreover, I participated as an experimental director in five final projects (Bachelor's and Master's) directly and indirectly related with the thesis.

Figures

Tables

List of acronyms and abbreviations

Acronym	Description
A-FU	Funtional unit based on area land occupied
AHP	Analytic hierarchy process
AIC	Akaike criterion
AM	Alternative modelling
AN	Andalucía
AWARE	Assessing impacts of water consumption based on available water remaining
AWU	Annual work unit
BIC	Schwartz criterion
BM	Baseline modelling
CAP	Common Agricultural Policy
Capg	Capital goods use
CC	Climate change
CIB	Conventional irrigated Bobal
CIT	Conventional irrigated Tempranillo
CL	Castilla y León
CM	Castilla-La Mancha
COP21	2021 conference of parties
CRB	Conventional rainfed Bobal
CRITIC	Criteria importance through inter-criteria correlation
CRT	Conventional rainfed Tempranillo
DEA	Data envelopment analysis
DOP	Protected designation of origin
E_NVA	Net value added
EBITDA	Earnings Before Interest Taxes Depreciation and Amortization
EC	European Commission
ECREA	Spanish acronym of the annual studies of costs and incomes of agricultural holdings (Estudios de costes y rentas de las explotaciones agrarias)
ECREA-FDAN	Non-standardised Spanish farm accountancy data network
EF	Emission factor (section 2.1 and 2.2); Environmental footprint in the remaining sections
EFs	Emission factors
E-FU	Economic-based functional unit
E-LCA	Environmental life cycle assessment
ELECTRE	elimination and choice translating reality
ET	Freshwater eco-toxicity
EU	European Union
EUCO	European Council
FADN	Farm Accountancy Data Networks
FAO	Food Agriculture Organization
FD	Fossil depletion midpoint category
FDAN	Farm Accountancy Data Networks
Fert	Fertiliser comsumption
FPMF	Fine particular matter formation category
FU	Functional unit

Acronym	Description
Fuel	Fuel consumption for machinery
FwE	Freshwater eutrophication midpoint category
GDP	Gross domestic product
G_{MA}	Generic information
HTc	Human health, cancer
HTnc	Human health, non-cancer
IG	Crops in greenhouse system
ILCD	International life cycle data system
IO	Crops in irrigated system
IPCC	Intergovernamental Panel on Climate Change
IQR	Interquartile range
IR	Ionizing radiation midpoint category
Irrig	Resources consumption for irrigation
ISO	International Organization for Standardization
JRC	European Join Research Centre
Land	Land use
LCA	Life cycle assessment
LCAs	Life cycle assessments
LCC	Life cycle costing
LCI	Life cycle inventory
LCIA	Life cycle impact assessment
LL	Lower limit
LU	Land use midpoint category
MA	Modelling approach
MAPA	Spanish acronym of the Spanish Agriculture Ministry
MAPA	Spanish Ministery of Agriculture, Fisheries and Food
MC	Murcia
MCDA	Multi-criteria decision analysis
MD	Metal depletion midpoint category
ME	Marine eutrophication midpoint category
M-FU	Mass-based functional unit
N_FWED	Damage to the quality of the freshwater ecosystem
N_MWED	Damage to the quality of the marine water ecosystem
N_RAD	Damage to the resource availability
N_TED	Damage to the quality of the terrestrial ecosystem
nd	No significant differences found
N-FU	Functional unit based on nutritional criteria
NUTS	Nomenclature of territorial units for statistics
NVA	Net value added
NVA_fc	Net value added at factor cost
OIB	Organic irrigated Bobal
OIT	Organic irrigated Tempranillo
OIV	International Organization of Vine and Wine
OLS	Ordinary least squares
ORB	Organic rainfed Bobal

Acronym	**Description**
ORT	Organic rainfed tempranillo
PAM	Partitioning around medionds
PCA	Principal component analysis
PEF	Product Environmental footprint
Pest	Pesticide consumption
PestLCI	A model for estimating field emissions of pesticides in agricultural LCA
POFe	Photochemical ozone formation, econsystem midpoint category
POFh	Photochemical ozone formation, human midpoint category
RECAN	Spanish acronym of Farm Sustainability Data Network
RMSE	Root mean square error
RO	Crops in rainfed system
RSD	Standard deviation relative to the mean
RSS	Residual sum square
S_GLE	Gender labour equity atribute
S_HH	Human health damage
SA	Sustainability assessment
SAFE	Sustainability Assessment of Farming and the Environment
SAW	Simple additive weighting
SCI	Composite indicator to asess sustainability agriculture
SDG	Sustainable Development Goals
S-LCA	Social life cycle assessment
SM	Supplementary material
S_{MA}	Site-specific information
SMART	Simple multi-attribute ranking technique
SO	Standard output
SOD	Stratospheric ozone depletion midpoint category
SS	Sustainability Science
TA	Terrestrial acitification midpoint category
TBL	Triple bottom line
UN	United Nations
UNCED	United Nations Conference on Environmental and Development
USEtox	UNEP-SETAC toxicity model
VC	Comunidad Valenciana
WBCS	World Business Council for Sustainable Development
WS	Water scarcity

CHAPTER I. INTRODUCTION

1.1.Spanish agriculture

The increasing demand for food and the marked imbalance between human dynamics with the social and natural environments require the development of a sustainable agriculture, which strengthens food security and promotes profitability, environmental health, and social and economic equity (FAO, 2023; Velten et al., 2015). Spanish agriculture is framed in the Common Agricultural Policy, CAP 2023-27 (EUCO, 2023), which sets out to the environmental objectives of the European Union (EU) towards the transition to sustainable agriculture, according to the Fork-to-Farm (EC, 2023a) and Biodiversity 2030 (EC, 2020) strategies and European Climate Law (EC, 2021a) of the EU Green Deal (EC, 2023b). Along these lines, CAP 2023-27 allows the member states to adopt those measures that best fit their local conditions (EUCO, 2023). Through the Strategic Plan of the Spanish CAP (MAPA, 2023a), approved by the European Commission (EC) in August 2022, the Green Deal and CAP goals have been adapted to the particular characteristics of Spanish agriculture, defining nine specific goals based on the three pillars of sustainability: to ensure a fair income; to increase competitiveness; to rebalance the power of the agri-food chain; to promote actions against climate change; to protect the environment and, conserve the landscape and biodiversity; to support the generational change; to promote lively rural areas; to preserve food quality and health; and to modernise the agricultural sector through knowledge, innovation and digitisation in rural areas (MAPA, 2023a).

Spain is the fourth largest agricultural producer in the European Union after France, Germany and Italy and the second in terms of agricultural surface area after France, highlighting Spanish agriculture as a strategic sector in both Spanish and EU economies (MAPA, 2022). Regarding crops, 32% of the Spanish surface area is cultivated, mainly with herbaceous crops (mostly barley, wheat, sunflower, oat and corn), followed by Mediterranean perennial crops (i.e. olives, vineyards and almonds) and fruit tree crops (mainly citrus), respectively. The proportion of the surface area dedicated to vegetable and industrial crops is smaller (Fig. 1.1). As regards productivity and as reported by the Spanish Ministry of Agriculture, Fisheries and Food, despite the relevant surface area devoted to herbaceous crops, it should be highlighted that vegetable crops exhibit significantly higher land productivity; for instance, from 2017 to 2019 the gross output of vegetable crops was around 24,000 €·ha^{-1}. The gross output of fruit tree crops was the second-best land productivity, close to 4,000 €·ha^{-1}; whereas the land productivity of Mediterranean perennial and herbaceous crops was below 2,500 €·ha^{-1} (MAPA, 2022).

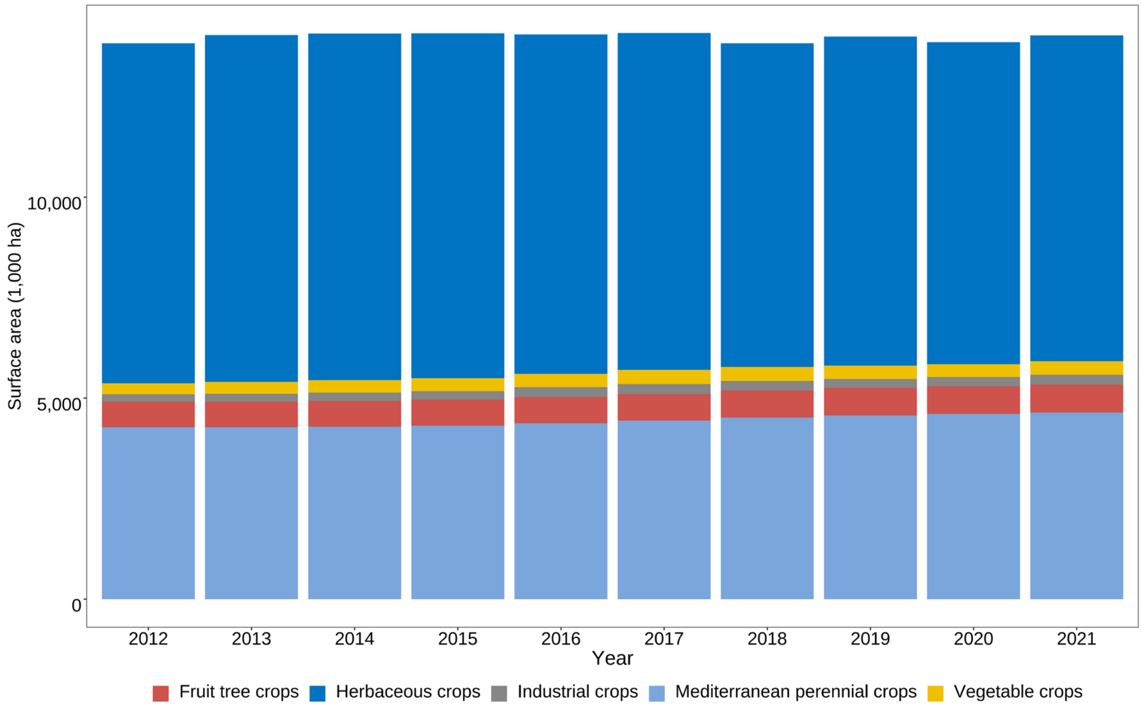

Fig. 1.1. Surface area of the main crops in Spain (MAPA, 2023b)

As shown in Fig. 1.2, herbaceous and Mediterranean perennial crops are mainly rainfed (85% and 72% respectively); as regards fruit tree and vegetable crops, however, the irrigation prevails (78% and 89% respectively), both in the open field system and in the greenhouse, with a greater surface area devoted to vegetables in the greenhouse system than to fruit trees. Irrigation also prevails in industrial crops, but the relationship between irrigated (61%) and rainfed (39%) systems is more balanced. In the 2012-2021 period, the surface areas corresponding to fruit trees, Mediterranean perennials, vegetables and industrial crops increased by 10%, 8%, 24% and 32%, respectively, with some throwbacks and rebounds in the intermediate year periods for vegetable and industrial crops. On the other hand, the surface area of herbaceous crops decreased by around 4% in the period analysed (Fig. 1.2).

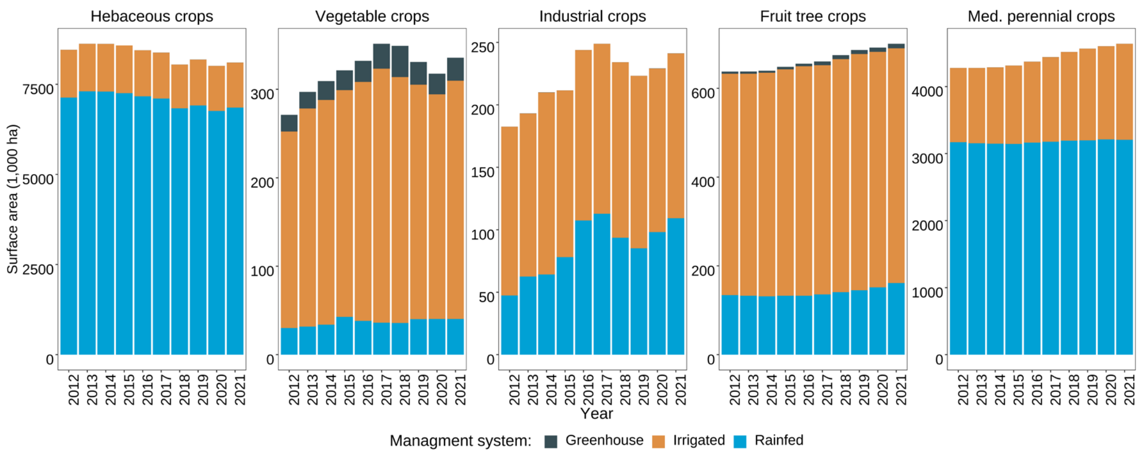

Fig. 1.2. Surface area cultivate on rainfed, irrigated and greenhouse systems (MAPA, 2023b).

Spanish agriculture is mainly organized into small holdings, in terms of both surface area and economic size (measured from the standard output-SO, € SO·year-1). In 2020, 49% of the holdings had an economic size of less than 8,000 € SO·year-1 and 23% of between 8,000 € SO·year-1 and 25,000 € SO·year-1, making up 72% of the Spanish holdings. From a surface area point of view, 66% of the holdings were smaller than 10 ha (Eurostat, 2023). Conventional farming systems are still the most representative in Spanish agriculture; what stand out, however, is the growth of organic farming, reaching 11% in 2021 (Fig. 1.3). Another relevant aspect of the Spanish agrarian structure is that it is mainly developed by an elderly male population (MAPA, 2022). It represents both a short and mid-term problem due to the difficulty of there being any generational change in agricultural activity.

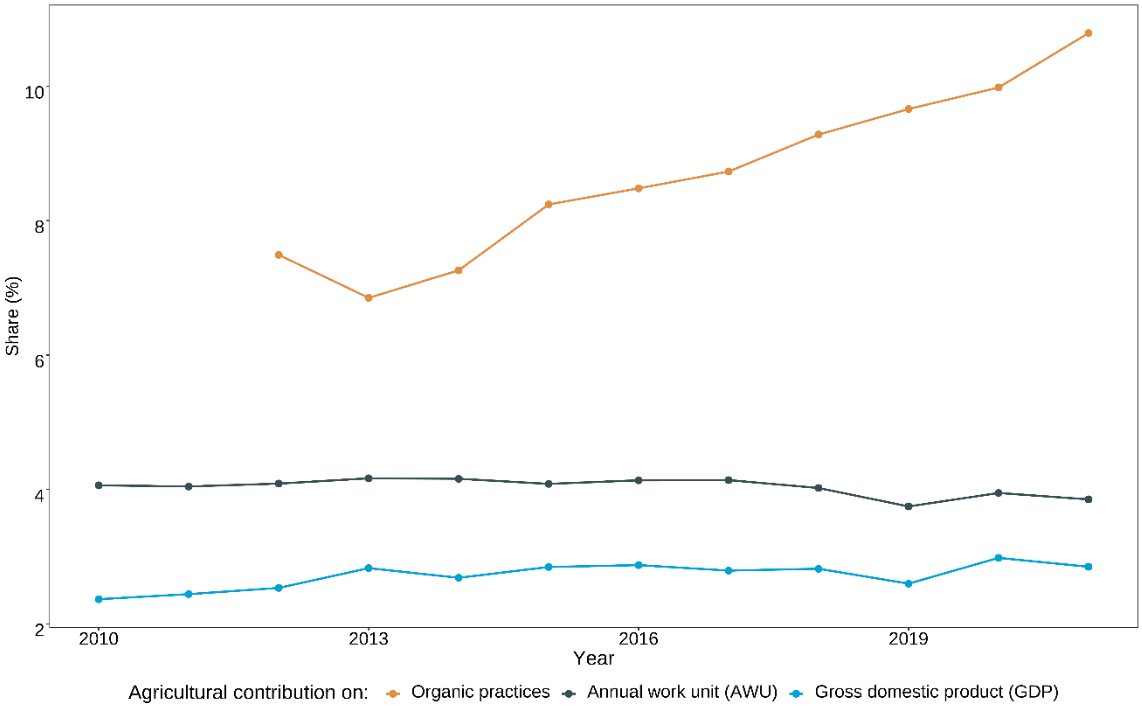

Fig. 1.3. Share of organic farming in terms of Spanish agricultural surface area (MAPA, 2023c), and agricultural contribution (%) to the total Spanish annual work unit (INE, 2023a) and gross domestic product (INE, 2023b).

As regards the economic dynamics, in the period ranging from 2010 to 2021, agriculture contributed around 2.7% (for instance, 60,816 million euros of gross domestic product, GDP, in 2021 at 2021 prices) and 4% (for instance, 707,300 annual work units, AWU, in 2021) to the production and labour in Spain (Fig. 1.3), respectively. At the same time, labour and land productivity, as well as the farmer's labour income, are directly related to the economic size of the holdings (Eurostat, 2023; MAPA, 2022). For instance, in the abovementioned years, holdings greater than 100,000 € SO·year^{-1} show labour and land productivities higher than 100,000 € SO·AWU^{-1} and 3,900 € SO·ha^{-1}, respectively; whereas these values were lower than 50,000 € SO·AWU^{-1} and 2,100 € SO·ha^{-1} for the smaller holdings (Fig. 1.4). In addition, on average, farmer's labour income is 58%, 46% and 25% lower than the average Spanish salary in holdings of between 8,000 € SO·year^{-1} and 25,000 € SO·year^{-1}, between 25,000 € SO·year^{-1} and 50,000 € SO·year^{-1}, and between 50,000 € SO·year^{-1} and 100,000 € SO·year^{-1}, respectively; whereas holdings of between 100,000 SO €·year^{-1} and 500,000 €·year^{-1}, and greater than 500,000 SO €·year^{-1} show farmer's labour income that is 16% and 473% higher than the average Spanish salary, respectively (Eurostat, 2023; MAPA, 2022).

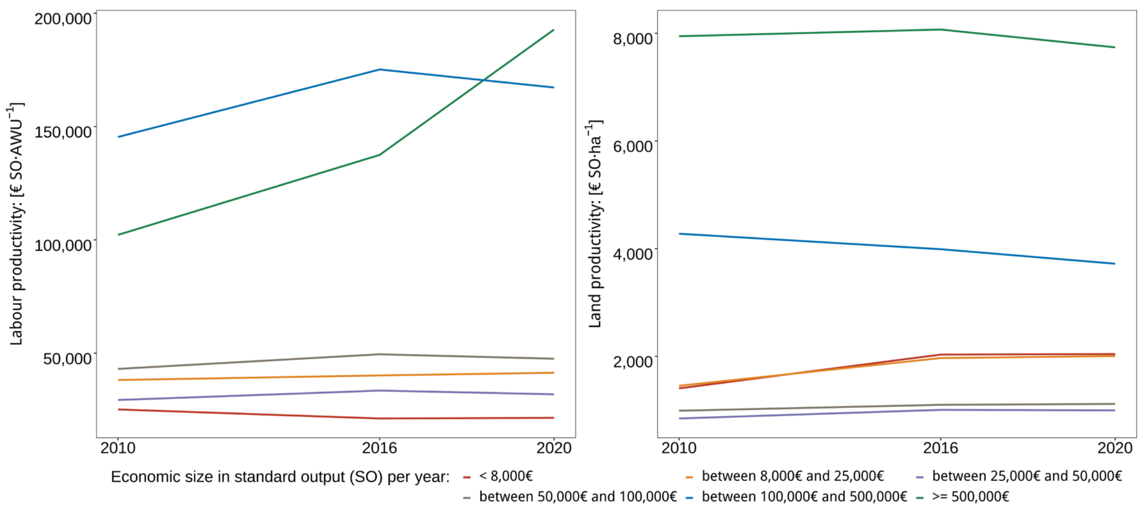

Fig. 1.4. Labour and land productivity of different economic sizes of the Spanish agriculture (Eurostat, 2023).

1.2.Sustainable agriculture

Sustainable agriculture subscribes to the concept of sustainable development, a concept that became widespread after the Brundtland report (WCED-UN, 1987) and the United Nations Conference on Environment and Development (UNCED), also known as the Rio Conference or the 1992 Earth Summit (UN, 1992). In general terms, sustainable development is presented as an alternative approach to the social and environmental issues derived from the hegemonic economic development models. The Brundtland report defines sustainable development as that which meets the current needs without compromising the ability of future generations to meet their own needs. This definition is debatable due to its ambiguous and normative excess (Amsler, 2009; Qizilbash, 2010; Spangenberg, 2009). On the one hand, some authors qualify these features as a weakness (e.g. Pesqueux, 2009; Ramsey, 2015). On the other hand, normative excess in terms of the concept of sustainability is understood as a strength (e.g. Hazenberg, 2015; Pezzoli, 2010), since sustainability is shown as a goal to be sought under sustainable development (Rosenau, 2003), and the dispute over the use of natural resources to satisfy current needs while trying to preserve them for future generations is looked at as an ethical dilemma. Thus, the definition of sustainable development must not only follow technical-scientific criteria, but it must also be open to democratic and social decision processes (López-Pardo, 2012). According to this framework, different definitions of agricultural sustainability have been proposed. For instance, the Food Agriculture Organisation (FAO) supports the classical definition of satisfying the needs of present and future generations while guaranteeing profitability, environmental health, and social and economic equity; according to this, sustainable agriculture should encourage food security together with the promotion of healthy ecosystems through the sustainable management of land, water and natural resources (FAO, 2023). Talukder et al. (2018) define agricultural sustainability as “the activity of growing food and fibre in a productive and economically efficient manner, using practices that maintain or enhance the quality of the local and surrounding environment - soil, water, air and all living things”. Van Cauwenbergh et al. (2007) describe sustainable agriculture as that which maintains or enhances the environmental, economic and social functions of an agroecosystem.

Overall, three dimensions may be made out in the field of sustainability. The first gathers the ecological or natural resources (renewable and non-renewable) and services provided by the natural environment without interacting with humans (e. g., non-managed forest). Some of them are essential for life on the planet. The social dimension is the second, which brings together the organisational bases of social and institutional agents; in this regard, intragenerational equity issues and no commercial capital developed or managed by humans are considered (e.g. human values, education, health protection and culture). The third dimension is the economic in which efficiency aspects and commercial capital developed by humans (i.e. manufactured and financial) are considered (Chen and Graedel, 2015; Comolli, 2006). Along these lines, agriculture is presented as a particular capital since it is developed by humans but preserves the characteristics of natural capital (Holland, 1999); from the point of view of ecological economics, agriculture is considered as part of the ecological capital (Cochrane, 2006).

The ambiguity and normative character of sustainability allow a connection between ecologists and developers (Antequera-Baiget, 2012; Maldonado et al., 2004). In that way, different approaches of sustainability are applicable in a continuous range from weak to strong, the weak being the closest to the status quo, and the strong one suggesting greater structural changes in the hegemonic relationship between humans and nature (López-Pardo, 2012; Maldonado et al., 2004; Selman, 2000). The capital that is sought to be preserved is key to differentiating between weak and strong sustainability (Ang and Passel, 2012; Deytieux et al., 2016). The former aims to maintain total capital regardless of the type, which allows for substitution between specific capitals. On the contrary, the strong vision of sustainability focuses on maintaining or increasing natural capital, understanding that it plays a unique role in generating living conditions on the planet (López-Pardo, 2012). Along these lines, the strong approach to sustainability limits the substitution of natural capital (especially critical capital) by manufactured capital. This substitution is determined by the carrying capacity of the ecological system and considering the precautionary principle (UN, 1992).

Nowadays, different initiatives are being developed to face the natural and social imbalances and the transition towards sustainable development. Globally, the 17 Sustainable Development Goals (SDG) of the 2030 Agenda for Sustainable Development (UN, 2023) must be highlighted; in particular, SDG 12 is directly related to agriculture since it aims to develop and promote sustainable practices in food production and consumption worldwide. In addition, the Paris Agreement is an international treaty on climate change adopted by 196 Parties at the UN Climate Change Conference (COP21) in Paris (UNFCCC, 2023). Included within these two global initiatives, and as mentioned above, the European Union presents the Green Deal (EC, 2023b) as a package of policy initiatives which aims to set the EU on the path to a fair and prosperous society with a modern and competitive economy from a green transition of the EU. Specifically, the Green Deal establishes the Biodiversity 2030 (EC, 2020) and Farm to Fork (EC, 2023b) strategies and European Climate Law (EC, 2021a), which address the common agricultural policy (CAP-2030) to support the transition to sustainable agriculture (MAPA, 2023a). Complementarity, a broad portfolio of tools from the academic-scientific field has been provided to quantify and assess sustainability from different approaches.

1.3.Sustainability assessment

The fundamental function of providing food and its environmental and social implications place agriculture at the forefront of political dynamics aimed at promoting sustainable development in some countries and regions. This is the case in the European Union, where agriculture is the main focus of the common policy. In this context, the quantitative evaluation of agricultural sustainability is relevant (Sala, 2020). For this reason, a brief description of sustainability frameworks and calculation methods is included below as they are relevant aspects for assessing agricultural sustainability.

1.3.1. Framework to represent sustainability

Different frameworks are proposed to represent sustainability, ranging from approaches in which only the environmental and social dimensions are distinguished, with an emphasis on a broad definition of the relationships between society and the environment (Giddings et al., 2002), to approaches where the economic (Van Cauwenbergh et al., 2007) and the institutional or governance dimension (FAO, 2014) are differentiated from the social dimension. In this regard, the most popular proposal is that which separately identifies the economic, social and environmental dimensions. Sustainability in each dimension is represented by items that seek to reflect the dynamics (maintain, increase or decrease) of the capitals implicit in each dimension. Overall sustainability is among the imperatives established in the integration of the dimensions; namely viable between the economic and the environmental, equitable between the economic and the social, and bearable between the social and the environmental. These imperatives are related to the trade-off levels established in the integrations mentioned above, an understanding that human activities, such as agriculture, simultaneously generate results in different directions (positive and adverse) in each of the dimensions of sustainability. Along these lines, the framework most widely used to represent and evaluate agricultural sustainability is the triple bottom line (TBL) (Figure 1.5 A). This framework was initially proposed by Elkington (Elkington, 1998) to account for and evaluate business results within the framework of sustainable development (Alhaddi, 2015; Bahadur and Waqqas, 2013).

One of the main criticisms to the framework represented in Fig. 1.5A refers to the non-existence of independence between the three dimensions (considering them as sectors) and the inaccuracy affording the same importance to the dimensions by representing them in circles of similar size (Giddings et al., 2002). Moreover, integrity, as a representative factor of the sustainability of each dimension, is formed by indicators representing the dynamics of the capitals (and not as sectors) that can be defined as independent items interconnected to achieve the goal sought (global sustainability and intermediate imperatives).

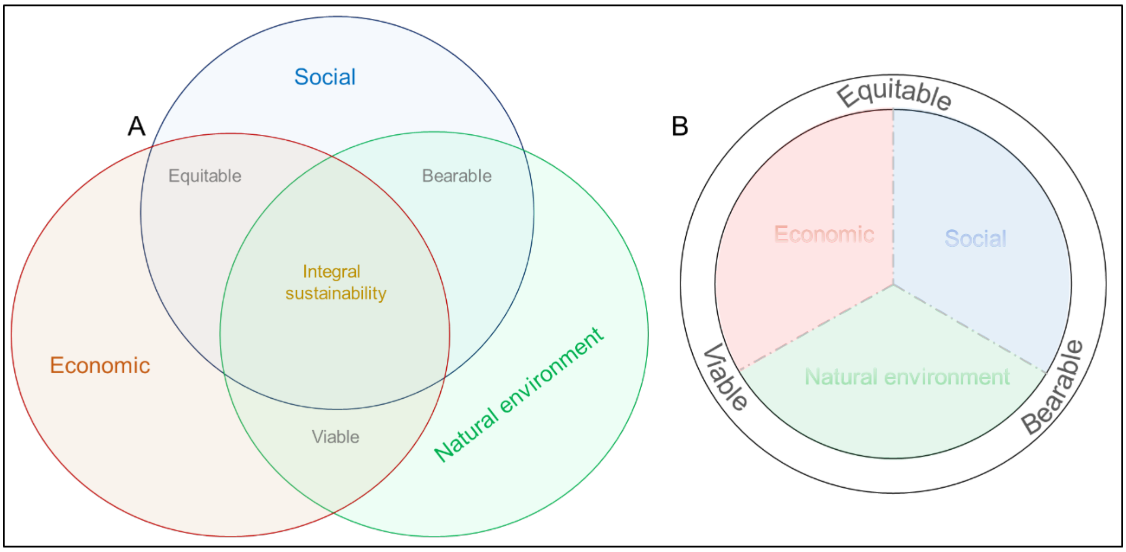

Fig. 1.5: Sustainability triple bottom line framework. A: Inductive approach B: Deductive approach.

In addition, the fact that the three circles are of the same sizes can be understood as a matter of graphic convenience since, pragmatically, the weight given to each dimension determines its size or importance. The TBL, as presented in Fig. 1.5A, can be understood as a framework developed from an inductive approach in which comprehensive sustainability is reached from the sustainability of each dimension. In this framework, the different figures formed from the integrity and integration make sense depending on the type of sustainability analysed, namely the circles when the analysis focuses on an individual dimension, the intermediate curvilinear triangles when two dimensions are studied, and the central curvilinear triangle when global sustainability is assessed. Another way of understanding this framework would be from a deductive approach (Fig. 1.5B) in which global sustainability is a desired whole, where the different objectives sought by human beings in interaction with their social and natural environment converge and diverge. In this way, although there is no real separation between dimensions (represented by the dotted lines between them), artificial divisions are conveniently established to highlight and evaluate particular or partial aspects of interest (e.g. environmental, social and economic sustainability).

1.3.2. Quantitative tools for agricultural sustainability assessment

The literature offers up a wide set of approaches and tools for the purposes of assessing agricultural sustainability. Tools based on life cycle thinking are the most widely used to individually study the dimensions of sustainability. For instance, environmental life cycle assessment (E-LCA) works to assess the potential adverse environmental impacts of a product, service or system (Martínez-Alvarez et al., 2023; Nicolò et al., 2018; Ribal et al., 2019). Social life cycle assessment (S-LCA) assesses social sustainability issues (Huertas-Valdivia et al., 2020; Iofrida et al., 2017); whereas life cycle costing (LCC) deals with the economic aspects of sustainability (Degieter et al., 2022; Escobar et al., 2022). The highly heterogeneous nature of agricultural systems and some particular features of these methodologies make it more complex to use them to assess agricultural sustainability. For instance, the representativeness of activity data (especially in regionalised studies) and a proper definition of the functional unit in E-LCA (Cerutti et al., 2014;

Pradeleix et al., 2022) are relevant challenges implicit in these methods. In addition, on-field emissions are crucial in E-LCA, and the lack of consensus and structured databases are issues to be solved in S-LCA and LCC (Frank et al., 2020; Mohamad et al., 2014).

E-LCA is a methodology that has been widely used in this thesis. It is suitable for the assessment of the environmental impact of a product or service from the production of raw materials to the end-of-life (ISO, 2017, 2006a, 2006b). An E-LCA comprises four main phases, namely goal and scope definition, inventory analysis (LCI), impact assessment (LCIA), and interpretation. In the first phase, relevant issues of the study are stablished such as the identification of the purpose of the study, the definition of the target audience, the decision context, the functional unit and the system boundaries, all of which are decisive for all the remaining LCA phases. The FU represents the base from which the LCA results are expressed and interpreted; thus, it must also properly satisfy the need for information of the target audience. The system boundaries determine the scope throughout the system's life cycle, considering the geographical, time horizon and technical limits. Both FU and system boundaries should be similar in comparative LCAs (Escobar, 2016). Depending on the purpose of the study, the LCA should be developed under a decision-context that determines the LCI modelling framework (such as attributional or consequential). The ILCD Handbook (EC-JRC, 2010) defines four potential decision contexts to perform an LCA. Two of them directly addresses to decision support at the micro-level (A) and the meso/macro-level (B) and are related to the consequential LCI framework. The other two focus on accounting and providing information about a specific system and moment including (C1) or not (C2) interactions with other systems. The LCI is the most data-intensive phase of an LCA because it implies accounting for all the inflows and outflows of the system. The definition of the attributional and consequential framework is a relevant aspect of this phase to be highlighted. Generally, attributional modelling sees at the system as a static technosphere, quantifying the inventory using historical and fact-based data, and it is thus helpful for developing accounting, retrospective or descriptive studies. On the other hand, consequential modelling is change-oriented since it seeks to quantify the consequences that a decision has on the systems, whether it be partial or total. This is usually applied in a hypothetic generic supply chain and works to develop marginal or prospective analysis. In the LCIA phase, the data estimated in the LCI phase are related using characterisation methods (e.g. ReCiPe or Product Environmental Footprint, PEF) to assess the potential environmental impacts of the system at the midpoint, endpoint or at a comprehensive level. Midpoint indicators show the impacts on the environmental dynamics (e.g. climate change and eutrophication). On the other hand, endpoint indicators express the impacts as damage done to an area of human interest (i.e. human health, natural ecosystems and abiotic resources); whereas a comprehensive indicator (e.g. environmental footprint-EF) represents the environmental impacts using a composite index. It must be highlighted that normalisation and weighting processes are needed for both endpoint and EF indicators. Finally, in the interpretation phase, the results are interpreted with the other phases through a feedback process, depending on the goal of the study; for instance, by assessing the sensitivity and uncertainty of the results.

Eco-efficiency, described in ISO 14045 (ISO, 2012), is one of the most widely used concepts for the purposes of simultaneously assessing the economic and environmental aspects (Fusco et al., 2023; Li et al., 2023). This tool has been popularised by the World Business Council for Sustainable Development (WBCS) in 1992, in an attempt to link business to sustainable development (Coluccia et al., 2020), by assessing the efficiency with which ecological resources are used to meet human needs (Magrini, 2021; Picazo-Tadeo et al., 2011). In practice, two main category approaches are found for the modelling of eco-efficiency, the first is based on a ratio between desirable and undesirable outputs (ratio method), whereas in the second, eco-efficiency is assessed as the operational efficiency but taking into account both desirable and undesirable outputs as well as the influence of the inputs (Berre et al., 2015; Gancone et al., 2017; Pishgar-Komleh et al., 2021; Rosano Peña et al., 2018; Rybaczewska-Błazejowska and Gierulski, 2018; You and Zhang, 2016). The most straightforward and communicative representation of eco-efficiency is a ratio using only one indicator in the numerator and denominator (Heijungs, 2022; Song and Chen, 2019); however, this method exhibits some nuances depending on the indicators used to represent the economic and environmental dimensions and the role that they play in the ratio. The aim of the most common ratio is maximisation, where the benefit is in the numerator and the environmental damage in the denominator, interpreted as an environmental productivity indicator (Heijungs, 2022; Müller et al., 2015; Orea and Wall, 2017), in line with the WBCS (WBCS, 2006) and the ISO 14045 (ISO, 2012). The United Nations adopts the opposite approach, in which eco-efficiency is understood as an environmental intensity indicator. This approach estimates similar indicators to those of a life cycle assessment expressed per economic or financial functional unit (Mouron et al., 2006; UNCTAD, 2004).

A widely applied strategy concerning the assessment of overall sustainability is constructing a composite indicator (Such as Gómez-Limón and Sanchez-Fernandez, 2010; Mili and Martínez-Vega, 2019). Along these lines, the European Commission (EC) proposes a comprehensive protocol with which develop composite indicators to assess multidimensional concepts, such as sustainability (JRC, 2008). Regardless of the protocol followed, multi-criteria decision analysis (MCDA) techniques play a critical role in the development of composite indicators and in the analysis of the overall sustainability, particularly for weighting and aggregating indicators. To this end, techniques such as the analytic hierarchy process-AHP and principal component analysis-PCA can be helpful in both processes.

Overall, weighting techniques can be either normative or positive. The normative techniques are based on the opinions of experts and external decision-makers (e.g. analytic hierarchy process-AHP pairwise comparison-based, Delphi, simple multi-attribute ranking technique-SMART); however, positive methods are based on mathematical and statistical procedures without considering value judgments (e.g. entropy, criteria importance through inter-criteria correlation-CRITIC, principal component analysis-PCA and data envelopment analysis-DEA) (Gómez-Limón and Sanchez-Fernandez, 2010; Odu, 2019; Zardari et al., 2015). On the other hand, aggregation techniques can be classified according to whether or not they allow the trade-off between attributes. In the first group, methods may be found such as AHP and simple additive weighting-SAW. Among those that do not allow trade-offs, the elimination and choice translating reality-ELECTRE family, dominance and disjunctive methods can be highlighted. In addition, the proposal of Díaz-Balteiro and Romero (2004), where SAW is joined with the Leontief preference model (Garg, 2014), allows the aggregation with different trade-off levels from total to null compensation between individual attributes. It is worth noting that the implementation of multivariate techniques, such as PCA, Cluster analysis, variance-based methods, linear regression and structural equations, have proved to be beneficial in the exploration of the dataset structure, the uncertainty and sensitivity analysis, or so as relate the composite indicator with exogenous-model factors.

1.4.Motivation for the dissertation

Quantitative indicators are a valuable input in the establishment of qualitative categories with which to make informed decisions when assessing alternatives. In terms of sustainability, quantitative indicators that allow an understanding of the performance of current practices represent a relevant starting point in transitioning to sustainable agriculture (Benoît et al., 2012; Pradeleix et al., 2022) since they help to identify hot spots and determine the magnitude of the differences in sustainability between alternatives forms of production. Given the current global crisis and its effects on Spanish agriculture, it is essential to carry out an in-depth examination into its sustainability by providing holistic indicators and emphasising the close link between agriculture and the environment (Streimikis and Baležentis, 2020). Although many studies focus on the topics of interest contained in this thesis, up-to-date studies that develop environmental and overall sustainability indicators for several agricultural units in Spain have yet to be found. The Development of this kind of study poses methodological challenges, as described below.

As mentioned above, LCA is the most widely used methodological framework with which to assess the environmental impacts of agriculture. Nevertheless, challenges must be met regarding the inventory analysis phase when developing agricultural LCAs for a range of agricultural units. These challenges are mainly due to the data-intensive characteristics of the LCI phase and the significant variability and uncertainty of agricultural systems, which are associated with climate and soil features and also with the farm management practices. In particular, a critical aspect of agricultural systems is the modelling of fertiliser and pesticide emissions. Having representative activity data with which to assess sustainability is another critical issue associated with the data-intensive characteristic of farming inventories, especially when the evaluation is performed at the regional level. Another debatable aspect of agricultural LCAs is the definition of the functional unit, which determines the presentation and interpretation of the results, mainly when developing comparative studies. As to the methodological challenges of assessing overall sustainability, the representation of the normative component of the sustainability concept is crucial. In particular, there is an ongoing discussion about the source from which the weights assigned to attributes and dimensions should be obtained and the trade-off level that should be considered when the sustainability attributes are aggregated in a composite indicator.

1.5.Goal of the dissertation

According to the motivation of the dissertation, the main goal of this doctoral thesis is to provide quantitative indicators to assess sustainability performance of Spanish agriculture at the regional level overall and into the environmental dimension. To this end, some methodological challenges must be addressed, which implies reaching the following specific goals:

- The assessment of the influence of the methods used to estimate on-field emissions in agricultural LCAs depending on site specificity level.
- The development of a multi-product approach to assessing the environmental impacts of the leading Spanish crops from representative inventories incorporating regional and temporal specificities and considering the uncertainty of the input parameters.
- The exploration of the use of a functional unit that properly represents the economic role of agricultural systems according to the target audience.
- The modelling of normative aspects when overall agriculture sustainability is assessed based on a composite indicator.

1.6.Methodological overview

Different tools were used to meet the goals of this dissertation. Environmental sustainability is analysed by applying an attributional LCA approach (ISO, 2017, 2006a, 2006b) under an account decision context (C) following to the ILCD Handbook (EC-JRC, 2010). On the other hand, global sustainability is assessed by constructing a composite sustainability indicator following the protocol of the European Joint Research Centre (JRC, 2008). As to the data sources, the annual studies into the costs and incomes of agricultural holdings, known as ECREA according to the Spanish acronym, were the central source of information; in addition, other statistic sources and some primary ones (interviews with experts) were considered.

Fig. 1.6. provides an overall structure of the dissertation. Chapter I is focused on a brief discussion regarding the theoretical framework of the agricultural sustainability and a characterisation of Spanish agriculture. In addition, the relevance and the definition of the goals of this dissertation are established, together with a framework for the methodological overview. Chapter II corresponds to the results section, in which the main goal is comprehensively developed, resulting in four sections, each addressing some specific goals. In section 2.1, the environmental impact of the conventional and organic vineyards in the Utiel-Requena DOP is assessed. This case study tackles the first specific goal, and the influence of the on-field emission modelling on the environmental indicators is analysed. Sections 2.2 and 2.3 respond to the second specific goal, developing an approach to estimate the environmental impacts from regionalised activity data that has been applied to the main representative crops of each region. Section 2.3 also provides an answer to the

third specific goal since it proposes an economic functional unit fitted to the target audience of the study in order to express and compare the environmental impacts of different agricultural commodities. The fourth specific goal is addressed in section 2.4, in which a composite indicator is developed to assess the overall sustainability performance of Spanish agriculture at a regional level, taking into account the preferences of the decision-makers and modelling the trade-off level between sustainability attributes.

What should be noted is the relationship between the sections in Chapter II, since the results of a subsection contribute to the development of the subsequent one. In this vein, the methods identified in section 2.1 as the best with which to model on-field emissions are used in sections 2.2 and 2.3, which develop an approach for the purposes of estimating agricultural inventories from farm accountancy. In section 2.4, the approach developed in section 2.2 and 2.3 is used to estimate the activity data of the agricultural holdings, whose environmental impacts are subsequently evaluated by using midpoint and endpoint impact indicators. The endpoint indicators estimated in section 2.4 are some of the sustainability attributes integrated into the environmental and social dimensions used for the development of the composite indicator in section 2.5.

In Chapter III, an overall discussion of the dissertation is presented; in addition, the results of section 2.4 are further analysed by proposing an inferential methodology that allows a deeper interpretation, since the focus of section 2.4 centres around modelling and accounting issues and even though the data variability is estimated, only their central tendency is analysed. In particular, the basis for the expression of the environmental footprint (EF) estimated in section 2.4 is an economic functional unit: the net value added at the factor cost. This is a type of eco-efficiency ratio, which is understood as an environmental intensity indicator that shows the potential environmental damage generated in the obtaining of a unit of economic or financial benefit (Mouron et al., 2006; UNCTAD, 2004). The analysis extension is concerned with the identification of homogeneous groups and any significant differences that may exist. The group of holdings that significantly show the best EF performance emulates the relative eco-efficient frontier, which is the reference for benchmarking. In particular, the percentage that each group should reduce its Dunn rank ($DunnRank_i$) in order to reach the eco-efficient frontier ($Dunnrank_0$) is considered as the non-eco-efficient measure ($NonEco_i$, %):

$$NonEco_i = \left(1 - \frac{DunnRank_0}{DunnRank_i}\right) 100 \tag{1.1}$$

A sample of 1,000 EF score simulations for each reference holding is used (Annex E.1, Table E1). These simulations are estimated from the approach and statistics gathered in the sections2.2 and 2.3. Due to the fact the simulations are not normally distributed, non-parametric techniques are used. In this vein, the Kruskal-Wallis and Dunn tests are used to assess the global and pairwise differences. These tests are run from "kruskal_test" and "dunn_test" functions of the "rstatix" package available in R Studio software (Kassambara, 2023).

Finally, Chapters IV and V include the overall conclusions of the dissertation and the annexes, respectively.

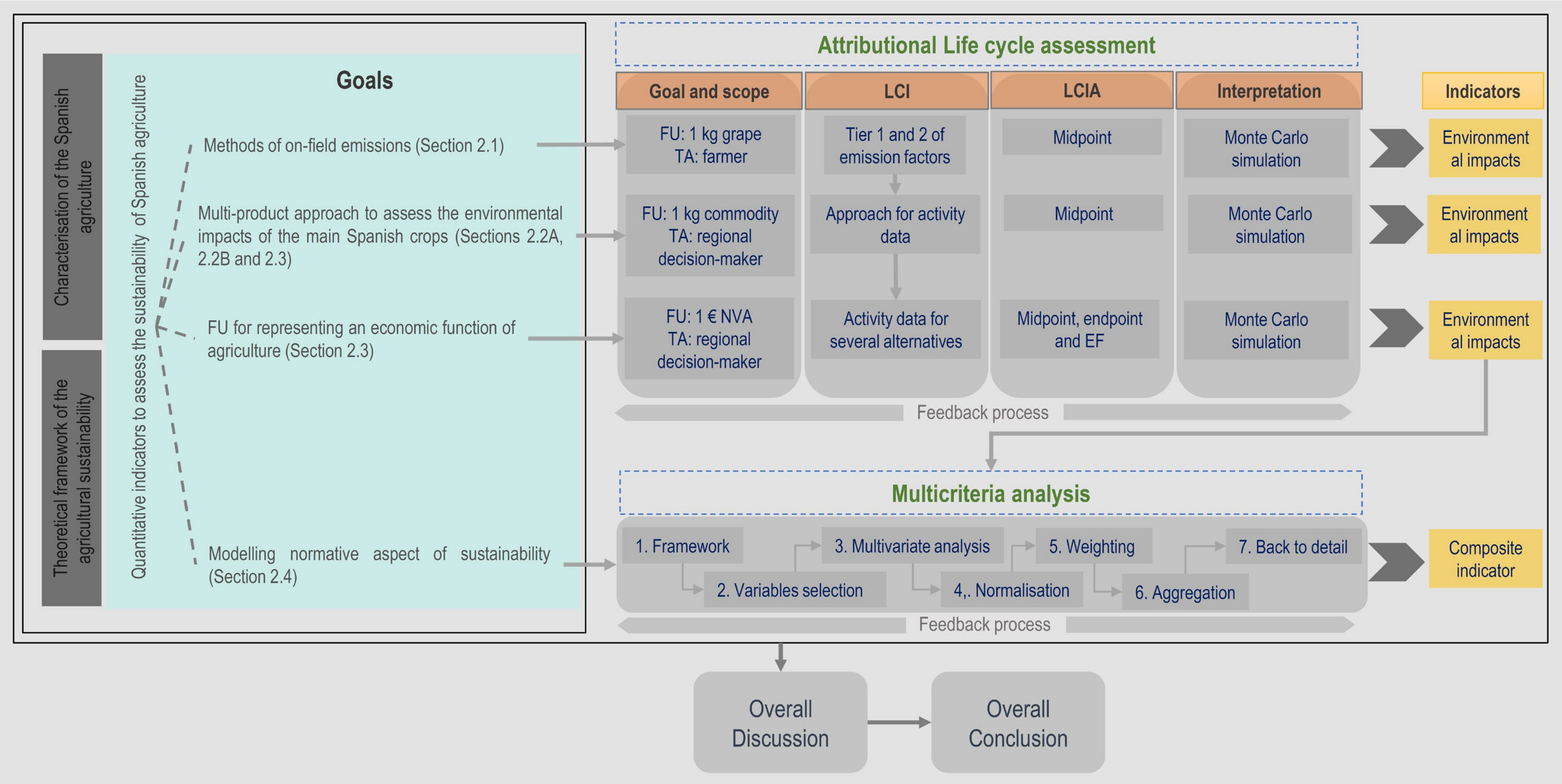

Fig. 1.6. Structure of the dissertation. FU: functional unit; EF: environmental footprint; LCI: life cycle inventory; LCIA: life cycle impact assessment; TA: target audience.

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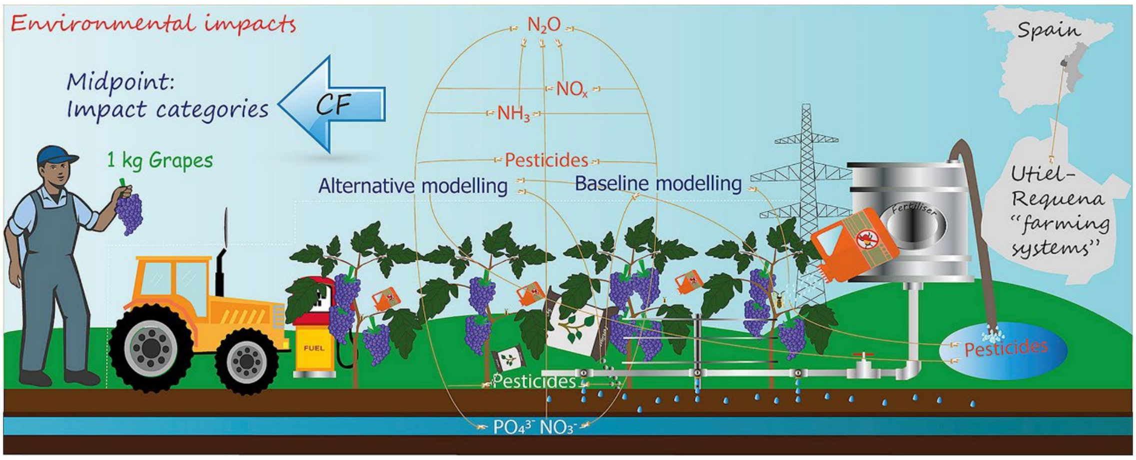
CHAPTER II. RESULTS

Journal of Environmental Management, 2020, 262:110325 [Published]

2.1. Title: Assessing the environmental impact of Spanish vineyards in Utiel-Requena PDO: the influence of farm management and on-field emission modelling.



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Abstract

Environmental studies into wine from different protected designations of origin (PDO) highlight farming and packaging stages as those contributing the most to the total environmental impacts of this product. However, farming impact, not only depends on the agricultural practices but also on data quality and modelling complexity. By using the life cycle assessment methodology, a twofold goal is aimed. Firstly, to analyse the environmental profile of the most widespread viticultural practices in the Utiel-Requena PDO (Spain). The second aim is to evaluate the differences between the environmental impacts estimated by means of modelling approaches using generic information (Baseline modelling) versus those using site-specific information (Alternative modelling). As regards the agricultural practices and grape cultivars, eight systems were defined and assessed per kg of grape at the farm gate. The differences between farming systems and modelling approaches were statistically assessed. The results show that, regardless of the grape cultivar, organic systems are more environmentally friendly than the conventional ones (on average, the greatest differences occur in the ionizing radiation, marine eutrophication and land use, being the values for organic vineyards 1678%, 648% and 171% lower than those of the conventional ones, respectively), the results for the Bobal cultivar being better than those for the Tempranillo because of the higher yield (differences in yield around 1.500 kg ha^{-1}). The use of site-specific modelling approaches guarantees the precision of the analysis; however, for some impact categories, namely climate change, fine particulate matter formation, marine eutrophication and terrestrial acidification, the possibility of using general methodologies is open; in this way, the modelling efforts can be minimised, and the results would be consistent with those of more specific methodologies. The results also underline the need for a consensus within LCA practitioners on which methodologies to use in order to estimate on-field emissions taking into account both complexity reduction and accuracy improvement.

Keywords

conventional farming, organic farming, fertiliser emission, pesticide fate, environmental impacts, vineyard.

2.1.1. Introduction

Agriculture as an anthropogenic activity generates significant externalities, both positive and negative, towards the well-being of the planet (Bruinsma, 2017). Among other aspects, negative externalities are associated with significant contributions to climate change (FAO, 2014), land degradation and soil erosion (Pereyra et al., 2020; Rodrigo-Comino, Brevik & Cerdà, 2018; Prosdocimi, Cerdà & Tarolli, 2016), freshwater depletion (Villanueva-Rey et al., 2018) and pollution from plant nutrients and pesticides (Renouf et al., 2018). Within agri-food sectors, wine stands out as one of the most important in the global food market (Bonamente et al., 2016; Bosco et al., 2011), especially in the European Mediterranean countries (Spain, Italy and France), which are the main wine producers in the world.

According to data from the International Organization of Vine and Wine (OIV, 2017), in 2016, Spain was the third biggest wine producer in the world, with the largest vineyard area, and the first world exporter of wine in terms of volume. In fact, grapes are the second most important Spanish commodity, after olives (Meneses, Torres & Castells, 2016). The Utiel-Requena protected designation of origin (PDO) is an important wine supplier in Spain (CAMACCDR, 2019a). Utiel-Requena is the PDO with the greatest grape area in the region and the fifth largest in Spain, with 6% of the total grape crop (MAPAMA, 2018a). According to the *Consejo Regulador de Utiel-Requena* PDO (2019), Bobal and Tempranillo are the main grape cultivars in the PDO, with 75% and 12% of the cultivated area, respectively.

Nowadays, international and governmental organizations are promoting environmental awareness in all human activities, making information available to the population and encouraging the inclusion of environmental parameters in consumer purchasing decisions (Martins et al., 2018; Schmidt Rivera et al., 2017). Along these lines, shared efforts between the different economic stakeholders have been developed. These efforts seek to improve the environmental profile of products and services from the technological point of view, creating innovative technologies which are more environmentally friendly, together with the development of methodologies that allow a better estimate of the environmental impacts generated by human activities.

Several environmental assessment studies applied to wine (Bosco et al., 2011; Bartocci et al., 2017; Petti, De Camillis, Raggi, & Vale, 2015) highlight the farming and packaging stages as those contributing the most to the total environmental impacts of wine. In this sense, organic farming is often proposed as a solution to mitigate the environmental effects caused by conventional farming (Seufert et al., 2012), which are mainly associated with a greater use of synthetic fertilisers and pesticides (Villanueva-Rey et al., 2014) and intensive tillage (Keesstra et al., 2018; Rodrigo-Comino et al., 2018). However, results tend to vary depending on the functional unit, and although the analyses per farm area usually show a greater impact of conventional agriculture, when taking the yield into account, the values of organic farming are higher in some impact categories (Meier et al., 2015).

Life cycle assessment (LCA) is a widely accepted methodology for evaluating the potential environmental impacts associated with the agri-food chain in general and with agricultural production systems in particular (Bosco et al., 2011; Schmidt Rivera et al., 2017). One of the main challenges when applying LCA to agricultural systems is that of modelling the emissions from fertiliser and pesticide application when performing the inventory analysis (Peña et al., 2019; Schmidt Rivera et al., 2017). These emissions are often estimated through models which consider generic emission factors (EFs). Specifically, the ones proposed in the IPCC (2006a) Tier 1 have been widely applied to estimate nitrogen emissions from fertilisers (e.g. Bacenetti et al., 2016; Ponstein, Meyer-aurich, & Prochnow, 2019; Ribal et al., 2017; Steenwerth et al., 2015), whereas the SALCA-P model (Prasuhn, 2006) is recommended by Nemecek et al. (2014) to estimate PO_4^{3-} emissions. In addition, the model proposed by Margni et al. (2002) is among the most widely used to calculate pesticide fate (e.g. Fusi et al., 2014; Neto, Diaz & Machado, 2013). However, other models take into account site-specific aspects, namely climate and soil characteristics. Among the most commonly used, both the one proposed by Brentrup et al. (2000) for fertiliser emissions and the PestLCI for pesticide fate can be highlighted (e.g. Bacenetti et al., 2015; Vázquez-Rowe et al., 2012; Villanueva-Rey et al., 2014). Consequently, some studies have discussed the implications of choosing different nitrogen fertiliser and pesticide emission models in the LCA of agricultural products (e.g. Goglio et al., 2018; Peña et al., 2019; Perrin et al., 2014; Perrin et al., 2017; Peter et al., 2016; Schmidt Rivera et al., 2017). Likewise, Peña et al. (2019) developed a proposal to calculate pesticide fates which was contrasted with two other models, the one from Margni et al. (2002), which considers fixed share percentages, versus another one that not only takes into account the initial distribution (i.e., application method and crop characteristics) but also includes field emissions (Balsari et al., 2007; Felsot et al., 2010; Gil et al., 2014; Gil & Sinfort, 2005).

When comparing modelling approaches (MA) for emissions derived from fertiliser and pesticide application, the direct correlation implicit between the accuracy of the estimates and the effort made to obtain the information needed for the model is an important issue to be evaluated. It can be assumed that MA using site-specific information (S_{MA}) are more accurate in their estimates than those requiring generic information (G_{MA}). Hence, when environmental impacts are estimated considering S_{MA} and the results are significantly different from those estimated considering G_{MA}, the choice of S_{MA} is suggested, although greater efforts are required to obtain the model data (IPCC, 2006b). Conversely, if no significant differences are observed or in the absence of more accurate information, G_{MA} allow reliable estimates to be computed.

LCA has been applied to different Spanish wine PDOs, such as Conca de Barberà in Catalonia (Meneses et al., 2016), Ribeiro in Galicia (Vazquez-Rowe et al., 2012; Villanueva-Rey et al., 2014; 2018) or la Rioja (Gazulla et al., 2010; Flor et al., 2018). In addition, other studies have addressed different aspects related to winemaking in Spain (e.g. González-García et al., 2011; Rives et al., 2011). In order to produce new LCA-related results for the Spanish wine sector, this study aims to analyse the environmental profile of the most widespread viticultural practices in the Utiel-Requena PDO. In addition, since the influence of the estimation of fertiliser and pesticide emission models in vineyards has not been previously addressed, this study also aims to evaluate the differences between the environment impacts estimated considering G_{MA} (Baseline modelling or BM) versus S_{MA} (Alternative modelling or AM) in vineyards.

2.1.2. Materials and methods

This study was carried out applying the LCA methodology based on ISO standard guidelines (ISO, 2006a; 2006b; ISO, 2017) and using Gabi software v. 9.2.0.58 (Thinkstep, Leinfelden-Enchterdigen, Germany).

2.1.2.1. Study area

Utiel-Requena is located in the west of the Valencian region (Fig. 2.1.1) and comprising nine municipalities, it is 60-90 km from the Mediterranean and at 600 to 900 m above sea level. This region has a Mediterranean climate with continental features. Its average annual rainfall is 385 mm, with a wet period of 7 months (October to April), a semi-humid period of 2 months (May and September) and a dry period of 3 months (from June to August). The average temperature is about 14.6 ºC with a maximum of 20.6 ºC and a minimum of 8.6 ºC. As to the soil characteristics, it corresponds to Mediterranean red soils, of sedimentary origin, with limestone and siliceous characteristics and with a second horizon of clay accumulation is stand out (Buesa et al., 2017; IVIA, 2019).

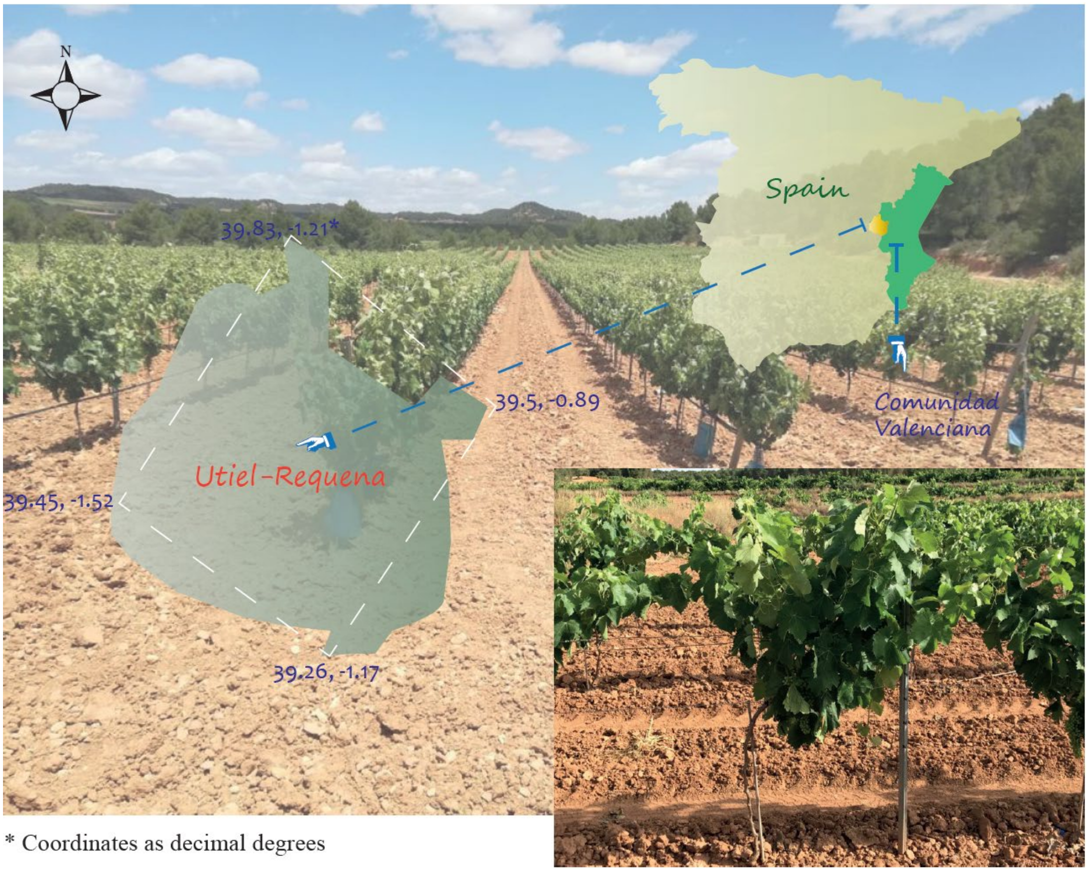


Fig. 2.1.1. Description of the area of study

2.1.2.2. Goal and scope

This LCA aims to carry out an environmental characterization of the most representative crop management systems in the production of wine grapes in the Utiel-Requena PDO and to evaluate the influence of fertiliser and pesticide emission modelling on the environmental profiles of the analysed systems. For this assessment, a season with standard agroclimatic conditions is considered. Following Villanueva-Rey et al. (2018), the functional unit (FU) is 1 kg of harvested grapes. System boundaries are set at the farm gate and the life cycle stages shown in Fig. 2.1.2 have been taken into account. The system is structured from the most representative agricultural practices for wine grape production in the Utiel-Requena PDO and it includes both the emissions caused by the production of inputs and those derived from field operations, especially the use of fertilisers, pesticides and machinery.

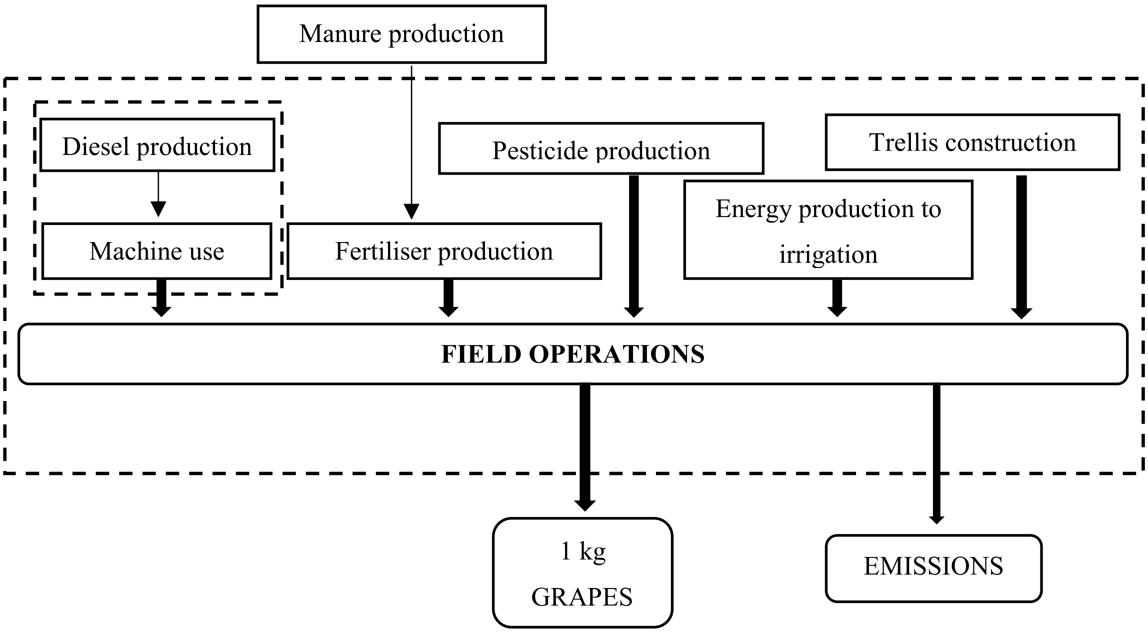


Fig. 2.1.2. System boundaries.

Using direct interviews with technical staff of grape production cooperatives belonging to the PDO as a starting point, information on both the most common agricultural practices and the amount of inputs used was obtained. Although conventional farming was identified as the most common system in the PDO, organic farming is on the increase; in addition, within each system there are two types of technical management. The first one consists of goblet spur pruning without irrigation (gs-rainfed crop), while in the second one double guyot cane pruning with trellis is used and the crop is irrigated (dg-irrigated). Moreover, considering the main grape cultivars in the PDO (Bobal and Tempranillo), for the purposes of this study, eight representative productive systems have been configured (Fig. 2.1.3).

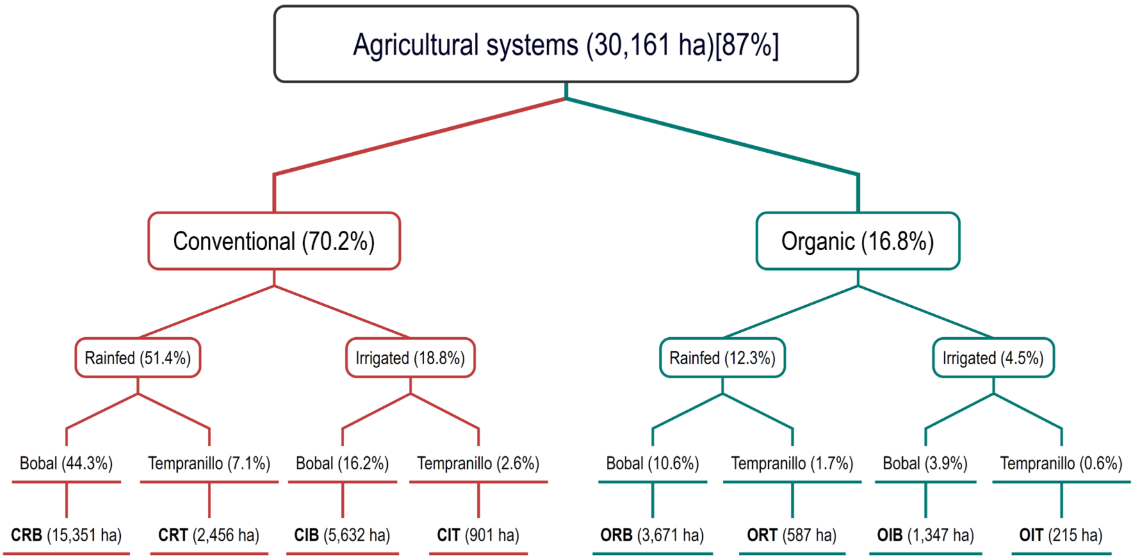


Fig. 2.1.3. Representative crop management systems of grape production in the Utiel-Requena PDO. In brackets, the area of each productive system is shown together with the percentage of area with respect to the total agricultural area in the PDO. (CAMACCDR, 2019b; Consejo Regulador de Utiel-Requena DO, 2019). CRB: conventional system, with goblet spur pruning, rainfed, Bobal variety; CRT: conventional system, with goblet spur pruning, rainfed, Tempranillo variety ; CIB: conventional system, with goblet guyot cane pruning with trellis, irrigated, Bobal variety; CIT: conventional system, with goblet guyot cane pruning with trellis, irrigated, Tempranillo variety; ORB: organic system, with goblet spur pruning, rainfed, Bobal variety; ORT: organic system, with goblet spur pruning, rainfed, Tempranillo variety ; OIB: organic system, with goblet guyot cane pruning with trellis, irrigated, Bobal variety; OIT: organic system, with goblet guyot cane pruning with trellis, irrigated, Tempranillo variety.

Fig. 2.1.3 also shows the total vineyard surface area corresponding to the systems studied in the PDO, the area of each productive system together with the percentage of area of each one with respect to the total agricultural area in the PDO, estimated from official data (CAMACCDR, 2019b; Consejo Regulador de Utiel-Requena PDO, 2019).

2.1.2.3. Life cycle inventory (LCI)

Tables 2.1.1 and 2.1.2 show the inputs and outputs, respectively, used in the environmental assessment of 1 kg of Bobal and Tempranillo grapes in the Utiel-Requena PDO for each productive system. In the subsequent sections, these data are detailed.

2.1.2.3.1. Agricultural field operations

Field operations in the gs-rainfed systems (CRB, CRT, ORB and ORT) include different activities, namely pruning, tillage, the application of fertilisers and pesticides, and harvesting. For the dg-irrigated systems (CIB, CIT, OIB and OIT), besides the activities included in the gs-rainfed ones, the trellis construction and irrigation activities are added.

2.1.2.3.2. Input production

The impacts from production of the inputs consumed have been calculated using the processes from different databases; namely, Ecoinvent 3.5 (Wernet et al., 2016) for the Spanish electricity mix, pesticides, potassium 0-0-15 and ammonium sulphate, and Professional Gabi 8.7 for diesel, NPK 15-15-15 and galvanized steel production, and machinery use. Table 2.1.1 shows the inputs consumption for each alternative.

It must be pointed out that manure and tractor production are not considered. Sheep manure has a low economic value and its environmental burdens are allocated to other co-products derived from sheep farming. The tractor has a relatively long economic life; therefore, the loads associated with 1 kg grapes are not significant. As to the trellis construction, only the production of galvanised steel is included because it was identified as the only material with relative importance.

Table 2.1.1. LCI Inputs.

	CRB	CRT	CIB	CIT	ORB	ORT	OIB	OIT
Inputs kg of grapes^{-1}								
Pruning								
tractor use (h)	$1.4\cdot10^{-4}$	$1.7\cdot10^{-4}$	$4.4\cdot10^{-4}$	$5.7\cdot10^{-4}$	$1.8\cdot10^{-4}$	$2.2\cdot10^{-4}$	$5.3\cdot10^{-4}$	$7.3\cdot10^{-4}$
Tillage								
tractor use (h)	$1.3\cdot10^{-3}$	$1.5\cdot10^{-3}$	$8.3\cdot10^{-4}$	$1.1\cdot10^{-03}$	$1.6\cdot10^{-3}$	$2.0\cdot10^{-3}$	$1.0\cdot10^{-3}$	$1.4\cdot10^{-3}$
glyphosate (kg)			$5.0\cdot10^{-04}$	$6.4\cdot10^{-04}$				
Fertiliser application								
tractor use (h)	$1.4\cdot10^{-4}$	$1.7\cdot10^{-4}$	$1.1\cdot10^{-4}$	$1.4\cdot10^{-4}$	$1.2\cdot10^{-4}$	$1.5\cdot10^{-4}$	$8.9\cdot10^{-5}$	$1.2\cdot10^{-4}$
manure (kg)	$5.7\cdot10^{-1}$	$6.7\cdot10^{-1}$	$4.4\cdot10^{-1}$	$5.7\cdot10^{-1}$	$7.3\cdot10^{-1}$	$8.9\cdot10^{-1}$	$5.3\cdot10^{-1}$	$7.3\cdot10^{-1}$
NPK 15-15-15 (kg)	$1.2\cdot10^{-2}$	$1.4\cdot10^{-2}$						
ammonia sulphate (kg)			$2.2\cdot10^{-2}$	$2.9\cdot10^{-2}$				
potassium 0-0-15 (kg)			$4.7\cdot10^{-2}$	$6.1\cdot10^{-2}$				
Pesticide application								
tractor use (h)	$6.4\cdot10^{-4}$	$7.5\cdot10^{-4}$	$5.0\cdot10^{-4}$	$6.4\cdot10^{-4}$	$5.5\cdot10^{-4}$	$6.7\cdot10^{-4}$	$4.0\cdot10^{-4}$	$5.5\cdot10^{-4}$
copper oxychloride (kg)	$2.1\cdot10^{-3}$	$2.5\cdot10^{-3}$	$1.7\cdot10^{-3}$	$2.1\cdot10^{-3}$	$1.8\cdot10^{-3}$	$2.2\cdot10^{-3}$	$1.3\cdot10^{-3}$	$1.8\cdot10^{-3}$
sulphur (kg)	$8.6\cdot10^{-3}$	$1.0\cdot10^{-2}$	$6.7\cdot10^{-3}$	$8.6\cdot10^{-3}$	$7.3\cdot10^{-3}$	$8.9\cdot10^{-3}$	$5.3\cdot10^{-3}$	$7.3\cdot10^{-3}$
Irrigation								
water (l)			$7.9\cdot10^{1}$	$1.0\cdot10^{2}$			$9.5\cdot10^{1}$	$1.3\cdot10^{2}$
energy (MJ)			$7.9\cdot10^{-3}$	$1.0\cdot10^{-2}$			$9.5\cdot10^{-3}$	$1.3\cdot10^{-2}$
Trellis								
galvanized steel (kg)			$2.6\cdot10^{-1}$	$3.3\cdot10^{-1}$			$3.1\cdot10^{-1}$	$4.2\cdot10^{-1}$
Harvest								
tractor use (h)	$6.0\cdot10^{-5}$	$6.9\cdot10^{-5}$	$2.2\cdot10^{-5}$	$2.9\cdot10^{-5}$	$6.0\cdot10^{-5}$	$7.3\cdot10^{-5}$	$2.7\cdot10^{-5}$	$3.6\cdot10^{-5}$
harvester use (h)			$6.5\cdot10^{-5}$	$8.3\cdot10^{-5}$			$7.8\cdot10^{-5}$	$1.1\cdot10^{-4}$

CRB: conventional system, with goblet spur pruning, rainfed, Bobal variety; CRT: conventional system, with goblet spur pruning, rainfed, Tempranillo variety; CIB: conventional system, double guyot cane pruning with trellis, irrigated, Bobal variety; CIT: conventional system, double guyot cane pruning with trellis, irrigated, Tempranillo variety; ORB: organic system, with goblet spur pruning, rainfed, Bobal variety; ORT: organic system, with goblet spur pruning, rainfed, Tempranillo variety; OIB: organic system, double guyot cane pruning with trellis, irrigated, Bobal variety; OIT: organic system, double guyot cane pruning with trellis, irrigated, Tempranillo variety.

2.1.2.3.3. Emissions from fertiliser and pesticide application

The methodological approaches compared in this study follow different guidelines. Namely, in the BM, the IPCC (2006a) Tier 1 guidelines and SALCA-P model (Prasuhn, 2006) were used to estimate nitrogen emissions (direct and indirect N_2O, NH_3, NO_x and NO_3^-) and PO_4^{3-} emissions from fertilisers, respectively; whereas pesticide fate was estimated from Margni et al. (2002). On the other hand, in the AM, different modelling approaches were used for fertiliser emissions. Direct N_2O emissions were estimated according to the IPCC (2006a) Tier 2, using an EF for grape cultivation in the Mediterranean region from Cayuela et al.

(2017), whereas indirect N_2O emissions were estimated following IPCC (2006a). As to NH_3, the Tier 2 EF of the European Environmental Agency guidelines (EMEP/EEA, 2019a) was used. For NO_x emissions, the Tier 1 EF from the same source was used, since no Tier 2 EF is proposed. Likewise, NO_3^- and PO_4^{3-} emissions were determined from nitrogen and phosphorus balances following MAPAMA (2018b;2018c). The primary data for the estimations are detailed on the annex (See A.2).

Table 2.1.2. LCI outputs generated.

	CRB	**CRT**	**CIB**	**CIT**	**ORB**	**ORT**	**OIB**	**OIT**
Outputs								
To the technosphere (kg ha^{-1})								
Products								
Grapes	7,000	6,000	9,000	7,000	5,500	4,500	7,500	5,500
To the environment kg grapes^{-1}								
Fertiliser emissions								
N_2O total_BM (kg)	$1.3\cdot10^{-4}$	$1.5\cdot10^{-4}$	$1.5\cdot10^{-4}$	$1.9\cdot10^{-4}$	$1.3\cdot10^{-4}$	$1.5\cdot10^{-4}$	$9.2\cdot10^{-5}$	$1.3\cdot10^{-4}$
N_2O total_AM (kg)	$4.2\cdot10^{-5}$	$5.9\cdot10^{-5}$	$1.1\cdot10^{-4}$	$1.6\cdot10^{-4}$	$4.2\cdot10^{-5}$	$6.0\cdot10^{-5}$	$5.1\cdot10^{-5}$	$6.9\cdot10^{-5}$
N_2O direct _BM (kg)	$1.1\cdot10^{-4}$	$1.2\cdot10^{-4}$	$1.3\cdot10^{-4}$	$1.7\cdot10^{-4}$	$1.0\cdot10^{-4}$	$1.2\cdot10^{-4}$	$7.5\cdot10^{-5}$	$1.0\cdot10^{-4}$
N_2O direct_AM (kg)	$3.1\cdot10^{-5}$	$3.6\cdot10^{-5}$	$6.7\cdot10^{-5}$	$8.7\cdot10^{-5}$	$3.1\cdot10^{-5}$	$3.8\cdot10^{-5}$	$4.3\cdot10^{-5}$	$5.9\cdot10^{-5}$
N_2O indirect_BM (kg)	$2.2\cdot10^{-5}$	$2.5\cdot10^{-5}$	$2.2\cdot10^{-5}$	$2.8\cdot10^{-5}$	$2.4\cdot10^{-5}$	$2.9\cdot10^{-5}$	$1.8\cdot10^{-5}$	$2.4\cdot10^{-5}$
N_2O indirect_AM (kg)	$1.1\cdot10^{-5}$	$2.2\cdot10^{-5}$	$3.8\cdot10^{-5}$	$7.0\cdot10^{-5}$	$1.0\cdot10^{-5}$	$2.2\cdot10^{-5}$	$7.7\cdot10^{-6}$	$1.0\cdot10^{-5}$
NH_3_BM (kg)	$8.7\cdot10^{-4}$	$1.0\cdot10^{-3}$	$8.8\cdot10^{-4}$	$1.1\cdot10^{-3}$	$9.7\cdot10^{-4}$	$1.2\cdot10^{-3}$	$7.1\cdot10^{-4}$	$9.7\cdot10^{-4}$
NH_3_AM (kg)	$6.7\cdot10^{-4}$	$7.8\cdot10^{-4}$	$1.2\cdot10^{-3}$	$1.5\cdot10^{-3}$	$6.4\cdot10^{-4}$	$7.8\cdot10^{-4}$	$4.7\cdot10^{-4}$	$6.4\cdot10^{-4}$
NO_X_BM (kg)	$1.4\cdot10^{-3}$	$1.6\cdot10^{-3}$	$1.4\cdot10^{-3}$	$1.8\cdot10^{-3}$	$1.5\cdot10^{-3}$	$1.9\cdot10^{-3}$	$1.1\cdot10^{-3}$	$1.5\cdot10^{-3}$
NO_X_AM (kg)	$3.0\cdot10^{-4}$	$3.5\cdot10^{-4}$	$3.4\cdot10^{-4}$	$4.4\cdot10^{-4}$	$3.0\cdot10^{-4}$	$3.7\cdot10^{-4}$	$2.2\cdot10^{-4}$	$3.0\cdot10^{-4}$
NO_3^-_BM (kg)	0	0	0	0	0	0	0	0
NO_3^-_AM (kg)	0	$3.6\cdot10^{-3}$	$7.5\cdot10^{-3}$	$1.8\cdot10^{-2}$	0	$3.5\cdot10^{-3}$	0	0
PO_4^{3-} _BM (kg)	$2.3\cdot10^{-3}$	$2.6\cdot10^{-3}$	$1.0\cdot10^{-3}$	$1.3\cdot10^{-3}$	$1.7\cdot10^{-3}$	$2.0\cdot10^{-3}$	$1.2\cdot10^{-3}$	$1.7\cdot10^{-3}$
PO_4^{3-} _AM (kg)	0	0	0	0	0	0	0	0
Pesticide emissions								
glyphosate to air_BM (kg)	0	0	$3.1\cdot10^{-5}$	$3.9\cdot10^{-5}$	0	0	0	0
glyphosate to agricultural soil_BM (kg)	0	0	$2.3\cdot10^{-4}$	$3.0\cdot10^{-4}$	0	0	0	0
glyphosate to fresh water_BM (kg)	0	0	$2.6\cdot10^{-5}$	$3.3\cdot10^{-5}$	0	0	0	0
glyphosate to air_AM (kg)	0	0	$1.5\cdot10^{-5}$	$2.0\cdot10^{-5}$	0	0	0	0
glyphosate to fresh water_AM (kg)	0	0	$2.6\cdot10^{-7}$	$3.3\cdot10^{-7}$	0	0	0	0
glyphosate to agricultural soil_AM (kg)	0	0	$8.4\cdot10^{-5}$	$1.1\cdot10^{-4}$	0	0	0	0
glyphosate to other soil_AM (kg)	0	0	$2.4\cdot10^{-5}$	$3.1\cdot10^{-5}$	0	0	0	0
copper oxychloride to air_BM (kg)	$7.5\cdot10^{-5}$	$8.8\cdot10^{-5}$	$5.8\cdot10^{-5}$	$7.5\cdot10^{-5}$	$6.4\cdot10^{-5}$	$7.8\cdot10^{-5}$	$4.7\cdot10^{-5}$	$6.4\cdot10^{-5}$
copper oxychloride to agricultural soil_BM (kg)	$5.7\cdot10^{-4}$	$6.7\cdot10^{-4}$	$4.5\cdot10^{-4}$	$5.7\cdot10^{-4}$	$4.9\cdot10^{-4}$	$6.0\cdot10^{-4}$	$3.6\cdot10^{-4}$	$4.9\cdot10^{-4}$
copper oxychloride to fresh water_BM (kg)	$6.4\cdot10^{-5}$	$7.4\cdot10^{-5}$	$5.0\cdot10^{-5}$	$6.4\cdot10^{-5}$	$5.4\cdot10^{-5}$	$6.6\cdot10^{-5}$	$4.0\cdot10^{-5}$	$5.4\cdot10^{-5}$
copper oxychloride to air_AM (kg)	$7.5\cdot10^{-6}$	$8.7\cdot10^{-6}$	$5.8\cdot10^{-6}$	$7.5\cdot10^{-6}$	$6.4\cdot10^{-6}$	$7.8\cdot10^{-6}$	$4.7\cdot10^{-6}$	$6.4\cdot10^{-6}$
copper oxychloride to fresh water_AM (kg)	$6.4\cdot10^{-7}$	$7.4\cdot10^{-7}$	$5.0\cdot10^{-7}$	$6.4\cdot10^{-7}$	$5.4\cdot10^{-7}$	$6.6\cdot10^{-7}$	$4.0\cdot10^{-7}$	$5.4\cdot10^{-7}$
copper oxychloride to agricultural soil_AM (kg)	$2.5\cdot10^{-4}$	$3.0\cdot10^{-4}$	$1.7\cdot10^{-4}$	$2.1\cdot10^{-4}$	$2.2\cdot10^{-4}$	$2.6\cdot10^{-4}$	$1.3\cdot10^{-4}$	$1.8\cdot10^{-4}$
copper oxychloride to other soil_AM (kg)	$6.2\cdot10^{-5}$	$7.3\cdot10^{-5}$	$4.9\cdot10^{-5}$	$6.2\cdot10^{-5}$	$5.3\cdot10^{-5}$	$6.5\cdot10^{-5}$	$3.9\cdot10^{-5}$	$5.3\cdot10^{-5}$
sulphur to air_BM (kg)	$8.5\cdot10^{-4}$	$9.9\cdot10^{-4}$	$6.6\cdot10^{-4}$	$8.5\cdot10^{-4}$	$7.2\cdot10^{-4}$	$8.8\cdot10^{-4}$	$5.3\cdot10^{-4}$	$7.2\cdot10^{-4}$
sulphur to agricultural soil_BM (kg)	$6.5\cdot10^{-3}$	$7.6\cdot10^{-3}$	$5.0\cdot10^{-3}$	$6.5\cdot10^{-3}$	$5.5\cdot10^{-3}$	$6.7\cdot10^{-3}$	$4.0\cdot10^{-3}$	$5.5\cdot10^{-3}$
sulphur to fresh water_BM (kg)	$7.2\cdot10^{-4}$	$8.4\cdot10^{-4}$	$5.6\cdot10^{-4}$	$7.2\cdot10^{-4}$	$6.1\cdot10^{-4}$	$7.5\cdot10^{-4}$	$4.5\cdot10^{-4}$	$6.1\cdot10^{-4}$
sulphur to air_AM (kg)	$1.3\cdot10^{-3}$	$1.5\cdot10^{-3}$	$9.9\cdot10^{-4}$	$1.3\cdot10^{-3}$	$1.1\cdot10^{-3}$	$1.3\cdot10^{-3}$	$7.9\cdot10^{-4}$	$1.1\cdot10^{-3}$
sulphur to fresh water_AM (kg)	$7.2\cdot10^{-6}$	$8.4\cdot10^{-6}$	$5.6\cdot10^{-6}$	$7.2\cdot10^{-6}$	$6.1\cdot10^{-6}$	$7.5\cdot10^{-6}$	$4.5\cdot10^{-6}$	$6.1\cdot10^{-6}$
sulphur to agricultural soil_AM (kg)	$2.5\cdot10^{-3}$	$2.9\cdot10^{-3}$	$1.6\cdot10^{-3}$	$2.1\cdot10^{-3}$	$2.1\cdot10^{-3}$	$2.6\cdot10^{-3}$	$1.3\cdot10^{-3}$	$1.8\cdot10^{-3}$
sulphur to other soil_AM (kg)	$6.1\cdot10^{-4}$	$7.1\cdot10^{-4}$	$4.7\cdot10^{-4}$	$6.1\cdot10^{-4}$	$5.1\cdot10^{-4}$	$6.3\cdot10^{-4}$	$3.8\cdot10^{-4}$	$5.1\cdot10^{-4}$

BM: baseline modelling; AM: alternative modelling; CRB: conventional system, with goblet spur pruning, rainfed, Bobal variety; CRT: conventional system, with goblet spur pruning, rainfed, Tempranillo variety; CIB: conventional system, double guyot cane pruning with trellis, irrigated, Bobal variety; CIT: conventional system, double guyot cane pruning with trellis, irrigated, Tempranillo variety; ORB: organic system, with goblet spur pruning, rainfed, Bobal variety; ORT: organic system, with goblet spur pruning, rainfed, Tempranillo variety; OIB: organic system, double guyot cane pruning with trellis, irrigated, Bobal variety; OIT: organic system, double guyot cane pruning with trellis, irrigated, Tempranillo variety.

Table 2.1.2 shows the on-field emissions for each production system and methodological approach. It must be noted that NO_3^- emissions are zero with BM because, according to the IPCC (2006a), if the difference between the rainfall during the rainy season and the potential evaporation in the same period is lower than the soil water holding capacity and drip irrigation is carried out, the leaching fraction is zero. On the other hand, PO_4^{3-}emissions are zero when using AM, whereas NO_3^- are also zero in CRB, ORB, OIB and OIT, because in these cases the phosphorus and nitrogen balances were negative. Finally, it is worth mentioning that, in general, the emissions from conventional irrigation models tend to be higher than those from the other productive systems. However, some heterogeneity is found which is further analysed along with the characterization of the environmental impacts.

When estimating pesticide emissions according to Peña et al. (2019), data from different sources were used. On the one hand, the leaf area index (LAI) was obtained from Pérez Bartolomé (2002) taking the simple average of the LAI for June over three consecutive years. The capture coefficient (Kp) was 0.55 (Peña et al., 2019), while the water-to-soil area ratio of 0.01 was obtained from Juraske & Sanjuán (2011). Finally, following Balsari et al. (2007) and with data from the Julius Kühn Institute (JKI, 2019), the drift percentage was set at 17% with a 50% reduction for the use of anti-drift nozzles; therefore, the drift percentage remained at 8.5%.

2.1.2.3.4. Blue water consumption from irrigation

Following AWARE guidelines (Pieper, Kupfer, Thylmann, & Bos, 2018), blue water consumption was estimated through the crop evapotranspiration by using equation (2.1.1):

$$ETc = Kc \cdot ETo \qquad (2.1.1)$$

Where, ETc is the crop evapotranspiration (mm·day-1), Kc is the crop coefficient (dimensionless), and ETo is the reference crop evapotranspiration (mm·d-1). Both ETo and KC were obtained as the average of the data for the Requena municipality published by IVIA (2019) corresponding to the last ten years (2009-2018). In annex A.1, detailed estimates of blue water consumption are shown.

2.1.2.4. Impact categories and impact assessment methods

The impact categories normally analysed in LCAs were calculated in this study, namely: climate change (CC) as CO_2-eq. for a time horizon of 100 years (kg); fine particulate matter formation (FPMF) as kg PM2.5 eq.; fossil (FD) and 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; ionizing radiation (IR) as Bq C-60 eq. to air; water scarcity (WS) as m^3 world equiv.; freshwater ecotoxicity (ET) as CTUe; both cancer (HTc) and non-cancer (HTnc) human toxicity as CTUh. The toxicity related impact categories were characterized through UseTox 2.3 (Hauschild et al., 2008; Rosenbaum et al., 2008), the water scarcity category with AWARE (Boulay et al., 2018) and for the remaining categories, the ReCiPe 2016 v1.1 method was used (Huijbregts et al., 2017). It should be mentioned that for the HTnc and ET, interim characterization factors were used to compute the effects of on-field pesticide emissions, as there are no recommended characterization factors for copper-based pesticides. It should also be noted that there are no characterization factors available for sulphur-based pesticides; hence, their toxic consequences were not taken into account.

2.1.2.5. Statistical analysis

The interpretation of the results is carried out from both descriptive and inferential analyses. The descriptive analysis allows a first approximation to identify the relative contribution of the different sources of emissions or the consumption of resources to each impact category and suggest possible differences between the results of the productive systems and methodological approaches analysed. The inferential analysis seeks to assess whether the differences identified in the descriptive analysis are statistically significant or not, to this end the IBM SPSS statistics software v25 was used. The Mann-Whiney U test was identified as the most appropriate technique for the development of the inferential comparisons. This is due to the fact that when applying Shapiro-Wilk and Kolmogorov-Smirnov tests to small samples (n <30) and large samples (n> 30), respectively, no normality in the distributions of each dependent variable analysed was found at a 5% significance level; in addition, it has been considered that there is no interdependence among the classification variables. In this study, the sample size is determined by combining the productive systems with the methodological approaches to estimate the emissions from fertilisers and pesticides. A 5% significance level is used; hence, when Mann-Whiney U's p-value is lower than 5%, it means that there are significant differences between the compared results. Detailed information about the statistical methodology applied in this study can be found in MacFarland & Yates (2016).

2.1.3. Results

2.1.3.1. Productive systems

Table 2.1.3 shows the results of the environmental impacts for each productive system using the AM and BM emissions estimation, while Fig. 2.1.4 shows the contribution analysis. It can be observed how field operations, together with the production of fertilisers and pesticides, are the main sources of environmental impacts in the conventional systems. In the context of the organic system, field operations, together with the use of machinery and pesticide production, are the main contributors to most of the impact categories. Nevertheless, in some productive systems, such as organic dg-irrigated systems (OIB, OIT), both irrigation and trellis construction take on importance for some environmental impact categories (CC, FD, LU, MD and IR). The high relative contribution that on-field emissions from fertilisers and pesticides (field operation) make to many impact categories (CC, FPMF, FwE, ME, POFh, POFe, SOD, TA, ET and HTnc) underlines the fact that the model used to estimate these emissions can modify the relative contribution of the life cycle stages to the total impact.

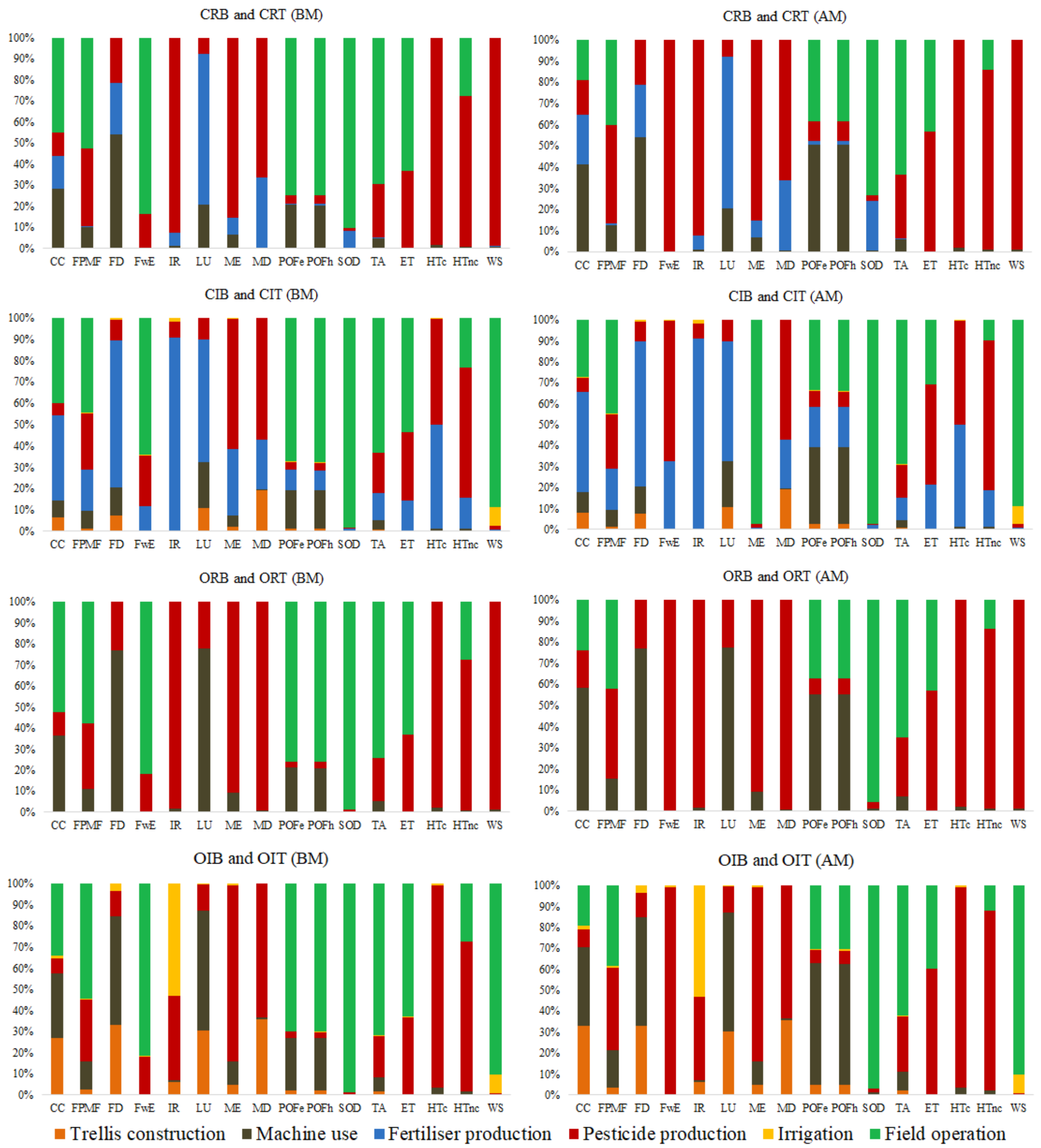
A first analysis of the environmental impacts obtained for the production systems being analysed (Table 2.1.3) indicates that, generally speaking, the environment impacts are higher for the Tempranillo cultivar than for the Bobal in every category. This is because, for a fixed amount of applied inputs, the yield of the Tempranillo grape cultivar is lower and, consequently, the environmental impacts generated per kg grapes are greater than those for the Bobal cultivar. As can be observed in Table 2.1.3, excepting the WS category, the heaviest pollutants are the conventional dg-irrigated systems (CIB and CIT) due to the fact that more synthetic fertilisers (specifically, ammonium sulphate and potassium 0-0-15) are used in these systems than in the others. Although potassium fertiliser is not associated with on-field emissions, the impacts related to its production contribute to the differences observed. As to the WS, organic dg-irrigated systems (OIB, OIT) are the ones that generate the greatest impact; this is because, despite the amount of water per hectare used being the same in every irrigated system, the organic dg-irrigated systems (OIB and OIT) are the ones with the lowest yield.

Table 2.1.3. Results of the environmental impacts of grape production in the Utiel-Requena PDO. FU: 1 kg grapes.

Impact Categories	**CRB**	**CRT**	**CIB**	**CIT**	**ORB**	**ORT**	**OIB**	**OIT**
Climate change [kg CO_2 eq.] BM	$9.3\cdot10^{-2}$	$1.1\cdot10^{-1}$	$2.5\cdot10^{-1}$	$3.2\cdot10^{-1}$	$7.8\cdot10^{-2}$	$9.6\cdot10^{-2}$	$9.2\cdot10^{-2}$	$1.3\cdot10^{-1}$
Climate change [kg CO_2 eq.] AM	$6.7\cdot10^{-2}$	$8.1\cdot10^{-2}$	$2.3\cdot10^{-1}$	$3.1\cdot10^{-1}$	$5.3\cdot10^{-2}$	$6.8\cdot10^{-2}$	$8.0\cdot10^{-2}$	$1.1\cdot10^{-1}$
Fine particulate matter formation [kg PM2.5 eq.] BM	$7.0\cdot10^{-4}$	$8.2\cdot10^{-4}$	$8.5\cdot10^{-4}$	$1.1\cdot10^{-3}$	$7.1\cdot10^{-4}$	$8.7\cdot10^{-4}$	$5.6\cdot10^{-4}$	$7.6\cdot10^{-4}$
Fine particulate matter formation [kg PM2.5 eq.] AM	$5.4\cdot10^{-4}$	$6.2\cdot10^{-4}$	$8.0\cdot10^{-4}$	$1.0\cdot10^{-3}$	$4.9\cdot10^{-4}$	$6.0\cdot10^{-4}$	$4.0\cdot10^{-4}$	$5.4\cdot10^{-4}$
Freshwater eutrophication [kg P eq.] BM	$8.9\cdot10^{-4}$	$1.0\cdot10^{-3}$	$5.2\cdot10^{-4}$	$6.7\cdot10^{-4}$	$6.7\cdot10^{-4}$	$8.2\cdot10^{-4}$	$4.9\cdot10^{-4}$	$6.7\cdot10^{-4}$
Freshwater eutrophication [kg P eq.] AM	$1.4\cdot10^{-4}$	$1.7\cdot10^{-4}$	$1.9\cdot10^{-4}$	$2.4\cdot10^{-4}$	$1.2\cdot10^{-4}$	$1.5\cdot10^{-4}$	$9.1\cdot10^{-5}$	$1.2\cdot10^{-4}$
Marine eutrophication [kg N eq.] BM	$1.1\cdot10^{-5}$	$1.3\cdot10^{-5}$	$1.3\cdot10^{-5}$	$1.7\cdot10^{-5}$	$8.8\cdot10^{-6}$	$1.1\cdot10^{-5}$	$7.0\cdot10^{-6}$	$9.5\cdot10^{-6}$
Marine eutrophication [kg N eq.] AM	$1.1\cdot10^{-5}$	$2.6\cdot10^{-4}$	$5.4\cdot10^{-4}$	$1.3\cdot10^{-3}$	$8.8\cdot10^{-6}$	$2.5\cdot10^{-4}$	$7.0\cdot10^{-6}$	$9.5\cdot10^{-6}$
Photochemical ozone formation, ecosystems [kg NOx eq.] BM	$1.9\cdot10^{-3}$	$2.2\cdot10^{-3}$	$2.2\cdot10^{-3}$	$2.8\cdot10^{-3}$	$2.1\cdot10^{-3}$	$2.6\cdot10^{-3}$	$1.7\cdot10^{-3}$	$2.3\cdot10^{-3}$
Photochemical ozone formation, Ecosystems [kg NOx eq.] AM	$8.2\cdot10^{-4}$	$9.6\cdot10^{-4}$	$1.1\cdot10^{-3}$	$1.4\cdot10^{-3}$	$8.4\cdot10^{-4}$	$1.0\cdot10^{-3}$	$7.6\cdot10^{-4}$	$1.0\cdot10^{-3}$
Photochemical ozone formation, human health [kg NOx eq.] BM	$1.9\cdot10^{-3}$	$2.2\cdot10^{-3}$	$2.2\cdot10^{-3}$	$2.8\cdot10^{-3}$	$2.1\cdot10^{-3}$	$2.5\cdot10^{-3}$	$1.7\cdot10^{-3}$	$2.3\cdot10^{-3}$
Photochemical ozone formation, human health [kg NOx eq.] AM	$8.2\cdot10^{-4}$	$9.5\cdot10^{-4}$	$1.1\cdot10^{-3}$	$1.4\cdot10^{-3}$	$8.4\cdot10^{-4}$	$1.0\cdot10^{-3}$	$7.6\cdot10^{-4}$	$1.0\cdot10^{-3}$
Stratospheric ozone depletion [kg CFC-11 eq.] BM	$1.6\cdot10^{-6}$	$1.8\cdot10^{-6}$	$1.7\cdot10^{-6}$	$2.2\cdot10^{-6}$	$1.4\cdot10^{-6}$	$1.7\cdot10^{-6}$	$1.0\cdot10^{-6}$	$1.4\cdot10^{-6}$
Stratospheric ozone depletion [kg CFC-11 eq.] AM	$6.4\cdot10^{-7}$	$8.5\cdot10^{-7}$	$1.2\cdot10^{-6}$	$1.8\cdot10^{-6}$	$4.8\cdot10^{-7}$	$6.9\cdot10^{-7}$	$5.8\cdot10^{-7}$	$7.9\cdot10^{-7}$
Terrestrial acidification [kg SO_2 eq.] BM	$3.2\cdot10^{-3}$	$3.7\cdot10^{-3}$	$3.6\cdot10^{-3}$	$4.6\cdot10^{-3}$	$3.3\cdot10^{-3}$	$4.1\cdot10^{-3}$	$2.5\cdot10^{-3}$	$3.5\cdot10^{-3}$
Terrestrial acidification [kg SO_2 eq.] AM	$2.4\cdot10^{-3}$	$2.8\cdot10^{-3}$	$3.8\cdot10^{-3}$	$4.9\cdot10^{-3}$	$2.2\cdot10^{-3}$	$2.7\cdot10^{-3}$	$1.7\cdot10^{-3}$	$2.4\cdot10^{-3}$
Human toxicity, non-canc. [CTUh] BM	$2.5\cdot10^{-7}$	$2.9\cdot10^{-7}$	$2.3\cdot10^{-7}$	$2.9\cdot10^{-7}$	$2.1\cdot10^{-7}$	$2.6\cdot10^{-7}$	$1.5\cdot10^{-7}$	$2.1\cdot10^{-7}$
Human toxicity, non-canc. [CTUh] AM	$2.1\cdot10^{-7}$	$2.4\cdot10^{-7}$	$2.0\cdot10^{-7}$	$2.5\cdot10^{-7}$	$1.8\cdot10^{-7}$	$2.2\cdot10^{-7}$	$1.3\cdot10^{-7}$	$1.7\cdot10^{-7}$
Freshwater ecotoxicity [CTUe] BM	$6.2\cdot10^{3}$	$7.2\cdot10^{3}$	$5.7\cdot10^{3}$	$7.3\cdot10^{3}$	$5.3\cdot10^{3}$	$6.4\cdot10^{3}$	$3.9\cdot10^{3}$	$5.3\cdot10^{3}$
Freshwater ecotoxicity [CTUe] AM	$4.0\cdot10^{3}$	$4.7\cdot10^{3}$	$3.8\cdot10^{3}$	$4.9\cdot10^{3}$	$3.4\cdot10^{3}$	$4.2\cdot10^{3}$	$2.4\cdot10^{3}$	$3.2\cdot10^{3}$
Fossil depletion [kg oil eq.]	$1.6\cdot10^{-2}$	$1.9\cdot10^{-2}$	$6.6\cdot10^{-2}$	$8.5\cdot10^{-2}$	$1.3\cdot10^{-2}$	$1.6\cdot10^{-2}$	$1.8\cdot10^{-2}$	$2.5\cdot10^{-2}$
Ionizing radiation [Bq C-60 eq. to air]	$8.9\cdot10^{-4}$	$1.0\cdot10^{-3}$	$3.5\cdot10^{-2}$	$4.5\cdot10^{-2}$	$7.1\cdot10^{-4}$	$8.7\cdot10^{-4}$	$1.3\cdot10^{-3}$	$1.8\cdot10^{-3}$
Land use [Annual crop eq.·y]	$9.0\cdot10^{-3}$	$1.0\cdot10^{-2}$	$8.2\cdot10^{-3}$	$1.1\cdot10^{-2}$	$2.7\cdot10^{-3}$	$3.2\cdot10^{-3}$	$3.5\cdot10^{-3}$	$4.7\cdot10^{-3}$
Metal depletion [kg Cu eq.]	$3.1\cdot10^{-3}$	$3.6\cdot10^{-3}$	$3.1\cdot10^{-3}$	$4.0\cdot10^{-3}$	$1.7\cdot10^{-3}$	$2.1\cdot10^{-3}$	$2.0\cdot10^{-3}$	$2.7\cdot10^{-3}$
Human toxicity, cancer [CTUh]	$9.1\cdot10^{-9}$	$1.1\cdot10^{-8}$	$1.5\cdot10^{-8}$	$1.9\cdot10^{-8}$	$7.8\cdot10^{-9}$	$9.5\cdot10^{-9}$	$5.8\cdot10^{-9}$	$7.9\cdot10^{-9}$
Water scarcity [m^3 world equiv.]	$6.4\cdot10^{-2}$	$7.5\cdot10^{-2}$	$3.5\cdot10^{0}$	$6.6\cdot10^{0}$	$5.4\cdot10^{-2}$	$6.7\cdot10^{-2}$	$4.2\cdot10^{0}$	$8.3\cdot10^{0}$

BM: baseline modelling; AM: alternative modelling; CRB: conventional system, with goblet spur pruning, rainfed, Bobal variety; CRT: conventional system, with goblet spur pruning, rainfed, Tempranillo variety; CIB: conventional system, double guyot cane pruning with trellis, irrigated, Bobal variety; CIT: conventional system, double guyot cane pruning with trellis, irrigated, Tempranillo variety; ORB: organic system, with goblet spur pruning, rainfed, Bobal variety; ORT: organic system, with goblet spur pruning, rainfed, Tempranillo variety; OIB: organic system, double guyot cane pruning with trellis, irrigated, Bobal variety; OIT: organic system, double guyot cane pruning with trellis, irrigated, Tempranillo variety.

Likewise, the impacts of conventional gs-rainfed systems (CRB, CRT) are greater than those of their organic peers (ORB, ORT) in every impact category, except POFh, POFe, FPMF and TA. These differences are associated with the production of pesticides, which are applied in greater quantity in conventional gs-rainfed systems, and also with the production of NPK 15-15-15, which is the only synthetic fertiliser applied in those conventional systems. In addition, the POFh and POFe values for organic gs-rainfed systems (ORB, ORT) are also higher with respect to the conventional gs-rainfed ones (CRB, CRT); this can be attributed to the higher NO_x emissions in the organic gs-rainfed systems brought about by the lower yield. As regards the FPMF and TA categories, comparisons between the gs-rainfed systems (CRT, CRB vs. ORT, ORB) evidence sensitivity to the modelling of NH_3 emissions.



BM: baseline modelling; AM: alternative modelling; CRB: conventional system, with goblet spur pruning, rainfed, Bobal variety; CRT: conventional system, with goblet spur pruning, rainfed, Tempranillo variety; CIB: conventional system, double guyot cane pruning with trellis, irrigated, Bobal variety; CIT: conventional system, double guyot cane pruning with trellis, irrigated, Tempranillo variety; ORB: organic system, with goblet spur pruning, rainfed, Bobal variety; ORT: organic system, with goblet spur pruning, rainfed, Tempranillo variety; OIB: organic system, double guyot cane pruning with trellis, irrigated, Bobal variety; OIT: organic system, double guyot cane pruning with trellis, irrigated, Tempranillo variety; CC: Climate change; FPMF: Fine particulate matter formation; FD: Fossil depletion; FeW: Freshwater eutrophication; IR: Ionizing radiation; LU: Land use; ME: Marine eutrophication; MD: Metal depletion; POFe: Photochemical ozone formation, ecosystems; POFh: Photochemical ozone formation, human health; SOD: Stratospheric ozone depletion; TA: Terrestrial acidification; ET: Freshwater ecotoxicity; HTc: Human toxicity, cancer; HTnc: Human toxicity, non-cancer; WS: Water scarcity.

Fig. 2.1.4. Relative contribution of life cycle stages to the environmental impacts of the productive systems.

Table 2.1.3 shows that when applying the BM approach, the results in these categories are favourable to those obtained the conventional gs-rainfed systems (CRB, CRT); conversely, when using the AM approach, opposite results are obtained. This is because NH_3 emissions per kg grapes are greater in the organic gs-rainfed systems and are overestimated when using the BM approach.

Table 2.1.4. Assessment of differences between productive factors per impact category analysed. Mann-Whiney U test, 5% significance level.

Impact Categories	**Tempranillo vs. Bobal**	**Conventional gs-rainfed vs. Organic gs-rainfed**	**Conventional dg-irrigated vs. Organic dg-irrigated**
Climate change	*	*	*
Fine particulate matter formation	*	nd	*
Fossil depletion	*	*	*
Freshwater eutrophication	*	*	*
Ionizing radiation	*	*	*
Land use	*	*	*
Marine eutrophication	*	*	*
Metal depletion	*	*	*
Photochemical ozone formation, ecosystems	*	**	*
Photochemical ozone formation, human health	*	**	*
Stratospheric ozone depletion	*	*	*
Terrestrial acidification	*	nd	*
Freshwater ecotoxicity	*	*	*
Human toxicity, cancer	*	*	*
Human toxicity, non-cancer	*	*	*
Water scarcity	*	*	**
nd: no differences	* Tempranillo > Bobal	* Conventional gs-rainfed > Organic gs-rainfed ** Organic gs-rainfed > Conventional gs-rainfed	* Conventional dg-irrigated > Organic dg-irrigated ** Organic dg-irrigated > Conventional dg-irrigated

Table 2.1.5. Assessment of differences between productive systems per impact category analysed. Mann-Whiney U test, 5% significance level.

	CRB	**CRT**	**CIB**	**CIT**	**ORB**	**ORT**	**OIB**	**OIT**
Climate change				**	*			
Fine particulate matter formation				**			*	
Fossil depletion				**	*			
Freshwater eutrophication		**		**			*	
Ionizing radiation				**	*			
Land use				**	*			
Marine eutrophication				**			*	
Metal depletion				**	*			
Photochemical ozone formation, Ecosystems				**			*	
Photochemical ozone formation, human health				**			*	
Stratospheric ozone depletion				**	*		*	
Terrestrial acidification				**			*	
Freshwater ecotoxicity				**			*	
Human toxicity, cancer				**			*	
Human toxicity, non-cancer				**			*	
Water scarcity					*			**

* Lowest impact; ** Greatest impact.
CRB: conventional system, with goblet spur pruning, rainfed, Bobal variety; CRT: conventional system, with goblet spur pruning, rainfed, Tempranillo variety; CIB: conventional system, double guyot cane pruning with trellis, irrigated, Bobal variety; CIT: conventional system, double guyot cane pruning with trellis, irrigated, Tempranillo variety; ORB: organic system, with goblet spur pruning, rainfed, Bobal variety; ORT: organic system, with goblet spur pruning, rainfed, Tempranillo variety; OIB: organic system, double guyot cane pruning with trellis, irrigated, Bobal variety; OIT: organic system, double guyot cane pruning with trellis, irrigated, Tempranillo variety.

Table 2.1.4 shows that all of these differences detailed in the above paragraphs are statistically significant, except in FPMF and TA in the gs-rainfed systems, which, as already mentioned, obtain different results depending on the modelling approach for NH_3 emissions. To sum up, the results in Table 2.1.5 suggest that of the analysed production systems, ORB is significantly more environmentally viable for CC, FD, IR, LU, MD and WS categories, whereas OIB is better for FPMF, FwE, ME, POFe, POFh TA, ET, HTc and HTnc categories. As to SOD, both OIB and ORB exhibit the lowest impact. Even though neither of these two systems present the best environmental profile individually, in none of the impact categories analysed do they have the worst environmental position. In this same vein, the worst environmental profile corresponds to the CIT system for every impact category except WS, where OIT is the worst. It must be highlighted that in the case of the FwE, no significant differences are found between CIT and CRT systems, thus sharing the worst position.

2.1.3.2. Emission modelling approaches

As to the modelling approach, the results of on-field fertiliser and pesticide emissions tend to be lower when applying AM than with BM; thus, for the impact categories in which those emissions have an effect, that is, CC, FPMF, FwE, POFe, POFh, SOD, TA, HTnc and ET, the results also lower (Table 2.1.3). However, it is worth mentioning that the NH_3 estimates for the conventional dg-irrigated systems (CIB and CIT) are higher with AM than with BM, making FPMF and TA higher in these production systems. In addition, as NO_3^- emissions for all the production systems are zero when using BM, ME is higher with AM than BM; however, when using AM, NO_3^- emissions are also zero for CRB, ORB, OIB and OIT production systems and no differences are observed for ME.

Table 2.1.6. Assessment of differences in modelling proposals for calculation of on-field emissions. Mann-Whiney U test, 5% significance level.

Impact Categories	**AM vs BM**	**N_2O**	**NH_3**	**NO_x**	**NO_3^-**	**PO_4^{3-}**	**Pesticides fate**
CC	nd	*	nd	nd	nd	nd	nd
FPMF	*	nd	nd	*	nd	nd	nd
FwE	*	nd	nd	nd	nd	*	nd
ME	nd	nd	nd	nd	nd	nd	nd
POFe	*	nd	nd	*	nd	nd	nd
POFh	*	nd	nd	*	nd	nd	nd
SOD	*	*	nd	nd	nd	nd	nd
TA	*a	nd	nd	*	nd	nd	nd
ET	*	nd	nd	nd	nd	nd	*
HTnc	*a	nd	nd	nd	nd	nd	*
	* BM>AM	* IPCC (2006a) Tier 1 > Tier 2		* IPCC (2006a) Tier 1 > EEA (2019a) Tier 1		* SALCA-P. >P Balance	* Margni et al. (2002) > Peña et al. (2019)

*a significance to 10%; nd: no significant differences found; BM: baseline modelling; AM: alternative modelling; CC: Climate change; FPMF: Fine particulate matter formation; FeW: Freshwater eutrophication; ME: Marine eutrophication; POFe: Photochemical ozone formation, ecosystems; POFh: Photochemical ozone formation, human health; SOD: Stratospheric ozone depletion; TA: Terrestrial acidification; ET: Freshwater ecotoxicity; HTnc: Human toxicity, non-canc.

Table 2.1.6 shows the significance of the differences between the methodological approaches to the estimation of on-field emissions. As expected, each emission-modelling approach is significant for those impact categories with which it is involved. That is, the modelling of N_2O emissions is significant for CC and SOD; NO_x modelling for PFMF, POFe, POFh and TA; PO_4^{3-} modelling for FwE and the modelling of pesticide emissions for HTnc and ET. The significant differences found suggest an overestimation of N_2O, NO_x, PO_4^{3-} and pesticide emissions when applying the BM approach with respect to those obtained with the AM approach. It should also be noted that, in the case of NH_3 and NO_3^- emissions, no significant differences were found between the two methodological approaches. Analysing the methodological approaches used (AM vs. BM) in an integral way (Table 2.1.6, first column), significant differences may be observed in the FPMF, FwE, POFe, POFh, SOD, TA, ET and HTnc impact categories. This indicates that the application of the BM approach instead of the AM leads to an overestimation of the results in every case. It is noteworthy that for the TA and HTnc impact categories the test was validated at 10% significance level, which is a widely accepted level for hypothesis tests, together with 5% and 1%.

2.1.3.3. Uncertainty Analysis

Models are a simplification of real systems and hence they are not exact, thus they inherently hold uncertainty. In this regard, modelling with specific data reduces uncertainty against generic modelling, since it reduces bias and better represents the complexity of the system under analysis (IPCC, 2006b). In this sense, it can be argued that the AM approach is more accurate and therefore with less uncertainty compared to the BM approach. However, it is possible that in the quantification of the uncertainty cases may occur in which the results show that the uncertainty of AM is greater than in BM; this is due to the incomplete quantification of the uncertainty either because of computational complexity or because of lack of information (IPCC, 2006b).

Table 2.1.7. Inputs parameters for uncertainty analysis

Parameter	Unit	Baseline	Min	Max	Source
Indirect N_2O from (NH_3+NO_X)	kg N_2O–N (kg NH_3–N + NO_X–N volatilised)$^{-1}$	1.00%	0.20%	5.00%	IPCC (2006a)
Indirect N_2O from (NO_3^-)	kg N_2O–N (kg N leaching/runoff)$^{-1}$	0.75%	0.05%	2.50%	IPCC (2006a)
BM					
Direct N_2O (EF)	kg N_2O-N kg N^{-1}	1.00%	0.30%	3.00%	IPCC (2006a)
NH_3 + NO_X (synthetic fertilisers)	(kg NH_3–N + NO_X–N) kg N^{-1}	10.00%	3.00%	30.00%	IPCC (2006a)
NH_3 + NO_X (Organic fertilisers)	(kg NH_3–N + NO_X–N) kg N^{-1}	20.00%	5.00%	50.00%	IPCC (2006a)
AM					
Direct N_2O rainfed (EF)	kg N_2O-N kg N^{-1}	0.27%	0.06%	0.48%	Cayuela et al. (2017)
Direct N_2O irrigated	kg N_2O-N kg N^{-1}	0.51%	0.25%	0.77%	Cayuela et al. (2017)
NO_X	Kg NO_X kg N^{-1}	4.00%	0.50%	10.40%	EEA (2019a)
NH_3_npk15	Kg NH_3 kg N^{-1}	9.40%	1.82%	23.50%	EEA (2019a; 2019b)
NH_3_sul_amo	Kg NH_3 kg N^{-1}	17.00%	1.82%	42.50%	EEA (2019a; 2019b)
NH_3_org	Kg NH_3 kg N^{-1}	8.00%	3.04%	20.00%	EEA (2019a; 2019b)

BM: baseline modelling; AM: alternative modelling.

For the present study, it is of interest to compare the uncertainty results between the two methodological approaches and for each of the productive models analysed. Following this idea, the uncertainty in the calculated impacts was estimated from the explicit uncertainty range of the emission factors used in the modelling approaches analysed (BM and AM). Due to lack of information in the literature used for the emission factors, latent uncertainties in NO_3^-, PO_4^{3-} emissions and pesticide fates were not considered for the uncertainty estimation. Consequently, only the explicit uncertainty for N_2O, NH_3 and NO_X emissions was considered (Table 2.1.7).

Table 2.1.8. Results of the Monte Carlo simulations of conventional system, with goblet spur pruning, rainfed, Bobal variety (CRB).

Impact categories	Mean	Variation coefficient	10%	90%
Climate change, default, excl biogenic carbon BM	$1.46 \cdot 10^{-1}$	33%	$8.81 \cdot 10^{-2}$	$2.13 \cdot 10^{-1}$
Climate change, default, excl biogenic carbon AM	$8.22 \cdot 10^{-2}$	22%	$6.27 \cdot 10^{-2}$	$1.07 \cdot 10^{-1}$
Fine Particulate Matter Formation BM	$9.26 \cdot 10^{-4}$	26%	$6.32 \cdot 10^{-4}$	$1.25 \cdot 10^{-3}$
Fine Particulate Matter Formation AM	$6.64 \cdot 10^{-4}$	23%	$4.78 \cdot 10^{-4}$	$8.70 \cdot 10^{-4}$
Photochemical Ozone Formation, Ecosystems BM	$2.66 \cdot 10^{-3}$	52%	$1.05 \cdot 10^{-3}$	$4.57 \cdot 10^{-3}$
Photochemical Ozone Formation, Ecosystems AM	$9.66 \cdot 10^{-4}$	37%	$5.59 \cdot 10^{-4}$	$1.45 \cdot 10^{-3}$
Photochemical Ozone Formation, Human Health BM	$2.65 \cdot 10^{-3}$	53%	$1.04 \cdot 10^{-3}$	$4.57 \cdot 10^{-3}$
Photochemical Ozone Formation, Human Health AM	$9.60 \cdot 10^{-4}$	37%	$5.54 \cdot 10^{-4}$	$1.45 \cdot 10^{-3}$
Stratospheric Ozone Depletion BM	$3.55 \cdot 10^{-6}$	51%	$1.40 \cdot 10^{-6}$	$6.00 \cdot 10^{-6}$
Stratospheric Ozone Depletion AM	$1.18 \cdot 10^{-6}$	56%	$4.61 \cdot 10^{-7}$	$2.10 \cdot 10^{-6}$
Terrestrial Acidification BM	$4.61 \cdot 10^{-3}$	38%	$2.44 \cdot 10^{-3}$	$7.05 \cdot 10^{-3}$
Terrestrial Acidification AM	$3.38 \cdot 10^{-3}$	37%	$1.92 \cdot 10^{-3}$	$5.01 \cdot 10^{-3}$

AM: baseline modelling; BM: alternative modelling.

The variation coefficient was used as a proxy variable to describe the uncertainty in each impact category in which the estimates are susceptible to changes due to changes in NH_3, NO_X and N_2O emissions. The variation coefficient is a relative dispersion statistic which allows the variability experienced in several models to be compared. The variation coefficients were obtained by applying Monte Carlo simulations to each production model within the framework of each modelling approach. The contribution to the uncertainty of the emission factors was assessed by means of 5,000 runs of the Monte Carlo simulation using the GaBi v. 9.2.0.58 Analyst Tool.

Table 2.1.8 shows the results of the Monte Carlo simulation for the CRB production system, whereas the results for the remaining productive systems are shown in annex A.3. From the variation coefficient two patterns can be observed. On the one hand, for CRB, CRT, ORB, ORT, OIB and OIT systems, higher coefficients with BM versus AM are observed, except in SOD. On the other hand, in CIB and CIT production systems, variation coefficients are also higher in BM, although in this case the exceptions are FPMF and TA. In general terms, these results show that the quantified uncertainty is greater when using BM versus AM. This supports the results of table 6, which shows the relevance of using the AM approach to analyse impact categories such as CC, FPMF, POFe, POFh and TA.

2.1.4. Discussion

In the context of this study, the Bobal cultivar is found to have a better environmental profile than the Tempranillo, due to the former's higher yield. Specifically, the results permit the organic production of Bobal grapes to be recommended as a feasible alternative to mitigate the environmental damage associated with farming. Nevertheless, in the cases of POFh and POFe, the conventional gs-rainfed systems are a better environmental alternative than the organic gs-rainfed ones. As regards FPMF and TA, not enough evidence was found to support the statement that the conventional gs-rainfed systems generate a greater environmental impact is than the organic gs-rainfed ones. Along these lines, there is a wide margin for improvement; in the short and medium term one proposal could be to replace conventional Bobal crops (approximately 60.5% of the agricultural area of Utiel-Requena) and conventional Tempranillo crops (approximately 9.7% of the agricultural area of Utiel-Requena) for their peers in organic farming. In the transition of Tempranillo crops from conventional to organic, it is recommended to start by changing CIT to OIT because CIT is the heaviest pollutant of all the systems analysed. Another alternative likely to improve the environmental profile of the Utiel-Requena vineyards is that of changing from the Tempranillo cultivar to Bobal. However, this would require greater technical and economic efforts and this cultivar imparts specific characteristics to wine. It is, thus, worth mentioning that this recommendation only considers an environmental approach and it is sensitive to the inclusion of social, quality and/or economic variables in the analysis.

It is important to state that these results may become sensitive to the functional unit; for instance, one considering the profit associated with each productive model. However, due to the scope of this investigation and the uncertainty and volatility of the economic variables of the productive sector being analysed, a kilogram of harvested grapes was considered as the functional unit.

On the other hand, the significant share of on-field fertiliser and pesticide emissions in most of the impact categories makes the modelling approaches a critical point of special interest when applying LCA to agricultural systems. The results of the inferential analysis indicate that, depending on the environmental impact category being analysed, the use of site-specific methodologies guarantees the precision of the analysis. Generic estimation approaches are presented as a robust alternative in the analysis of CC and ME; in this way, the modelling efforts can be minimised, and the results would be consistent with those of more specific methodologies. However, as to the results of FwE, POFe, POFh, SOD, TA, ET and HTnc, the use of the generic modelling approaches shows a significant overestimation when compared to the site-specific ones. When analysing the influence of the modelling approach on each individual emission, there is a greater consistency in the modelling of the NH_3 and NO_3^- emissions in which no significant differences were found, this is not the case when the rest of the emissions are modelled.

The results of this study are consistent with those from Schmidt Rivera et al. (2017) and Peter et al (2016) insofar as there is an overestimation of the environmental impacts associated with on-field fertiliser emissions using generic modelling approaches as compared to those approaches using site-specific information. In line with that found by Goglio et al. (2018), the results also show that, in the absence of specific information, the application of general models for the purposes of estimating fertiliser emissions when analysing CC, a widely analysed impact category, are not invalidated. Mechanistic models for the simulation of water and nitrogen balances in crops, such as STIC (Brisson et al., 1998) or LEACHM (Wagenet and Hutson, 1989), would also be recommended for the purposes of estimating fertiliser emissions, although greater effort is needed to understand the model and to gather the data. Those models have already been successfully applied in other agricultural LCAs (Perrin et al. 2017 and Fenollosa et al., 2014) and take into account irrigation practices, which is also a decisive factor for NO_3^- emissions.

On the other hand, as to toxicity related impacts, an overestimation of ET and HTnc using the modelling approach proposed by Margni et al. (2002) to estimate on-field pesticide emissions has been found in this study and also in Schmidt Rivera et al. (2017); however, in the reference scenario of Peña et al. (2019), no significant differences were found between these two modelling proposals.

The results obtained in this study, together with those from other authors in other regions and for other agricultural products (Goglio et al., 2018; Peña et al., 2019; Schmidt Rivera et al., 2017), highlight the greater variability in the results obtained when modelling pesticide fate than when modelling fertiliser emissions.

The literature of LCA on vineyards in Italy and Spain, shows that CC is the most analysed impact category (Bonamente et al., 2016; Bosco et al., 2011; Chiriaco et al., 2019; Meneses et al., 2016; Mohseni, Borghei & Khanali, 2018; Neto, Diaz & Machado, 2013; Ponstein et al., 2019; Villanueva-Rey et al., 2014). In addition, the IPCC tier 1 methodology (2006a) is the most used to estimate on-field emissions from fertilisers. When comparing CC results of the literature with those obtained in this study with BM, Neto et al. (2013) and Mohseni et al. (2018) show values of 1.82 and 0.51 kg CO_2 eq.·kg of grapes^{-1} respectively, far superior to those of the present study and the rest of the literature. The average results for this impact category in the rest of the reviewed literature is 0.20 kg CO_2 eq. kg of grapes^{-1} versus the average 0.15 kg CO_2 eq.· kg of grapes-1 of the systems analysed in this study, that is, a 33% difference.

Among the reviewed literature, Falcone et al., (2015) analysed several impacts with ReCiPe 2008 (Goedkoop et al., 2009) to compare organic and conventional vineyard per ha. The results are similar in both studies indicating greater environmental impacts of conventional crops compared to organic ones in the CC, FPMF, ME, POFe, POFh, FD, MD, LU, IR and TA categories.

2.1.5. Conclusion

The present study assesses wine grapes in the Utiel-Requena PDO, where vineyards account for 87% of the agricultural area of the municipalities. The results show that, regardless of the grape cultivar, organic systems are more environmentally friendly (e.g., on average, the greatest differences are observed for IR, ME and LU, with impacts 1678%, 648% and 171% lower for organic vineyards). In addition, the results for the Bobal cultivar are better than those for Tempranillo thanks to the higher yield. As to the organic management practices, depending on the impact category, the lowest values were those of both irrigated double guyot cane pruning with trellis and rainfed goblet spur pruning systems. These results underline the need to converge to a single indicator in which most of the environmental implications could facilitate the decision-making related to differentiating between the best and worst environmental profiles in production systems.

The results show that, in some cases, the use of modelling approaches that require generic information can make an estimation of fertiliser and pesticide emissions that is as good as those modelling approaches which use site-specific information. It can be concluded that the choice of the methodological approach to be used depends on the impact categories to be analysed, the availability of information and the characteristics of the fertilisers and pesticides that are being applied. In line with other authors, the results also point to the need for a consensus within LCA practitioners on which methodologies to use in order to estimate on-field emissions as they can affect the LCA results considerably. The suggested approaches using site-specific data involve an agreement between the complexity of the data and the minimization of inaccuracies for the purposes of assessing environmental impacts.

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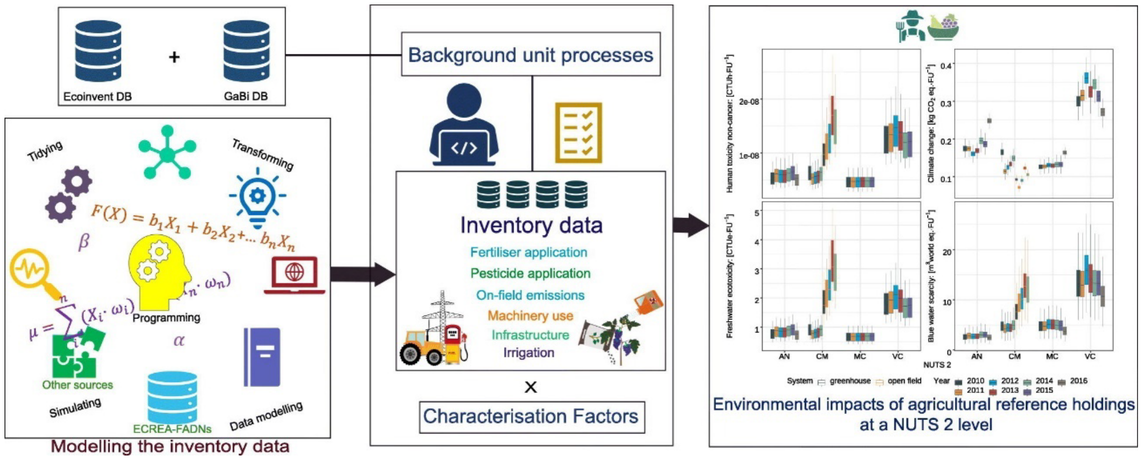
2.2. An approach to regionalise the life cycle inventories of Spanish agriculture: Monitoring the environmental impacts of orange and tomato crops



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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 average 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 the 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.

Keywords

Agricultural LCA; NUTS 2; FADN; Temporal variability; Uncertainty assessment; Monte Carlo simulation

2.2.1. 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, 2022a) 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, 2021a), among other things, 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., 2021a). 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., 2016a; Pradeleix et al., 2022b). 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, 2010a), 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.

2.2.2. Methodological approach

This proposal corresponds to an attributional LCA, according to the ISO standards (ISO, 2017, 2006b, 2006a) and the ILCD (EC-JRC, 2010a), 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., 2014, 2013; 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, 2015a, 2015b, 2015c, 2015d, 2014a, 2014b, 2014c, 2014d, 2014e, 2014f, 2013a, 2013b, 2013c, 2013d, 2013e, 2012a; MAPA, 2020a, 2020b, 2019a, 2019b, 2019c, 2018a, 2018b, 2018c; MAPAMA, 2017, 2015). 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, 2022b). 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, reference holdings 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, 2018d, 2017). The raw data from ECREA-FADN used in this study for orange and tomato production in Spain using each management system is detailed in Annex B.1.

2.2.2.1. 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. 2.2.1).

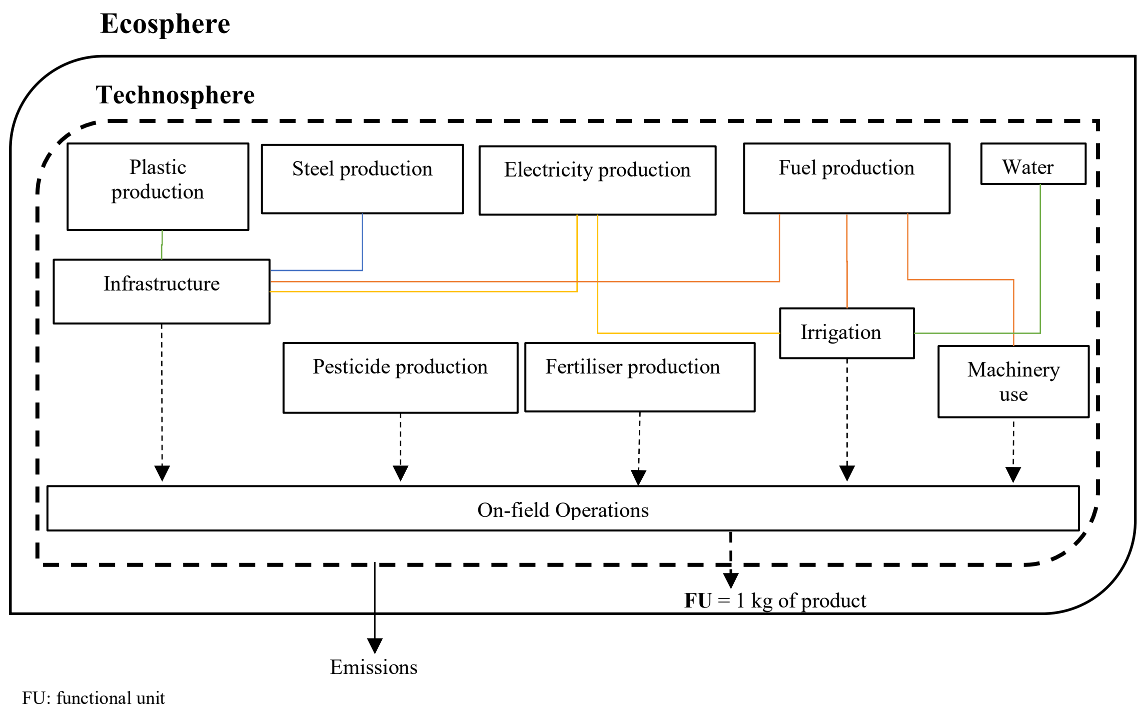

Fig. 2.2.1. System boundaries for the environmental assessment of the orange and tomato crops in Spain in the period 2010-2017.

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 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).

2.2.2.2. 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.

2.2.2.2.1. 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. 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).

2.2.2.2.2. 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, 2022b, 2022c) 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 (Eq. (2.2.1) to Eq. (2.2.6)) follows the structure below:

$$Min \qquad f\ (X_1 \dots X_n) = C_1X_1 + \cdots + C_nX_n \tag{2.2.1}$$

Subject to:

$$a_{11}X_1 + \cdots + a_{1n}X_n \geq b_1 \tag{2.2.2}$$

$$a_{21}X_1 + \cdots + a_{2n}X_n \geq b_2 \tag{2.2.3}$$

$$a_{31}X_1 + \cdots + a_{3n}X_n \geq b_3 \tag{2.2.4}$$

$$a_{41}X_1 + \cdots + a_{4n}X_n \leq b_4 \tag{2.2.5}$$

$$X_1, \dots, X_n \geq 0 \tag{2.2.6}$$

Being:

$f\ (X_1 \dots X_n)$: 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}).

2.2.2.2.3. 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, 2021a) 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, 2022d).

2.2.2.2.4. 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.

2.2.2.2.4.1. 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) (N 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, 2018e, 2018f). 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).

2.2.2.2.4.2. 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. (2.2.7), 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. (2020b). 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.

$$E_{AS,c} = E_{app,AS} \cdot EF_{AS,c} \quad (2.2.7)$$

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. (2.2.8) to (2.2.10), 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, 2015e, 2014g, 2013f, 2013g, 2012b; MAPA, 2017, 2016; MARM, 2011).

$$f_{agri} = \frac{A_{agri}}{A_{total}} \quad (2.2.8)$$

$$f_{fw} = \frac{A_{fw}}{A_{total}} \quad (2.2.9)$$

$$f_{nat} = 1 - f_{agri} - f_{fw} \quad (2.2.10)$$

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.

2.2.2.2.5. 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. (2.2.11)):

$$F_D = \frac{C}{MV} \cdot \frac{1}{Y} \tag{2.2.11}$$

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.

2.2.2.2.6. 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 Annex B.2.

2.2.2.3. 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., 2008a), water scarcity with AWARE 1.2c (Boulay et al., 2018a), and ReCiPe 2016 v1.1 (Huijbregts et al., 2017a) 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., 2017a).

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 B4.5 in Annex B.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).

2.2.2.4. 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 1,000 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 2.2.1.

2.2.2.5. Software

Excel spreadsheets (Microsoft Co.) are used to gather the information. Following Wickham and Grolemund (2016), R programming language (R Core Team, 2021a) and RStudio interface (RStudio Team, 2023) 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., 2022, 2020), “feather” v0.3.5 (Wickham et al., 2019c), “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., 2022a), “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, 2019a).

2.2.2.6. Data types and quality requirements

The input data used in this approach to estimate the LCIs come from different sources. As shown in section 2.2.1.2, on-field activity data (i.e. dose of 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., 2016a) and GaBi DB (SPHERA, 2022b) databases (see Annex B.3). 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 2.2.1 summarises the features of the input data used to develop the LCI. Sinisterra-Solís et al. (2022) [Data in brief article, in review] 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.

Table 2.2.1. 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)	(5.1) (6.5)	*	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 ($C_1 \dots C_n$),	(2.2.1)	*	(MAPA, 2022b, 2022c)	Very good
Minimum N, P2O5 and K2O supply to the crop and maximum fertiliser expense (b_1, b_2, b_3, b_4)	(2.2.1) to (2.2.5)	*	ECREAs	Very good
N, P2O5 and K2O content and cost of the fertiliser products ($a_{11}, \dots, a_{4n}$)	(2.2.1) to (2.2.5)	*	ECREAs	Very good
Pesticide consumption				
Dose of pesticide product ($E_{app,AS}$)	(2.2.7)	*	(MAPA, 2021a)	Good
Fertiliser emissions				
Tier 2 NH3 emission factors		Triangle distribution [a,b,c]	(N 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 N2O emission factors		Triangle distribution [a,b,c]	(Cayuela et al., 2017a)	Very good
Tier 1 indirect N2O emission factors		Triangle distribution [a,b,c]	(Hergoualc'h et al., 2019; Paciornik et al., 2019)	Good
NO_3^-		*	(MAPA, 2018e, 2018f)	Good
$PO4_3^-$		*		Good
Pesticide emissions				
Pesticide active substance ($E_{app,AS}$)	(2.2.7)	*	(MAPA, 2021a)	Good
Total agricultural area in the respective NUTS 2 (A_{agri}), Eq. (4.2)	(2.2.8)	*	(MAGRAMA, 2015e, 2014g, 2013f, 2013g, 2012b; MAPA, 2017, 2016; MARM, 2011)	Very good
Total area of the respective NUTS 2 (A_{total}),	(2.2.8) and (2.2.9)	*		Very good
Total area corresponds to surface water in the respective NUTS 2.	(2.2.10)	*		Very good
Fraction of AS that goes to compartment c ($EF_{AS,c}$)	(2.2.7)	Replace random sample from the primary distribution values	(Melero et al., 2020)	Very good

Data input	Related equation	Monte Carlo simulation setting	Source	Quality
		estimated by PestLCI Consensus model.		
Machinery				
Fuel expenses (C)	(2.2.11)	*	ECREAs	Very good
Fuel market value (MV)	(2.2.11)	Uniform distribution [a,b]	(MITECO, 2022)	Very good
Water for irrigation				
Rooting depth (Z_r)	(B2.1, Annex B.2)	Uniform distribution [a,b]	(Allen et al., 1998)	Very good
Water in the soil ($\theta_{FC} - \theta_{WP}$)	(B2.1, Annex B.2)	Triangle distribution [a,b,c]	(ESDAC, 2020; Jones et al., 2020)	Very good
Soil water depletion fraction for no stress (p)	(B2.2, Annex B.2)	Triangle distribution [a,b,c]	(Allen et al., 1998)	Good
Precipitations (P_i)	(B2.3, Annex B.2)	Triangle distribution [a,b,c]	(SIAR, 2022)	Very good
Crop reference evapotranspiration (ET_o)	(B2.4, Annex B.2)	Triangle distribution [a,b,c]		Very good
Crop coefficient (K_c)	(B2.5, Annex B.2)	Triangle distribution [a,b,c]		Very good
Power for irrigation				
Pump efficiency (μ_{pump})	(B2.7, Annex B.2) and (B2.8, Annex B.2)	Triangle distribution [a,b,c]	(Daccache et al., 2014)	Good
Friction losses (p_l)	(B2.9, Annex B.2)	Triangle distribution [a,b,c]		Good
Pressure required to transport the water from the source because of gravity energy (p_{W_s})	(B2.9, Annex B.2)	*	(Espinosa-Tasón et al., 2020)	Good
Standard operating pressure associated with furrow method (p_m)	(B2.9, Annex B.2)	*		Good
Standard operating pressure associated with sprinkler method (p_m)	(B2.9, Annex B.2)	*		Good
Standard operating pressure associated with drip method (p_m)	(B2.9, Annex B.2)	*		Good
Pressure required to lift surface water (l_{W_s})	(B2.10, Annex B.2)	*		Good
Pressure required to lift groundwater (l_{W_g})	(B2.10, Annex B.2)	Triangle distribution [a,b,c]		Good
Efficiency of diesel motor (μ_{Dm})	(B2.11, Annex B.2)	Triangle distribution [a,b,c]	(Daccache et al., 2014)	Good
Efficiency of electric motor (μ_{Em})	(B2.11, Annex B.2)	Triangle distribution [a,b,c]		Good
Conveyance efficiency (μ_{conv})	(B2.22, Annex B.2)	Triangle distribution [a,b,c]	(Espinosa-Tasón et al., 2020)	Good
Distribution efficiency (μ_{dis})	(B2.22, Annex B.2)	Triangle distribution [a,b,c]		Good
Furrow efficiency method (μ_{fs})	(B2.21, Annex B.2)	Triangle distribution [a,b,c]	(Berbel et al., 2018; Daccache et al., 2014; Espinosa-Tasón et al., 2020; Phocaides, 2007)	Good
Sprinkler efficiency method (μ_{ss})	(B2.21, Annex B.2)	Triangle distribution [a,b,c]		Good
Drip efficiency method (μ_{ds})	(B2.21, Annex B.2)	Triangle distribution [a,b,c]		Good
Number of diesel engines for irrigation ($Diesel\_motors$)	(B2.12 and B2.13, Annex B.2)	*	(Espinosa-Tasón et al., 2020)	Good
Number of electric engines for irrigation ($Electric\_motors$)	(B2.12 and B2.13, Annex B.2)	*		Good
Desalinated water used in agriculture (W_d)	(B2.15, Annex B.2) and (B2.16, Annex B.2)	*		Good
Reclaimed water used in agriculture (W_r)	(B2.15, Annex B.2) and (B2.16, Annex B.2)	*		Good
Energy consumption for the use of desalinated water (E_d)	(B2.14, Annex B.2)	*		Good
Energy consumption for the use of reclaimed water (E_r	(B2.14, Annex B.2)	*		Good
Available water from surface source (W_s)	(B2.10, Annex B.2) and (B2.20, Annex B.2)	*	(INE, 2022a, 2022b)	Very good
Available water from ground source (W_g)	(B2.10, Annex B.2) and (B2.20, Annex B.2)	*		Very good
Desalinated and reclaimed water for irrigation (W_{treat})	(B2.17, Annex B.2)	*		Very good
Total water availability ($W_{total\_sources}$)	(B2.17, Annex B.2)	*		Very good

Data input	Related equation	Monte Carlo simulation setting	Source	Quality
Water irrigated using furrow method (W_{fm})	(B2.17, Annex B.2)	*	(MAGRAMA, 2015e, 2014g, 2013f, 2013g, 2012b; MAPA, 2017, 2016; MARM, 2011)	Very good
Water irrigated using sprinkler method (W_{sm})	(B2.17, Annex B.2)	*		Very good
Water irrigated using drip method (W_{dm})	(B2.17, Annex B.2)	*		Very good
Total water irrigated (W_{tm})	(B2.17, Annex B.2)	*		Very good
Area irrigated using furrow method (A_{fm})	(B2.21, Annex B.2)	*		Very good
Area irrigated using sprinkler method (A_{sm})	(B2.21, Annex B.2)	*		Very good
Area irrigated using drip method (μ_{dm})	(B2.21, Annex B.2)	*		Very good
Total irrigated area (A_{total})	(B2.21, Annex B.2)	*		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

2.2.2.7. 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 2.2.2).

Table 2.2.2. The main characteristics of the tomato and orange cropping systems in the principal Spanish NUTS 2 producers, 2010-2017. Data retrieved from Annex B.1.

		Yield ($kg \cdot ha^{-1} \cdot yr^{-1}$)		Surface (ha)		Number of years
NUTS 2	System	Mean	Sd	Mean	Sd	
Orange						
Andalucía (AN)	Open-field	30,668	3,006	13.71	7.40	8
Comunidad Valenciana (VC)	Open-field	23,101	2,357	2.96	0.35	8
Región de Murcia (MC)	Open-field	27,237	9,731	20.92	7.79	8
Tomato						
Andalucía (AN)	Greenhouse	88,255	6,502	2.08	0.47	7
Castilla-La Mancha (CM)	Greenhouse	87,942	7,151	0.48	0.07	5
Comunidad Valenciana (VC)	Greenhouse	41,993	6,202	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	8,332	1.69	0.29	5

Sd: standard deviation

Table 2.2.2 shows that orange reference holdings display an average yield ranging from 30.7 t of oranges$\cdot ha^{-1} \cdot yr^{-1}$ in AN to 23.1 t of oranges$\cdot ha^{-1} \cdot yr^{-1}$ in VC; likewise, the mean surface area of the holdings in AN and MC is 13.71 ha$\cdot$holding^{-1} and 20.92 ha$\cdot$holding^{-1}, respectively; in VC, whereas, smallholdings prevail, with 2.96 ha$\cdot$holding^{-1}. As to the tomato crop, in the case of the greenhouse system, the average yield ranges from 114.15 t of tomato$\cdot ha^{-1} \cdot yr^{-1}$ in MC to 41.99 t of tomato$\cdot ha^{-1} \cdot yr^{-1}$ 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}.

The results of the activity data for the reference holdings obtained by applying the approach explained in section 2.2.2.2 are shown in Annex B.4. This data is subsequently used to estimate the midpoint impact categories described in section 2.2.2.4. 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 2.2.2.4 are detailed in Annex B.5. 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.

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

2.2.3.1. 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 2.2.3 and Fig. 2.2.2.

Table 2.2.3. Average impacts of orange crops in the main NUTS 2 producers in Spain, years 2010 to 2017.

		Impact per kg of product^{-1}							
Impact category	NUTS 2	Mean	Median	SD	IQR	RSD	RIQR	$P_{2.5}$	$P_{97.5}$
Blue water scarcity (WS: m³ world eq.·FU^{-1})	Andalucía (AN)	$1.14\cdot10^{1}$	$1.14\cdot10^{1}$	2.12	3.02	19%	26%	7.34	$1.55\cdot10^{1}$
	Comunidad Valenciana (VC)	$1.35\cdot10^{1}$	$1.34\cdot10^{1}$	2.37	3.23	18%	24%	9.4	$1.87\cdot10^{1}$
	Región de Murcia (MC)	$1.67\cdot10^{1}$	$1.74\cdot10^{1}$	4.79	7.45	29%	43%	8.19	$2.52\cdot10^{1}$
Freshwater ecotoxicity (ET: CTUe·FU^{-1})	Andalucía (AN)	$5.83\cdot10^{-3}$	$5.61\cdot10^{-3}$	$1.93\cdot10^{-3}$	$2.54\cdot10^{-3}$	33%	45%	$2.88\cdot10^{-3}$	$1.05\cdot10^{-2}$
	Comunidad Valenciana (VC)	$7.45\cdot10^{-3}$	$7.03\cdot10^{-3}$	$2.54\cdot10^{-3}$	$3.24\cdot10^{-3}$	34%	46%	$3.59\cdot10^{-3}$	$1.35\cdot10^{-2}$
	Región de Murcia (MC)	$6.53\cdot10^{-3}$	$6.30\cdot10^{-3}$	$2.59\cdot10^{-3}$	$3.57\cdot10^{-3}$	40%	57%	$2.46\cdot10^{-3}$	$1.28\cdot10^{-2}$
Climate change (CC: kg CO_2 eq.·FU^{-1})	Andalucía (AN)	$1.96\cdot10^{-1}$	$1.89\cdot10^{-1}$	$3.55\cdot10^{-2}$	$6.62\cdot10^{-2}$	18%	35%	$1.47\cdot10^{-1}$	$2.57\cdot10^{-1}$
	Comunidad Valenciana (VC)	$1.99\cdot10^{-1}$	$1.94\cdot10^{-1}$	$2.39\cdot10^{-2}$	$3.00\cdot10^{-2}$	12%	15%	$1.62\cdot10^{-1}$	$2.56\cdot10^{-1}$
	Región de Murcia (MC)	$1.84\cdot10^{-1}$	$1.86\cdot10^{-1}$	$2.34\cdot10^{-2}$	$3.60\cdot10^{-2}$	13%	19%	$1.42\cdot10^{-1}$	$2.25\cdot10^{-1}$
Human toxicity non-cancer (HTnc: CTUh·FU^{-1})	Andalucía (AN)	$3.16\cdot10^{-11}$	$3.10\cdot10^{-11}$	$8.87\cdot10^{-12}$	$1.41\cdot10^{-11}$	28%	46%	$1.70\cdot10^{-11}$	$4.92\cdot10^{-11}$
	Comunidad Valenciana (VC)	$4.17\cdot10^{-11}$	$4.16\cdot10^{-11}$	$1.20\cdot10^{-11}$	$1.75\cdot10^{-11}$	29%	42%	$2.26\cdot10^{-11}$	$6.60\cdot10^{-11}$
	Región de Murcia (MC)	$3.82\cdot10^{-11}$	$3.72\cdot10^{-11}$	$1.39\cdot10^{-11}$	$2.33\cdot10^{-11}$	36%	63%	$1.43\cdot10^{-11}$	$6.41\cdot10^{-11}$

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

These results include the uncertainty simulated from the LCI parameters as well as the interannual variability according to the years studied, which is detailed in Annex B.4. 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.

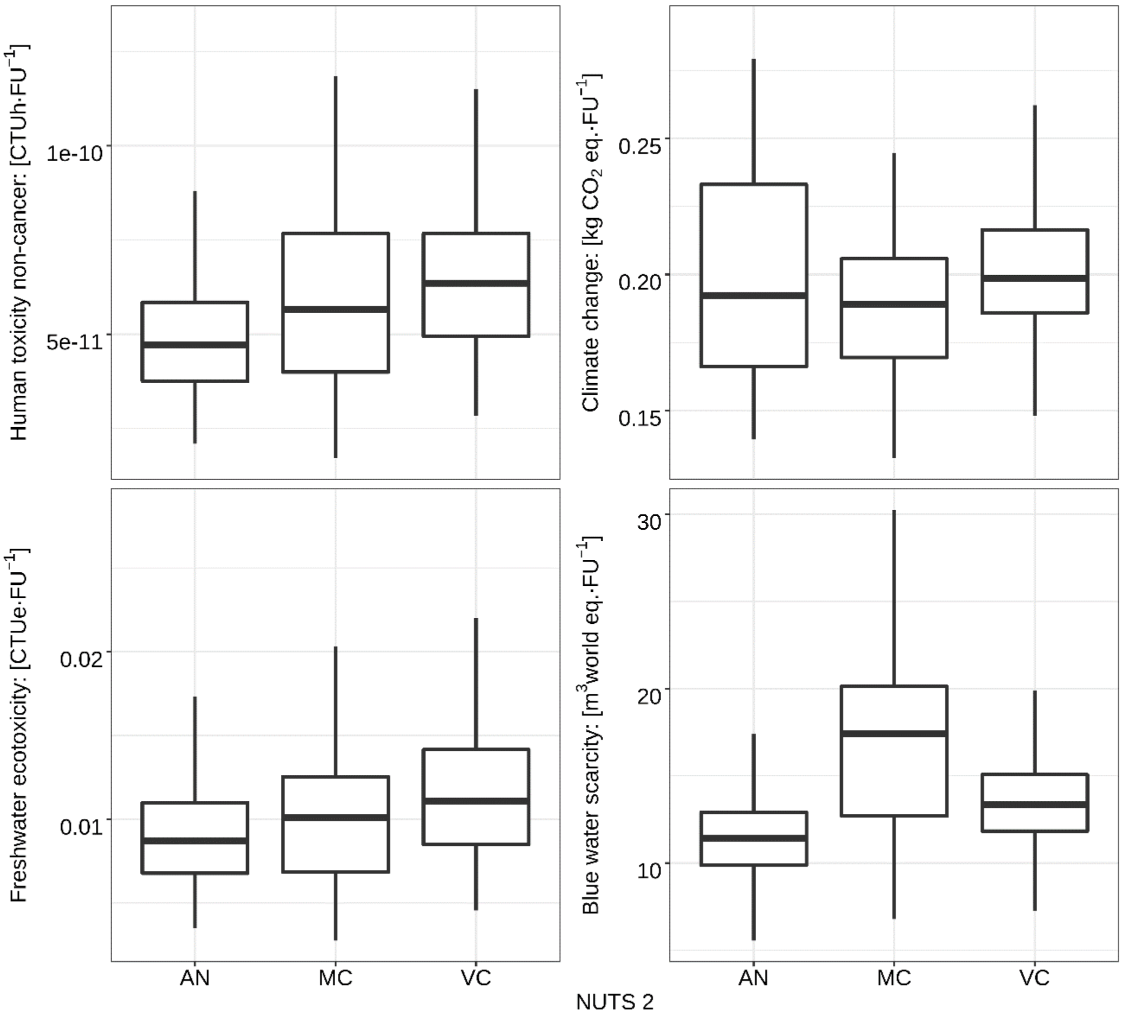

Fig. 2.2.2. Box and whisker plots of the aggregated environmental impacts of orange crops in the main NUTS 2 producers in Spain, in the period 2010-2017. AN: Andalucía; CM: Castilla-La Mancha; VC: Comunidad Valenciana; MC: Región de Murcia.

The contribution analysis (Fig. 2.2.3) 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 (24%) and infrastructure (18%) in VC; and fertiliser production (33%), irrigation (21%), infrastructure (19%) and on-field operations (19%) in MC.

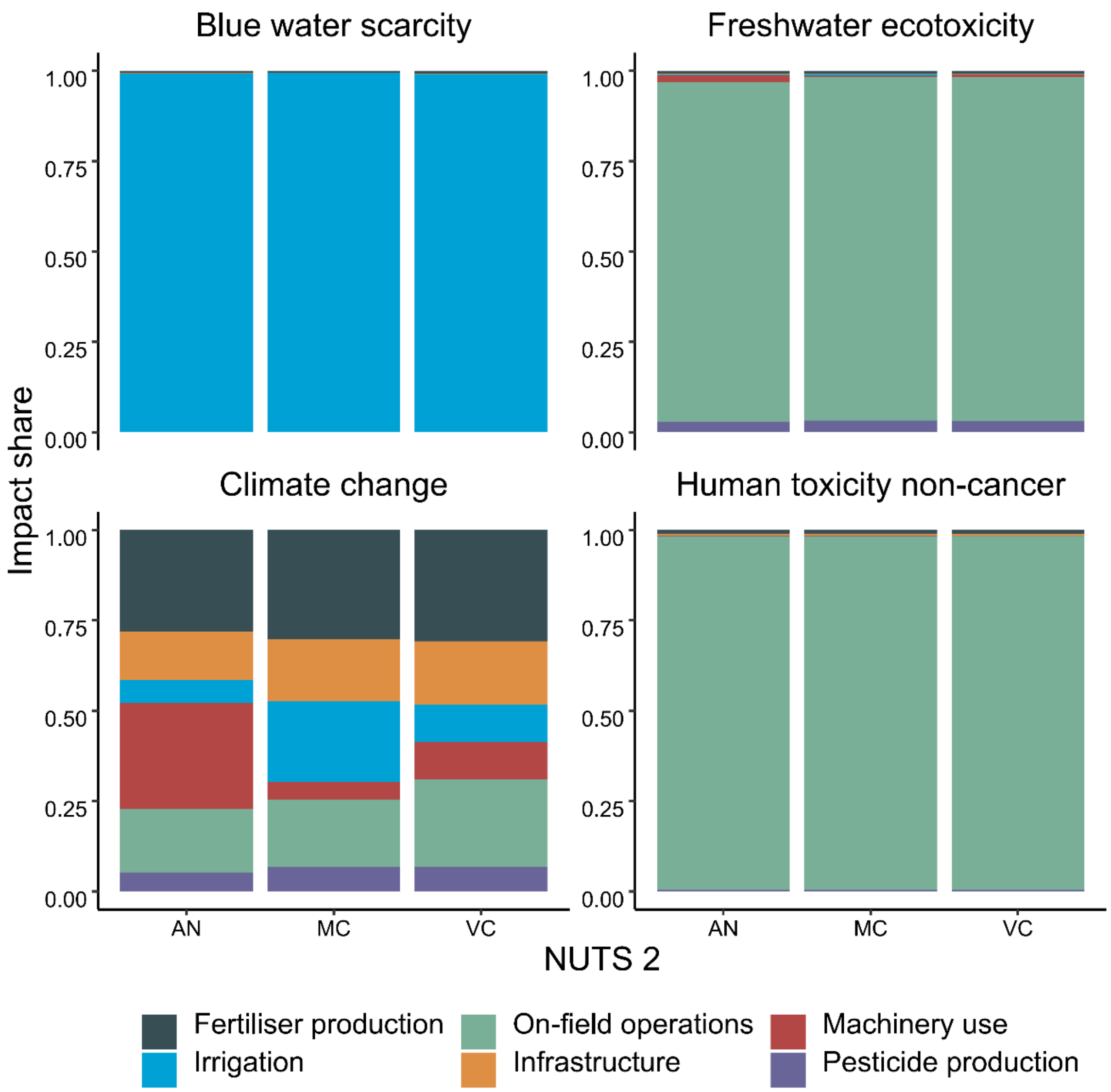

Fig. 2.2.3. Relative contribution of life cycle stages to the environmental impacts of orange crop in the main NUTS 2 producers in Spain, in the period 2010-2017. AN: Andalucía; CM: Castilla-La Mancha; VC: Comunidad Valenciana; MC: Región de Murcia.

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. 2.2.4). 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.

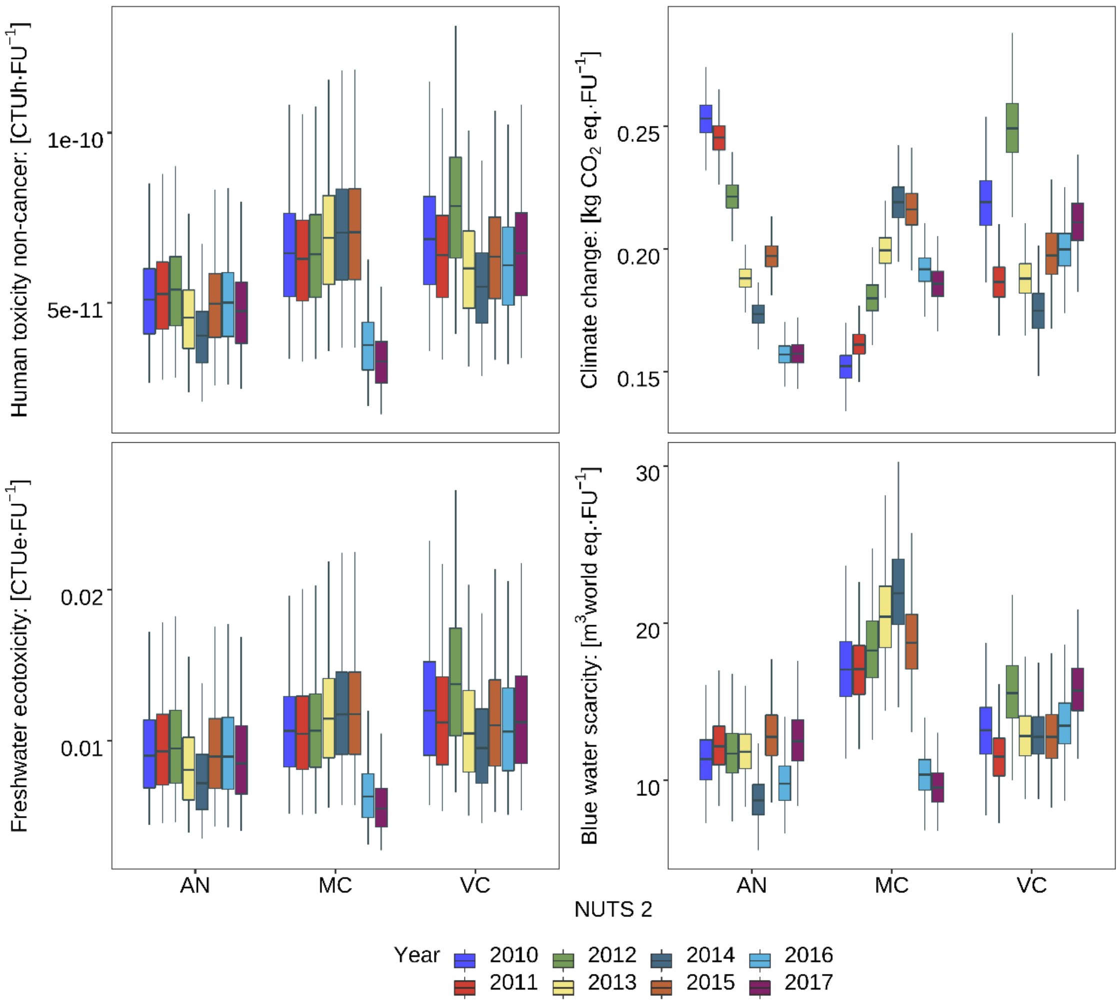

Fig. 2.2.4. Box and whisker plots of the aggregated environmental impacts of orange crops in the main NUTS 2 producers in Spain, in the period 2010-2017. AN: Andalucía; CM: Castilla-La Mancha; VC: Comunidad Valenciana; MC: Región de Murcia.

2.2.3.2. 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 2.2.4 and Fig. 2.2.5. 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.

Table 2.2.4. Average impacts of tomato crops in the main NUTS 2 producers in Spain, in 2010-2017.

			Impact per kg of tomato^{-1}							
Impact category	**NUTS 2**	**System**	**Mean**	**Median**	**SD**	**IQR**	**RSD**	**RIQR**	**$P_{2.5}$**	**$P_{97.5}$**
Blue water scarcity	Andalucía (AN)	IG	2.82	2.74	$8.01\cdot10^{-1}$	1.13	28%	41%	1.5	4.53
(WS: m^3 world eq.$\cdot$FU^{-1})	Castilla-La Mancha (CM)	IG	4.65	4.53	1.32	1.83	28%	40%	2.43	7.43
	Comunidad Valenciana (VC)	IG	$1.37\cdot10^{1}$	$1.33\cdot10^{1}$	4.14	5.74	30%	43%	6.93	$2.26\cdot10^{1}$
	Región de Murcia (MC)	IG	4.84	4.74	1.42	2.03	29%	43%	2.49	7.79
	Castilla-La Mancha (CM)	IO	$1.07\cdot10^{1}$	$1.01\cdot10^{1}$	3.8	5.31	36%	52%	4.95	$1.94\cdot10^{1}$
Freshwater ecotoxicity	Andalucía (AN)	IG	$7.38\cdot10^{-1}$	$6.77\cdot10^{-1}$	$2.46\cdot10^{-1}$	$3.49\cdot10^{-1}$	33%	52%	$4.14\cdot10^{-1}$	1.22
(ET: CTUe$\cdot$FU^{-1})	Castilla-La Mancha (CM)	IG	$7.41\cdot10^{-1}$	$6.86\cdot10^{-1}$	$2.48\cdot10^{-1}$	$3.48\cdot10^{-1}$	33%	51%	$4.23\cdot10^{-1}$	1.23
	Comunidad Valenciana (VC)	IG	1.57	1.5	$5.49\cdot10^{-1}$	$7.20\cdot10^{-1}$	35%	48%	$7.62\cdot10^{-1}$	2.75
	Región de Murcia (MC)	IG	$5.74\cdot10^{-1}$	$5.00\cdot10^{-1}$	$1.94\cdot10^{-1}$	$2.45\cdot10^{-1}$	34%	49%	$2.87\cdot10^{-1}$	$9.01\cdot10^{-1}$
	Castilla-La Mancha (CM)	IO	2.21	2.06	$7.66\cdot10^{-1}$	1.05	35%	51%	1.07	3.97
Climate change	Andalucía (AN)	IG	$1.88\cdot10^{-1}$	$1.78\cdot10^{-1}$	$3.11\cdot10^{-2}$	$2.74\cdot10^{-2}$	17%	15%	$1.50\cdot10^{-1}$	$2.65\cdot10^{-1}$
(CC: kg CO_2 eq.$\cdot$FU^{-1})	Castilla-La Mancha (CM)	IG	$1.37\cdot10^{-1}$	$1.35\cdot10^{-1}$	$2.04\cdot10^{-2}$	$3.12\cdot10^{-2}$	15%	23%	$1.04\cdot10^{-1}$	$1.77\cdot10^{-1}$
	Comunidad Valenciana (VC)	IG	$3.18\cdot10^{-1}$	$3.18\cdot10^{-1}$	$3.50\cdot10^{-2}$	$4.87\cdot10^{-2}$	11%	15%	$2.53\cdot10^{-1}$	$3.89\cdot10^{-1}$
	Región de Murcia (MC)	IG	$1.35\cdot10^{-1}$	$1.31\cdot10^{-1}$	$1.62\cdot10^{-2}$	$1.42\cdot10^{-2}$	12%	11%	$1.14\cdot10^{-1}$	$1.76\cdot10^{-1}$
	Castilla-La Mancha (CM)	IO	$9.65\cdot10^{-2}$	$9.44\cdot10^{-2}$	$1.82\cdot10^{-2}$	$2.34\cdot10^{-2}$	19%	25%	$6.60\cdot10^{-2}$	$1.30\cdot10^{-1}$
Human toxicity non-cancer	Andalucía (AN)	IG	$4.82\cdot10^{-9}$	$4.42\cdot10^{-9}$	$1.61\cdot10^{-9}$	$2.29\cdot10^{-9}$	33%	52%	$2.70\cdot10^{-9}$	$8.01\cdot10^{-9}$
(HTnc: CTUh$\cdot$FU^{-1})	Castilla-La Mancha (CM)	IG	$4.84\cdot10^{-9}$	$4.48\cdot10^{-9}$	$1.63\cdot10^{-9}$	$2.28\cdot10^{-9}$	34%	51%	$2.76\cdot10^{-9}$	$8.07\cdot10^{-9}$
	Comunidad Valenciana (VC)	IG	$1.03\cdot10^{-8}$	$9.80\cdot10^{-9}$	$3.60\cdot10^{-9}$	$4.71\cdot10^{-9}$	35%	48%	$4.96\cdot10^{-9}$	$1.80\cdot10^{-8}$
	Región de Murcia (MC)	IG	$3.75\cdot10^{-9}$	$3.26\cdot10^{-9}$	$1.27\cdot10^{-9}$	$1.61\cdot10^{-9}$	34%	49%	$1.87\cdot10^{-9}$	$5.89\cdot10^{-9}$
	Castilla-La Mancha (CM)	IO	$1.12\cdot10^{-8}$	$1.02\cdot10^{-8}$	$4.29\cdot10^{-9}$	$5.51\cdot10^{-9}$	38%	54%	$5.42\cdot10^{-9}$	$2.23\cdot10^{-8}$

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

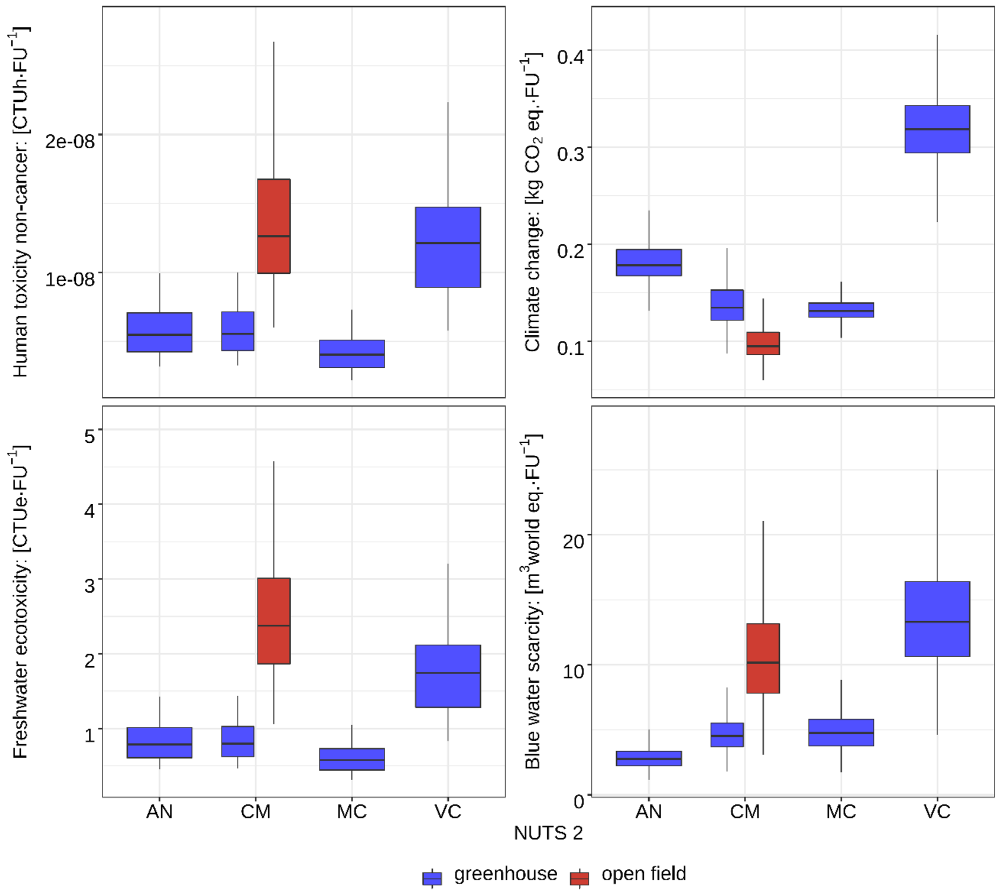

Fig. 2.2.5. Aggregated environmental impacts of tomato crops in the main NUTS 2 producers in Spain, in the period 2010-2017. AN: Andalucía; CM: Castilla-La Mancha; VC: Comunidad Valenciana; MC: Región de Murcia.

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 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. 2.2.6) 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.

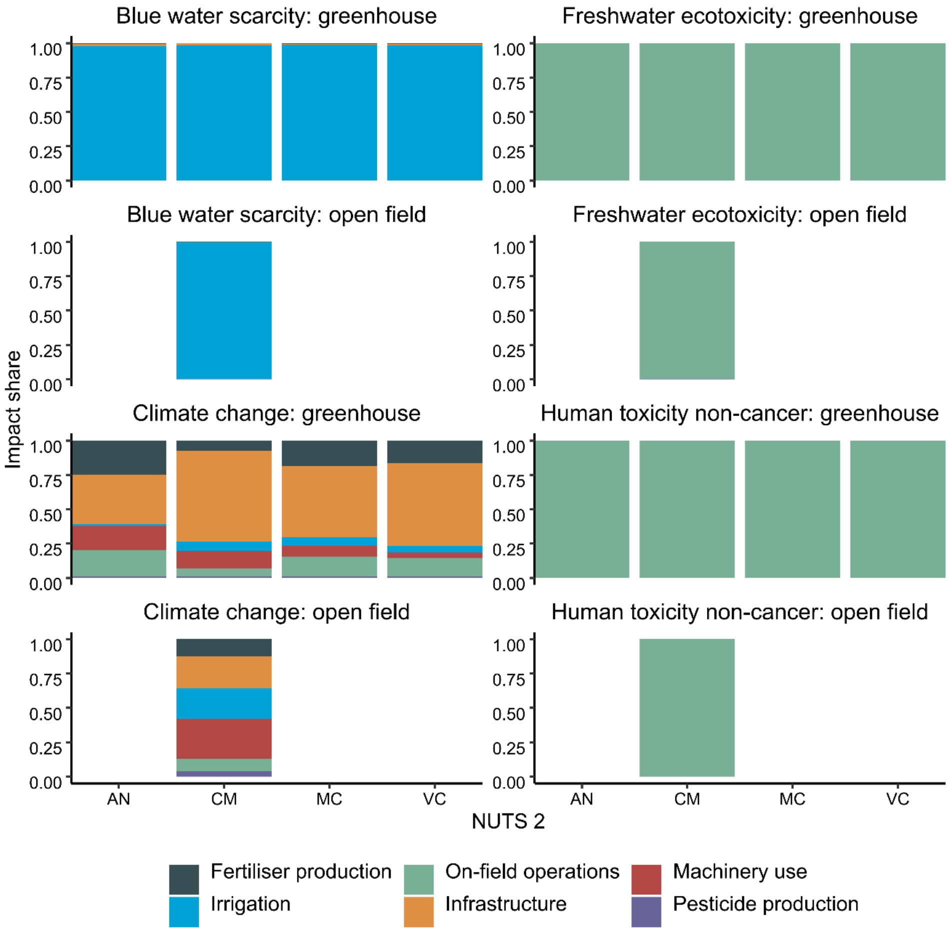

Fig. 2.2.6. Relative contribution of life cycle stages to the environmental impacts of the tomato crop in the main NUTS 2 producers in Spain in the period 2010-2017. AN: Andalucía; CM: Castilla-La Mancha; VC: Comunidad Valenciana; MC: Región de Murcia.

When analysing the evolution of the impact results in the years studied (Fig. 2.2.7), 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.

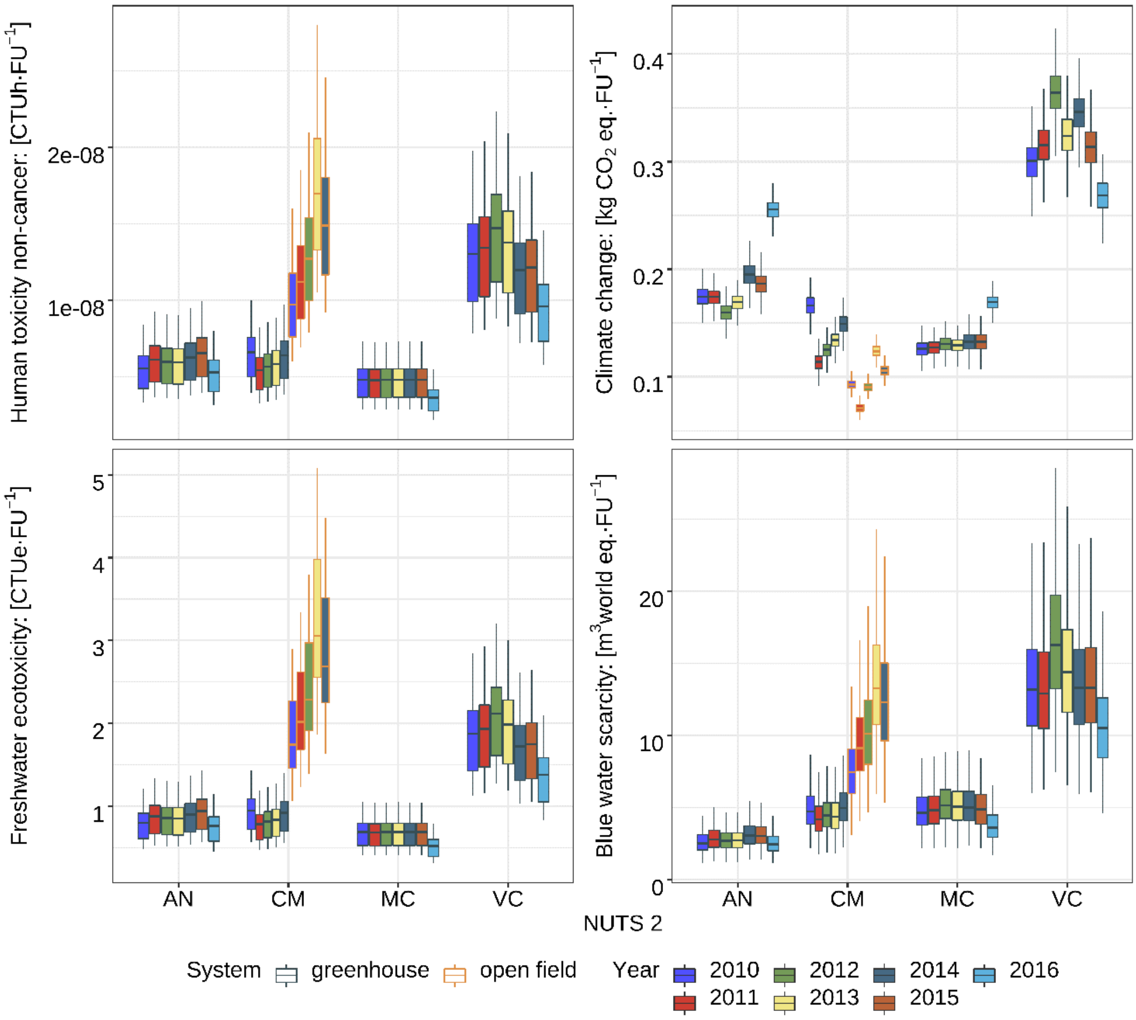

Fig. 2.2.7. Aggregate environmental impacts of tomato crops in the main NUTS 2 producers in Spain, in the period 2010-2017. AN: Andalucía; CM: Castilla-La Mancha; VC: Comunidad Valenciana; MC: Región de Murcia.

2.2.3.3. 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. 2.2.2, 2.2.4, 2.2.5, and 2.2.7, 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 the NUTS 2 and the system on the environmental impacts of orange and tomato reference holdings.

Table 2.2.5. Effect sizes of the Kruskal-Wallis tests applied to the impacts of orange and tomato crops using different systems and in differing NUTS 2.

	Epsilon square ~ ε^2			
Reference holdings	**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

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 different NUTS 2 and cropping systems in each year. Table 2.2.6 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 2.2.6. Pairwise comparisons between orange and tomato farming impacts in the main NUTS 2 producers in Spain from 2010-2017.

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 2.2.6 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.

2.2.4. 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 2.2.7). 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 2.2.7) 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 2.2.7, they are replaced by human toxicity (HT) calculated as the sum of the HTc plus HTnc scores (as detailed in Annex B.5, Table B5.4), 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 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.

Table 2.2.7. 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 [$t·ha^{-1}$]	CC [d]	HT [e]	ET[f]	WS[g]	Source
Orange	OS	Andalucía	$3.07·10^{1}$, 3.01	$1.96·10^{-1}$, $3.55·10^{-2}$	$3.11·10^{-9}$, $3.10·10^{-10}$	$5.83·10^{-3}$, $1.93·10^{-3}$	$1.14·10^{1}$, 2.12	This study
Orange	OS	Region de Murcia	$2.31·10^{1}$, 9.73	$1.84·10^{-1}$, $2.34·10^{-2}$	$3.78·10^{-10}$, $9.39·10^{-10}$	$6.53·10^{-3}$, $2.59·10^{-3}$	$1.67·10^{1}$, 4.79	This study
Orange	OS	Comunidad Valenciana	$2.72·10^{1}$, 2.36	$1.99·10^{-1}$, $2.39·10^{-2}$	$4.13·10^{-9}$, $4.73·10^{-10}$	$7.45·10^{-3}$, $2.54·10^{-3}$	$1.35·10^{1}$, 2.37	This study
Orange	OS	Region de Murcia	$2.09·10^{1}$	$4.16·10^{-1}$	-	-	$3.79·10^{1}$[b]	Martin-Gorriz et al. (2020)
Orange	OS	Comunidad Valenciana	$3.34·10^{1}$, 9.93	$3.10·10^{-1}$, $7.93·10^{-1}$	$2.49·10^{-8}$, $2.65·10^{-8}$	$1.28·10^{1}$, $1.44·10^{1}$	-	Ribal et al. (2017)
Citrus	OS	Spain	$4.20·10^{1}$, 8.62	$1.59·10^{-1}$, $4.98·10^{-2}$ [c]	-	-	-	Aguilera et al. (2015)
Tomato	GS	Andalucía	$8.83·10^{1}$, 6.50	$1.78·10^{-1}$, $3.11·10^{-2}$	$4.94·10^{-9}$, $1.62·10^{-9}$	$6.77·10^{-1}$, $2.46·10^{-1}$	2.74, $8.01·10^{-1}$	This study
Tomato	GS	Region de Murcia	$1.14·10^{2}$, $1.34·10^{1}$	$1.31·10^{-1}$, $1.62·10^{-2}$	$3.85·10^{-9}$, $1.28·10^{-9}$	$5·10^{-1}$, $1.94·10^{-1}$	4.74, 1.42	This study
Tomato	GS	Comunidad Valenciana	$4.20·10^{1}$, 6.20	$3.18·10^{-1}$, $3.5·10^{-2}$	$1.05·10^{-8}$, $3.63·10^{-9}$	1.5, $5.49·10^{-1}$	$1.33·10^{1}$, 4.14	This study
Tomato	GS	Castilla - La Mancha	$8.79·10^{1}$, 7.15	$1.35·10^{-1}$, $2.04·10^{-2}$	$4.97·10^{-9}$, $1.64·10^{-9}$	$6.86·10^{-1}$, $2.48·10^{-1}$	4.53, 1.32	This study
Tomato	GS	Catalonia	$1.59·10^{2}$	$1.53·10^{-1}$	-	-	3.31[b]	Martínez-Blanco et al. (2011)
Tomato	GS	Mediterranean conditions	$8.83·10^{1}$	$6.17·10^{-1}$, $2.02·10^{-1}$	-	-	-	Romero-Gámez et al. (2017)
Tomato	GS	Andalucía	$1.65·10^{2}$	$2.50·10^{-1}$	-	-	-	Torrellas et al. (2012)
Tomato	OS	Castilla - La Mancha	$3.78·10^{1}$, 8.33	$9.44·10^{-2}$, $1.82·10^{-2}$	$1.38·10^{-8}$, $4.82·10^{-9}$	2.06, $7.66·10^{-1}$	$1.01·10^{1}$, 3.8	This study
Tomato	OS	Catalonia	$1.03·10^{2}$	$1.56·10^{-1}$	-	-	5.74[b]	Martínez-Blanco et al. (2011)
Tomato	OS	Mediterranean conditions	$6.23·10^{1}$	$2.16·10^{-1}$, $3.34·10^{-2}$	-	-	-	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.]

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 2.2.3.2) 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. Romero-Gámez et al. (2017). 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 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., 2017a). Comparing with Martínez-Blanco et al. (2011) results, both the CC and WS scores, the latter is estimated by multiplying the respective subnational CF of WS by the water use calculated in 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).

2.2.5. 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 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, 2020b), 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.

2.2.6. References

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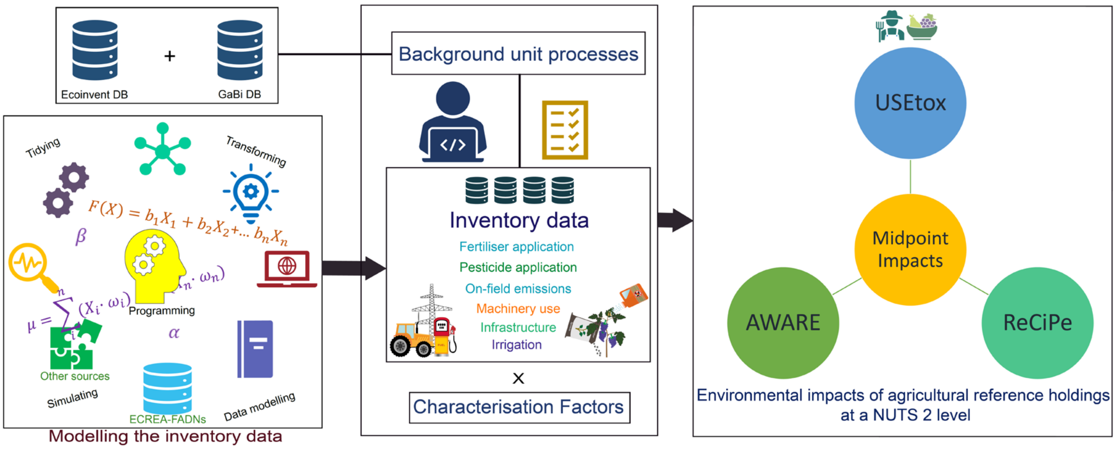
2.3. Dataset to monitor regionalised environmental impacts of the main agricultural products in Spain



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Abstract

Estimating the average environmental impacts of a representative crop in a specific region can be a helpful reference from which to propose improvements in the sector. However, data collection from official representative sources is complex, and these data often require subsequent treatment to be transformed into meaningful inventory data. This article shows a comprehensive dataset for obtaining inventory data and developing an environmental life cycle impact assessment of representative agricultural production corresponding to reference holdings at a regional level (NUTS 2) in Spain. The dataset comprises Excel files with the data compiled from secondary sources to be used in the assessment and the R code scripts to transform the data into relevant inventory data and estimate the reference holdings' environmental impacts. This dataset is a reliable tool for researchers, and other potential users, to be used as a secondary information source for further studies. If the R code is adjusted, it can also be used to estimate the environmental impacts of the farming activity of agri-food products in other regions or countries after collecting similar data for the specific region.

Keywords:

Agricultural LCA, Inventory data, Environmental inventory, NUTS 2, R programming

2.3.1. Specifications table

Item	Description
Subject	Agricultural Science Environmental Science
Specific subject area	Agricultural Economics Environmental engineering
Type of data	Tables in Excel files R project including the abovementioned code scripts and folder structure
How the data were acquired	Data gathered from Spanish official statistics from 2010 to 2017, specialised literature. Unit impacts from the unit processes estimated in GaBi software v10.6.1.35 Original R code developed to estimate the environmental impacts of representative agricultural production in Spain at a NUTS 2 level.
Data format	Raw data: xlsx Processed (data conversion and data enrichment, network calculation): (xlsx) Code: R files, R project file
Description of data collection	*The collected data correspond to the parameters for estimating resource consumption and environmental emissions from the main farming activities.* Specifically, we collected data on material consumption and emissions from infrastructure building and management, fertiliser and pesticide production, on-field fertiliser and pesticide emissions, fuel consumption from machinery use, and irrigation. These data, together with the environmental impacts of the unit processes (e.g. electricity mix, production of agricultural inputs) are required to assess the environmental impacts from a data panel of reference holdings at the main NUTS 2 in Spain. The data were compiled in a set of Excel sheets and subsequently operated on (tidying, transforming, visualisation and modelling operations) by developing a set of scripts using R programming language and RStudio interface.
Data source location	Raw data were extracted from the sources listed below. In the “Data description” section, these sources are related to the corresponding raw data of each excel file.

Item	Description
	• Agriculture, Ecosystems & Environment Journal, https://doi.org/10.1016/J.AGEE.2016.10.006 • Department of Agriculture of the United State of America (USDA), https://www.usda.gov/ • European Environmental Agency (EEA), https://www.eea.europa.eu/ • European Soil Data Centre (ESDAC), https://esdac.jrc.ec.europa.eu/ • Eurostat, https://ec.europa.eu/eurostat/web/main/home • Food and Agriculture Organization of the United Nations, https://www.fao.org/home/en • GaBi software, https://sphera.com/ • INE-Instituto Nacional de Estadísticas (Spanish National institute of statistics), https://www.ine.es/en/index.htm • International Journal of Life Cycle Assessment, https://doi.org/10.1007/s11367-013-0607-z • Intergovernmental Panel on Climate Change (IPCC), https://www.ipcc.ch/ • Journal of Cleaner Production, https://doi.org/10.1016/J.JCLEPRO.2020.121656 • Environmental Science & Technology Journal, • MAPA-Ministerio de Agricultura, Pesca y Alimentación (Spanish Ministry of Agriculture, Fisheries and Food), https://www.mapa.gob.es/es/ • MITECO-Ministerio para la Transición Ecológica y el Reto Demográfico (Spanish Ministry for the Ecological Transition and Demographic Challenge), https://www.miteco.gob.es/en/ • Nutrient Cycling in Agroecosystems Journal, https://doi.org/10.1007/S10705-006-9000-7 • PestLCI Consensus, https://pestlciweb.man.dtu.dk/ • SIAR-Sistema de Información Agroclimática para el Regadío (Spanish Agricultural INformation System for Irrigation), https://eportal.mapa.gob.es/websiar/NecesidadesHidricas.aspx • USEtox software, https://usetox.org/ • WULCA working group, https://wulca-waterlca.org/

Item	Description
Data accessibility	Repository name: Mendeley Data Data identification number: (Sinisterra-Solís et al., 2023a) 10.17632/dd49c8y2cc.2 Direct URL to data: https://data.mendeley.com/datasets/dd49c8y2cc
Related research article	N. Sinisterra-Solís, N. Sanjuán, J. Ribal, V. Estruch, G. Clemente, An approach to regionalise the life cycle inventories of Spanish agriculture: Monitoring the environmental impacts of orange and tomato crops, Science of The Total Environment. 856 (2023) 158909. https://doi.org/10.1016/J.SCITOTENV.2022.158909.

2.3.2. Value of the data

- This dataset provides a comprehensive approach to assess the environmental impacts of the main agricultural commodities corresponding to reference holdings at the Spanish NUTS 2 level.
- The dataset can be relevant for researchers and decision-makers who want to study the environmental impacts of the farming stage of agricultural commodities.
- The dataset can be used as secondary information sources for other studies, as well as to assess the environmental impacts of the agriculture stage of agri-food products at a NUTS 2 level in Spain.
- The R script can be adapted to assess the environmental impacts of the farming stage in other regions or countries.

2.3.3. Objective

This dataset was generated to provide the input data and the computational code to estimate the environmental impact of representative agricultural production in Spain at a NUTS 2 level. The methodology has been applied to monitor the environmental impacts of orange and tomato crops (Sinisterra-Solís et al., 2023b).

2.3.4. Data description

2.3.4.1. Excel files

Input data collected to develop the life cycle inventory data to assess the environmental impacts of the reference holdings were gathered in 21 excel files. A description of each one is made below.

Dbi1_ECREA: This dataset gathers information from the annual studies on costs and incomes of agricultural holdings of the Spanish Ministry of Agriculture, Fisheries and Food, also known by their acronym in Spanish ECREA. ECREA is a type of report of the Spanish farm accountancy data network (from now on ECREA-FADN). *Dbi1_ECREA* refers to 26 ECREA-FADN reports, available on 22 April 2022 (Ministerio de Agricultura Pesca y Alimentación (MAPA), 2022). The data file provides information on the number of the holdings sampled in the ECREA-FADN reports; specifically, the yield (kg·ha^{-1}), the average surface of the holdings (ha·holding^{-1}), expenses on fertilisers and fuel (€·ha^{-1}), and macronutrients supplied (kg macronutrient·ha^{-1}) for a set of reference holdings at NUTS 2 level in Spain, considering different crops (e.g. tomato, orange, olive, etc.) and farm systems (greenhouse, open-field irrigated or open-field rainfed) in the years 2010 to 2017. Data corresponding to orange and tomato references holdings are provided in Annex B.1; therefore, to estimate life cycle inventory and the environmental impacts of orange and tomato reference holdings, this data should be taken from Annex B.1 and should be included in the corresponding cells of this file (Dbi1_ECREA) before running the R code. The columns "Id_holding" and "Id_holding_yr" are added as identification variables of the reference holdings and the corresponding year, respectively; whereas, "Key1", "Key2" and "Key3" are added as key variables that help to relate this dataset with others. The dataset has been filtered to show only the data for tomato and orange reference holdings, which are the object of the case study (Sinisterra-Solís et al., 2023a). Macronutrient data for some reference holdings in some years were not reported in the corresponding ECREA-FADN report. Therefore, these data are imputed (Table 1) by applying a rule of three, between, before or after yield, and macronutrient data with the present yield data of the respective reference holding. The data imputed are calculated in the Excel file.

Table 2.3.1. Reference holdings in which macronutrient data were imputed

Crop	System	Year	NUTS 2
Almond	Irrigated open field	2015	Comunidad Valenciana
Almond	Irrigated open field	2016	Comunidad Valenciana
Almond	Irrigated open field	2017	Comunidad Valenciana
Almond	Rainfed open field	2016	Aragón
Almond	Rainfed open field	2017	Aragón
Almond	Rainfed open field	2013	Castilla-La Mancha
Almond	Rainfed open field	2017	Castilla-La Mancha
Almond	Rainfed open field	2016	Región de Murcia
Almond	Rainfed open field	2017	Región de Murcia
Almond	Rainfed open field	2016	Comunidad Valenciana

Crop	System	Year	NUTS 2
Almond	Rainfed open field	2017	Comunidad Valenciana
Apple	Irrigated open field	2016	Aragón
Apple	Irrigated open field	2017	Aragón
Apricot	Irrigated open field	2016	Región de Murcia
Apricot	Irrigated open field	2017	Región de Murcia
Kaki	Irrigated open field	2016	Comunidad Valenciana
Kaki	Irrigated open field	2017	Comunidad Valenciana
Lemon	Irrigated open field	2016	Región de Murcia
Lemon	Irrigated open field	2017	Región de Murcia
Lemon	Irrigated open field	2016	Comunidad Valenciana
Lemon	Irrigated open field	2017	Comunidad Valenciana
Mandarin	Irrigated open field	2016	Comunidad Valenciana
Mandarin	Irrigated open field	2017	Comunidad Valenciana
Nectarine	Irrigated open field	2016	Aragón
Nectarine	Irrigated open field	2017	Aragón
Nectarine	Irrigated open field	2016	Extremadura
Nectarine	Irrigated open field	2017	Extremadura
Nectarine	Irrigated open field	2016	Región de Murcia
Nectarine	Irrigated open field	2017	Región de Murcia
Nectarine	Irrigated open field	2016	Comunidad Valenciana
Nectarine	Irrigated open field	2017	Comunidad Valenciana
Orange*	Irrigated open field	2016	Andalucía
Orange	Irrigated open field	2017	Andalucía
Orange	Irrigated open field	2016	Región de Murcia
Orange	Irrigated open field	2017	Región de Murcia
Orange	Irrigated open field	2016	Comunidad Valenciana
Orange	Irrigated open field	2017	Comunidad Valenciana
Peach	Irrigated open field	2016	Aragón
Peach	Irrigated open field	2017	Aragón
Peach	Irrigated open field	2016	Extremadura
Peach	Irrigated open field	2017	Extremadura
Peach	Irrigated open field	2016	Región de Murcia
Peach	Irrigated open field	2017	Región de Murcia
Peach	Irrigated open field	2016	Comunidad Valenciana
Peach	Irrigated open field	2017	Comunidad Valenciana
Pear	Irrigated open field	2016	Aragón
Pear	Irrigated open field	2017	Aragón
Pear	Irrigated open field	2016	Región de Murcia
Plum	Irrigated open field	2016	Extremadura

Crop	System	Year	NUTS 2
Plum	Irrigated open field	2017	Extremadura
Plum	Irrigated open field	2016	Región de Murcia
Plum	Irrigated open field	2017	Región de Murcia
Alfalfa	Irrigated open field	2016	Aragón
Alfalfa	Irrigated open field	2016	Castilla y León
Alfalfa	Rainfed open field	2016	Castilla y León
Barley	Irrigated open field	2016	Aragón
Barley	Irrigated open field	2016	Castilla y León
Barley	Irrigated open field	2016	Castilla-La Mancha
Barley	Rainfed open field	2016	Aragón
Barley	Rainfed open field	2016	Castilla y León
Barley	Rainfed open field	2016	Castilla-La Mancha
Barley	Rainfed open field	2016	Extremadura
Beet_sugar	Irrigated open field	2016	Andalucía
Beet_sugar	Irrigated open field	2016	Castilla y León
Corn	Irrigated open field	2016	Andalucía
Corn	Irrigated open field	2016	Castilla y León
Corn	Irrigated open field	2016	Extremadura
Dried peas	Rainfed open field	2010	Aragón
Dried peas	Rainfed open field	2016	Aragón
Dried peas	Rainfed open field	2012	Castilla y León
Dried peas	Rainfed open field	2016	Castilla y León
Dried peas	Rainfed open field	2016	Castilla-La Mancha
Durum wheat	Irrigated open field	2016	Aragón
Durum wheat	Rainfed open field	2016	Andalucía
Durum wheat	Rainfed open field	2016	Aragón
Fodder corn	Irrigated open field	2016	Castilla y León
Forage vetch	Rainfed open field	2016	Castilla y León
Lentils	Rainfed open field	2016	Castilla y León
Oat	Rainfed open field	2016	Andalucía
Oat	Rainfed open field	2016	Castilla y León
Oat	Rainfed open field	2016	Castilla-La Mancha
Oat	Rainfed open field	2016	Extremadura
Colza	Irrigated open field	2016	Castilla y León
Colza	Rainfed open field	2016	Castilla y León
Ryegrass	Irrigated open field	2016	Aragón
Rice	Irrigated open field	2016	Andalucía
Rice	Irrigated open field	2016	Extremadura
Rye	Rainfed open field	2016	Aragón

Crop	System	Year	NUTS 2
Rye	Rainfed open field	2016	Castilla y León
Sunflower	Irrigated open field	2016	Castilla y León
Sunflower	Rainfed open field	2016	Andalucía
Sunflower	Rainfed open field	2013	Castilla y León
Sunflower	Rainfed open field	2014	Castilla y León
Sunflower	Rainfed open field	2016	Castilla y León
Sunflower	Rainfed open field	2016	Castilla-La Mancha
Soft wheat	Irrigated open field	2016	Aragón
Soft wheat	Irrigated open field	2016	Castilla y León
Soft wheat	Irrigated open field	2016	Extremadura
Soft wheat	Rainfed open field	2016	Andalucía
Soft wheat	Rainfed open field	2016	Aragón
Soft wheat	Rainfed open field	2016	Castilla y León
Soft wheat	Rainfed open field	2016	Castilla-La Mancha
Soft wheat	Rainfed open field	2016	Extremadura
Triticale	Rainfed open field	2016	Castilla-La Mancha
Olive to oil	Irrigated open field	2016	Andalucía
Olive to oil	Irrigated open field	2017	Andalucía
Olive to oil	Irrigated open field	2016	Aragón
Olive to oil	Irrigated open field	2017	Aragón
Olive to oil	Irrigated open field	2016	Castilla-La Mancha
Olive to oil	Irrigated open field	2017	Castilla-La Mancha
Olive to oil	Irrigated open field	2016	Extremadura
Olive to oil	Irrigated open field	2017	Extremadura
Olive to oil	Rainfed open field	2016	Andalucía
Olive to oil	Rainfed open field	2017	Andalucía
Olive to oil	Rainfed open field	2016	Aragón
Olive to oil	Rainfed open field	2017	Aragón
Olive to oil	Rainfed open field	2016	Castilla-La Mancha
Olive to oil	Rainfed open field	2017	Castilla-La Mancha
Olive to oil	Rainfed open field	2016	Extremadura
Olive to oil	Rainfed open field	2017	Extremadura
Olive	Irrigated open field	2016	Andalucía
Olive	Irrigated open field	2017	Andalucía
Olive	Rainfed open field	2016	Andalucía
Olive	Rainfed open field	2017	Andalucía
Olive	Rainfed open field	2016	Extremadura
Olive	Rainfed open field	2017	Extremadura
Artichoke	Irrigated open field	2016	Región de Murcia

Crop	System	Year	NUTS 2
Broccoli	Irrigated open field	2016	Región de Murcia
Cantaloupe	Irrigated greenhouse	2015	Andalucía
Cantaloupe	Irrigated open field	2016	Castilla-La Mancha
Cantaloupe	Irrigated open field	2016	Región de Murcia
Celery	Irrigated open field	2016	Comunidad Valenciana
Chard	Irrigated greenhouse	2016	Comunidad Valenciana
Cucumber	Irrigated greenhouse	2015	Andalucía
Cucumber	Irrigated greenhouse	2016	Andalucía
Lettuce	Irrigated open field	2016	Región de Murcia
Onion	Irrigated open field	2016	Castilla-La Mancha
Onion	Irrigated open field	2016	Comunidad Valenciana
Pepper	Irrigated greenhouse	2015	Andalucía
Pepper	Irrigated greenhouse	2016	Andalucía
Pepper	Irrigated greenhouse	2016	Región de Murcia
Pepper	Irrigated greenhouse	2016	Comunidad Valenciana
Pepper for pepper	Irrigated open field	2016	Extremadura
Extra early potato	Irrigated greenhouse	2016	Comunidad Valenciana
Extra early potato	Irrigated open field	2016	Comunidad Valenciana
Mid-season potato	Irrigated open field	2016	Castilla y León
Strawberry	Irrigated greenhouse	2015	Andalucía
Strawberry	Irrigated greenhouse	2016	Andalucía
Tomato industry	Irrigated open field	2016	Andalucía
Tomato industry	Irrigated open field	2016	Extremadura
Tomato	Irrigated greenhouse	2015	Andalucía
Tomato	Irrigated greenhouse	2016	Andalucía
Tomato	Irrigated greenhouse	2015	Región de Murcia
Tomato	Irrigated greenhouse	2016	Región de Murcia
Tomato	Irrigated greenhouse	2016	Comunidad Valenciana
Watermelon	Irrigated greenhouse	2015	Andalucía
Watermelon	Irrigated greenhouse	2016	Andalucía
Watermelon	Irrigated open field	2010	Andalucía
Watermelon	Irrigated open field	2015	Andalucía
Watermelon	Irrigated open field	2016	Andalucía
Watermelon	Irrigated open field	2016	Castilla-La Mancha
Watermelon	Irrigated open field	2016	Región de Murcia
Watermelon	Irrigated open field	2016	Comunidad Valenciana
Courgette	Irrigated greenhouse	2015	Andalucía
Courgette	Irrigated greenhouse	2016	Andalucía
Wine grape	Irrigated open field	2016	Andalucía

Crop	System	Year	NUTS 2
Wine grape	Irrigated open field	2017	Andalucía
Wine grape	Irrigated open field	2016	Castilla-La Mancha
Wine grape	Irrigated open field	2017	Castilla-La Mancha
Wine grape	Rainfed open field	2016	Aragón
Wine grape	Rainfed open field	2017	Aragón
Wine grape	Rainfed open field	2016	Castilla y León
Wine grape	Rainfed open field	2017	Castilla y León
Wine grape	Rainfed open field	2016	Castilla-La Mancha
Wine grape	Rainfed open field	2017	Castilla-La Mancha
Wine grape	Rainfed open field	2016	Extremadura
Wine grape	Rainfed open field	2017	Extremadura

Dbi2_subnational_WS: subnational water scarcity characterisation factors (m3 world eq.·m3 of water consumed in agriculture-1) for Spanish NUTS 2 from (Boulay and Lenoir, 2020).

Dbi3_unit_impact: unit environmental impact scores of the background unit processes and characterisation factors of the on-field emissions from fertilisers to evaluate the environmental impacts from the reference holdings. Original data are taken from the databases Ecoinvent v3.8 (Wernet et al., 2016) and GaBi DB (SPHERA, 2022a, 2022b), by using GaBi software (SPHERA, 2022c); nevertheless, to avoid copyright issues, original values are replaced by 1 (non-real value). Therefore, to replicate the estimation of the environmental impacts, those values should be replaced by the real ones by accessing the databases mentioned above.

Dbi4_input_infrastructure: material for building the greenhouse (Antón et al., 2013) and irrigation systems (Antón et al., 2014; Martin-Gorriz et al., 2020), as well as electricity consumption (kWh·ha-1) necessary to operate the vents on the greenhouse system (Antón et al., 2014).

Dbi5_fertiliser_product: data on the purchase value of the fertiliser products (€·kg-1), without indirect tax, available in Spain in the years 2010 to 2017 (MAPA, 2022a, 2022b) and their respective macronutrient content (kg of macronutrient · kg of fertiliser -1) (MARM, 2010).

Dbi6_pest_dose: data on the dose of the pesticide products used on different crops (kg of active substance·ha-1) and surfaces (ha) with at least one application per year (Ministerio de Agricultura Pesca y Alimentación (MAPA), 2021). In addition, available USEtox characterisation factors (CFs), both recommended and interim, for the midpoint Human toxicity (total, cancer and non-cancer) and freshwater ecotoxicity impacts of the active substances (Rosenbaum et al., 2008; UNEP/SETAC, 2019).

Dbi7_fertiliser_ef: data on on-field emission factors (EF) to air from the application of nitrogen fertilisers. Specifically, Tier 2 EF for ammonia (NH3) (Hutchings et al., 2019; Kuenen and Dore, 2019), Tier 1 EF for nitrogen oxides (NOx) (Hutchings et al., 2019; Stehfest and Bouwman, 2006), Tier 2 EF for direct nitrous oxide (N_2O) (Cayuela et al., 2017) and Tier 1 EF for indirect N_2O from NH_3 volatilisation and NO_3^- leaching (Hergoualc'h et al., 2019) are shown.

Dbi8_n_and_p_balances1: data on supplies of nitrogen and phosphorus and their balance at the end of 2016 for different crops at Spanish NUTS 2 level (MAPA, 2018a, 2018b).

Dbi9_n_and_p_balances2: data on total supplies of nitrogen and phosphorus in Spanish agriculture and their balances from 2010 to 2017 (MAPA, 2018c, 2018d).

Dbi10_pestl_consensus_sim: results of primary pesticide distribution to air, soil and crop for a set of crops, modelled through PestLCI Consensus v1.0 (Melero et al., 2020) and considering the different settings of the technological input parameters for each crop in Spanish agriculture.

Dbi11_land_surface: annual time series (from 2010 to 2017) of the total, agricultural and freshwater surfaces (ha) at the Spanish NUTS 2 level (Ministerio de Agricultura Pesca y Alimentación, 2022).

Dbi12_pest_CF_recipe: ReCiPe CFs for the midpoint human toxicity (total, cancer and non-cancer) and freshwater ecotoxicity for the on-field emissions of the active substances and considering the three-time perspectives of the impacts, namely individualist, hierarchist and egalitarian (SPHERA, 2022c).

Dbi13_fuel_for_machinery: monthly time series (2010 to 2017) of the purchase value of type B diesel at a Spanish NUTS 2 level (MITECO, 2022).

Dbi14_surface_irrigated: annual time series (2010 to 2017) of agricultural surface area (ha) irrigated by furrow, sprinkler and drip methods at a Spanish NUTS 2 level (Ministerio de Agricultura Pesca y Alimentación, 2022).

Dbi15_water_source_and_use: annual time series (2000 to 2017) of the quantity of water (m^3) irrigated by furrow, sprinkler and drip methods, as well as groundwater, surface water and other types of freshwater (reclaimed and desalinated) available at a Spanish NUTS 2 level (INE, 2022a, 2022b).

Dbi16_ECREA_sample: Contribution of NUTS3 to the number of holdings surveyed in the ECREAs for each crop at a Spanish NUTS 2 level (Ministerio de Agricultura Pesca y Alimentación (MAPA), 2022).

Dbi17_NUTS: Name of a NUTS 2 considered in ECREA-FADN reports and their respective NUTS 3 (Eurostat, 2021).

Dbi18_water_irri1: data on sowing and harvesting dates of the crops for the NUTS 3 more widely represented in the ECREA-FADN samples (MAPA, 2021). Dichotomous variables were created for the sowing and harvesting date, where 1 means that the respective month is part of the crop season, otherwise, it is 0. The dataset also provides information on the minimum and maximum rooting depth (m) and soil water depletion fraction (dimensionless) for the different crops (Allen et al., 1998).

Dbi19_water_irri2_soil: data on the composition of a sample of soil (clay, sand and silt content) at a Spanish NUTS 3 level, obtained from Lucas Topsoil 2015 DB (ESDAC, 2020; Jones et al., 2020). By using “Soil water characteristics” software v6.02 (USDA, 2022), those soil composition data were used to define the class texture of the soil (e.g. loam, sandy loam, clay, etc.) and its respective available water was estimated (mm).

Dbi20_water_irri3_Eto: monthly time series (from 2010 to 2017) of precipitation and reference evapotranspiration in the NUTS 3 considered in the ECREA-FADN samples. To gather these data, four weather stations were selected randomly in each NUTS 3. For Ávila (one of the NUTS 3 of Castilla y León), due to data limitations, only three weather stations were considered (SIAR, 2022).

Dbi21_water_irri4_Kc: values of the crop evapotranspiration coefficients for different crops (dimensionless). Data were obtained from the monthly time series (2010-2017) reported by the weather stations referenced in the previous paragraph (SIAR, 2022). A variable was created to count the number of times that each value appears in the time series.

2.3.4.2. R objects

R scripts were developed to estimate the environmental impacts from the reference holdings studied, using as functional unit (FU) 1 kilogram of commercial product from each reference holding. The code was developed through nine scripts and the setup R file. The scripts include an explanation of the detailed procedure; however, a brief description of them is made below.

SR0_library: this script calls the extra packages that, together with R base functions, run the code. In addition, it creates the paths of the R project (Project_path) and the input data files (InputData_path).

SR1_base_script: code that calls the transversal input datasets to be used in the other scripts, such as “Dbi1_ECREA”, “Dbi2_subnational_WS”, and “Dbi3_unit_impact” files, and creates two more parameters, “n_simulation”, which represents the number of simulations considered when developing the estimations, and “Diesel_density”, which indicates the density of the diesel fuel. Through this script, tidying and transformation operations are applied to obtain suitable “ECREA” and “unit_process_impacts” Tibble objects to be related to the other scripts.

SR2_infrastructure: code to estimate the inventory data and environmental impacts associated with building the greenhouse and the irrigation system infrastructure (e.g. plastics, steel, etc.), and managing the greenhouse (electricity consumption to operate the vents for greenhouse crops) of each reference holding.

SR3_fertiliser_consumption: code to estimate the inventory data and environmental impacts from the production of the fertilisers consumed in each reference holding.

SR4_pesticide_consumption: code to estimate the inventory data and environmental impacts from the production of the pesticide active substances consumed in each reference holding.

SR5_on_field_emissions: code to estimate the inventory data (on-field emissions) and environmental impacts from the application of fertiliser and pesticide products. In particular, emissions from fertiliser (NH3, NOx, N2O, NO3- and PO43-) and pesticide application were calculated.

SR6_machinery_use: code to estimate the inventory data and environmental impacts from machinery use, particularly from the fuel consumption, in on-field operations, except those from irrigation.

SR7_irrigation: code to estimate the inventory data and environmental impacts from irrigation, taking into account water and energy consumption.

SR8_impacts_agg: code to join the environmental impacts estimated to the other scripts.

2.3.5. Experimental design, materials and methods

From ECREA-FADN reports, a reference dataset was created (*Dbi1_ECREA*) in which the reference holdings studied were defined. Additional information, as specific as possible, from other secondary sources, was gathered to develop the life cycle inventory data with which to assess the environmental impacts of the reference holdings. This analysis is restricted to the farming stage, and boundaries are, thus, set at the farm gate including all the relevant stages from the production of raw materials to the farm gate (i.e. material consumption and emissions from infrastructure building and management, fertiliser and pesticide production, on-field fertiliser and pesticide emissions, fuel consumption from machinery use, and irrigation). Most of the collated data were compiled in Excel files; only some parameters for the estimation of energy for irrigation were included directly in the R code. By and large, in the R code, functions of filter, select, join, summarise, simulate, etc., were applied to obtain the inventory data and the environmental impact scores of the reference holdings from the input data. For the right code execution, file names and variable names should be kept as defined in the data files and R scripts. The file location and folder structure should remain the same, too.

2.3.6. Software

Name	Type	Source
"R" version 4.1.4	Programming language	(R Core Team, 2021)
"RStudio" version 2022.2.3.492	Programming interface	(RStudio Team, 2022)
"Tidyverse" version 1.3.1	Package	(Wickham et al., 2019)
"Openxlsx" version 4.2.4	Package	(Schauberger and Walker, 2021)
"Linprog" version 0.9-2	Package	(Henningsen, 2012)
"Triangle" version 0.12	Package	(Carnell, 2019)
"Feather" version 0.3.5	Package	(Wickham, 2019)

2.3.7. References

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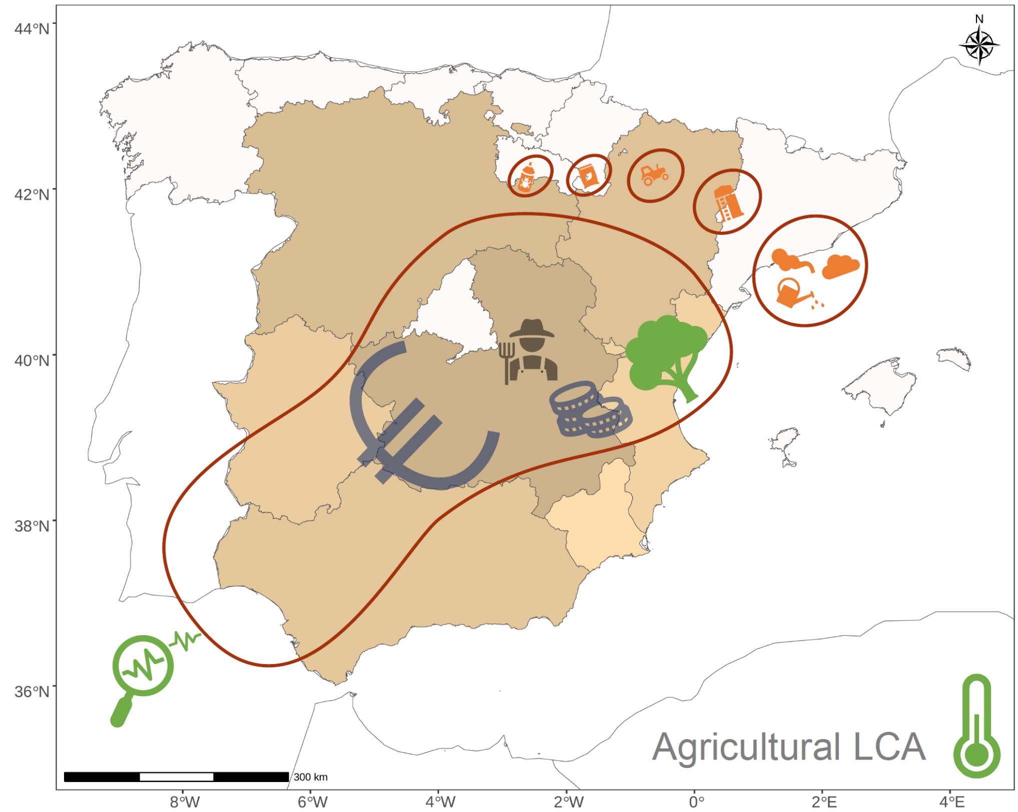
2.4. From farm accountancy data to environmental indicators: monitoring the environmental performance of Spanish agriculture at a regional level



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Abstract

Understanding the environmental impacts of current agricultural practices is a starting point for transitioning towards sustainable agriculture, which is a goal to be achieved by the European Union. This study aims to provide a set of environmental impact indicators with which to assess and compare the environmental performance of a broad group of agricultural reference holdings at the Spanish NUTS 2 level. A life cycle assessment approach based on statistical data on farm accountancy is applied. The unit of analysis is a reference holding on which a specific crop is grown in a NUTS 2 and follows a specific management system (open-field irrigated, open-field rainfed, or greenhouse). The system boundaries are set at the farm gate, and the impact results are expressed per 1 € of net value added. For most reference holdings, the EF scores per net value added are similar regardless of their EF scores per kg commodity, suggesting a correspondence between the use of resources and the economic results. The environmental footprint is clustered into four groups. The first one accounts for 78% of the sample and represents the holdings with the lowest impact (between $9.7 \cdot 10^{-5}$ and $2.88 \cdot 10^{-3}$ EF score$\cdot NVA_{fc}^{-1}$); the second cluster groups seven reference holdings (3 herbaceous and 4 Mediterranean perennial crops) with an environmental footprint of between $3.04 \cdot 10^{-3}$ and $9.01 \cdot 10^{-3}$ EF score$\cdot NVA_{fc}^{-1}$; the third group comprises four irrigated herbaceous crops holdings with the highest impact (between $1.37 \cdot 10^{-2}$ and $2.13 \cdot 10^{-2}$ EF score$\cdot NVA_{fc}^{-1}$); and the last group corresponds to the holdings with economic losses (mostly herbaceous and two Mediterranean perennial crops). This research highlights the challenge of improving the competitiveness and profitability of Spanish farming. In this way, agricultural practices that generate environmental impacts without achieving their economic goals would be avoided.

Keywords:

NUTS 2; environmental footprint; economic functional unit; net value added; regionalised inventory.

2.4.1. Introduction

Not only must agriculture respond to its primary function of supplying food, but also has to adapt to the social and economic needs of the region, as well as to the environmental challenges that societies face. As a fundamental link of the food chain, it causes both positive (e.g. soil functionality improvement, carbon sequestration) and negative (e.g. pollution of soil, air, and freshwater) externalities on the environment (Chen et al., 2014; Pajewski et al., 2020). In fact, most of the negative environmental loads of the food chain are associated with the agricultural stage (Djekic et al., 2018; Pandey et al., 2011; Ribal et al., 2019).

Through the European Green Deal (EC, 2023a), two strategies are set out that address agriculture, namely Farm-to-Fork and Biodiversity 2030. These strategies seek to reduce the use of pesticides and the excess of nutrients in the environment (EC, 2023b, 2020) by promoting precision agriculture, organic farming, and agroecology (EC, 2019). Consequently, the new CAP 2023-27 aims to contribute to the Green Deal goals and the current challenges of European agriculture by reinforcing the support to smaller farms and offering greater flexibility for the state members to adopt those measures which best fit their local conditions (EUCO, 2023). The CAP goals are adapted to Spanish agriculture by means of the Spanish CAP Strategic Plan (MAPA, 2023a). As far as environmental sustainability is concerned, in addition to the mitigation of and adaptation to climate change, the Spanish Plan highlights the need to promote efficient irrigation and improve soil quality (MAPA, 2023a). Hence, understanding the environmental impacts of agriculture is a starting point for transitioning towards sustainable systems, and a basis for contrasting the results of future policies to enhance agricultural sustainability.

Life cycle assessment (LCA) is the most widely used methodology with which to assess the negative environmental impacts of anthropogenic activities (Hélias et al., 2022), such as agriculture, and is a valuable tool to support sustainable transitions (Sala et al., 2021). The vast body of literature on agricultural LCAs shows that the decision context, the functional unit (FU), and the representativeness of the inventory data are critical issues. The ILCD Handbook (EC-JRC, 2010) defines four potential decision contexts (A, B, C1, or C2) not always explicit in agricultural case studies; however, the definition of the decision context is crucial as it determines the modelling framework for the life cycle inventory (LCI), either attributional or consequential. The FU must adequately represent the system's functions, especially in comparative studies (Djekic et al., 2018; O et al., 2023; Ponsioen and van der Werf, 2017). Four types of FU are used in agricultural LCAs (Alhashim et al., 2021; Notarnicola et al., 2015), based on the mass of the product (M-FU), area of land occupied (A-FU), nutritional criteria (N-FU), or economic parameters (E-FU). These FUs work similarly in identifying hotspots (O et al., 2023), although in comparative LCAs, their performance may vary (Cerutti et al., 2013; Notarnicola et al., 2015). M-FU (e.g. 1 kg of a commodity) is the most commonly used (Cerutti et al., 2014, 2013; Djekic et al., 2018), and indicates the impacts per weight of a desired output without accounting for its quality (O et al., 2023). A-FU (e.g. 1 ha) expresses the impacts per unit of land required to grow a product and allows the farm management intensity to be assessed (Mouron et al., 2006a).

N-FU (e.g. 1 kg protein) gathers the properties of agricultural commodities as a nutrient source; however, foods provide an array of macro and micronutrients, and the key nutrients can substantially differ from product to product, making comparisons difficult (e.g. oranges are a source of fibre and vitamin C and olives of fat). E-FU (e.g. 1 € income) uses an economic or financial indicator to relate the impacts (Cerutti et al., 2014; O et al., 2023). It makes it feasible to integrate the quantity and quality of a product in a single FU, broadly representing the function of agricultural commodities as economic goods and being appropriate for comparative LCAs (Mouron et al., 2006a; Ponsioen and van der Werf, 2017; Van Der Werf and Salou, 2015). The main disadvantage of E-FU concerns the uncertainty associated with the economic context, which can be mitigated by considering several years (Cerutti et al., 2014; Mouron et al., 2006a). Ponsioen and van der Werf (2017) recommend reporting the value of the economic indicator and the environmental impacts per M-FU when using E-FUs.

Regionalised LCAs should be promoted in the agricultural context since policies to achieve sustainable agriculture must be developed at the regional level and adapted to its opportunities and constraints (Benoît et al., 2012; Pradeleix et al., 2022). Regionalised LCAs pose a challenge regarding the accuracy and representativeness of the inventory analysis (Avadí et al., 2016; Pradeleix et al., 2022). Different approaches to obtaining the activity data may be found in the literature; although those based on primary sources represent greater accuracy, they require significant efforts to acquire representativeness. Avadí et al. (2016) developed a regionalized inventory combining the calculation of LCAs at the farm level from a representative sample, followed by a principal component analysis to develop farm typologies. Avadí et al. (2018) constructed virtual representative farms using regional statistics, representing the dominant farm types of a given region. Pradeleix et al. (2022) proposed an approach based on Agrarian System Diagnosis; whereas Jan et al. (2012), Dolman et al. (2014), and Sinisterra-Solís et al. (2023a, 2023b) used Farm Accountancy Data Network (FADN) as the main data source for the development of the LCIs.

Several studies assess Spanish agriculture at the regional level. Aguilera et al. (2015a, 2015b) estimated the global warming potential of representative herbaceous and fruit tree crops, both conventional and organic, using average data from personal interviews with farmers. Ribal et al. (2017) assessed orange production in the Valencia region (Spain); they elicited the activity data from a broad survey of farmers and applied a bootstrap technique to obtain confidence intervals of the average impact scores. Martin-Gorriz et al. (2020) evaluated the impacts of fruit and vegetables in the Region of Murcia (Spain) using representative data from agricultural information systems and other literature sources to develop the LCI. Sinisterra-Solís et al. (2023a, 2023b) proposed an approach to account for the impacts of representative holdings at the NUTS 2 level using the annual studies of costs and incomes of agricultural holdings, the so-called ECREA database (MAPA, 2023b). To validate their approach, they estimated the impacts of tomatoes and oranges and compared their results with the literature in the same NUTS 2.

To the authors' knowledge, a comprehensive environmental assessment at a NUTS 2 level in Spain applied to a broad group of crops is not found in the literature. Understanding the importance of data generation, this study aims to account for the environmental impacts and compare the environmental performance of a broad group of agricultural reference holdings at the Spanish regional level (i.e. NUTS 2). The EF has been selected for comparison purposes because it is a comprehensive indicator. To capture both the temporal variability and that of the management practices, data from an 8-year period (from 2010 to 2017) have been used. These indicators can serve as a basis for a comparison with those resulting from the application of future policies supporting the transition to sustainable agriculture within the framework of the CAP 2023-27.

2.4.2. Materials and methods

This study corresponds to an attributional LCA, which considers a type C accounting decision-context according to the ILCD Handbook (EC-JRC, 2010), where regionalised LCIs are developed using ECREA-FADN data and other representative secondary sources (i.e. official statistics) to estimate representative activity data for farming typologies (reference holdings) at the NUTS 2 level. The approach developed by Sinisterra-Solís et al. (2023a, 2023b) to account for the environmental impacts of Spanish agriculture at the NUTS 2 level is used. ECREA-FADN is a non-standardised Spanish FADN that reports farm activity accountancy in the Spanish regions in greater detail than in the RECAN, the Standardised Spanish FADN (MAPA, 2023c, 2008).

2.4.2.1. Context of the study

Reference holdings configured from ECREA-FADN are the unit of analysis of this study. For each crop under a particular management system in a specific NUTS 2, ECREA-FADN gathers annual information on the average financial results of a group of farms (e.g. income, expenses and profit indicators) together with the description of the agricultural practices and some activity data (e.g. amount of macronutrient supplied, yield), which represent a reference holding. In particular, the ECREA-FADN compiled in the "Dbi1_ECREA" dataset in Sinisterra-Solís et al. (2023b) was used. This dataset collects data from 200 reference holdings from 2010 to 2017, the most up-to-date in ECREA-FADN when this study was developed, representing 64 crops in 9 of the 17 NUTS 2 of the Spanish territory (MAPA, 2023b).

An ID variable was created to name the reference holdings assessed, as detailed in Table 2.4.1, which consists of four items separated by hyphens. The first item is an acronym that groups the reference holdings according to the type of crops in the ECREA-FADN classification (i.e. fruit tree, herbaceous, Mediterranean perennial, and vegetables crops). The second corresponds to the crop's name, the third to the management system used, and the last to the NUTS 2.

To account for the temporal variability, following Cerutti et al. (2014), those reference holdings with data for four or more years are considered in this study, resulting in a total of 140 reference holdings. As explained in Sinisterra-Solís et al. (2023a), not all the reference holdings were analysed since the source used to estimate the consumption of pesticides (MAPA, 2021) only provides data for some of the crops gathered in ECREA-FADN; thus, 115 of the 140 reference holdings were included in the study.

Table 2.4.1. Name and acronym, in parentheses, of the items assigned to the ID variable of the analysed reference holdings.

Type of crop:
Fruit trees (Fr); Herbaceous (He); Mediterranean perennials (Me); Vegetables (Ve).
Crop:
Apple (App); Apricot (Apr); Cherry (Che); Lemon (Lem); Mandarin (Man); Melon (Mel); Nectarine (Nec); Orange (Ora); Peach (Pea); Pear (Per); Persimmon (Pers); Plum (Plu); Barley (Bar); Durum wheat (Dwh); Oat (Oat); Rye (Rye); Sunflower (Sun); Soft wheat (Swh); Triticale (Tri); Almond (Alm); Olive (Ol); Olive for oil (Olo); Wine grape (Wgr); Artichoke (Art); Broccoli (Bro); Cabbage (Cab); Cauliflower (Cau); Celery (Cel); Chard (Cha); Courgette (Cou); Cucumber (Cuc); Extra early potato (Eep); Garlic (Gar); Lettuce (Let); Midseason potato (Mpo); Onion (Oni); Pepper (Pep); Pepper for paprika (Ppe); Strawberry (Str); Tomato industry (Toi); Tomato (Tom); Watermelon (Wat).
Management system:
Irrigated open field (IO); Rainfed open field (RO); Irrigated greenhouse (IG).
NUTS 2:
Aragón (AR); *Región de Murcia* (MC); *Comunidad Valenciana* (VC); *Extremadura* (EX); *Andalucía* (AN); *Castilla-La Mancha* (CM); *Castilla y León* (CL).

Table 2.4.2 shows the number of reference holdings that make up the sample in each NUTS 2, and the number of reference holdings assessed and excluded; in addition, the studied crops are detailed, as are the management systems (greenhouse, irrigated open-field and rainfed open-field) used in each NUTS 2. Annex C.1 (Table C1.1) provides information about the yield, average farm area and the number of years with data of the reference holdings to be analysed.

To give an idea of the representativeness of the study, the percentage of the agricultural surface area analysed in each NUTS 2 has been identified (Fig. 2.4.1) by linking the reference holdings analysed in this study with the agricultural surface area of the corresponding NUTS 2, excluding the fallow surface area (MAPA, 2023d). Specifically, the sample assessed for each NUTS 2 represented 87.59% of the agricultural surface area of *Castilla-La Mancha* (CM); 79.14% of *Castilla y León* (CL); 74.91% of *Aragón* (AR); 71.06% of *Andalucía* (AN); 65.99% of *Extremadura* (EX); 61.54% of *Comunidad Valenciana* (VC); and 52.22% of *Murcia* (MC). In addition, the representativeness of this study regarding the production of the 42 crops considered for the year 2017 is shown in Table C1.3 (Annex C.1). According to production statistics from MAPA (2023d), most of the crops (28) in the NUTS 2 assessed represent more than 56% of the total Spanish production of the crop in that very year. Nine of the assessed crops (olive, olive for oil, orange, strawberry, watermelon, sunflower, durum wheat and tomato) represent more than 90% of the total production. For eighteen of the crops, this representativeness is between 57% and 87% (e.g. oat, almond, wine grape, barley and soft wheat). In thirteen crops, the cover is lower than 46% and lower than 15% in five (apple, extra early potato, cherry, cauliflower and cabbage). Still, this last group is not relevant with respect to the surface area cultivated in Spain. Finally, it must be highlighted that production data for persimmon were not found in the MAPA (2023d). Other representative crops in some of the studied NUTS 2 are outside ECREA-FADN and have, thus, not been included. Both these crops and those excluded due to the above criteria are shown in Annex C.1, Table C1.2.

Table 2.4.2. Reference holdings at the NUTS 2 level in Spain with data available for four or more years.

	AN	**AR**	**CL**	**CM**	**EX**	**MC**	**VC**	**Total**
Number of reference holdings	24	20	21	24	15	15	21	140
Number of reference holdings assessed	20	16	10	21	13	15	20	115
Number of reference holdings not assessed	4	4	11	3	2	0	1	25
Crop								
Fruit trees								*26*
Apple		IO						1
Apricot						IO	IO	2
Carob*							RO	1
Cherry							RO	1
Persimmon							IO	1
Lemon						IO	IO	2
Mandarin							IO	1
Nectarine		IO			IO	IO	IO	4
Orange	IO					IO	IO	3
Peach		IO			IO	IO	IO	4
Pear		IO				IO		2
Plum				IO	IO	IO	IO	4
Herbaceous								*54*
Alfalfa*		IO	RO, IO					3
Barley		RO, IO	RO, IO	RO, IO	RO			7
Sugar Beet *	IO		IO					2
Chickpeas*			RO					1
Rapeseed*			RO, IO					2
Corn*	IO	IO	IO	IO	IO			5
Cotton*	IO							1
Dried peas*		RO	RO	RO, IO				4
Durum wheat	RO	RO, IO						3
Fodder corn*			IO					1
Forage vetch*			RO					1
Lentils*			RO					1
Oat	RO		RO	RO	RO			4
Ryegrass*		IO						1
Rice*	IO				IO			2
Rye		RO	RO					2
Sunflower	RO	RO	RO, IO	RO				5
Soft wheat	RO	RO, IO	RO, IO	RO	RO, IO			8
Triticale				RO				1
			Mediterranean perennials					*23*
Almond		RO		RO		RO	RO, IO	5
Olive for oil	RO, IO	RO, IO		RO, IO	RO, IO		RO	9
Olive	RO, IO				RO			3
Wine grape	IO	RO	RO	RO, IO	RO			6
Vegetables								*37*
Artichoke						IO		1
Broccoli						IO		1
Cabbage				IO				1
Cantaloupe	RO, IO			IO		IO		4
Cauliflower				IO				1
Celery							IO	1
Chard				IG			IG	2
Cucumber	IG							1
Garlic				IO				1
Lettuce						IO		1
Onion				IO			IO	2
Pepper	IG					IG	IG	3
Pepper for Paprika					IO			1
Extra early potato							IO, IG	2
Midseason potato			IO					1
Strawberry	IG							1
Tomato industry	IO				IO			2
Tomato	IG			IO, IG		IG	IG	5
Watermelon	RO, IO			IO		IO	IO	5
Courgette	IG							1

* Crops not assessed because the data on pesticide consumption were not found in the sources consulted

AN: *Andalucía*; AR: *Aragón*; CL: *Castilla y León*; CM: *Castilla-La Mancha*; EX: *Extremadura*; MC: *Murcia*; VC: *Comunidad Valenciana*; RO: crop in rainfed system; IO: crop in irrigated system; IG: crop in greenhouse

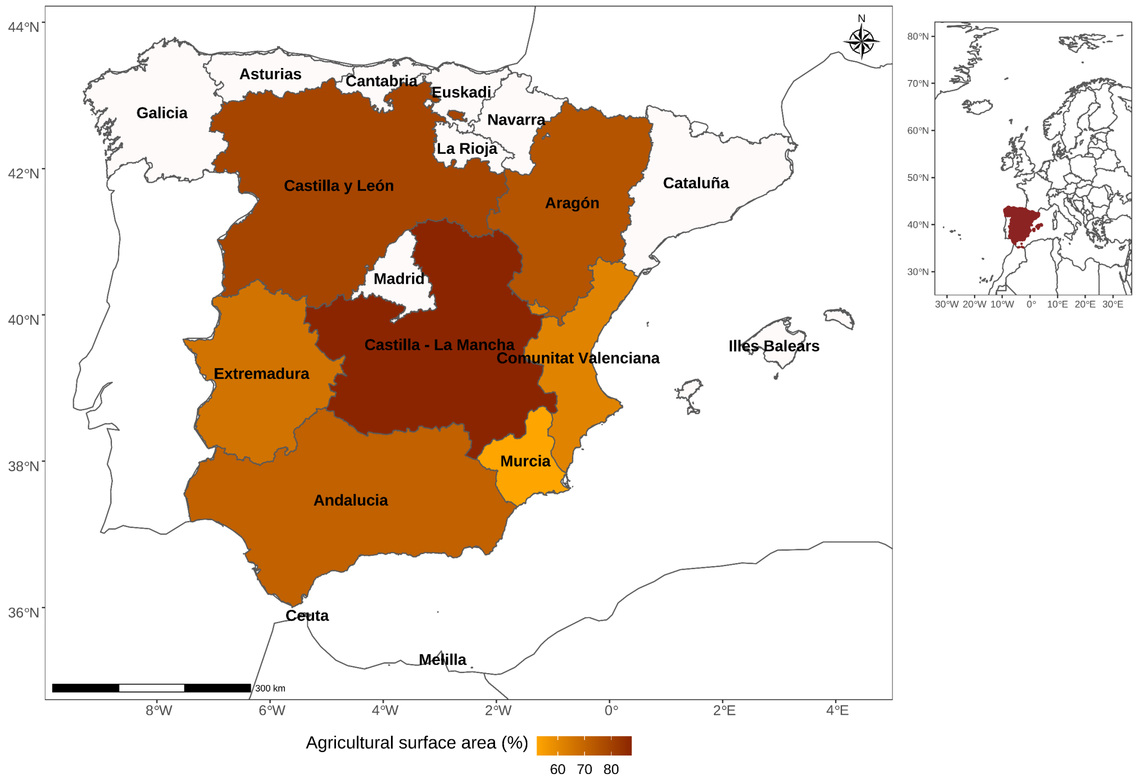

Fig. 2.4.1. Agricultural surface area (%) covered, excluding the fallow surface area, of the Spanish NUTS 2 represented in this study.

2.4.2.2. System boundaries and functional unit

The approach applied was restricted to the farming stage; thus, the system boundaries were set at the farm gate, including all the relevant stages from the production of agricultural inputs to the farm gate (see Fig. 2.2.1 in section 2.2). As explained in Sinisterra-Solís et al. (2023a), the transport of agricultural inputs was not taken into account because its environmental loads are not relevant.

The definition of the FU is critical since it can dramatically influence the LCA results and their interpretation, especially in comparative studies. Thus, the FU should pertinently represent both the qualitative and quantitative issues of the function of the system under study from the perspective of the information user, that is, the stakeholders of the supply chain (Hauschild et al., 2018). In this study, an E-FU is used because, as commented on in Section 2.4.1, it allows for the comparison of commodities with different physical and nutritional features. In particular, considering that this study aims to generate data to be potentially used by policymakers (target audience), the net value added (NVA) is used. Specifically, the NVA at factor cost generated per kg of commodity (NVA_{fc}) has been chosen to represent the economic results of the holdings, without considering government interventions, such as taxes and subsidies; this expresses the endogenous holdings' capacity to generate value added. Hence, the environmental impacts are expressed per 1 € NVA_{fc}. NVA_{fc} is calculated as the difference between the output value and that of the intermediary consumption (Eq. 2.4.1) reported in ECREA-FADN and in line with (MAPA, 2019).

$$NVA_{fc} = \frac{gi+in-dc-mc-ci-bc-oc-ac}{y} \quad (2.4.1)$$

Where gi is the gross income and in is the damage insurance compensation, and the remaining variables of the numerator represent the intermediary consumption: dc is the direct cost, mc is the machinery cost, ci is the capital insurance cost, bc are the maintenance costs, oc are other costs, and ac is the amortisation of non-current assets. These variables are originally expressed at nominal prices per hectare and year, and they are thus converted to actual prices to disregard the inflation effect. In particular, the income (gi and in) and cost (dc, mc, ci, cb, oc and ac) variables have been adjusted on the basis of the price indices received and paid by farmers, taking 2010 as the base year (MAPA, 2023e, 2023f). In addition, they are divided by the yield per hectare (y) of the respective year to obtain the NVA_{fc} per kg commodity. Following the recommendation of Ponsioen and van der Werf (2017), the impacts per M-FU (1 kg of commodity) and the NVA_{fc} scores are provided in Annex C.3.

2.4.2.3. Inventory data

The activity data for the life cycle inventory (LCI) of each reference holding (i.e. input consumption and on-field emissions) were estimated following Sinisterra-Solís et al. (2023a) from ECREA-FADN data, other official sources and the scientific literature gathered in Sinisterra-Solís et al. (2023b).

According to Notarnicola et al. (2015), the commodity's mass was the reference unit of analysis at the inventory level and the inputs and emissions were expressed per 1 kg of agricultural commodity (Annex C.2). Therefore, the impacts were calculated per 1 kg of the commodity and subsequently divided by their respective NVA_{fc} to estimate the impacts per 1 €.

2.4.2.4. Impact categories and impact assessment methods

Following the EU recommendations for the measurement of environmental performance, the most up-to-date version of its method (EF v3.0) when this study was developed (EC, 2023c) was used to estimate the environmental footprint indicator (EF) and the midpoint impact categories. In addition, the ReCiPe endpoint indicators v1.1 (Huijbregts et al., 2017) were calculated to provide decision-makers with a comprehensive environmental impact dataset considering the three levels of analysis.

2.4.2.5. Uncertainty modelling

As far as data availability is concerned, two sources of uncertainty are assessed. Firstly, the temporal variability has been addressed by considering various years, as recommended for agricultural LCAs (Cerutti et al., 2014). It should be noted that cross-sectional variability (i.e. that from the holdings sample) is not considered as only average values are reported in ECREA (MAPA, 2023). Secondly, the uncertainty associated with some input data was modelled as in Sinisterra-Solís et al. (2023b, 2023a), assuming non-parametrical distributions and considering 1000 simulations for each year assessed. Consequently, for each impact indicator, results were estimated as the median of the simulations for every year analysed, indicating its confidence interval (between 2.5% and 97.5% of the data). 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.

2.4.2.6. Software and background processes databases

The code files in the R programming language (R Core Team, 2021) and the dataset to estimate the environmental impacts of the reference holdings are presented in Sinisterra-Solís et al. (2023b). It must be remarked that in that publication, the unit environmental impacts associated with upstream processes were not reported in the respective file ("Dbi3_unit_impact") due to copyright issues; thus, when applying the code, the actual impact scores of upstream processes and the impact scores of on-field emissions from fertiliser application were included in the "Dbi3_unit_impact" file. These values were taken from Ecoinvent v3.8 (Wernet et al., 2016) and GaBi DB (SPHERA, 2022) databases using GaBi professional v10 software.

2.4.3. Results

The complete set of environmental impacts is shown in Annex C.3, where statistics of central tendency, dispersion and confidence are provided. In the following sections, descriptive statistics are used to develop a comparative analysis of the EF scores of the reference holdings.

2.4.3.1. Environmental footprint analysis

The median of the EF scores of the reference holdings is grouped in four panels according to the crop type (Fig. 2.4.2): fruit tree, herbaceous, Mediterranean perennial (almonds, olives and wine grapes) and vegetable crops. For interpretative convenience, the results are clustered into four groups. The first one shows the lowest EF (between $9.7 \cdot 10^{-5}$ and $2.88 \cdot 10^{-3}$ EF score$\cdot NVA_{fc}{}^{-1}$), and is made up of 77.74% of the sample, namely 11 herbaceous crops, 17 Mediterranean perennial crops, and all the fruit tree and vegetable crops. It is the most diverse group with a broad type of reference holdings showing a broad range of EF scores per kg commodity. The correspondence between the use of resources and the economic results is evident in this group; this is because, despite the wide range of EF scores per kg commodity, they converge when expressed per NVA_{fc}, which is the group with the narrowest dispersion in terms of the EF scores per NVA_{fc}. The second cluster presents an intermediate performance, between $3.04 \cdot 10^{-3}$ and $9.01 \cdot 10^{-3}$ EF score$\cdot NVA_{fc}{}^{-1}$, and it is made up of 7 reference holdings (3 herbaceous and 4 Mediterranean perennial crops); whereas the third group includes 4 irrigated herbaceous crops (soft wheat and barley in AR, CM and CL) with the greatest impacts (between $1.37 \cdot 10^{-2}$ and $2.13 \cdot 10^{-2}$ EF score$\cdot NVA_{fc}{}^{-1}$). In these last two clusters, it is possible to observe a high degree of dispersion both in the results per kg commodity and NVA_{fc}, suggesting there is less correspondence between the use of resources and the economic results. The fourth cluster is made up of 14 reference holdings (12 herbaceous and 2 Mediterranean perennial crops) which showed negative NVA_{fc} (economic losses). Even though 86% of this group corresponds to herbaceous crops in rainfed (12 reference holdings), irrigated soft wheat in EX and irrigated barley in CL were the most critical reference holdings because they exhibited the highest EF scores per loss of NVA_{fc}. In addition, it should be noted that the four oat holdings studied are included in the fourth cluster. The negative economic results of these reference holdings can be explained by the low land productivity (yield) of these crops in the corresponding NUTS 2, which was lower than the average Spanish yield for the same crops in the years analysed reported in FAO (2023).

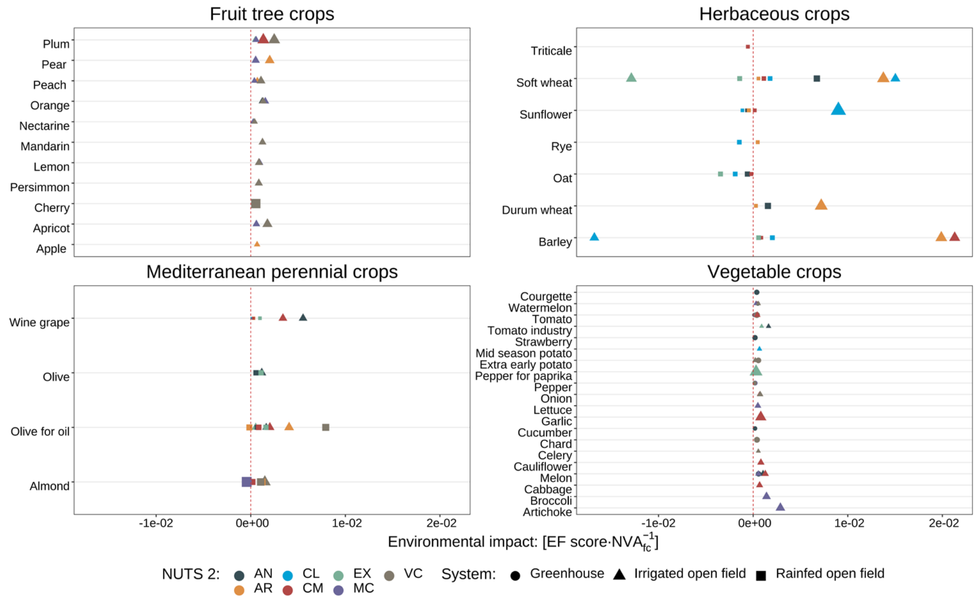

Fig. 2.4.2. Median environmental footprint scores of the reference holdings. The size of the symbol is proportional to the EF score per kg commodity.

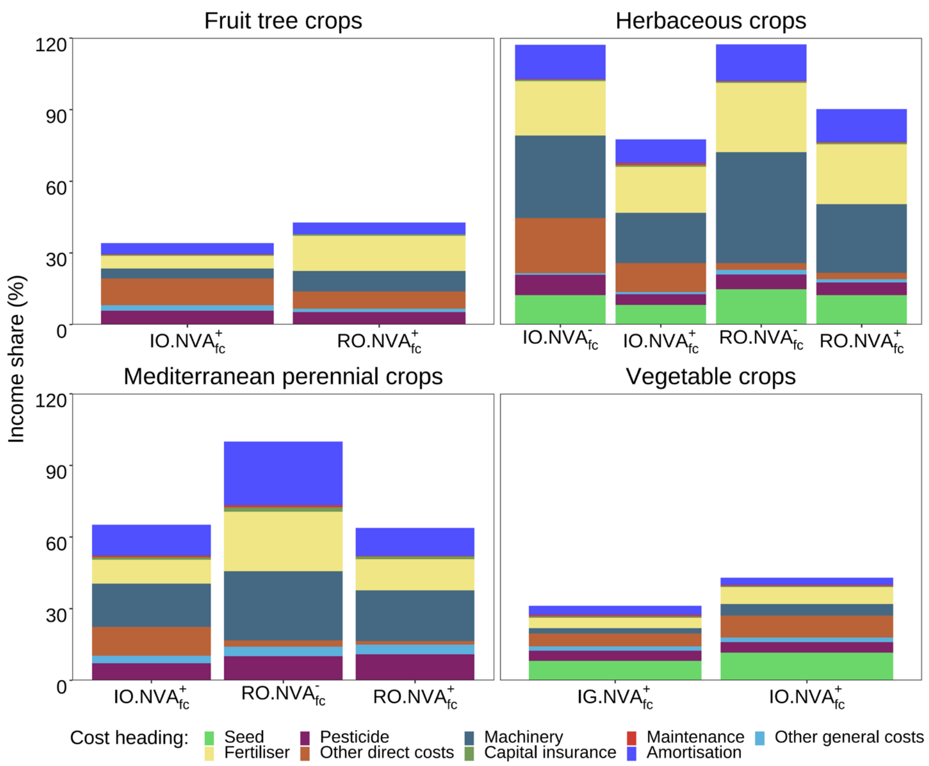

Fig. 2.4.3. Average of the intermediate costs of the reference holdings analysed RO, IO and IG indicate rainfed and irrigated open field and greenhouse systems, respectively. + and - indicate positive and negative NVA_{fc}

Exploring the structure of the NVA_{fc} (Fig. 2.4.3) can help to better understand the results. Fruit tree and vegetable crops show the best economic performance. In the fruit tree crops, intermediate costs, mainly those of fertilisers, and general direct costs are the ones with the greatest share, and for the vegetables group, seed costs and general direct costs predominate. Machinery (including fuel, maintenance, and the price of the outsourced service), amortisation and fertilisers are the most relevant operating costs through the holdings of herbaceous and Mediterranean perennial crops, and are relatively greater in those with a negative economic result. Another heading to be highlighted in the irrigated herbaceous crops with negative NVA is the direct general cost.

2.4.3.2. Contribution analysis

Generally speaking, the relative contribution of the life cycle stages analysed to the EF scores of the reference holdings substantially differ depending on the type of crop and management system (Fig. 2.4.4). The relative contribution of the stages in each NUTS 2 is similar, except in the case of the vegetable crops, where the share varies depending on the NUTS 2. It must also be noted that in the case of the irrigated fruit tree crops, the contribution of the on-field operation stage for the reference holdings in EX is greater than in the remaining NUTS 2. As for the herbaceous crops, no differences can be found between the relative contribution of the stages of the reference holdings with positive and negative NVA_{fc} .

Irrigation is the most influential stage in the EF scores of the reference holdings of fruit tree and vegetable crops, followed by on-field operations and infrastructure. In contrast, the stages of fertiliser and pesticide production were those that contributed the least to the EF. It must be noted that due to the relatively high amount of fertilisers applied or the lower irrigation dose, , the stages contributing the most in some fruit tree and vegetable reference holdings were on-field operation (e.g. Fr_Pea_IO_EX, Fr_Nec_IO_EX, Ve_Eep_IO_VC and Ve_Mpo_IO_CL) and infrastructure (namely Ve_Eep_IG_VC, Ve_Cha_IG_VC and Ve_Cha_IG_CM). In addition, irrigation was not influential in Fr_Che_RO_VC because it was the only rainfed reference holding of fruit tree crops; therefore, the stage that contributed the most to its EF was that of on-field operation. Different patterns are observed for the reference holdings corresponding to Mediterranean perennial and herbaceous crops. On the one hand, similar to fruit tree and vegetable crops, irrigation, on-field operation and infrastructure were the stages with the greatest share for the irrigated reference holdings, with irrigation being the most influential stage. Secondly, the on-field operation had the greatest share in the rainfed reference holdings, although fertiliser production and machinery were also relevant. The sunflower reference holdings were an exception to this (He_Sun_RO_AN, He_Sun_RO_AR, He_Sun_RO_CL and He_Sun_RO_CM), in which the use of machinery was the stage with the highest share; this can be explained by the low contribution of on-field operation, due to the low quantity of fertilisers applied in these holdings.

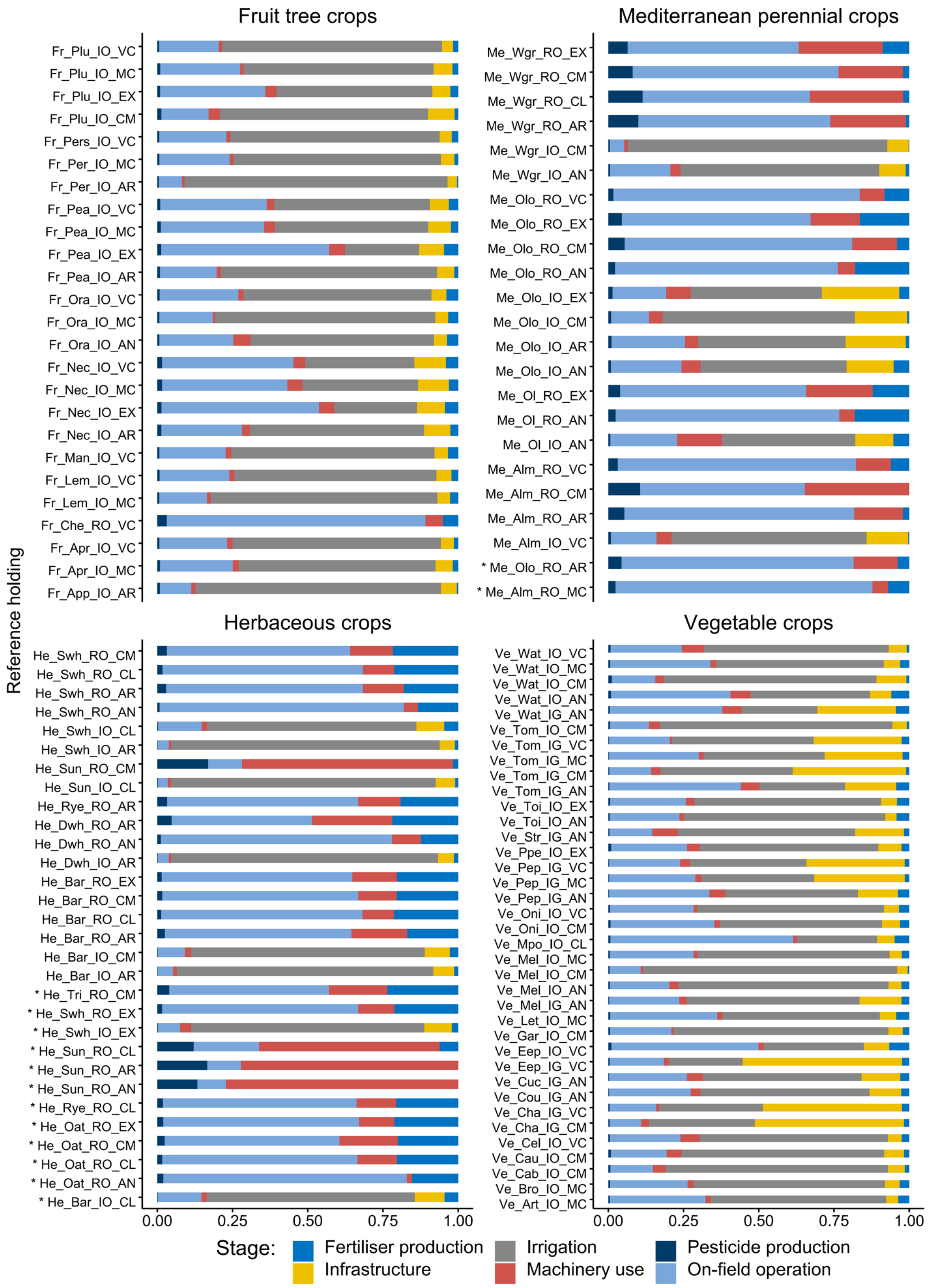

Fig. 2.4.4. Relative contribution of life cycle stages to the environmental impacts of the reference holdings at the Spanish NUTS 2 level in the period 2010–2017. Acronyms of the y-axis are depicted in the annex C.1. The reference holdings with negative NVA are highlighted with *.

2.4.3.3. Implications of the selection of the functional unit

The environmental performance of the reference holdings as EF score per euro of NVA_{fc} is compared versus that expressed per kg of commodity since it is the most commonly used in agricultural LCAs.

Rankings are developed in descending order for each crop, since M-FU only works if comparing the environmental impacts of similar products. The rankings of the impacts of the reference holdings using both FUs are shown in Annex C.3, while Fig. 2.4.5 shows the differences in the ranking position when the EF score is expressed per M-FU instead of E-FU.

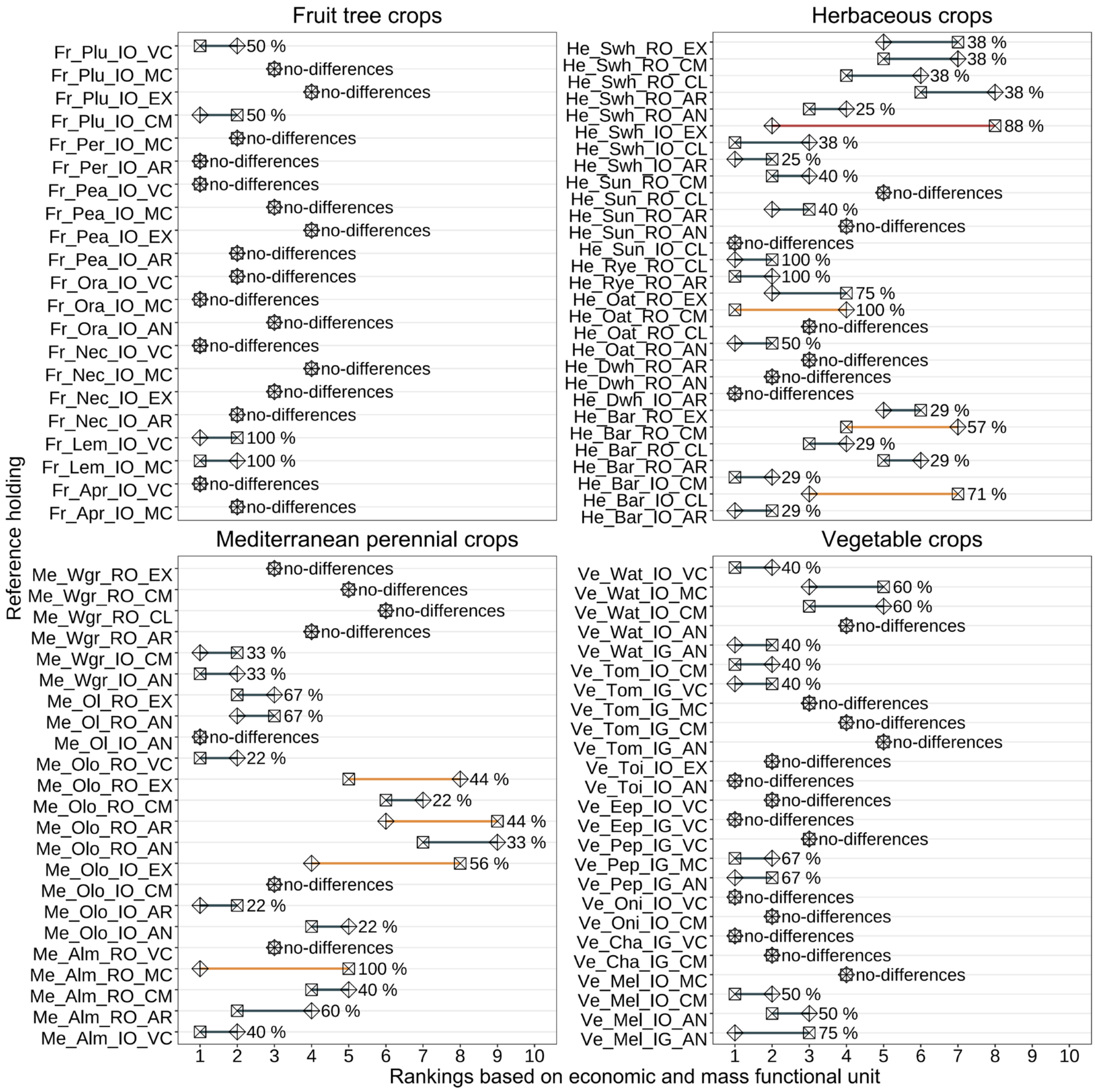

Fig. 2.4.5. Ranking in descending order of the environmental footprint performance using 1 € of net value added (square) versus 1 kg commodity (rhombus) as functional unit.

It can be observed that 54% of the holdings do not change their ranking positions when using a M-FU, whereas the remaining 46% show a shift of a different order of magnitude. In particular, in the groups of fruit tree and vegetable crops, most of the holdings keep their position in the ranking (80.77% and 70.27%, respectively). In the case of herbaceous and Mediterranean perennial crops, only 26.67% and 30.43% of the holdings keep their position, and some of the holdings of these two groups exhibit a marked shift in the ranking. For instance, of the eight holdings growing soft wheat in the herbaceous crop group, He_Swh_IO_EX shifts its position in the ranking by 88%; it has the greatest impact when the scores are expressed per E-FU and the second best when using M-FU. Of the five holdings growing almonds in the

Mediterranean perennial crops, the worst performance is that of the one in Murcia (Me_Alm_RO_MC) with the E-FU and the best is with the M-FU. These findings once more confirm the influence of the FU in the results when comparative LCAs are developed.

In this study, the economic value added is the FU used, as policymakers are the potential target audience of the accounted impacts; however, other economic and financial indicators can better represent the E-FU depending on the target audience. For instance, in some studies aimed at farmers, the receipts have been used as FU (Cerutti et al., 2013; Mouron et al., 2006a, 2006b); nevertheless, the use of profit-based indicators (e.g., Earnings Before Interest Taxes Depreciation and Amortization-EBITDA) can be a better methodological choice, since they relate the environmental impacts with the economic goal sought by the farmers. If customers were the target audience, a suitable FU should represent the money paid by a customer to obtain goods or services, such as the price, which was the FU used by Van Der Werf and Salou (2015) and O et al. (2023).

2.4.3.4. Adverse economic results versus negative environmental consequences

The results of this study show that 14 of the 115 reference holdings assessed presented consistent economic losses over the years analysed. Spanish agriculture is framed in a competitive market economy, where many farmers provide the same commodities, making substitutions between them feasible. Taking this into account, it is debatable whether, even under a weak vision of sustainability, where the substitution of natural capital for manufactured is allowed (Hediger, 1999; López Pardo, 2012), it is convenient to support the adverse effects on the environment of the holdings with negative economic results. Assuming that these losses are not due to an inconsistency derived from working with average data from ECREA-FADN, since information on its distribution and dispersion is not provided, the continuation of the economic activity of these holdings can be justified for different reasons: among others, cultural aspects, the opportunity cost of the land, the fact that agriculture is often developed as a secondary activity, and in some cases because of subsidy collections. However, nowadays most of the subsidies are decoupled from yield and linked to meet eco-conditionality. It must be noted that agriculture contributes to fixing the population in the so-called “emptied regions”, a decisive problem in some Spanish NUTS 2, and also in other southern countries of the EU (EUROSTAT, 2022; Newsham and Rowe, 2023). These positive externalities should be weighed through a comprehensive cost-benefit analysis.

In this case study, most of the holdings showing consistently negative output correspond to herbaceous crops, which should facilitate the implementation of standard measures to face this issue. As commented on in section 2.4.3.1, machinery and fertiliser present the greatest share in the herbaceous group. To improve the performance of these crops, political decisions aimed at achieving an efficient use of agricultural inputs are needed in line with objective 1 of the Spanish CAP Strategic Plan.

2.4.3.5. Assessing the representativeness of the results

The data sources used to configure the life cycle inventories of the reference holdings in the Spanish NUTS 2 can be considered representative of the regional and technical levels of the crops analysed. Even with this, the relationship between the average surface area of the reference holdings and their environmental impacts needs to be analysed to know whether the impact scores can be used to assess the environmental impacts of the crops without considering the farm size. If no significant correlation between the two variables is found, it can be assumed that the estimated scores can represent the environmental damages of farms regardless of their surface area, suggesting that there is no differential impact as a result of the size effect.

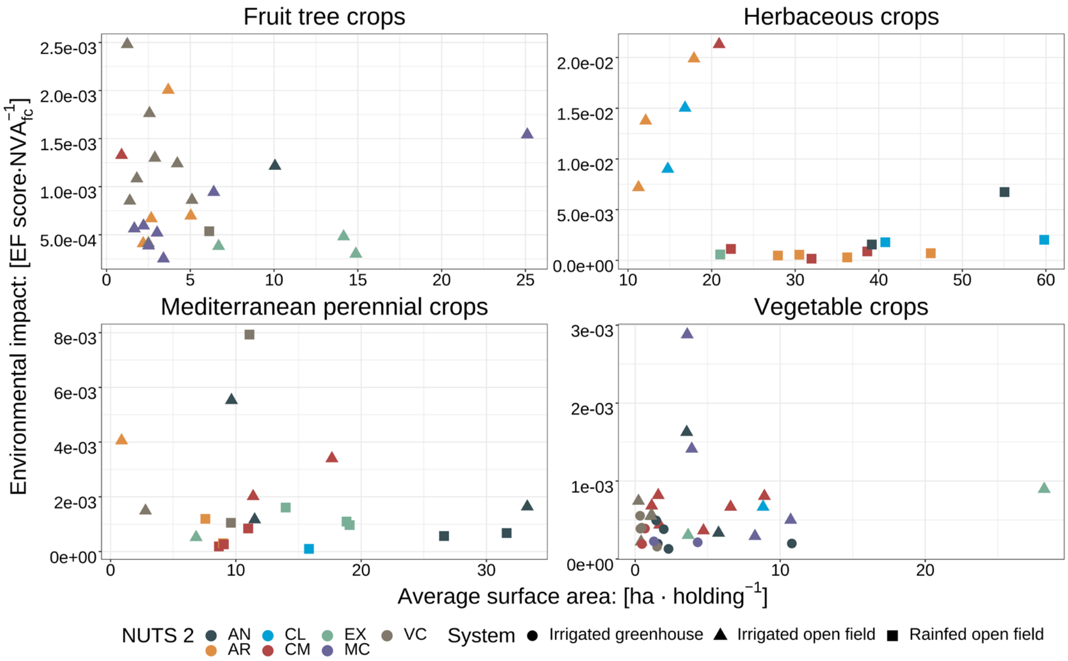

Fig. 2.4.6. Environmental footprint per 1 € of net value added versus the surface area of the farms.

As shown in Fig 2.4.6, no correlation between the average size of the reference holding and the EF scores is observed for the four types of crops, which supports the idea that the environmental performance of the reference holdings estimated in this study was not affected by the size of the reference holdings. Therefore, as long as the opposite is not proven, the impact results of this study can be used as a reference for a specific crop in a NUTS 2 in Spain, regardless of the size of the holdings.

2.4.4. Discussion

The impacts accounted for in this study are subject to two kinds of limitations: the LCA approach and the data source used. Regarding the LCA approach, it should be remarked that this study corresponds to a C decision context in which purely descriptive accounting is considered (EC-JRC, 2010). In particular, a retrospective analysis is carried out, in which the performance of alternative systems in recent years is assessed. Along these lines, the C decision context works as the starting point to understand the context of a system and not as the definitive source to develop recommendations and decisions with future implications, which should be supported by A or B decision contexts; that is, a consequential LCA. Nevertheless, these results can be used to identify hotspots where measures to support sustainable agriculture should be applied, and can also be used as a basis for comparison with those resulting from the implementation of the new CAP. In addition, political measures could be suggested, whose consequences should be assessed by applying a consequential LCA. Analogously to how financial accounting is used in the calculation of income taxes, environmental impact accounting from a C decision context could be the basis for calculating environmental taxes. Even though median EF scores are analysed descriptively in section 3, future inferential analyses would allow their monitorisation over the years, assessing the relation with the structural factors (such as yield and price of commodities). In addition, it should be noted that the calculated impacts can be used as input data in both explained and predictive studies based on historical data.

As to the data source used, although ECREA-FADN is open to the seventeen Spanish NUTS 2, consistent data for only seven of them were available in the years analysed (i.e. Andalucía, Aragón, Castilla y León, Castilla-La Mancha, Extremadura, Murcia and Comunidad Valenciana), and some relevant crops were not accounted for in some NUTS 2 (e.g. corn in AN, AR, CL, CM and EX; and olive and wine grapes in MC and VC), due to the reasons reported in section 2.4.2.1. Yet, it does not provide information regarding the structure of the data (e.g. dispersion, distribution), and the technological itineraries of the farms are poorly described as there is no data on the surface area of the surveyed holdings, type of farming system (conventional, organic) or irrigation system (sprinkler, drip irrigation); thus, it is assumed that the reference holdings follow conventional farming practice, which is the prevailing type in Spanish agriculture. Along these lines, increasing the NUTS 2 and crops represented, improving ECREA reports with statistics on the distribution and dispersion of the quantitative data together with a systematisation of the description of the management practices followed in the reference holdings would increase the reliability and representativeness of the database and, therefore, that of the results obtained.

The new version of ECREA (MAPA, 2023c) has recently been developed based on the RECAN database, where anonymised microdata of the farms surveyed can be accessed. Microdata implies greater detail, mitigating the loss of information due to third-party data processing. In this way, the development of the ECREA-FADN from the RECAN increases the representativeness of the data and, together with the transition of existing FADN to the Farm Sustainability Data Network (FSDN) proposed by the EU (EC, 2023d), represents a relevant effort to improve the estimation of the environmental impacts of agricultural systems from this data source.

In the transition to a FSDN, the synergy between governmental institutions and researchers in the field of agricultural sustainability must be promoted to obtain a FSDN that satisfies the demand for research data. This data could be the basis for further studies; for instance, to improve the regionalisation of agricultural LCIs and to develop the social life cycle assessment or life cycle costing of representative agricultural commodities. On the other hand, decisions aimed at the opening up of accessibility to detailed data in other official statistics and at facing up to the challenge of digitalisation of Spanish agriculture may help to develop more comprehensive R-LCAs.

Methodological efforts in the application of R-LCAs should address representativeness and accuracy not only as concerns activity data but also in terms of the emissions factors: for instance, the metanalysis of Cayuela et al. (2017) compile emission factors for N_2O for Mediterranean cropping systems. The use of regionalised impact assessment methods is also recommended, such as IMPACT World+ (Bulle et al., 2019), LC-Impact (Verones et al., 2020), or AWARE (Boulay et al., 2018; Boulay and Lenoir, 2020).

2.4.5. Conclusions

A set of indicators suitable for the purposes of comparing the recent environmental performance of reference holdings at the Spanish NUTS 2 level has been obtained. One strength of these indicators is that they have been developed for a broad group of reference holdings using the same data source, that is, avoiding bias resulting from the use of diverse sources. The analysis of the EF scores helped to identify how, in most of the reference holdings, the environmental impacts were proportionally compensated for by the economic goal sought. This was not the case for most of the reference holdings of herbaceous and some Mediterranean perennial crops, in which, neither was the economic goal achieved (negative NVA) nor did the greater use of resources in the irrigated reference holdings necessarily lead to a higher yield and better economic performance, but instead increased the environmental impact. The existence of holdings with a recurrent negative contribution to the gross domestic product highlights one of the main challenges of Spanish agriculture: how to improve competitiveness and return (MAPA, 2023a). Following this study's findings, policies addressing a more efficient use of fertilisers and machinery are needed to improve the return and the environmental performance of the reference holdings, particularly in the cases of herbaceous and Mediterranean perennial crops. In particular, farm subsidies to improve the digitalisation and the development of precision farming can help to make an efficient use of the resources, such as fertilisers and machinery use; this is a valuable effort towards achieving sustainable agriculture.

In this study, the NVA is the E-FU used to compare the environmental performance of different agricultural commodities. In addition, considering that economic decisions around the supply chains is the main source of environmental impacts, E-FUs relate the environmental impacts more precisely than other options. In this context, impacts expressed on M-FU should be seen as an intermediate item to obtain impacts expressed on E-FU, which is helpful for results interpretation.

The availability of quantitative indicators is essential in decision-making towards achieving agricultural sustainability. The EU and the scientific community have robust methodologies for quantifying environmental indicators at the midpoint and a comprehensive environmental footprint indicator. Applying these methodologies to economic activity links methodological advances in science to society's needs for decision-making and policy development based on scientific arguments.

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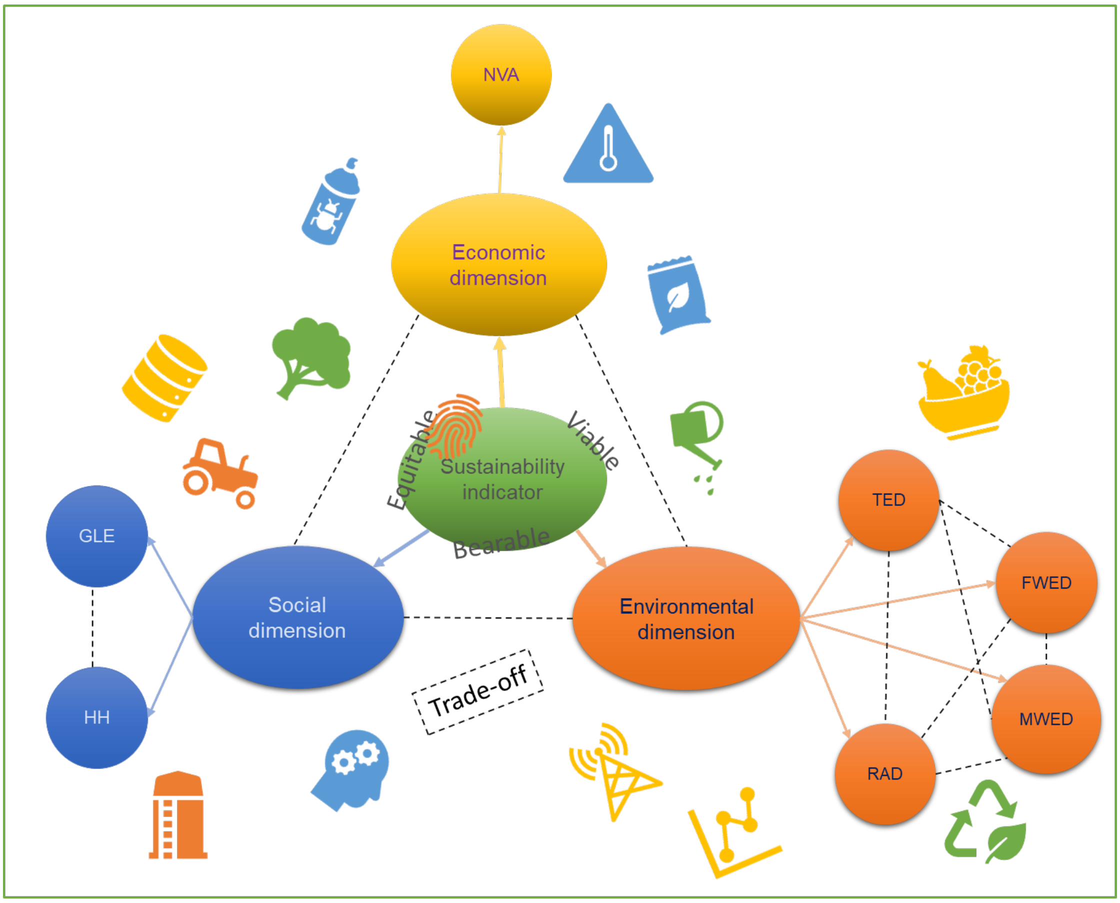

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Abstract

Assessing the sustainability of agriculture is a relevant methodological issue with practical implications. In this study, a systematic approach is followed to develop a composite indicator that ranks the sustainability performance of Spanish reference farms at the NUTS 2 level. The classical three-dimension approach is considered under a deductive point of view to represent sustainability. To weigh and aggregate the three dimensions' attributes, multicriteria techniques suitable to model the trade-offs between individual attributes are used, allowing for different normative standpoints to be expressed. The sensitivity and uncertainty arising from the methodological choices are assessed using a variance-based technique. The ordinary least squares technique is applied to evaluate the sensitivity of the composite indicator to shifts in the consumption of relevant inputs. The results show that the trade-off level does not leverage most of the analysed units. In addition, the ranking obtained made it possible to discriminate the herbaceous farms as those with the worst sustainability performance. Methodologically, the most influential parameters in the indicator are related to the ethical complexity of evaluating overall sustainability. In addition, the indicator shows a high sensitivity to shifts in the consumption of machinery fuel and irrigation resources. In short, the indicator developed represents a relevant input to improve the interpretation of the sustainability performance of agriculture as a multidimensional issue, emphasising its normative character.

Keywords

AHP, Sobol' indices, triple bottom line, weak/strong sustainability, trade-off modelling

2.5.1. Introduction

Sustainability is becoming a pivotal concept to support decision-making aiming at improving or, at least, maintaining the planet's welfare in the medium-long term (Dao et al., 2011). Regardless of how controversial the concept of sustainability can be (Hallin et al., 2021), and in line with the well-spread concept of sustainable development of the Brundtland report (WCED-UN, 1987), different definitions of agricultural sustainability have been proposed (Hansen 1996). In this regard, the sustainable development goal 12 (UN, 2023) and, in the European Union context, the Farm-to-Fork (EC, 2023) and Biodiversity 2030 (EC, 2023) strategies, as well as the Common Agricultural Policy-CAP 2023-30 (MAPA, 2023a), interpret sustainability as the kind of agriculture to be promoted, it is understood as a set of management strategies. This interpretation of agricultural sustainability is helpful for motivating change (Hansen 1996). A more comprehensive definition of agricultural sustainability conceives sustainability as a property of agriculture that can be assessed, which is suitable for guiding change (Hansen 1996). Along these lines the Food Agriculture Organisation (FAO) supports the classical definition of satisfying the needs of present and future generations while guaranteeing profitability, environmental health, and social and economic equity (FAO, 2023). Talukder et al. (2018) define agricultural sustainability as "the activity of growing food and fibre in a productive and economically efficient manner, using practices that maintain or enhance the quality of the local and surrounding environment - soil, water, air and all living things". Van Cauwenbergh et al. (2007) describe agricultural sustainability as maintaining or enhancing the environmental, economic and social functions of an agroecosystem.

The interest in the sustainability assessment (SA) of agriculture is growing since it fulfils a basic and indispensable social role as a food supplier, also provisioning other private and public goods, associated with intensive use of natural resources that need appropriate and timely sustainable management (Mili and Martínez-Vega, 2019). Literature provides methods to fulfil this thriving need, some of which significantly impact policy and praxis. Therefore, assessing the sustainability of agriculture is of paramount importance to analyse the effects of agricultural and environmental dynamics and policies (Sala et al., 2015; Xavier et al., 2018) at different levels, namely product, sector, farm, region, or country (Coteur et al., 2020; Mili and Martínez-Vega, 2019).

Assessing sustainability in general, and that of agriculture in particular, is a complex process due to its multidisciplinary nature and because it involves a dynamic and simultaneous balance among its dimensions (Bartzas and Komnitsas, 2020; Sala et al., 2015). In this regard, different theoretical frameworks are identified for representing the integrity and integration of sustainability (Chopin et al., 2021). The classical one is represented by a triple bottom line (Cicciù et al., 2022; Cinelli et al., 2014; De Luca et al., 2017; Deytieux et al., 2016), where the economic (economic viability), social (social equity) and natural environmental (ecological integrity) dimensions are interconnected rings (Sala, 2020). Other proposals add dimensions to the classical framework, such as the institutional one (O'Connor, 2006), or emphasise on sustainability imperatives (e.g. resilience, viability and stability), proprieties of the system that are intrinsic to the classical pillars (Dominguez-Hernandez et al., 2018; Talukder et al., 2015). Overall, each dimension can be defined using different attributes enabling trade-offs between and within them. A trade-off implies that a disadvantage in one attribute can be offset by an advantage in another (Ceballos et al., 2016; Lampridi et al., 2019; Yu et al., 2019; Zardari et al., 2015). The trade-off level can vary from null to total, which usually is associated with two extreme normative approaches, namely strong and weak sustainability (Cinelli et al., 2014; Deytieux et al., 2016; OCDE-JRC, 2008) (Cinelli et al., 2014; Deytieux et al., 2016; Diaz-Balteiro et al., 2018; OCDE-JRC, 2008). Nevertheless, supported by scientific evidence and based on the precaution principle (UN, 1992), under a positive view, strong sustainability implies a deeply held conviction of applying limits to the substitution between natural capital and manufactured one.

It is worth noting that aspects such as social responsibility, consumer utility function and policy strategies toward sustainable agriculture, have led to the inclusion of sustainability into management strategies of the decision-makers (e.g. governmental organizations, farmers, NGOs and consumers). Thus, agricultural sustainability is a decision-making issue (Sadok et al., 2008) where its quantitative evaluation is relevant to obtaining objective measures (Coteur et al., 2018). Thus, assessing agricultural sustainability in a holistic way, at least considering the three classical dimensions, is crucial (Van Asselt et al., 2014).

The different perceptions of sustainability, the heterogeneity in farming practices (Coteur et al., 2020) as well as the wide number of multi-criteria decision analysis (MCDA) techniques available have led to various tools to assess agricultural sustainability in a comprehensive and quantitative way at the crop, farm, regional and national levels (Diaz-Balteiro et al., 2017; Marchand et al., 2014; Sadok et al., 2008; Triste et al., 2014). Examples of these tools are Sustainability Assessment of Farming and the Environment-SAFE (Van Cauwenbergh et al., 2007); Sustainability Assessment of Food and Agriculture Systems-SAFA (FAO, 2014); Public Goods Tool-PG (Gerrard et al., 2011); and Monitoring Tool for Integrated Farm Sustainability-MOTIFS (Meul et al., 2008). Furthermore, the OECD-Joint Research Centre (OCDE-JRC, 2008) introduced a protocol for constructing a composite indicator. Encapsulated within a synthetic index, this tool amalgamates potentially conflicting attributes associated with multidimensional concepts, such as agricultural sustainability (Greco et al., 2019; OCDE-JRC, 2008). Composite indicator is popular in a broad group of research areas, global institutions and policy-making's environment (Greco et al., 2019); for instance, it is considered as a valuable item in the designing sensible environmental policies (Diaz-Balteiro et al., 2018); nevertheless, it shows some weakness, especially when it is poorly constricted (OCDE-JRC, 2008). The growing increase in this type of tools has awakened the concern of researchers about how to choose among them considering normative, systematic and procedural aspects (Chopin et al., 2021; De Olde et al., 2016; Diaz-Balteiro et al., 2017; Gómez-Limón and Sanchez-Fernandez, 2010; Sadok et al., 2008; Triste et al., 2014). The tools can be either oriented to goal or to means, with a parsimonious or complex representation of the system, assigning the importance of the attributes (weighting) from a normative or positive way, with different treatment of the compensation between attributes when the tool includes an aggregation step, that can be classified attending to the type of data (quantitative, qualitative or both) and the sources used (e.g. database and surveys). The taxonomy described here does not intend to represent all the choices for assessing agricultural sustainability, but it helps in the description of this study.

Within the MCDA techniques used to assess agricultural sustainability, Sadok et al. (2008) distinguished between multiple-objective (MODM) and multiple-attribute (MADM) decision-making tools. Based on mathematical programming models, MODM looks for the optimal solution of an objective function subject to a set of constraints. On the other hand, MADM consists of ranking a finite number of units of analysis in terms of their sustainability performance. MADM tools can be classified between multi-attribute utility and outranking ones, depending on how the ranking is reached. In particular, it must be remarked that weighting and aggregation are pivotal issues that have been widely discussed when assessing overall sustainability in a quantitative way. In this respect, the reviewed literature shows a trend to support normative weightings and non-compensatory aggregation approaches (Diaz-Balteiro et al., 2017; Díaz-Balteiro and Romero, 2004), since from a participatory or consultation process, the weighting helps to gather the sustainability notion of the stakeholders (Marchand et al., 2014; Triste et al., 2014), while a non-compensatory aggregation avoids substituting a disadvantage in one attribute by an advantage in another. Additional literature on the most used tools to assess agricultural sustainability is gathered in the reviews by Deytieux et al. (2016), Lampridi et al. (2019) and Cicciù et al. (2022).

The accumulated research efforts around SA highlight the relevancy of sustainability science (SS) consolidated as a new field of research, which is fed from the knowledge (theoretical and methodological approaches and tools) contributed from different disciplines (multidisciplinarity), their integration (interdisciplinarity), and their direction to solve real-world problems (transdisciplinarity). However, few studies (e.g. Bausch et al., 2014) on SA robustly apply SS concepts (Troullaki et al., 2021). In addition, the broad number of alternatives to modelling overall agricultural sustainability demand a sensitivity analysis of the results due to changes in critical methodological choices.

Sinisterra-Solís et al. (2023) estimated a pool of indicators related to the environmental and social dimensions (e.g. damage to natural ecosystem and to human health) for a group of Spanish farms, representative at the NUTS 2 level. The study was driven by the need of having quantitative indicators available at the regional scale (NUTS 2), since it is the level at which the CAP is managed in Spain, the third country in cultivated area and the fifth in production in the European Union (MAPA, 2022). Nevertheless, the authors highlight the need to develop a composite indicator to complement their results, gathering the multidimensional nature of sustainability and enabling a ranking that makes it possible a straightforward interpretation of the sustainability performance of the analysed units. Previous studies have evaluated the sustainability of Spanish agriculture (Egea and Pérez y Pérez, 2016; Gómez-Limón and Sanchez-Fernandez, 2010; Mili and Martínez-Vega, 2019; Parra-López et al., 2008; Reig-Martínez et al., 2011; Rodríguez Sousa et al., 2020) focusing either on specific crops or at other levels different to NUTS 2; therefore, to the author's knowledge, the need expressed here remains to be filled.

The goal of this study is to develop a composite indicator for SA applying systematically SS, and modelling the sensitivity of the results to some critical methodological choices. The sustainability composite indicator, hereinafter SCI, is used to assess Spanish representative farms of the main crops at the NUTS 2 level, to complement the results from Sinisterra-Solís et al. (2023).

2.5.2. Case study

This case study assesses the sustainability of Spanish agriculture at the NUTS 2 level, using the sample of 115 reference farms studied in Sinisterra-Solís et al. (2023). The root sources are the annual studies of costs and incomes of agricultural farms (ECREAs) disseminated by the Spanish Ministry of Agriculture, Fisheries and Food (MAPA), which represent a type of Spanish Farm Accountancy Data Network-FADN (MAPA, 2023b). Sinisterra-Solís et al. (2023) gather these ECREAs in a dataset, which is the sample of the case study. The reference farms represent the main crops at the reported NUTS 2 level in ECREAs and are named according to (i) the group of crops (fruit trees, herbaceous, Mediterranean perennial, and vegetables); (ii) the specific crop for each group (e.g. tomato, olive, etc); (iii) the agricultural practices (irrigated open field, rainfed open field, and irrigated greenhouse) and (iv) the Spanish NUTS 2 where they are located (Aragón-AR, Región de Murcia-MC, Comunidad Valenciana-VC, Extremadura-EX, Andalucía-AN, Castilla-La Mancha-CM, and Castilla y León-CL). The sample gathers data from 2010 to 2017. However, due to a lack of information, for some reference farms, fewer years were considered, in no case less than four. Supplementary material (SM-1, Table S1) provides information on the sample assessed.

2.5.3. Methodology

This study is based on the (OCDE-JRC, 2008) protocol for constructing composite indicators. The protocol was chosen because it enables the development of a comprehensive approach that is flexible to the normative, systemic, and procedural aspects from which agricultural sustainability is assessed. The protocol is adapted to the research goals, and includes the following steps: 1) Development of a theoretical framework, 2) Selection of the variables and definition of the target audience, 3) Multivariate analysis, 4) Normalisation of data, 5) Weighting and aggregation, 6) Robustness and sensitivity, 7) Back to the details and links to other variables, 8) Results presentation. Fig. 1 shows how these phases (blue outline) are developed in the remainder of the paper, detailing the information sources used (grey outline), the methodological techniques applied (orange outline) and the partial results obtained (green outline).

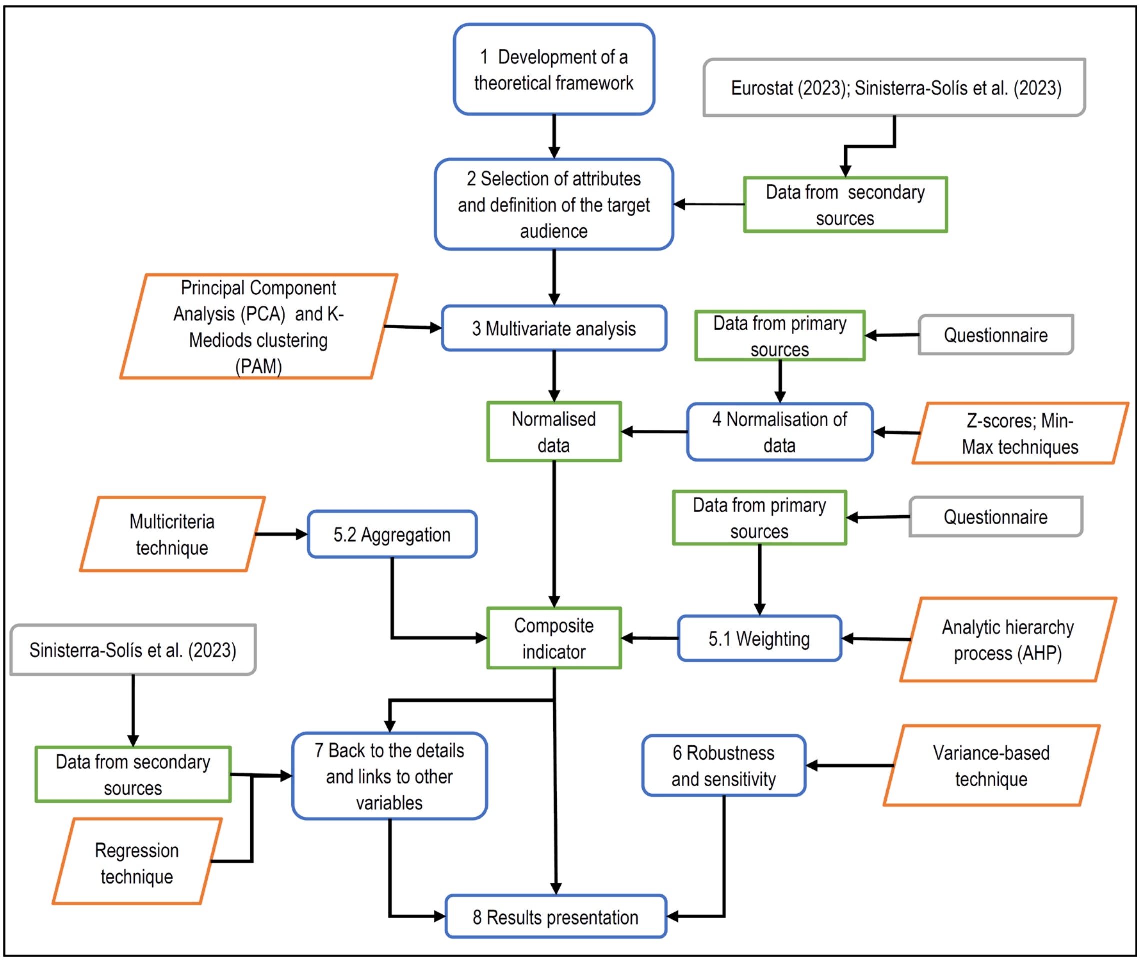

Fig. 2.5.1. Methodology approach followed in the study. Data sources in grey; data in green; step of the approach in blue; methodological techniques applied in each step in orange.

2.5.3.1. Development of a theoretical framework

In this study, from a deductive view, agricultural sustainability is represented by the classical three dimensions (Fig. 2), in which overall sustainability is understood as a global search, where particular aims are formulated conveniently according to the economic, social and environmental dimensions. In particular, similar to many of the existing tools to quantitatively assess agricultural sustainability, a hierarchical-quantitative approach (De Olde et al., 2016) is developed to rank the sustainability performance of the units analysed (Fig. 3). The first hierarchical level is formed by the principles of supply (stock) of biotic and abiotic resources function in the environmental dimension, the physical well-being of the farming community in the social dimension, and the economic function in the economic one (Van Cauwenbergh et al., 2007). The second level gathers the criteria to be optimised. This means minimising the damage to biodiversity and resources' availability concerning the environmental dimension, minimising the damage to the farming community health, and optimising the labour conditions in the social dimension, and maximising the economic benefit in the economic dimension. The last level is made up of the individual sustainability attributes in measurable quantities, as detailed below in section 2.2.2. In brief, the study is developed under a utilitarian ethical approach, which seeks the best sustainability performances that maximise the positive outputs (e.g., net value added) and minimise the negative ones (e.g. potential environmental damages), considering that no cut-off points are established in most of the sustainability attributes, such as setting limits to the capacity to assimilate natural environmental impacts (Veisi et al., 2016).

In some of the next steps, different methodological choices are considered as complementary or as uncertainty sources based on which the sensitivity of the final results (ranking) is assessed.

2.5.3.2. Selection of attributes and definition of the target audience

Beyond measuring agricultural sustainability in absolute terms, this case study focuses on developing a composite indicator tailored to the attribute variables of the units of analysis (reference farms) gathered from official databases and other literature sources; due to data, time, and budgetary constraints (Triste et al., 2014). Hence, the scores obtained with the composite indicator aim to be used to rank and analyse the sustainability performance of the reference farms; therefore, it is a relative measure. The attributes selected to represent each sustainability dimension are described below.

The economic dimension is represented by the net value added (E_NVA), which quantifies the contribution of the reference farms to the regional and country economies. It refers to the economic value that the reference farms add to the transformation of intermediate goods (e.g. seeds, fertilisers, pesticides) into agricultural commodities, also considering the consumption of capital goods. E_NVA remunerates the economic agents who invest their efforts in the development of the economic activity (e.g. farmers, labour and government) and is widely used as a well-being measure generated by an economic activity and allows the comparison between farms regardless of the nature of the production factors used (MAPA, 2023c). Those reference farms with E_NVA < 0 are considered non-sustainable because they break the threshold of the economic dimension and are therefore not accounted for in the following steps. The social dimension is made up of the damage to human health (S_HH) and the gender labour equity (S_GLE), which represents the female full-time equivalent employment (Annual Work Units, AWU) per male full-time equivalent employment. The natural environment dimension is defined by the damage to the quality of ecosystems, namely terrestrial (N_TED), freshwater (N_FWED), and marine water (N_MWED), and resource availability (N_RAD).

The scores for these attributes were obtained from Sinisterra-Solís et al. (2023), except S_GLE, which was estimated from Eurostat data (Eurostat, 2023) and assigned to each reference farm as a function of the NUTS 2 factor. The data from Sinisterra-Solís et al. (2023) are based on the implementation of a life cycle assessment using activity data estimated from official accountancy data. In particular, S_HH, N_TED, N_FWED, N_MWED and N_RAD are endpoint impact categories of the ReCiPe method (Huijbregts et al., 2017). E_NVA is also estimated in Sinisterra-Solís et al. (2023).

In short, with the selected attributes for the three dimensions' integrity, a composite indicator is built based on output attributes of positive effects on the economic and social dimensions (E_NVA and S_GLE) and the negative externalities on the social and natural dimensions (S_HH and all attributes corresponding to the natural environment dimension) of the average result of the reference farms in the period 2010-2017. The reference farms are variable in the crop grown; hence, they cannot be compared and ranked using the attributes expressed per commodity outcome. To address this, an economic base (i.e. 1 € of income) is used to express most sustainability attributes (Fig. 3).

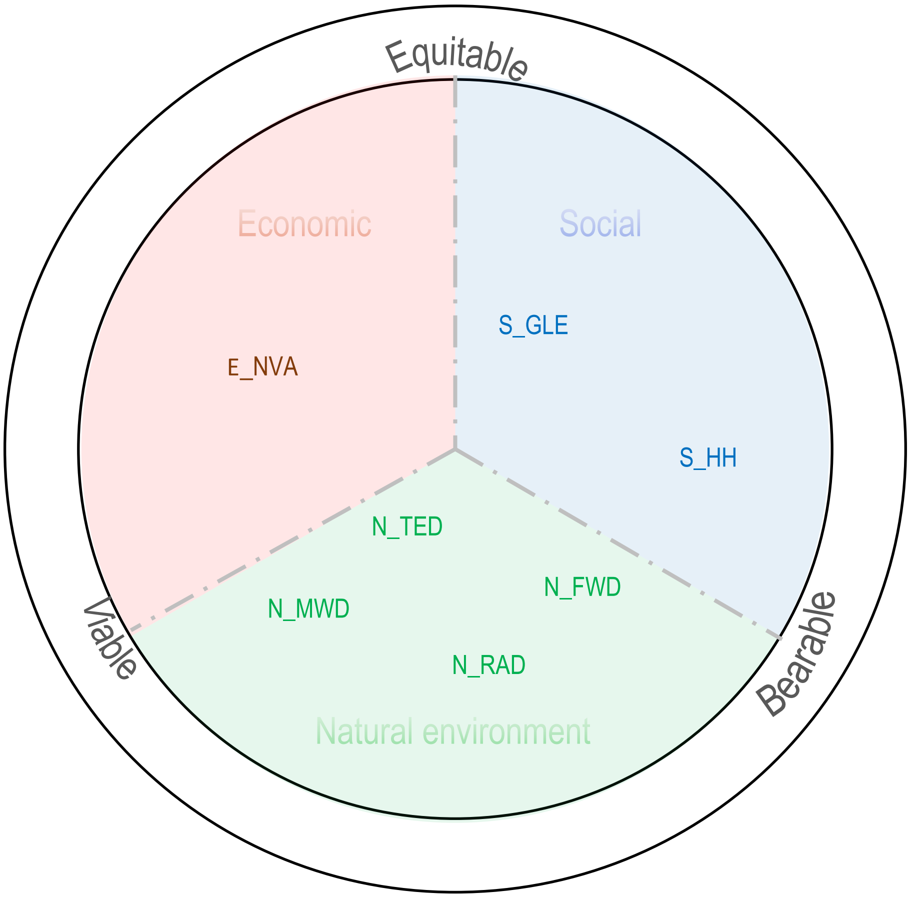

Fig. 2.5.2. Application of the triple bottom line framework to the case study of sustainability assessment of the reference farms at the Spanish NUTS 2 level. E_NVA: net value added at factor cost and at constant price, base-year 2010; S_GLE: gender labour equity; S_HH: damage to human health; N_TED: damage to the terrestrial ecosystems quality; N_FWD: damage to the freshwater ecosystems quality; N_MWD: damage to the marine water ecosystems quality; N_RAD: damage to the resource availability.

Agricultural sustainability involves a broad group of stakeholders (e.g. farmers, governmental organizations, and academics specialised in this topic); nevertheless, only some of them are able to manage direct decisions based on a particular evaluation (target audience). In this case, the sustainability attributes considered in this study go beyond of direct objectives of farmers and are more related to aspects within the scope of policy management; that is, adding value to the economy beyond profits, seeking gender balance and mitigating negative externalities of farming. Along these lines, policymakers can be considered as a potential target audience of the study. In addition, from a procedural point of view, academics can also be considered as the target audience due to the methodological approach addressed.

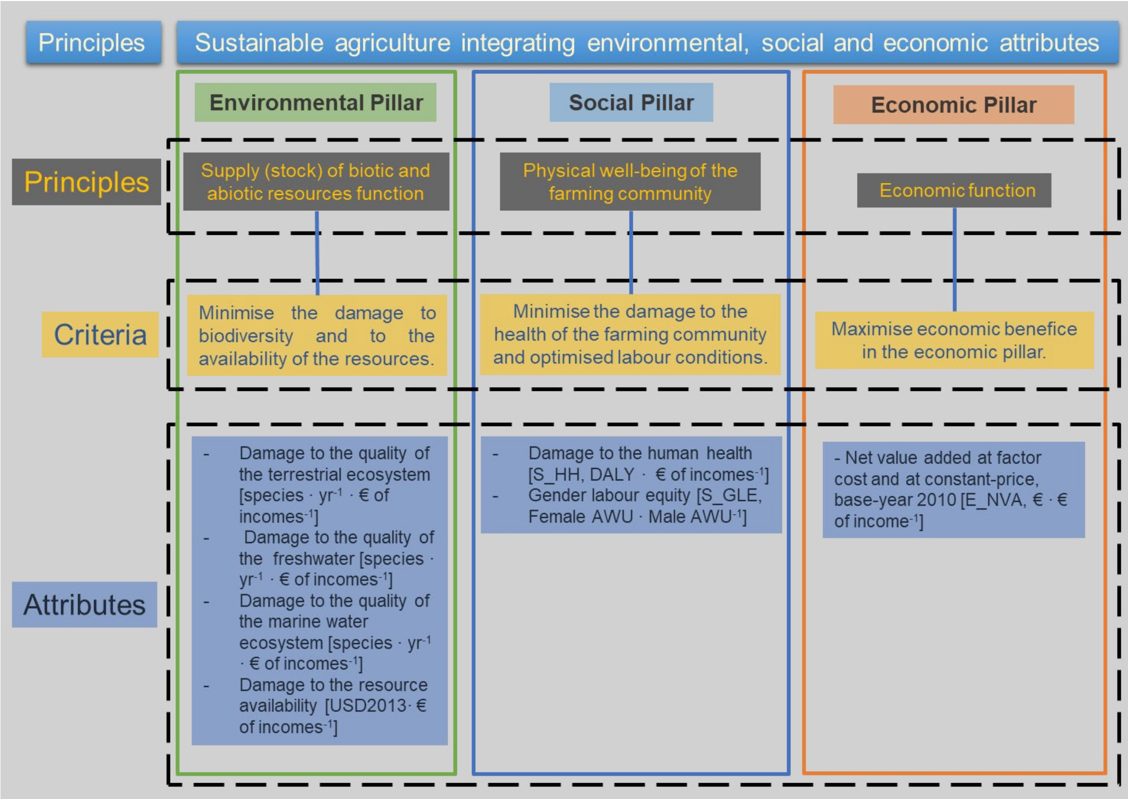

Fig. 2.5.3. Framework to assess the overall sustainability of a set of reference farms at the Spanish NUTS 2 level. Species·yr is time-integrated species loss; DALY is disability-adjusted life year (Huijbregts et al., 2017) and AWU expresses the full-time equivalent employment (EUROSTAT, 2023).

2.5.3.3. Multivariate analysis

Before calculating the composite indicator, a multivariate analysis is developed to explore the dataset's structure. This step helps to identify correlations within the dataset and groups of indicators or groups of farms that are statistically similar, to enhance the visualisation and interpretation of the results. A high correlation between attributes can imply a double counting issue (Gómez-Limón and Sanchez-Fernandez, 2010; OCDE-JRC, 2008), but the hierarchic structure of this approach mitigates the effects of double counting in the final result. In this study, principal component analysis (PCA) is applied to describe the correlation between attributes and to identify homogeneous groups of reference farms. For that, varimax rotation is taken into account to guarantee the independence between the extracted components. Besides multivariate control statistics, the residual sum square (RSS) and Hotelling T^2 (T^2) are applied to the residuals of PCA to examine the existence of multivariate outliers in the dataset, which can influence the data normalisation step (OCDE-JRC, 2008). The control limits of both multivariate statistics were computed using the 95% percentile.

Outliers potentially distort the representation of data in the orthogonal space since they can disproportionately influence the variance of the data. These types of observations can come from different sources, ranging from those belonging to a new population to an inconsistency in its calculation, and based on this, decisions to retain or remove them can be made (Wooldridge, 2013). As a general rule, removing outliers is an option when they come from errors in recording observations; otherwise, careful investigation is needed (Gujarati and Porter, 2009). As mentioned in Sinisterra-Solis et al. (2023), the sources from which the attribute scores were estimated correspond to average data, which are susceptible to generating outliers due to inconsistencies in their calculation. In this sense, and because this is an exploratory analysis, if multivariate outliers are identified, they will be removed to avoid the noise they may cause and obtain PCA results representative of the most significant number of observations. In this regard, observations with RSS and T2 greater than twice the control limits are considered multivariate outliers and are removed from the dataset to obtain the refined PCA results. The “FactoMineR” package (Husson et al., 2022) in the R Studio software (RStudio Team, 2023) was used to model the PCA.

Complementary, a cluster analysis was developed to confirm the observed patterns identified with the PCA, especially in the reference farms, because it can help visualise and discuss the final results. It is modelled with the Partitioning Around Medoids technique (PAM), a more robust version of K-means, which groups the data into k clusters around medoids (Maechler et al., 2022). To this aim, the “NbClust” function of the “NbClust” R package (Charrad et al., 2015) has been used to define the optimum clusters, considering the model on the selection criteria, as well as the “pam” function of the “cluster” R package (Maechler et al., 2022) to run the model in the RStudio software. Likewise, the components and the residues estimated in the PCA were considered as the dataset. In addition, since the groups gathered from PAM are stochastics, the stability of the clusters is assessed from the mean Jaccard similarity value (JS) (Hennig, 2023). The cluster is considered valid and stable if the JS is 0.75 or higher, t. Along these lines, the “clusterboot” function of the “fpc” R package (Hennig, 2023) was applied, using non-parametric bootstrap as the method used for resampling and considering 1,000 resampling runs.

2.5.3.4. Normalisation of data

This step helps express the data on a similar scale before aggregating the attributes since they are described with different units and scales. The debate regarding the best normalisation technique is open since, beyond data commensurability, the techniques available show certain limitations (Diaz-Balteiro et al., 2018). In particular, Min-Max (unity-based) and the Z-scores standardised with a mean equal to zero and unit variance are the most applied to estimate composite indicators, but they are sensitive to outliers and, depending on the distribution, they can distort the distance between ratings within the attributes (OCDE-JRC, 2008). Stanujkic and Zavadskas (2015) suggest adjusting the indicator results to the preferred ratings. Considering the uncertainty in their choice, these three normalisation techniques are tested previous to the aggregation step and are shown in section 2.2.5.

Min-Max-ad enables normalising data as a function of a preferred rating in attributes. This helps identify a grade of leverage related to the overlapping with respect to the preferred rating. In this study, a preferred rating is not predefined and Min-Max-ad is applied so that the leverage of the outliers is explicit. The preferred rating in the attributes to minimise (x_a) is defined as the lowest value between the $\max(x_a)$ and the $Quantile_{75}(x_a) + 1.5IQR(x_a)$ of the respective attributes; whereas in the attributes to maximise (x_b), it corresponds to the highest value between $\min(x_a)$ and the $Quantile_{25}(x_b) - 1.5IQR(x_b)$ of the respective attributes.

2.5.3.5. Weighting and aggregation

Analytic hierarchy process (AHP) has been chosen as the weighting technique because it allows to represent the importance of the attributes from the sustainability perception of the stakeholders; besides, AHP is the normative method most widely used (Cicciù et al., 2022; Greco et al., 2019). Current literature supports participatory analysis to assign the importance of sustainability attributes based on the perception of the stakeholder. However, either due to a lack of judgment or bias because of the result's interest, not all stakeholders are suitable for this purpose. For instance, in this study, policymakers might not appropriately define the weights of the attributes since they are potential users of the study's final results and could make decisions that impact other stakeholders. Academic experts, a priori, can mitigate the latent bias of policymakers; therefore, as they are assumed to have a more holistic perception of sustainability. In addition, these experts can be more sensitive to the positive aspects of sustainability, which is a key issue to take into account when assigning weights to attributes, especially in this kind of study, in which there are no established cut-off points for attributes. According to this, a panel of 15 academic experts on issues related to sustainable agriculture in the European context was surveyed; in particular, six professors in agricultural economics and environmental science and nine researchers from institutes specialised on environmental sustainability applied to agricultural systems. Table S2a in SM-1 shows more details about the experts surveyed. Each expert indicated how important one attribute was against another using a scale from 1 to 9, see Annex D.1.2, where 1 means equal importance and 9 extreme importance (Saaty, 2004). The questionnaire and the experts' features are provided in Annex D.2.

Simple additive weighted-SAW (eq. 2.5.1) is a type of aggregation commonly used in composite sustainability indicators (Cinelli et al., 2014) that suggests a total trade-off between the economic, social, and natural environmental capitals, which is attractive within a weak SA framework (Cinelli et al., 2014; Deytieux et al., 2016; OCDE-JRC, 2008). On the other extreme, models such as Eq. 2.5.2 suggest non-substitution between the dimensions' capital, in line with the strong SA (Cinelli et al., 2014; Díaz-Balteiro and Romero, 2004). To aggregate the SA attributes considering a range of trade-off level (λ), Díaz-Balteiro and Romero (2004) developed Eq. 2.5.3.

$$S_i = \sum_{j=1}^{j=n} w_j I_{i,j} \tag{2.5.1}$$

$$S_i = \min_j \left(w_j \cdot I_{i,j}\right) \tag{2.5.2}$$

$$S_i = (1-\lambda) \cdot \left[\min_j \left(w_j \cdot I_{i,j}\right)\right] + \lambda \cdot \sum_{j=1}^{j=n} w_j I_{i,j} \tag{2.5.3}$$

Where:

S_i is the composite sustainability score of the i alternative; w_j is the weight of j indicator; $I_{i,j}$ is the standardised score of the i alternative on the j criterion; and λ denotes the substitution degree between attributes, where $\lambda = 0$ implies null trade-off, $\lambda = 1$ total trade-off, and when $0 < \lambda < 1$ denotes partial trade-off.

On the other hand, Stanujkic and Zavadskas (2015) proposed a factor based on the distances from the preferred ratings (ωC_i) that, with the data normalised from Min-Max-ad, removes the trade-offs related to the overlapping of the preferred ratings in the individual attributes (Eq. 2.5.4).

$$S'_i = Eq.(1) - \omega C_i \quad (2.5.4)$$

Where:

$$C_i = \varphi d_i^{max} + (1 - \varphi)\bar{S}_i^+ \quad (2.5.5)$$

$$d_i^{max} = \max_i w_j \cdot I_{i,j} \quad (2.5.6)$$

where S'_i denotes the adjusted overall performance rating of the alternative i; C_i is the trade-off coefficient; ω and φ are coefficients between 0 and 1; and $\bar{S}_i^+$ is the average of $(w_j \cdot I_{i,j}) \leftrightarrow I_{i,j} > 0.$

In this study, the methods proposed by Díaz-Balteiro and Romero (2004) (Eq. 2.5.3) and Stanujkic and Zavadskas (2015) (Eq. 2.5.4) are used for the aggregation step, as they consider a range of trade-off levels instead of focusing only on extreme points.

Similar to the weighting, the normative nature of sustainability suggests determining trade-off levels between attributes based on the stakeholders' opinions. However, we consider that the trade-off is a complex issue to be captured from a participatory or consultation process since it is an intrinsic characteristic of the attribute's relationship. As a first approximation, in this study, the trade-off level chosen to model the composite indicator is based on the dataset, complementary applying two tools described by Eqs. 2.5.3 and 2.5.4. Eq. 2.5.3 is selected to estimate SCI since it enables to understand the trade-offs in a scale ranging from zero (null trade-off) to one (total trade-off). Eq. 2.5.4 is used as a pivot to modelling with a trade-off level (λ) that mitigates the bias of a direct choice. In this regard, the proposals of Stanujkic and Zavadskas (2015) to normalise (Min-Max-ad), as mentioned in section 2.5.3.4, and aggregate (Eq. 2.5.4) are applied to obtain an interim composite indicator (SCI^*) following the authors' recommendation of ω = 1 and φ = 0.5. In this case, the λ value chosen is the one that minimises the average shift in the ranking ($\bar{R}_{SCI^*}$) of the M reference farms (Eq. 2.5.7). Although the values for ω and φ are deterministic, their effect in λ is a black box.

$$\bar{R}_{SCI^*} = \frac{1}{M}\sum_{h=1}^{M}|Rank(SCI_h^*) - Rank(SCI_h)| \quad (2.5.7)$$

Consequently, the base SCI of a holding h (SCI_h) is calculated as the average of the SCI considering the unity-based ($SCI_{h,1}$) and the Z-scores ($SCI_{h,2}$) as normalisation methods:

$$SCI_h = \frac{SCI_{h,1} + SCI_{h,2}}{2} \tag{2.5.8}$$

2.5.3.6. Robustness and sensitivity

Analysing the uncertainty of the SCI is relevant to express its robustness. When developing the SCI, different uncertainty sources were identified, namely that associated with the choice of the weights assigned by the experts, the normalisation method, and the uncertainty of the λ value.

To analyse these uncertainties and the sensitivity of the SCI to shifts in the uncertainty sources, a variance-based technique appropriate for non-linear models such as the SCI was used (OCDE-JRC, 2008; Saisana et al., 2005). Precisely, example 2 of Puy et al. (2021) was chosen, using the “sensobol” R package (Puy et al., 2022) to model this uncertainty. Latin Hypercube Sampling Design (LHS) was the approach chosen to construct the sample matrix (McKay et al., 2012, 2000). LHS is a multidimensional systematic sampling approach recommended in non-linear models such as the present one. It ensures a representative sampling across the entire multidimensional input space, a characteristic not achieved by purely random sampling (Puy et al., 2022). The sampling design considers an initial sample size of N = 10,000 and three model inputs (i.e. normalisation, expert weighting and λ). After the multidimensional sampling, the scores are adjusted to distributions particular of each input parameter of the model (Table 2.5.1).

Table 2.5.1. Distribution associated with the uncertainty parameters

Model input	Function of probability	Range
Normalisation method	Discrete, uniform	[1, 2], where 1≡ Min-Max method; 2≡ standardised Z method
Expert weighting	Discrete, uniform	[1, 2, …,15] indicating the expert surveyed to define the weight of the individual sustainability attributes.
Trede-off level (λ)	Uniform	[0,1]

To compute first-order and total-order sensitivity indices, the Sobol’ sensitivity index (Sobol’, 1993) and the estimators proposed by Azzini et al. (2020) were used. To determine the confidence intervals of the sensitivity indices calculated, 1,000 bootstrap replications with a 5% significance level and the percentile method were used.

In addition to the estimated SCI scores, the ranking and $\bar{R}_{SCI}$ (Eq. 2.5.9) stablished from them are interesting outputs to analyse the uncertainty and sensitivity and present the results (JRC, 2008). The rank uncertainty gives an uncertainty interval for each ranking position assigned by the SCI to a given h reference holding ($Rank_{ref}(SCI_h)$). At the same time, $\bar{R}_{SCI}$ is an input for the sensitivity analysis.

$$\bar{R}_{SCI} = \frac{1}{M}\sum_{h=1}^{M}|Rank(SCI_h) - Rank(SCI_h^r)| \tag{2.5.9}$$

$\bar{R}_{SCI}$ denotes the average shift in the ranking of the reference holdings. It captures the relative shift in the position of the entire system of reference holdings in a single number and is calculated as the average of the absolute differences in references holdings' ranks, $Rank(SCI_h)$, with respect to rankings calculated with other methodological settings $Rank(SCI_h^r)$, over the M reference holdings (JRC, 2008).

2.5.3.7. Back to the detail and links to other variables

The SCI developed is the result of integrating the net value added generated and the potential impacts on the environment and human health derived from the activity of the reference farms, also considering a gender equity component of the labour. A previous study with the same sample of reference farms (Sinisterra-Solís et al., 2023) highlighted the consumption of some intermediate inputs (fertilisers, pesticides, fuel for machinery, and water and power for irrigation) as well as the use of some capital goods (greenhouse infrastructure and irrigation system) as determinant items in most of the sustainability attributes considered in this study.

This step helps assess the relationship between SCI and exogenous indicators susceptible to influence changes in the sustainability attributes (back to the details) or that can have another link with the evaluated SCI. In this study, a linear regression model is thus developed, where the SCI is explained by the use or consumption of the relevant operative inputs and production factors. This approach goes two steps back, assessing the influence of the aspects that determined the sustainability attributes on the SCI estimation.

The power consumption for irrigation was not included in the model as it presents a high correlation with the variable water consumption, causing a collinearity issue. In short, the model defined using the variables of Table 2 attempts to assess the influence of the independent variables on the SCI. In addition, land use is included in the model to represent the land factor. The factors system management and NUTS 2, used to configure the reference farms, are independent structural variables considered as control variables in the model due to issues related to the completeness of the model. The crop factor was not included as a control variable as it significantly decreases the model's degrees of freedom (i.e. 39), and generates multicollinearity issues in the model.

The stage back to detail and links to other variables is developed through the application of a linear regression model, where the SCI is explained by the use or consumption of the relevant operative inputs and production factors. This approach goes two steps back, assessing the influence of the aspects that determined the sustainability attributes on the SCI estimation.

Table 2.5.2. Model to relate the composite indicator with their operative determinants.

Item	Indicator	Function of the variable in the model	Source
Sustainability	Sustainability Composite Indicator (SCI)	Explained	Estimated
Constant term	Represents the value of the SCI when the independent variables are null	Constant term	Estimated
Fertiliser consumption	Euros spent on fertiliser products to obtain 1 euro of incomes	Independent	Sinisterra-Solís et al. (2023)
Pesticide consumption	Euros spent on pesticide products to obtain 1 euro of incomes	Independent	Sinisterra-Solís et al. (2023)
Fuel consumption for machinery	Euros spent on fuel to obtain 1 euro of incomes	Independent	Sinisterra-Solís et al. (2023)
Resources consumption for irrigation	Water used (m3) on irrigation to obtain 1 euro of incomes	Independent	Sinisterra-Solís et al. (2023)
Capital goods use	Euros of amortisation per euro of incomes	Independent	Sinisterra-Solís et al. (2023)
Land use	Hectare of land used to obtain 1 euro of incomes	Independent	Sinisterra-Solís et al. (2023)
NUTS 2	Factor of seven levels (e.g. Aragón, Andalucia)	Independent/control	Sinisterra-Solís et al. (2023)
Agricultural system management	Factor of three levels (i.e. rainfed, irrigated and greenhouse)	Independent/control	Sinisterra-Solís et al. (2023)
Residuals	Stochastic error term	Independent	Estimated

The independent variables other than the control ones are expressed per 1 € income so that the scores of each independent variable are comparable between reference farms. When running the model, the independent variables other than the control ones were centralised to obtain standardised coefficients, which makes them comparable to each other, indicating the magnitude of the SCI sensitivity to a change of 1 standard deviation in the independent variables. On the other hand, to avoid perfect multicollinearity, the control factors are included in the model as n-1 dummy variables, where n is the number of levels of the respective control factor.

2.5.4. Results and discussion

2.5.4.1. Selected variables

Facing to how the variables have been defined and to the restriction criterion established in section 2.5.3.2 for the E_NVA, 14 out of 115 reference holdings were excluded from the analysis because they showed negative E_NVA (Annex D.1, Table D1.1); therefore, 101 reference holdings were analysed.

2.5.4.2. Multivariate analysis

From the PCA results, fourteen multivariate outliers were identified and removed, which represent 14 % of the sample. These outliers correspond to six reference farms with herbaceous crops (He_Bar_IO_CM, He_Sun_IO_CL, He_Swh_RO_AN, He_Dwh_RO_AN, He_Sun_RO_CM and He_Swh_IO_CL); five farms of Mediterranean perennials (Me_Alm_RO_CM, Me_Alm_IO_VC, Me_Alm_RO_AR, Me_Alm_RO_VC and Me_Olo_RO_VC) and three fruit tree farms (Fr_Apr_IO_VC, Fr_Che_RO_VC and Fr_Plu_IO_VC). Fig. 4 shows the behaviour of the outliers in each sustainability attribute. Overall, these outliers are positioned above of the distributions of the undesirable attributes.

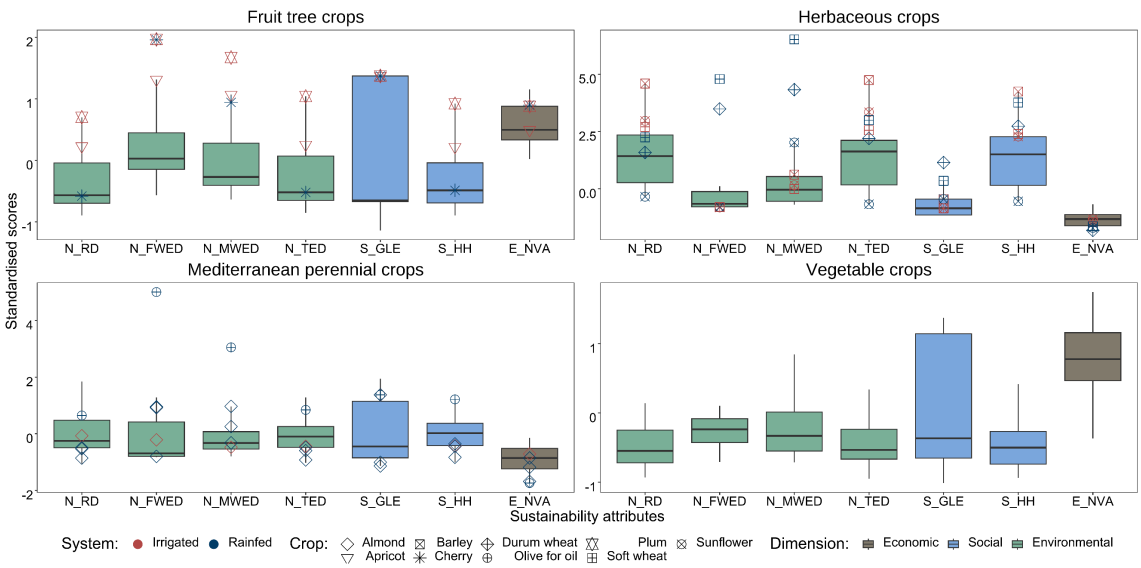

Fig. 2.5.4. Distribution of the sustainability attributes and multivariate outliers identified in the Principal Component Analysis. E_NVA: net value added at factor cost and at constant price base-year 2010; S_GLE: gender labour equity; S_HH: damage to human health; N_TED: damage to the terrestrial ecosystems quality; N_FWD: damage to the freshwater ecosystems quality; N_MWD: damage to the marine water ecosystems quality; N_RAD: damage to the resource availability.

The PCA results (Table 2.5.3) show that the first four components explained 94 % of the dataset variability. The most significant variability orthogonal component gathers a relevant variability from S_HH, N_TED and N_RD and a slight variability from E_NVA. Component 2 is mostly integrated by N_MWED, followed by N_FWED and S_GLE, and moderately by E_NVA. Component 3 gathers part of the variability of S_GLE and N_FWE; whereas E_NVA is the variable contributing the most to Component 4.

Table 2.5.3. Results of the Principal Component Analysis applied to the sustainability attributes of the assessed reference holdings at the Spanish NUTS 2 level.

	Component						
Loading (dimensionless)	**1**	**2**	**3**	**4**	**5**	**6**	**7**
E_NVA	-0.39	0.20	0.03	0.88	-0.14	-0.08	0.04
S_GLE	-0.15	0.40	0.75	-0.10	0.48	0.14	0.02
S_HH	0.52	0.05	0.12	0.17	-0.13	0.21	0.79
N_TED	0.52	0.04	0.03	0.30	0.01	0.56	-0.57
N_FWED	-0.02	0.55	-0.64	-0.02	0.49	0.15	0.13
N_MWED	0.15	0.70	0.06	-0.20	-0.61	-0.22	-0.15
N_RD	0.51	0.00	0.04	0.23	0.35	-0.74	-0.14
eigenvalue (dimensionless)	3.40	1.55	1.05	0.51	0.32	0.07	0.02
percentage of variance (%)	49.09	22.38	15.13	7.33	4.66	1.08	0.33
cumulative percentage of variance (%)	49.09	71.47	86.60	93.93	98.59	99.67	100.00

A PCA-biplot chart helps to better understand how the variables and the active individuals (reference holdings) are related in a particular orthogonal subset. Fig. 2.5.5 shows those relationships in the orthogonal subset with the greatest explanation of the data variability (components 1 and 2), colouring the position of the reference holdings by the crop type; besides, Annex D.3 gathers PCA-biplots of the five-remaining combinations between the first four components. (Figs. D3.1 to D3.5) E_NVA, S_HH, N_TED and N_RD are mainly projected on the X-axis (component 1), indicating that they contribute more to component 1 than component 2; whereas N_MWED, N_FWED and S_GLE are mostly projected on the Y-axis (component 2). The PCA-biplots developed from the interactions of the four first components reveal a relevant positive correlation between S_HH, N_TED and N_RD. Correlation statistics/coefficients are used to explore this relationship further. The Pearson correlation (r), as well as non-parametric alternatives such as the Spearman (ρ) and Kendall rank correlation (τ), are calculated to assess the sustainability attributes' relationship (Annex D.3, Figs. D3.6 to D3.8). The analysis confirms a strong linear positive correlation (r = 0.91 to 0.96) between S_HH, N_TED, and N_RD, which are higher than 0.9 (Annex D.3, Fig. D3.6), which is close to a limit level to avoid over-specification in the modelling, in line with the rule of the variance inflation factor-VIF <= 5 (Signorell, 2022). These results show that the agricultural holdings analysed generated relative damage of the same order of magnitude in the areas of protection human health, terrestrial ecosystem quality and resource scarcity. This could suggest over-specification or double counting if these three variables are included in the estimation of the SCI; however, excluding one of these implies a theoretical mismatch. To avoid this, an option is to substitute the three attributes with the first orthogonal component of the PCA; however, this is different from the proposal of this study to assign the weight of the sustainability attributes based on decision-makers' preferences, also because the variables are integrated in different dimensions. Despite the high collinearity between some variables, the methodology applied in this study mitigates the double counting since the sustainability attributes are weighted according to the importance of the dimension of which it is a part.

Regarding the active individuals (reference holdings), overall, no strong discrimination pattern was found for the factors that make up the reference holdings (i.e. crop, management system and NUTS 2). Nevertheless, a determinant group of the herbaceous crop holdings with high scores in S_HH, N_TED and N_RD and low E_NVA was discriminated (Fig. 2.5.5 and Annex D.3, Figs. D3-1 to D3.5).

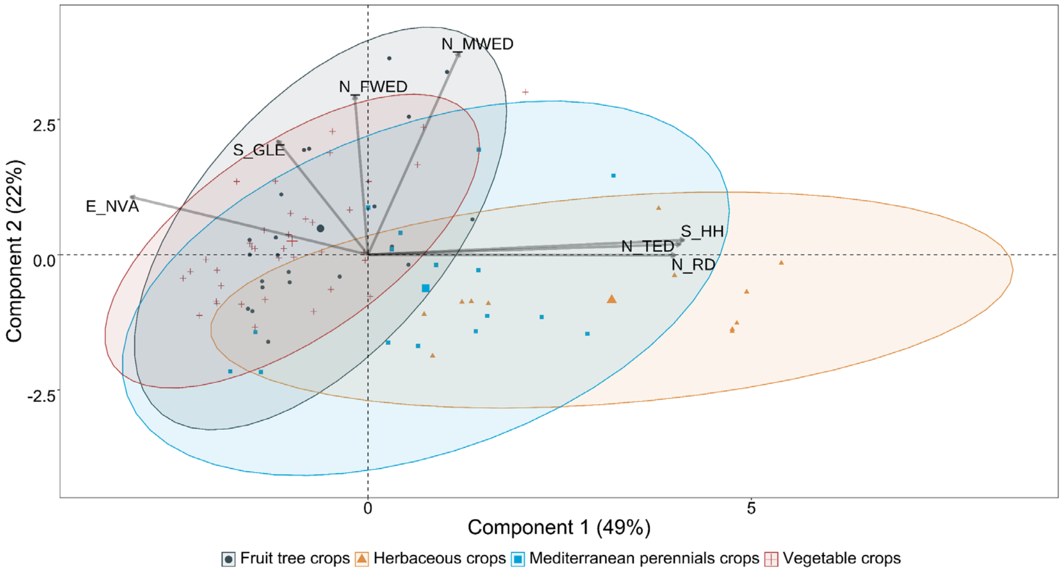

Fig. 2.5.5. PCA-Biplot of the orthogonal subset component 1 vs component 2 of the sustainability attributes of reference farms at the Spanish NUTS 2 level. E_NVA: net value added at factor cost and at constant price base-year 2010; S_GLE: gender labour equity; S_HH: damage to human health; N_TED: damage to the terrestrial ecosystem quality; N_FWD: damage to the freshwater ecosystems quality; N_MWD: damage to the marine water ecosystems quality; N_RAD: damage to the resource availability.

Table 2.5.4. Cluster found for the reference farm at the NUTS 2 level in Spain. JS: Jaccard similarity value.

Cluster	JS	Total	Vegetable	Fruit tree	Herbaceous	Mediterranean
1	0.87	24	17	4		3
2	0.88	31	15	13		3
3	0.69	12	5	4		3
4	0.78	13		1	5	7
5	0.87	5			5	

From the results of the cluster analysis and following the majority rule (Charrad et al., 2015), the dataset can be partitioned into five clusters (Table 2.5.4). Four of the five groups showed high stability, with Jaccard similarity higher than 0.75, whereas Cluster 3 exhibited a moderated stability. The scores of the sustainability attributes per cluster (Fig. 2.5.6) show Cluster 1 is the one with the best global performance since it offers high scores in the attributes to maximise (E_NVA, S_GLE) and low in the ones to minimise (N_TED, N_FWED, N_MWED and N_RAD). Cluster 2 shows similar scores to Cluster 1 but differs in S_GLE, where it obtained a low score. Cluster 3 shows the highest scores in N_FWED and MWED and moderate ones in the remaining attributes. Regarding Cluster 4 and Cluster 5, they present low scores in E_NVA, S_GLE, N_FWED and MWED, and differ in S_HH, N_TED and N_RD, where Cluster 5 exhibits the greatest scores. These results suggest that the farms gathered in Clusters 1 and 5 probably exhibit the best and worst performance in the SCI, respectively; however, the trade-off level and weight assigned to each sustainability attribute can influence the final SCI result. This classification is used below as a visual aid in the representation of the SCI results.

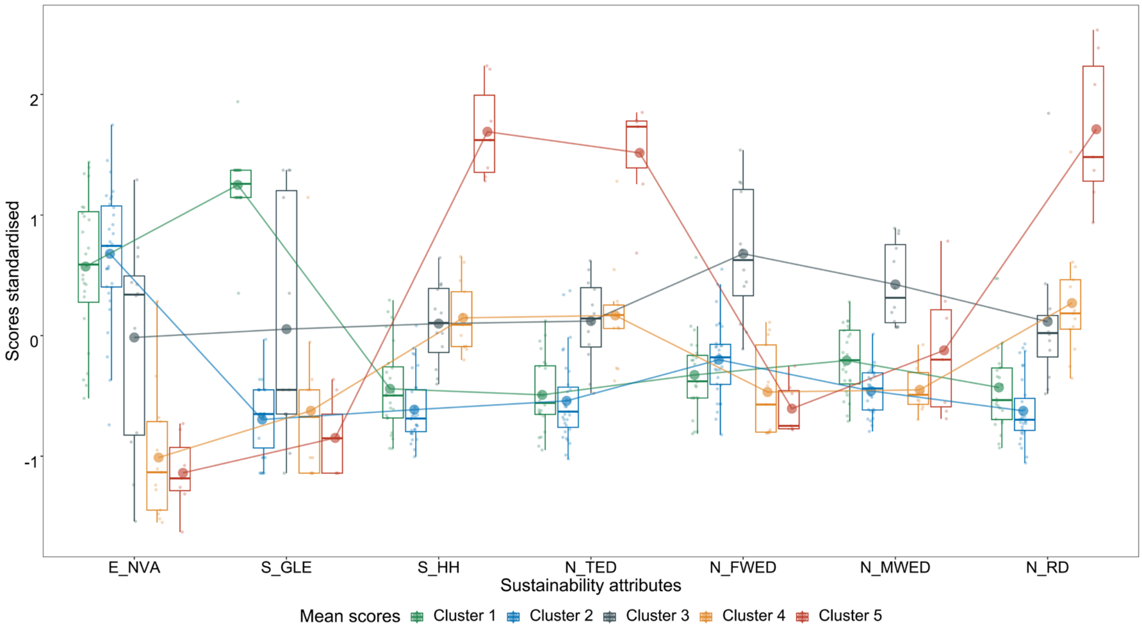

Fig. 2.5.6. Sustainability attributes scores of the clusters found for the reference farms at the NUTS 2 level in Spain. The points express the clusters' average scores in each attribute. E_NVA: net value added at factor cost and at constant price base-year 2010; S_GLE: gender labour equity; S_HH: damage to human health; N_TED: damage to the terrestrial ecosystems quality; N_FWD: damage to the freshwater ecosystems quality; N_MWD: damage to the marine water ecosystems quality; N_RAD: damage to the resource availability.

2.5.4.3. Weighting

The weight assigned to each sustainability attribute (Table 2.5.5) was determined from the geometric mean of the individual expert judgments, as this measure preserves the reciprocal property established in the pairwise comparisons, typical of the AHP method, and has shown to be robust for the normalisation method chosen (Aczél and Saaty, 1983; Krejčí and Stoklasa, 2018). It must be noted that before aggregating the individual judgments, the consistency level of the pairwise comparisons was verified, obtaining tolerable consistency scores in all the answers of the 15 experts consulted (Annex D.1, Tables D1.2a to D1.2c).

Table 2.5.5. Weight assigned to the sustainability attributes of the reference holdings at the NUTS 2 level in Spain.

Attribute	Weight (%)	
Economic pillar	26.81	
Net value added (E_NVA)		26.81
Social pillar	32.96	
Gender labour equity attribute (S_GLE)		7.99
Human health damage (S_HH)		24.97
Natural environment pillar	40.23	
Damage to the quality of the terrestrial ecosystem (N_TED)		11.05
Damage to the quality of the freshwater ecosystem (N_FWED)		14.58
Damage to the quality of the marine water ecosystem (N_MWED)		8.36
Damage to the resource availability (N_RAD)		6.24

2.5.4.4. Sustainability composite indicator

The $\bar{R}_{SCI}$ were computed applying Eq. (2.5.8), where $Rank(SCI_h)$ is the rank for the SCI calculated with Eq. (2.5.5), to evaluate the possible λ levels in the interval [0.00, 1.00]. With this procedure, the lowest average shift in the ranking of the reference holdings was found for λ = 0.58 (4.23 and 4.34 considering

Min-Max and Z-scores, respectively). This means that the SCI was calculated assuming, approximately, a 58% trade-off between the sustainability attributes.

The ranking obtained from the SCI and the uncertainty of the position of each reference holding in the ranking is shown in Fig. 2.5.7. It can be observed that the first decile with the best SCI performance is formed by holdings that grow vegetable crops (nine in greenhouse and two in open field). Nine of these holdings are in the cluster with the best global performance (Cluster 1), and two in Cluster 2, which shows a similar performance with Cluster 1, except in S_GLE (Fig. 2.5.6).

At the other end, the eleven reference holdings with the most unfavourable SCI comprise nine holdings of herbaceous crops (five rainfed and four irrigated) and two Mediterranean perennial crops (one rainfed and one irrigated). Of these, the six worst are identified as multivariate outliers, four holdings are in Cluster 5, and the remaining one in Cluster 3. Most of the reference holdings that grow fruit trees (68%) and vegetables (86%) are in 50% of the best positions of the SCI ranking. In contrast, 95 % of the Mediterranean perennial crops are in the 50% of the worst positions of the SCI ranking; and the best holding among those that grow herbaceous crops is located in the 72 position; hence, herbaceous crops are in the 29% worst positions of the SCI ranking.

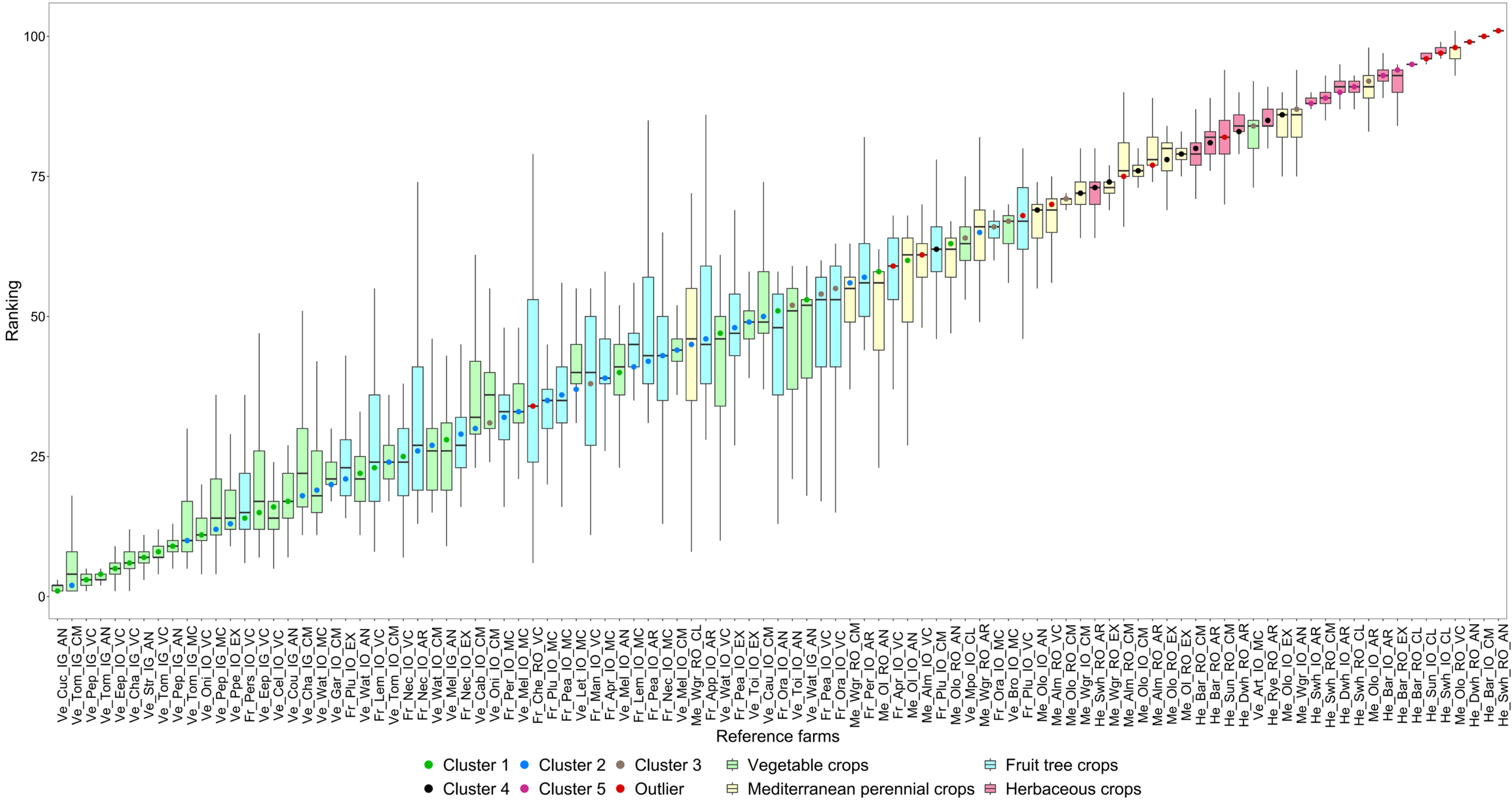

Fig. 2.5.7 Ranking in descending order of the sustainability composite (SCI) indicator for the Spanish reference farms at the NUTS 2 level. Trade-off level = 0.58. Acronym of reference farms (x axis) are defined in Table D1.1 of Annex D.1.

2.5.4.5. Uncertainty and sensitivity analysis

The simultaneous effect of all the uncertainty sources does not greatly influence the extreme positions of the SCI ranking, as observed in Fig 2.5.7. On the other hand, in the central part of that chart, large shifts are observed in the ranking positions of the reference holdings. However, the position of Ve_Tom_IG_CM (second best position in Fig 2.5.7) has a high uncertainty and is potentially worsened due to a change in the model setting since the position obtained in the SCI are in the low part of the distribution of its ranking position. Globally, the average shift in the ranking of the reference holdings due to modelling choices is around 5 positions, showing a non-normal distribution with positive skewness (Fig. 2.5.8) derived from the high $\bar{R}_{ASI}$ that low λ value generated (see Annex D.3, Fig. D3.9).

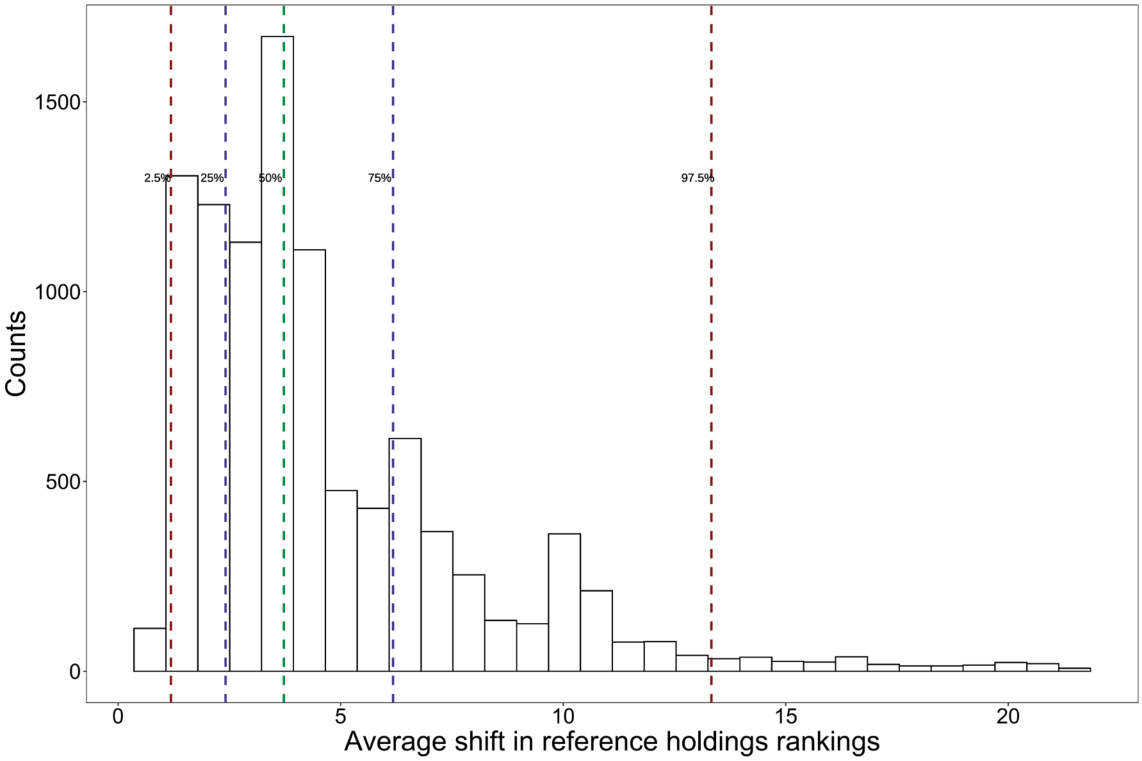

Fig. 2.5.8. Histogram of the simulation of the average shift reference holdings rankings ($\bar{R}_{ASI}$).

Table 2.5.6 shows the Sobol' results. Before interpreting the estimators' values, their significance is assessed by verifying that the lower limit of the confidence interval of each estimator at a 95% of confidence is greater than zero. Another way to assess the significance of the first-order and total-order estimators is by representing the first-order and total-order results for each uncertainty parameter as bars with their respective confidence interval (Fig. 2.5.9). For each estimator a dummy parameter was calculated, which has not influence on the model output to estimate the numerical approximation error. These dummy parameters help to identify the uncertainty of those parameters whose contribution to the output variance is lower than the approximation error and hence cannot be considered influential (Puy et al., 2021). In Fig. 2.5.9, the horizontal, red and green dashed lines mark the upper limit of the first-order and total-order indices of the dummy parameter, respectively. According to Puy et al. (2021), only those parameters whose lower confidence intervals are above the first-order and total-order indices of the dummy parameter can be considered truly influential. According to these two criteria, all the estimators calculated are significant.

Table 2.5.6. Sensitivity estimator for $\bar{R}_{ASI}$. First-order estimator: Azzini|Total-order estimator: Azzini| Total number of models run: 160,000.

sensitivity	parameters	original	bias	std.error	low.ci	high.ci
First-order	Expert selection	$1.94 \cdot 10^{-1}$	$1.02 \cdot 10^{-4}$	$6.75 \cdot 10^{-3}$	$1.84 \cdot 10^{-1}$	$2.11 \cdot 10^{-1}$
	Normalisation method	$1.02 \cdot 10^{-2}$	$1.39 \cdot 10^{-4}$	$3.40 \cdot 10^{-3}$	$3.86 \cdot 10^{-2}$	$1.70 \cdot 10^{-2}$
	λ	$5.16 \cdot 10^{-1}$	$-6.41 \cdot 10^{-4}$	$8.06 \cdot 10^{-3}$	$5.07 \cdot 10^{-1}$	$5.38 \cdot 10^{-1}$
Total-order	Expert selection	$3.44 \cdot 10^{-1}$	$4.29 \cdot 10^{-4}$	$8.03 \cdot 10^{-3}$	$3.28 \cdot 10^{-1}$	$3.61 \cdot 10^{-1}$
	Normalisation method	$2.28 \cdot 10^{-1}$	$3.44 \cdot 10^{-4}$	$5.29 \cdot 10^{-3}$	$2.19 \cdot 10^{-1}$	$2.39 \cdot 10^{-1}$
	λ	$7.73 \cdot 10^{-1}$	$-4.07 \cdot 10^{-4}$	$7.77 \cdot 10^{-3}$	$7.56 \cdot 10^{-1}$	$7.87 \cdot 10^{-1}$
Second-order	Expert selection. Normalisation method	$1.74 \cdot 10^{-2}$	$6.42 \cdot 10^{-5}$	$3.84 \cdot 10^{-3}$	$9.84 \cdot 10^{-2}$	$2.48 \cdot 10^{-2}$
	Expert selection. λ	$5.15 \cdot 10^{-2}$	$-1.27 \cdot 10^{-5}$	$6.35 \cdot 10^{-3}$	$4.10 \cdot 10^{-2}$	$6.48 \cdot 10^{-2}$
	Normalisation method. λ	$1.26 \cdot 10^{-1}$	$3.31 \cdot 10^{-4}$	$9.35 \cdot 10^{-3}$	$1.10 \cdot 10^{-1}$	$1.47 \cdot 10^{-1}$
Third-order	Expert selection. Normalisation method. λ	$8.45 \cdot 10^{-2}$	$1.24 \cdot 10^{-4}$	$8.66 \cdot 10^{-3}$	$6.97 \cdot 10^{-2}$	$1.03 \cdot 10^{-1}$

The Sobol' results show a non-additive model, which means that the sum of the main effects (first-order or local effects) is lower than 1, and that the Total-order estimators are greater than the First-order ones. This means that the variability in $\bar{R}_{ASI}$ is not only explained by the main effects of the uncertainty parameters and that the interaction between them can explain part of the uncertainty in $\bar{R}_{ASI}$ too. The first-order values indicate that locally, the λ, expert selection and normalisation method parameters convey 51.6%, 19.4% and 1% of the uncertainty in $\bar{R}_{ASI}$, respectively. As the model is not additive, high-order effects are assessed to explore the significance of the interactions among uncertainty parameters. "sensobol" package allows to obtain sensitivity estimators of second-order and of third-order. Table 2.5.6 shows that the second-order interactions between expert selection and normalisation method, expert selection and λ, and normalisation method and λ, as well as the third-order interaction (expert selection versus normalisation method versus λ) convey 1.7 %, 5.2 %, 12.6 % and 8.5 % of the uncertainty in $\bar{R}_{ASI}$, respectively. Summarising, the model explains 72% locally and 28% from the interactions between parameters the uncertainty in $\bar{R}_{ASI}$, being λ and expert selection the most influential parameters. Therefore, the trade-off level is critical when defining the conservatism degree in sustainability assessment. In addition, the use of normative weighting techniques (such as AHP) in composite indicator development is also relevant. The experts weighting represents the sustainability notion of agents external to the study, λ is a methodological choice of the modeller that indicates the level of trade-off to integrate the sustainability attributes, it is a continue variable ranging between [0,1], where 0 means a null trade-off, attributed to strong sustainability and 1 is the other extreme resembling a weak sustainability because the possibility of substituting the perceived sustainability from a natural capital by one perceived from another capital form (such as manufactured capital) is open (Deytieux et al., 2016).

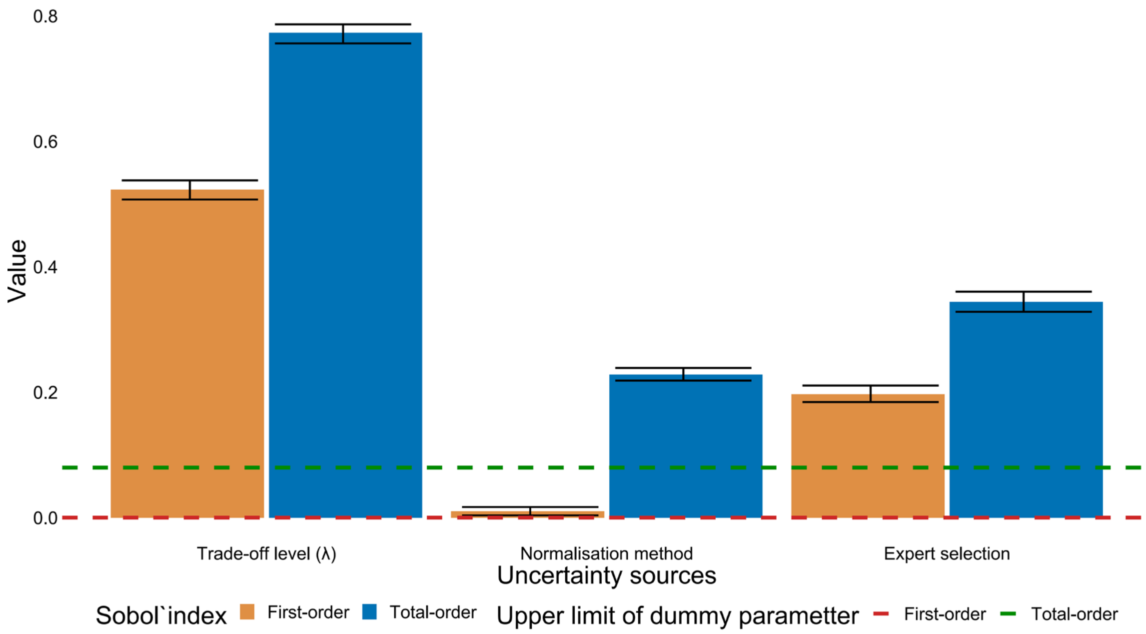

Fig. 2.5.9. Sobol' first-order and total-order estimators for sensitivity analysis of the $\bar{R}_{ASI}$

Understanding the theoretical importance of the trade-off level and the relevant effect in the SCI uncertainty, SCI rankings are calculated considering null and total trade-off and provided in Annex D.3, Figs. D3.10 and D3.14. The SCI ranking is similar to a total trade-off but different to a null trade-off. For instance, $\bar{R}_{SCI}$ is around 5 position both in SCI and with total trade-off, increasing to around 15 position when null trade-off is considered. This can be explained by the logarithmic effect of λ on the SCI ranking, with high shifts of the ranking positions for λ values approximately less than 0.25, (Fig. 2.5.10, complemented with Figs. D3.9, D3.12 and D3.16 in the annex D.3). Anexx D.3 also gathers the other uncertainty and sensitivity results for SCI rakings estimated with null and total trade-off, similar to λ = 0.58. Regarding the behaviour of the holdings in the rankings, most of them obtain better positions with null trade-off, especially those of herbaceous and Mediterranean perennial crops, where plateau patterns are observed (Fig. D3.14), indicating groups of holdings with the same position in the ranking. For instance, holdings such as Me_Ol_RO_AN and Me_Alm_RO_VC show the highest shifts in their positions due to the trade-off level. On the contrary, some vegetable crops such as Ve_Tom_IG_CM and Ve_Tom_IG_MC show the highest leverage due to λ level since their ranking position worsens when λ = 0. Other holdings, such as Fr_Pers_IO_VC and Fr_Apr_IO_MC, show a negligible shift in the ranking position across the range of λ.

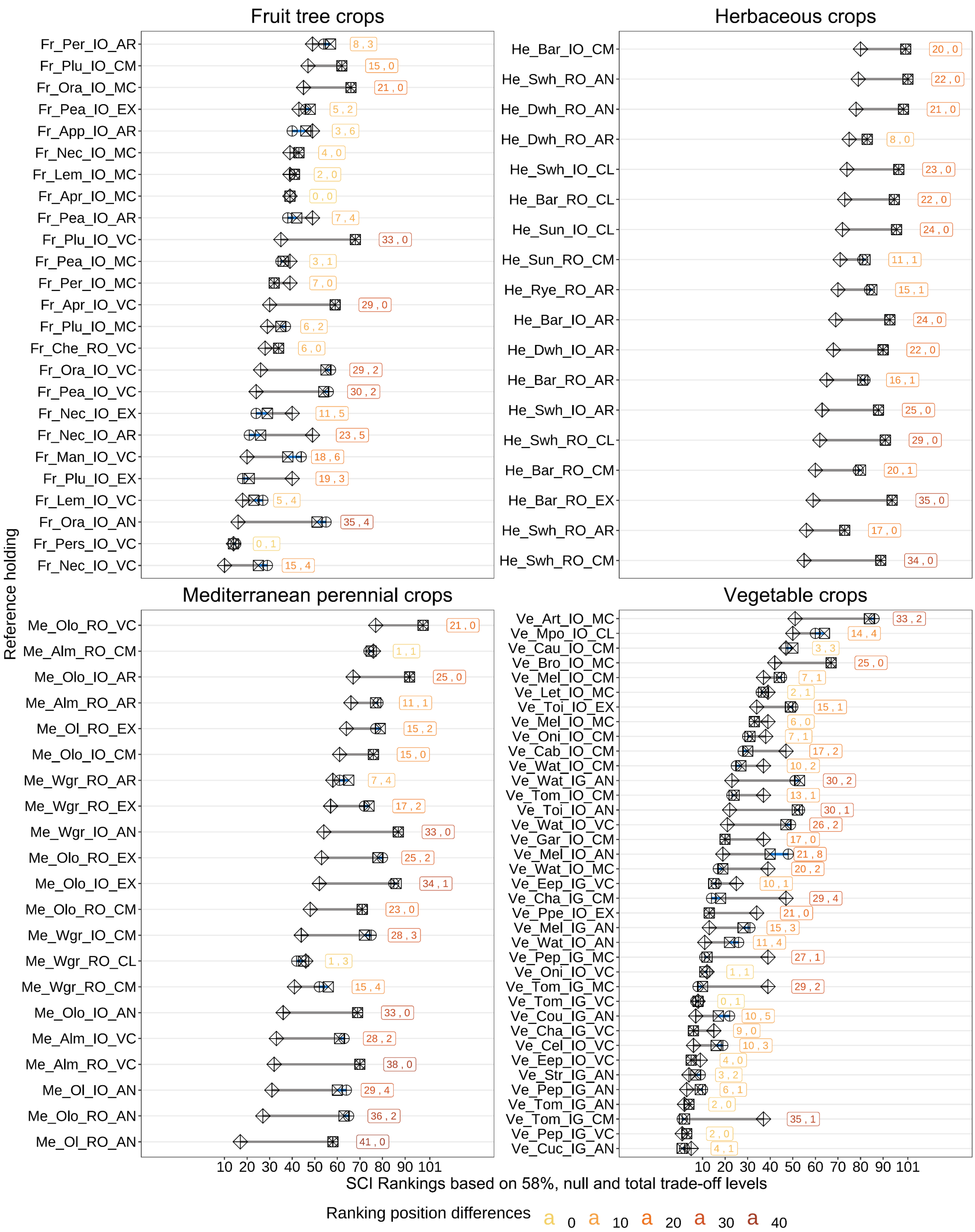

Fig. 2.5.10. Differences of the positions obtained in the SCI ranking at 58% of trade-off (square), versus SCI rankings at null (diamond) and total (circle) trade-off. The lines which joint the figures denote the distance between them.

2.5.4.6. Linking the composite indicator with sustainability determining factors

To assess the influence of the agricultural inputs on the SCI according to the criteria described in Table 2.5.2, a model is developed based on four alternatives in which the control variables are either added or removed to calibrate the model. In this way, the consistency of the coefficients estimated can be explored through different fixed effects in the model. In the first alternative, no control variables are considered, in the second and third alternatives the factors “System” and “NUTS 2” are included as control variables, respectively; whereas in the fourth one, both factors are included. The way in which the SCI was calculated generates a standardised variable with mean = 0 and sd = 1, hence the model is also run with the standardised independent variables for better interpretation, and to permit the comparison between coefficients. Thus, the coefficient obtained must be interpreted as the shift of the SCI in standard deviations due to a shift of one standard deviation in the respective independent variable.

The normality and homoscedasticity of the residual variables is tested to verify the feasibility of applying the ordinary least squares (OLS) method for the modelling, as this method provides the best unbiased estimators, that is, the ones with the minimum variance (Gujarati and Porter, 2022). In addition, other assumptions typical of multiple linear regression models are contrasted (i.e. functional form of the model and not strong multicollinearity between independent variables). The normality was tested with Shapiro-Wilk, with "stats" R package, and Jarque Bera robust and classical, with "DescTool" R package (Signorell, 2022). Similarly, Breus-Pagan and Ramsey's RESET tests, with "lmtest" R package (Hothorn et al., 2022), were applied to assess the homoscedasticity in the residuals and the functional form of the models, respectively. In addition, variance-inflation factors (VIF) were estimated, with "DescTool" R package, to assess the multicollinearity in the independent variables.

In a first run, the assumption of normality in the residuals was not fulfilled, because of the outliers (Me_Alm_RO_CM, He_Bar_IO_CM, He_Dwh_RO_AN, He_Sun_IO_CL, He_Swh_IO_CL, He_Swh_RO_AN, Me_Olo_IO_CM, Ve_Art_IO_MC, Ve_Cuc_IG_AN and Me_Wgr_IO_AN) in the residuals; thus, these observations were extracted from the sample to proceed with the modelling. For a 5% significance level and VIF < 5, all the modelling assumptions described here were fulfilled; thus, standard OLS was considered as the more suitable method to estimate the proposed model alternatives. Table D1.3 in Annex D.1 shows complete statistic results of the assumptions evaluated.

Model estimation are shown in Table 2.5.7, where it can be observed that the values of the F statistic are significant; therefore, the four modelling alternatives significantly explain the SCI. In addition, the adjusted R^2 reflects the goodness of fit for the model alternatives proposed, with an explanatory capacity ranging from 83% in OLS_1 to 89% in OLS_4. It must also be noted that a parsimonious criterion (Akaike-AIC) and the root mean squared error (RMSE) suggest that OLS_4 is the best of the four alternatives to model the SCI, showing the importance of NUTS 2 and Management system as control variables. Hence, OLS_4 is the best calibrated model used as a reference to define the magnitude of the coefficients; whereas the other three alternatives are used to explore the consistency of the significance of the coefficients. It must be highlighted that OLS_3 is the best option according to the Schwartz-BIC criterion.

The regressors represent the standardised consumption and use of resources in the reference holdings to obtain 1 € of income. Great scores in the regressors imply that a great amount of resources is consumed to obtain a fixed quantity of a desired output, which consequently increases the potential negative effects on the natural environment and human health of that fixed desired output. In this context, an inverse correlation between the SCI and the regressors is expected, confirmed by the negative sign of the significant coefficients (see Table 2.5.7).

Table 2.5.7. Linear regression model alternatives to explain the influence of the intensity of the resource used on the sustainability composite indicator (SCI).

	Ordinary/Standard least squares (OLS) models			
	(OLS_1)	**(OLS_2)**	**(OLS_3)**	**(OLS_4)**
Parameters	**Composite sustainability indicator (SCI)**			
Fertiliser consumption (Fert)	-0.18***	-0.18***	-0.24***	-0.22***
	(0.05)	(0.05)	(0.04)	(0.04)
Pesticide consumption (Pest)	-0.16***	-0.13***	-0.14***	-0.12***
	(0.04)	(0.04)	(0.04)	(0.04)
Fuel consumption for machinery (Fuel)	-0.38***	-0.29***	-0.48***	-0.42***
	(0.06)	(0.06)	(0.05)	(0.06)
Resources consumption for irrigation (Irrig)	-0.43***	-0.44***	-0.35***	-0.38**
	(0.06)	(0.06)	(0.06)	(0.06)
Capital goods use (Capg)	0.02	-0.02	0.03	-0.05
	(0.05)	(0.04)	(0.04)	(0.04)
Land use (Land)	-0.15**	-0.11*	0.01	0.02
	(0.06)	(0.06)	(0.06)	(0.06)
Constant	0.07	0.07	0.42***	0.36**
	(0.04)	(0.05)	(0.08)	(0.09)
System_c		Yes		Yes
NUTS 2_c			Yes	Yes
Model validation				
Observations	91	91	91	91
F Statistic	73.76*** (df = 6; 84)	67.42*** (df = 8; 82)	59.02*** (df = 12; 78)	53.82*** (df = 14; 76)
Goodness fit				
Adjusted R^2	0.829	0.855	0.886	0.891
Akaike criterion (AIC)	63.5	50.2	32.2	29.0
Schwartz criterion (BIC)	83.6	75.3	67.4	69.2
Root mean squared error (RMSE)	0.314	0.286	0.248	0.238

*p < 0.1; ** p < 0.05; *** p < 0.01

At a 5% significance level, the OLS_4 shows that the consumption of intermediate products and resources (fertiliser, fuel for machinery and water for irrigation) significantly explains the sustainability performance of the Spanish reference holdings at the NUTS 2 level. On the other hand, the use of capital goods (Capg) and land do not significantly determine the SCI. The results suggest a strong sensitivity of SCI to shifts in the consumption of machinery fuel and irrigation resources, as well as moderate sensitivity to shifts in fertiliser and pesticide consumption (Fig. 2.5.11).

The λ value is a critical methodological parameter, not only due to its influence on the SCI uncertainty (section 2.5.4.5), but also because it represents the ethical vision of sustainability. We consider thus interesting to explore the behaviour of the OLS_4 regression model for the whole λ range. The results (Annex D.1, Table D1.4) show that the model is consistent in a wide range of λ values ($0.05 < \lambda < 1$); in the remaining λ range, the assumption of normality is questioned. The significant coefficients are plotted in Fig 2.5.12, in which non-significant differences are observed through the λ range where all the OLS assumptions are fulfilled; nevertheless, the influence of the λ value is highlighted on each parameter of the SCI, which generate a significance loss of the fertiliser consumption for $\lambda \leq 0.02$.

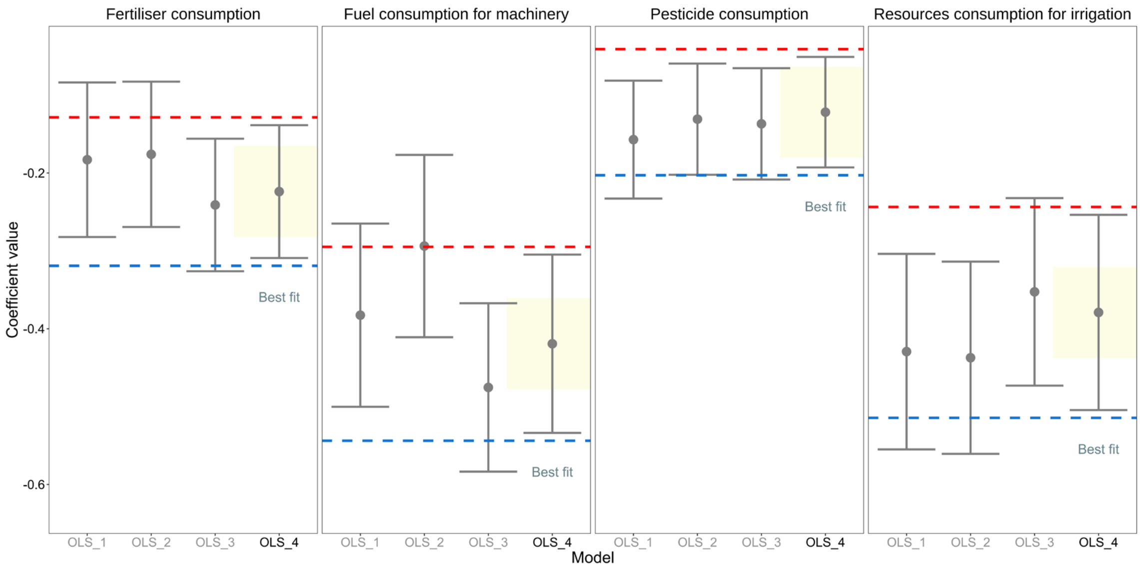

Fig. 2.5.11. Performance in the four alternatives models of the coefficients that are significant in the calibrated model (OLS_4). Dashed horizontal lines represent the upper (in red) and lower (in blue) limits of the confidence interval of the OLS_4 coefficients.

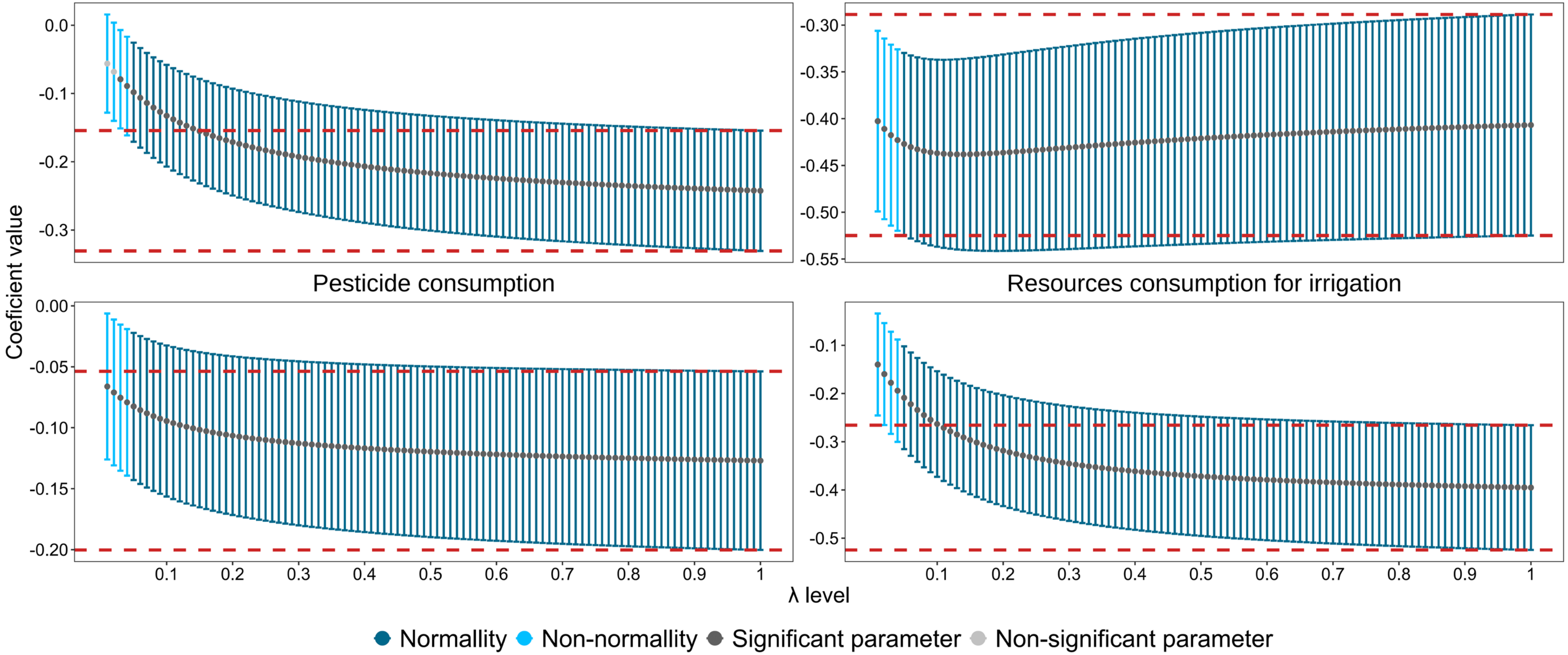

Fig. 2.5.12. Behaviour of the coefficients that are significant in the calibrated model (OLS_4), through the trade-off level range. Dashed horizontal red lines represent the upper and lower limits of the confidence interval of the coefficients at the total trade-off level.

2.5.5. Discussion

Under the taxonomy described in the introduction section, the proposed approach can be considered as an ex-post accounting tool interpreting agricultural sustainability as oriented to goals. It is based on a composite indicator constructed from quantitative attributes selected from a top-down approach, in which weights are assigned normatively to the attributes and considering a partial trade-off in their aggregation. Based on the reviewed literature, some of these assumptions can be questionable, and can be seen as a weakness of the approach. Criticisms associated with composite indicators arise from the fact that they invite simplistic policy conclusions and can send misleading policy messages when poorly constructed or misinterpreted (Gómez-Limón and Sanchez-Fernandez, 2010; OCDE-JRC, 2008), In this regard, Triste et al. (2014) and Chopin et al. (2021) support tools such as MOTIFS (Meul et al., 2008) where each farm attribute is separately presented and related in a radar plot. Nevertheless, these kinds of tools do not make it possible to rank alternatives from their overall performance in a multidimensional concept such as agricultural sustainability, because as (Meehl, 1954) pointed out "while humans are good at finding important variables, they are not as good at integrating such diverse information sources optimally". In addition, the approach followed in this study mitigates the risk of motivating simplistic conclusions and misleading messages since a comprehensive procedure is applied previous to the aggregation. This procedure is used to characterise the dataset structure both from the attributes and the reference farms (multivariate analysis). In addition, the sensitivity and robustness of the SCI to methodological choices (section 2.5.4.5) and to changes in some technical parameters (section 2.5.4.6) are assessed.

Involving the stakeholders in the attribute selection and weighting is crucial for a robust assessment of agricultural sustainability (Marchand et al., 2014; Triste et al., 2014). The top-down attributes selection adopted in this study is not in line with that; thus, its enhancement is open; however, under a cost-benefit view, a top-down approach is attractive in data-intensive studies like the present one, where a wide set of reference farms is assessed. In addition, understanding the hierarchical character of sustainability decision-making, this study supports that not all the stakeholders should assign weight to the attributes and sustainability dimensions, and only unbiased stakeholders (without conflict of interest with the study results) should be taken into account.

Compensatory approaches are also associated with disadvantages; nevertheless, in this study non-trade-off is perceived as a chimera from a practical point of view. It is considered that, whether capital substitution does not exceed the limits of the critical capital or put it at risk, the normative character of sustainability enables the trade-off between attributes and dimensions, which could be defined through a participatory process (López Pardo, 2012). In this study, two substitute methodologies are used to obtain the trade-off level based on the dataset structure, assuming that it is not a straightforward parameter to be defined by stakeholders. Understanding the trade-off as a critical issue when assessing agricultural sustainability, the holistic way in which this study assesses the sensitivity of the SCI ranking to changes in the trade-off level must be noted. In particular, the trade-off level is treated as a continuous variable, whereas in other studies such as Gómez-Limón and Sanchez-Fernandez (2010) and Van Der Voet et al. (2014) only a few discrete points are considered (e.g. λ = 0, λ = 0.5 and λ = 1).

The intensive use of statistical and MCDA tools and the wide number of choices increase the latent risk of making deterministic choices poorly supported. For instance, the choice of the normalisation method is not straightforward, since, beyond some recommendations, the definition of the best method is open in the sustainability field (Diaz-Balteiro et al., 2018). (Diaz-Balteiro et al., 2017; Ibáñez-Forés et al., 2014) highlight the necessity of proper normalisation to improve the accuracy of the results, although a wide number of studies are found where no normalisation or a poor normalisation procedure is applied. In this study, two widely accepted normalisation methods are used. Both methods have disadvantages in relation to the data structures; however, the SCI was defined as the average of the SCI obtained by considering each standardisation method. In addition, to gain transparency, the normalisation method was taken into account to model the uncertainty and sensitivity of the SCI.

2.5.6. Conclusion

A systematic approach has been developed to assess agricultural sustainability based on a composite indicator that gathers the multidimensionality of the concept. The approach assumes as the central point the ranking of the units of analysis according to their rating in SCI, previously understanding the theoretical context of the study and the dataset structure. Subsequently, the sensitivity of SCI to methodological choices is assessed, emphasising the parameters of the aggregation function that gather normative aspects of agricultural sustainability. The proposal developed supports assigning weights to the attributes and defining the trade-off between them from reasoned judgments without conflict of interest. In addition, the sensitivity of SCI to technical factors (input consumption) is evaluated to understand the relationship between the SCI with technical factors influencing the attributes. The approach is open to improvement, although it is subject to data availability and processing capacity in each step. In particular, considering that the attributes attempt to represent sustainability aspects, further studies should consider differential trade-off levels as a function of specific relationships between attributes.

2.5.7. References

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CHAPTER III. OVERALL DISCUSSION

Different methodological tools are used to respond to the specific goals sought by this research. In addition, as commented on above, this thesis has been developed following a process, in which the approaches and results of previous sections form a basis upon which the subsequent work is developed. The most relevant results and the related methodological aspects of this dissertation are discussed below from a global perspective.

3.1.Overall discussion of the results

The results of this dissertation emphasise the high degree of heterogeneity inherent to agriculture and the complexity of identifying more sustainable practices. Along these lines, the assessment of the environmental impacts of vineyards in a relevant wine production region (section 2.1) indicated that the organic vineyards show better environmental performance than the conventional in most of the impact categories assessed; except for the impact on water scarcity. The differential factors taken into account when monitoring orange and tomato crops were the NUTS 2 (AN, CM, MC and VC) and the management practices (irrigated open-field, rainfed open-field, and greenhouse) (Section 2.2). The results did not permit the identification of those holdings that performed the best in every impact category analysed (CC, WS, ET, HTnc). Nevertheless, it can be highlighted that both greenhouse-grown tomatoes and oranges produced in VC obtained the worst results compared to their peers in other NUTS 2, except in the case of WS, where oranges from MC performed the worst. On the one hand, the results highlight the complexity of the selection of the best alternative since this selection would imply additional methodological choices regarding the weighting and aggregating processes of different impact categories to facilitate the decision-making process. On the other hand, these results point to the fact that VC represents an environmental hotspot for the two crops, especially oranges.

The environmental assessment of Section 2.2 has been extended to cover a wide range of crops and a set of midpoint and endpoint impacts and the EF indicators have been estimated in Section 2.4. The results of this section are expressed using an economic functional unit (NVA_fc) to allow the comparison between holdings producing different commodities. In addition, the impacts are modelled considering the temporal variability and the uncertainty of the input parameters. Due to the fact that the context of this study is accounting, only a descriptive interpretation of the central tendency of the aggregated EF scores is made in section 2.4. Overall, a relationship can be observed between the use of resources and the economic results. This is not the case for 40% (12) of the herbaceous and 9% (2) of the Mediterranean perennial crops, which show negative NVA_fc and, therefore, negative median EF scores. The irrigated herbaceous crops show the highest median EF scores, and it should be noted that no other consistent pattern is identified when exploring the factors that make up the reference holdings (i.e. NUTS 2, crop and management system). Below, subsection 4.1.1 complements this analysis by taking into account all the EF scores estimated for each reference holding.

As regards the assessment of the overall sustainability, the composite indicator developed shows that most of the reference holdings in which vegetables and fruit tree crops are grown present a good sustainability performance, the greenhouse grown vegetables being the best. Conversely, most of the Mediterranean perennial crops and all the herbaceous crops performed the worst.

3.1.1. Eco-efficiency benchmarking of the Spanish reference holdings at the NUTS 2 level

The EF is an indicator to be minimised, as it represents the damage caused to the environment in order to satisfy an anthropogenic need, with economic implications (e.g. agriculture). In section 2.4, the EF has been related to the NVA, a proxy that captures the market compensation for the regional decision-makers of the environmental damage of agriculture. As a consequence, the results have been expressed as a ratio $EF \cdot NVA^{-1}$ per kg of commodity. These results have been descriptively analysed and holdings with median negative EF scores were identified, determined by a negative NVA_fc. Other reference holdings also had negative EF scores in some specific years (Annex E.1, Table E1.1) without showing a negative median. This shows that although agriculture always generates environmental impacts, it is not always reciprocated by its economic result, which suggests a loss of both environmental and economic values and implies some ambiguities. On the one hand, a spurious relationship between EF and negative NVA (impairment of NVA) is presented, breaking the economic logic and preventing the direct interpretability of the results. The continuity of agriculture in those holdings with negative NVA can be explained by positive externalities not captured by the market, such as the opportunity cost of fixed factors and the expectations of the decision-makers to the agriculture dynamics, which is highly sensitive to natural and market factors. Operatively, the ambiguity is shown as a decoupling in the effect that $EF \cdot kg^{-1}$ and $NVA \cdot kg^{-1}$ generate in the orientation of $EF \cdot NVA^{-1}$, which must be maximised and minimised, respectively. This means that the lower the $NVA \cdot kg^{-1}$ value, the closer the ratio is to zero, and conversely, the higher the $EF \cdot kg^{-1}$ value, the more negative the ratio. Despite the lack of a direct interpretation of the negative scores of $EF \cdot NVA^{-1}$, they can be transformed in order to compare the results in the negative range, as proposed in Eq. 3.1; in that way, the $EF \cdot NVA^{-1}$ that are lower than 0 are understood as range-oriented to maximise, showing the EF per impairment of NVA.

$$EF_{NVA^-,i} = \frac{EF_{kg,i}}{-NVA_i + \min(NVA^-) + max(NVA^-)} \tag{3.1}$$

Where, $EF_{NVA^-,i}$ is the negative EF · NVA-1 of the i holding corrected and oriented to maximise; $EF_{kg,i}$ is the EF · kg-1 of commodity of the holding i; NVA_i is the NVA score of holding $i$and NVA^- is the series of negative scores of NVA.

Another ambiguity refers to the rupture of the continuity when negative and positive EF scores are compared. That is, the negative scores are closer to the highest positive score. Therefore, before applying the inferential analysis, a new EF (EF_{adj}) is obtained using Eq. 3.2:

$$EF_{adj,i} = \max(EF) - EF_{NVA^{-}i} \tag{3.2}$$

After this transformation, the Kruskal-Wallis test reveals significant differences in the EF performances of the holdings. Subsequently, the post-hoc Dunn's pairwise comparisons test (Annex E.1, Table E1.2) enables the 115 reference holdings to be grouped considering two approaches. In a first approach, the reference holdings are grouped based on their significant differences, but discrimination may not be complete as significant differences can be found within a group. Under this approach, nine groups are obtained (Fig. 3.1), of which Group 1 has the best EF performance and Group 9 the worst. As commented in the methodological overview (section 1.6), the group with the best performance is usually considered as a reference to emulate the eco-efficient frontier; notwithstanding this, the results suggest that Group 1 is an outlier since it is only made up of one holding (Me_Wgr_RO_CL, rainfed grapes in Castilla y León), and Group 2 is 92% away from it. Therefore, the eco-efficient frontier is established in the medoid of Group 2, which works as a benchmark for the remaining groups. Group 2 is made up of six reference holdings (5% of the sample), in three of which vegetable crops are grown (Ve_Tom_IG_AN, Ve_Pep_IG_AN and Ve_Pep_IG_VC), in two Mediterranean crops (Me_Wgr_RO_CM and Me_Wgr_RO_AR), and in one fruit tree crops (Fr_Nec_IO_MC). The results of section 2 evidenced that the type of crop is the factor that best describes the performance pattern of the holdings. Along these lines, this analysis confirms that the herbaceous crops have the worst EF performance, as depicted in Fig. 3.1. The results show that 93% of the herbaceous and 52% of the Mediterranean perennial crops fall within the five furthest groups from the eco-efficient frontier. It is worth noting that the three worst groups are made up only of five herbaceous crops (He_Bar_IO_CM, He_Rye_RO_CL, He_Oat_RO_EX, He_Bar_IO_CL and He_Swh_IO_EX), which analogous to Me_Wgr_RO_CL, may be considered outliers; He_Bar_IO_CL and He_Swh_IO_EX make up the worst group. Besides, rainfed wine grapes in Castilla y León (Me_Wgr_RO_CL) exhibit the best performance of the sample. On the other hand, more than 91% of vegetable crops and 88% of fruit tree crops are concentrated in the eco-efficient group and the two closest groups.

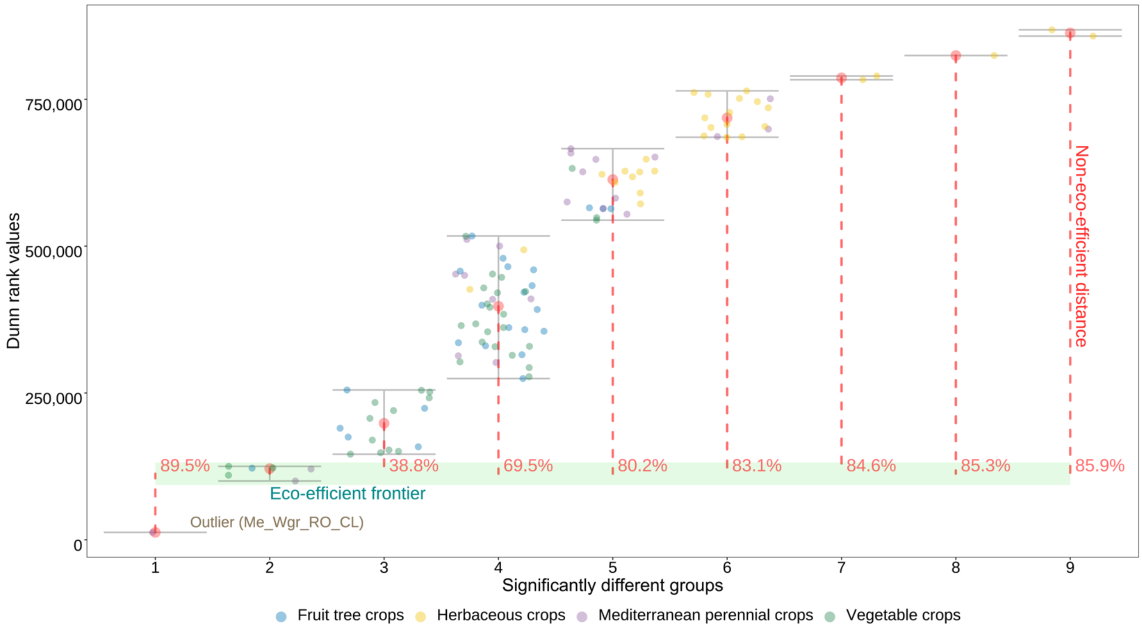

Fig. 3.1. Reference holdings discriminated into groups with significantly different EF performances according to Dunn's test pairwise comparison. The red points are the medoids of each group.

The second approach avoids significant differences within the groups and keeps the differences between them. However, there is a chance that some reference holdings located at the upper limit of a group may not show significant differences with some reference holdings located at the lower limit of the next group. Along these lines, through an iterative process, the nine groups of Fig. 3.1 are reorganised in a larger number of groups (thirty-one groups) remarking the highly heterogeneous nature of the environmental performance of the holding analysed. According to Fig. 3.2, two reference holdings make up the eco-efficient group (Me_Wgr_RO_CM and Ve_Tom_IG_AN), and the remaining three shown as eco-efficient in Fig. 3.1 have to decrease 14% their Dunn rank values to achieve the eco-efficiency. The other groups shown in Fig. 3.1 are also disaggregated, He_Bar_IO_CL and He_Swh_IO_EX are again the furthest from the eco-efficient group. In brief, as observed in Figs. 3.1 and 3.2, the type of crops partially explains the EF comparison between the reference holdings. This suggests that some of the differences is due to the particular farming and financial practices of each reference holding or to other factors that define the reference holdings (i.e. NUTS 2 and management system).

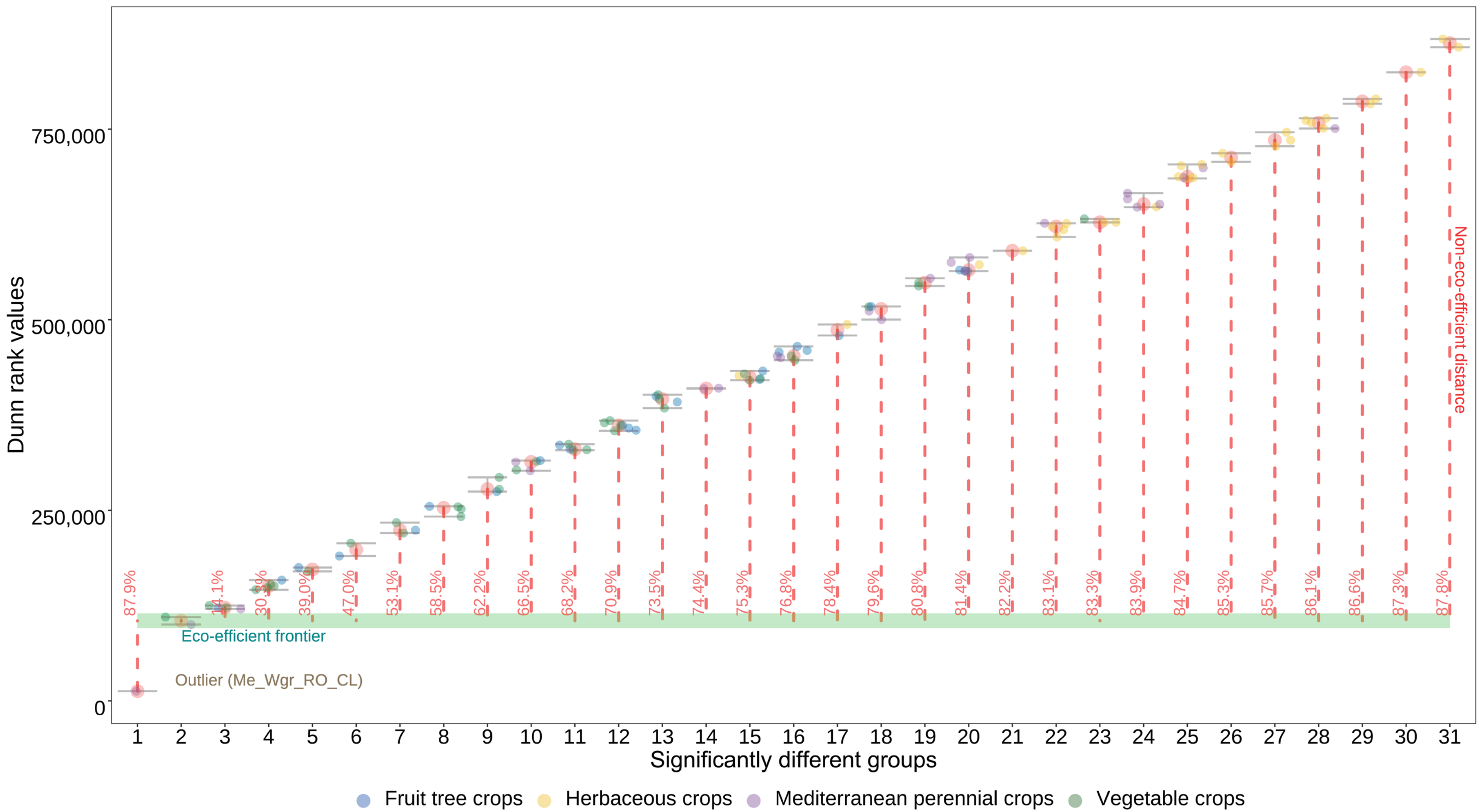

Fig. 3.2. Reference holdings discriminated into groups with significantly different EF performances according to Dunn's test pairwise comparison. The red points are the medoids of each group.

3.2.Overall discussion regarding methodological issues and future research

In accordance with the general goal, the accounting context of this dissertation has enabled us to obtain ex-post indicators to monitor and compare the results. However, prospective, confirmatory and consequential studies can complement this research supporting comprehensive decision-making. In line with the first and second specific goals, this study shows the strengths of the sustainability assessment of a range of agricultural units by applying data-intensive techniques, capturing different agricultural practices, temporal variability, and the uncertainty of key methodological issues, such as the use of Tier 2 and 3 methods to model on-field emissions. It must also be highlighted that developing LCAs based on regionalised activity data, estimated from official statistics such as FDAN, is an alternative to using primary data, which are not always feasible considering the budget and time constraints.

As to the third specific goal, the use of an economic FU relates the environmental impacts with their anthropogenic origin more comprehensively, as compared to other options (e.g. a mass-based FU). In addition, economic FUs allow the comparison of the environmental impacts of different commodities considering that the main goal of agriculture, as an economic activity, is providing a positive economic value. The use of NVA as FU highlights the complexity of assessing the environmental performance of agriculture, understanding it as an economic activity influenced by climate and market factors, where economic ambiguity can be presented in practice.

The sustainability composite indicator (specific goal 4) made it possible to compare the overall sustainability performances of the holdings under study. Regardless of whether technical substitutability is possible between the holdings analysed, relating their sustainability performances helps to understand the comparative advantage among them. The LCA-based methods chosen to characterise the environmental impacts (i.e. EF, ReCiPe, USEtox and AWARE) allowed most of the impact categories at the midpoint, endpoint and aggregated levels to be accounted for; nevertheless, it should be noted that some relevant categories related to agriculture, such as the effects on ecosystems, services and biodiversity loss associated with land use, have not been taken into account.

In line with the fourth specific goal, a composite indicator considering the normative character of the sustainability concept was developed by simulating the relevance of the attributes for decision-makers, and modelling the trade-off level between individuals' sustainability attributes. However, efforts to improve the modelling of the trade-off are needed; for instance, establishing cut-points to support positive criteria (such as the carrying capacity in the environmental dimension) to determine the trade-off level to be considered between the attributes of the sustainability.

The huge demand for data from different disciplines promoted the use of secondary data sources. The use of ECREA-FADN as the main data source helped to study a wide range of agricultural units, reducing the cost and effort involved in data collection, as well as lessening the bias as regards the use of different sources, such as in meta-analysis. However, it is subject to the bias of the data source as well as to that source's reliability and accuracy. ECREA-FADN can be potentially improved by providing more statistical details about the variables and more specificities regarding the agricultural practices. In addition, over four-years' worth of data have been used to represent the temporal variability but the structural imbalance in the panel data generated from ECREA-FADN hindered the development of dynamic LCAs in the period analysed.

CHAPTER IV. OVERALL CONCLUSIONS

In this dissertation, a set of sustainability indicators for agricultural holdings is developed at the regional level in Spain under an accounting context. The indicators permitted the monitoring and comparison of the results across different reference holdings, a starting point for transitioning towards sustainable agriculture in accordance with the goals of the European Union. The indicators provided should be considered as complementary, ranging from midpoint environmental impacts to a composite sustainability indicator, strengthening the advantages and mitigating the limitations implicit in each indicator level. Midpoint indicators provide information closer to the environmental mechanisms, which is technically relevant and helps the identification of environmental hotspots in specific attributes and proposing improvements. Endpoint indicators link the environmental impacts with human areas of interest, further aggregated in the EF indicator, giving a broader perspective of the environmental impacts suitable for decision-making. All of these indicators can be considered as an ecoefficiency indicator when expressed per economic functional unit. Ultimately, the sustainable composite indicator is also aimed at decision-making and enhances the understanding of sustainability as a multi-dimensional concept.

Several methodological challenges are tackled in this dissertation, using statistical data and multicriteria techniques and approaches for assessing agricultural sustainability. The assessment of the environmental sustainability of agriculture through LCA highlights the significance of site-specific- models with which to estimate on-field emissions. However, models based on generic information should not be ruled out a priori since they are a feasible alternative in contexts where more specific information is unavailable. Secondary sources (e.g. ECREA) are a viable option to obtain activity data for the inventory analysis, especially when analysing a range of crops at the regional level. To improve the accuracy of the indicators, modelling the uncertainty and variability of the parameters, in particular the on-field emission factors and activity data, becomes imperative. The NVA, as a proxy of the economic value generated by an activity, represents an alternative functional unit with respect to other options widely used in agricultural LCAs (e.g. mass-based). The NVA shows the complex relationship between agriculture and its environmental impacts, highlighting how non-compliance with market expectations and adverse agroecological conditions can result in a loss of both the environmental and economic value of agriculture. When assessing the overall sustainability of Spanish agriculture, the trade-off between attributes is highlighted in the results as a critical modelling parameter.

The quantitative evaluation of agricultural sustainability is a complex issue due to the ambiguity of the concept and the intensive data requirement together with the highly sensitive nature of farming systems to environmental and market factors. The implicit ambiguity of the sustainability concept, more than a weakness, represents a strength to the extent that it recognises its normative nature. This relativises the evaluation of sustainability based on the ethics of the society in which it is assessed. In addition, its positive (technical) nature allows limits to be established to protect critical natural capital, which is essential for life on the planet.

This dissertation delves into crucial aspects of agriculture, a critical link of the agri-food chain, which is heavily dependent on non-controllable natural factors, that contribute to its environmental impacts. To support decision-making and policy development, methodological standardisation should be promoted. In this sense, the efforts of the European Union to provide an LCA-based comprehensive methodology are required to assessing the environmental impacts of products and organisations.

CHAPTER V. ANNEXES

Annex A. Supplementary material of section 2.1.

A.1. Fresh water consumption

Fresh water consumption was estimated following AWARE guidelines. For that purpose, the yield and irrigation data were elicited from direct interviews with technical staff. The rainfall, reference crop evapotranspiration (ET_o) and crop coefficient (K_c) were taken from IVIA (2019). The crop evapotranspiration was calculated as (ET_o* K_c). To express the data per FU (1 kg grapes), they were all divided by the yield.

Table A1.1. Fresh water consumption in the analysed grape systems

	CRB	**CRT**	**CIB**	**CIT**	**ORB**	**ORT**	**OIB**	**OIT**
Yield (kg grapes·ha^{-1})	7000	6000	9000	7000	5500	4500	7500	5500
Rainfall (mm)	379.38	379.38	379.38	379.38	379.38	379.38	379.38	379.38
Irrigation water (mm)	0	0	71.40	71.40	0	0	71.40	71.40
Total water (mm)	379.38	379.38	450.78	450.78	379.38	379.38	450.78	450.78
ET_o (mm)	1052.39	1052.39	1052.39	1052.39	1052.39	1052.39	1052.39	1052.39
K_c	0.21	0.33	0.21	0.33	0.21	0.33	0.21	0.33
ET_c (mm)	224.16	342.03	224.16	342.03	224.16	342.03	224.16	342.03
Rainwater use (kg·kg grape^{-1})	541.97	632.30	421.53	541.97	689.78	843.07	505.84	689.78
Blue water use (kg·kg grape^{-1})	0.00	0.00	79.33	101.99	0.00	0.00	95.19	129.81
Fresh water use (kg·kg grape^{-1})	541.97	632.30	500.86	643.97	689.78	843.07	601.03	819.59
Green Water consumption (kg·kg grape^{-1})	320.23	570.04	209.62	411.22	407.56	760.06	251.54	523.37
Blue Water consumption (kg·kg grape^{-1})	0.00	0.00	39.45	77.39	0.00	0.00	47.34	98.49
Fresh Water consumption (kg·kg grape^{-1})	320.23	570.04	249.07	488.61	407.56	760.06	298.88	621.87

A.2. Nitrogen and Phosphorus Balances

For the nitrogen and phosphorus balance estimation, the guidelines and data (nitrogen and phosphorus extraction coefficients, nitrogen distribution in the tree and the final fate of nitrogen in each part of the tree) of the MAPAMA (2018a, 2018b) were followed. Tables S2 and S3 show the balances, including the different terms and emission factors (EFs) considered in the balances.

Table A2.1: Phosphorus balance ($kg \cdot ha^{-1}$) in the analysed grape systems

	CRB	CRT	CIB	CIT	ORB	ORT	OIB	OIT
Inputs (kg $P_2O_5 \cdot ha^{-1}$)	29.02	29.02	16.52	16.52	16.52	16.52	16.52	16.52
NPK15-15-15	12.50	12.50	0.00	0.00	0.00	0.00	0.00	0.00
Sheep manure	16.52	16.52	16.52	16.52	16.52	16.52	16.52	16.52
Outputs (kg $P_2O_5 \cdot ha^{-1}$)	55.15	47.27	70.91	55.15	43.33	35.45	59.09	43.33
Extraction coefficient	7.88	7.88	7.88	7.88	7.88	7.88	7.88	7.88
Yield ($t \cdot ha^{-1}$)	7.00	6.00	9.00	7.00	5.50	4.50	7.50	5.50
Harvest withdrawals	55.15	47.27	70.91	55.15	43.33	35.45	59.09	43.33
P_2O_5 balance	-26.13	-18.25	-54.39	-38.63	-26.81	-18.93	-42.57	-26.81
PO_4^{3-} emissions	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table A2.2: Nitrogen balance (kg ha^{-1}) in the analysed grape systems

	Min	Max	CRB	CRT	CIB	CIT	ORB	ORT	OIB	OIT
Nitrogen inputs			**62.29**	**62.29**	**98.31**	**98.31**	**48.39**	**48.39**	**48.39**	**48.39**
NPK15-15-15			12.50	12.50	0.00	0.00	0.00	0.00	0.00	0.00
Ammonia sulphate			0.00	0.00	42.00	42.00	0.00	0.00	0.00	0.00
Sheep manure			44.04	44.04	44.04	44.04	44.04	44.04	44.04	44.04
Atmospheric deposition			5.75	5.75	12.27	12.27	4.35	4.35	4.35	4.35
Nitrogen outputs			63.29	57.44	83.03	70.16	52.77	44.87	64.58	52.88
Harvest withdrawals										
Extraction coefficient (1/1000)	7.8	8.97	8.19	8.58	7.80	8.19	8.78	8.97	8.00	8.78
Yield (t)	5	8	7.00	6.00	9.00	7.00	5.50	4.50	7.50	5.50
Total nitrogen extracted by the crop	39	71.76	57.33	51.48	70.20	57.33	48.26	40.37	59.96	48.26
N distribution in the tree										
Harvest	19.50	35.88	28.67	25.74	35.10	28.67	24.13	20.18	29.98	24.13
Leaf	12.99	23.90	19.09	17.14	23.38	19.09	16.07	13.44	19.97	16.07
Wood	5.23	9.62	7.68	6.90	9.41	7.68	6.47	5.41	8.03	6.47
Root	1.29	2.37	1.89	1.70	2.32	1.89	1.59	1.33	1.98	1.59
Fate of N content in each part of the tree										
Harvest withdrawn	19.50	35.88	28.67	25.74	35.10	28.67	24.13	20.18	29.98	24.13
Wood withdrawn	5.23	9.62	7.68	6.90	9.41	7.68	6.47	5.41	8.03	6.47
Leaves left on the field as waste	12.99	23.90	19.09	17.14	23.38	19.09	16.07	13.44	19.97	16.07
Roots removed	0.64	1.18	0.95	0.85	1.16	0.95	0.80	0.67	0.99	0.80
Roots left on field as waste	0.64	1.18	0.95	0.85	1.16	0.95	0.80	0.67	0.99	0.80
Total withdrawn	25.3695	46.67988	37.29	33.49	45.67	37.29	31.39	26.26	39.01	31.39
Total left as waste	13.6305	25.08012	20.04	17.99	24.53	20.04	16.87	14.11	20.96	16.87
Fertiliser volatilisation										
NH_3-N[a]			4.70	4.70	10.66	10.66	3.52	3.52	3.52	3.52
Sheep manure EF[1]			0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08
NPK15-15-15 EF			0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
Ammonia sulphate EF			0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17
NO_x-N[b]			1.06	1.06	1.61	1.61	0.82	0.82	0.82	0.82
Sheep manure EF			0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02

	Min	Max	CRB	CRT	CIB	CIT	ORB	ORT	OIB	OIT
NKP15-15-15 EF			0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Ammonia sulphate EF			0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
N_2O-N[c]			0.21	0.21	0.56	0.56	0.16	0.16	0.27	0.27
Indirect N_2O-N			0.06	0.06	0.12	0.12	0.04	0.04	0.04	0.04
Direct N_2O-N			0.15	0.15	0.44	0.44	0.12	0.12	0.22	0.22
Sheep manure EF			0.0027	0.0027	0.0051	0.0051	0.0027	0.0027	0.0051	0.0051
NPK15-15-15 EF			0.0027	0.0027	0.0051	0.0051	0.0027	0.0027	0.0051	0.0051
Ammonia sulphate EF			0.0027	0.0027	0.0051	0.0051	0.0027	0.0027	0.0051	0.0051
Balance			-1.00	4.85	15.28	28.15	-4.38	3.51	-16.19	-4.49
NO_3^--N			0.00	4.85	15.28	28.15	0.00	3.51	0.00	0.00

[a][calculation according to tier 2 EF from EMEP/EEA (EEA, 2019)]

[b][calculation according to tier 1 EF from EMEP/EEA (EEA, 2019)]

[c][calculation according to tier 2 EF from IPCC (2006)]

A.3. Results of the Monte Carlo simulations

Table A3.1. Results of the Monte Carlo simulations of conventional system, with goblet spur pruning, rainfed, Bobal variety (CRB)

Impact categories	Mean	Variation coefficient	10%	90%
Climate change, default, excl biogenic carbon BM	$1.46\cdot10^{-1}$	33%	$8.81\cdot10^{-2}$	$2.13\cdot10^{-1}$
Climate change, default, excl biogenic carbon AM	$8.22\cdot10^{-2}$	22%	$6.27\cdot10^{-2}$	$1.07\cdot10^{-1}$
Fine Particulate Matter Formation BM	$9.26\cdot10^{-4}$	26%	$6.32\cdot10^{-4}$	$1.25\cdot10^{-3}$
Fine Particulate Matter Formation AM	$6.64\cdot10^{-4}$	23%	$4.78\cdot10^{-4}$	$8.70\cdot10^{-4}$
Photochemical Ozone Formation, Ecosystems BM	$2.66\cdot10^{-3}$	52%	$1.05\cdot10^{-3}$	$4.57\cdot10^{-3}$
Photochemical Ozone Formation, Ecosystems AM	$9.66\cdot10^{-4}$	37%	$5.59\cdot10^{-4}$	$1.45\cdot10^{-3}$
Photochemical Ozone Formation, Human Health BM	$2.65\cdot10^{-3}$	53%	$1.04\cdot10^{-3}$	$4.57\cdot10^{-3}$
Photochemical Ozone Formation, Human Health AM	$9.60\cdot10^{-4}$	37%	$5.54\cdot10^{-4}$	$1.45\cdot10^{-3}$
Stratospheric Ozone Depletion BM	$3.55\cdot10^{-6}$	51%	$1.40\cdot10^{-6}$	$6.00\cdot10^{-6}$
Stratospheric Ozone Depletion AM	$1.18\cdot10^{-6}$	56%	$4.61\cdot10^{-7}$	$2.10\cdot10^{-6}$
Terrestrial Acidification BM	$4.61\cdot10^{-3}$	38%	$2.44\cdot10^{-3}$	$7.05\cdot10^{-3}$
Terrestrial Acidification AM	$3.38\cdot10^{-3}$	37%	$1.92\cdot10^{-3}$	$5.01\cdot10^{-3}$

AM: baseline modelling; BM: alternative modelling.

Table A3.2. Results of the Monte Carlo simulations of conventional system, with goblet spur pruning, rainfed, Tempranillo variety (CRT)

Impact categories	Mean	Variation coefficient	10%	90%
Climate change, default, excl biogenic carbon BM	$1.72\cdot10^{-1}$	32.3%	$1.05\cdot10^{-1}$	$2.45\cdot10^{-1}$
Climate change, default, excl biogenic carbon AM	$1.02\cdot10^{-1}$	21.0%	$7.90\cdot10^{-2}$	$1.30\cdot10^{-1}$
Fine Particulate Matter Formation BM	$1.07\cdot10^{-3}$	25.5%	$7.23\cdot10^{-4}$	$1.42\cdot10^{-3}$
Fine Particulate Matter Formation AM	$7.60\cdot10^{-4}$	20.9%	$5.66\cdot10^{-4}$	$9.69\cdot10^{-4}$
Photochemical Ozone Formation, Ecosystems BM	$3.09\cdot10^{-3}$	53.0%	$1.19\cdot10^{-3}$	$5.35\cdot10^{-3}$
Photochemical Ozone Formation, Ecosystems AM	$1.14\cdot10^{-3}$	37.4%	$6.21\cdot10^{-4}$	$1.72\cdot10^{-3}$
Photochemical Ozone Formation, Human Health BM	$3.08\cdot10^{-3}$	53.2%	$1.19\cdot10^{-3}$	$5.34\cdot10^{-3}$
Photochemical Ozone Formation, Human Health AM	$1.14\cdot10^{-3}$	37.6%	$6.14\cdot10^{-4}$	$1.71\cdot10^{-3}$
Stratospheric Ozone Depletion BM	$4.20\cdot10^{-6}$	48.9%	$1.73\cdot10^{-6}$	$6.89\cdot10^{-6}$
Stratospheric Ozone Depletion AM	$1.60\cdot10^{-6}$	49.3%	$7.60\cdot10^{-7}$	$2.65\cdot10^{-6}$
Terrestrial Acidification BM	$5.33\cdot10^{-3}$	36.9%	$3.01\cdot10^{-3}$	$8.00\cdot10^{-3}$
Terrestrial Acidification AM	$3.82\cdot10^{-3}$	33.5%	$2.31\cdot10^{-3}$	$5.55\cdot10^{-3}$

AM: baseline modelling; BM: alternative modelling.

Table A3.3. Results of the Monte Carlo simulations of conventional system, double guyot cane pruning with trellis, irrigated, Bobal variety (CIB)

Impact categories	Mean	Variation coefficient	10%	90%
Climate change, default, excl biogenic carbon BM	$3.11\cdot10^{-1}$	18.0%	$2.44\cdot10^{-1}$	$3.89\cdot10^{-1}$
Climate change, default, excl biogenic carbon AM	$2.63\cdot10^{-1}$	11.3%	$2.30\cdot10^{-1}$	$3.02\cdot10^{-1}$
Fine Particulate Matter Formation BM	$1.10\cdot10^{-3}$	19.2%	$8.33\cdot10^{-4}$	$1.38\cdot10^{-3}$
Fine Particulate Matter Formation AM	$9.71\cdot10^{-4}$	26.0%	$6.50\cdot10^{-4}$	$1.30\cdot10^{-3}$
Photochemical Ozone Formation, Ecosystems BM	$3.09\cdot10^{-3}$	39.0%	$1.63\cdot10^{-3}$	$4.71\cdot10^{-3}$
Photochemical Ozone Formation, Ecosystems AM	$1.25\cdot10^{-3}$	33.8%	$7.60\cdot10^{-4}$	$1.82\cdot10^{-3}$
Photochemical Ozone Formation, Human Health BM	$3.08\cdot10^{-3}$	39.2%	$1.61\cdot10^{-3}$	$4.70\cdot10^{-3}$
Photochemical Ozone Formation, Human Health AM	$1.24\cdot10^{-3}$	34.1%	$7.48\cdot10^{-4}$	$1.81\cdot10^{-3}$
Stratospheric Ozone Depletion BM	$4.07\cdot10^{-6}$	50.7%	$1.57\cdot10^{-6}$	$6.95\cdot10^{-6}$
Stratospheric Ozone Depletion AM	$2.27\cdot10^{-6}$	48.1%	$1.09\cdot10^{-6}$	$3.75\cdot10^{-6}$
Terrestrial Acidification BM	$5.16\cdot10^{-3}$	29.4%	$3.20\cdot10^{-3}$	$7.25\cdot10^{-3}$
Terrestrial Acidification AM	$5.09\cdot10^{-3}$	40.4%	$2.46\cdot10^{-3}$	$7.84\cdot10^{-3}$

AM: baseline modelling; BM: alternative modelling.

Table A3.4. Results of the Monte Carlo simulations of conventional system, double guyot cane pruning with trellis, irrigated, Tempranillo variety (CIT)

Impact categories	Mean	Variation coefficient	10%	90%
Climate change, default, excl biogenic carbon BM	$3.99 \cdot 10^{-1}$	18.3%	$3.10 \cdot 10^{-1}$	$4.95 \cdot 10^{-1}$
Climate change, default, excl biogenic carbon AM	$3.51 \cdot 10^{-1}$	12.0%	$3.02 \cdot 10^{-1}$	$4.06 \cdot 10^{-1}$
Fine Particulate Matter Formation BM	$1.43 \cdot 10^{-3}$	19.0%	$1.08 \cdot 10^{-3}$	$1.79 \cdot 10^{-3}$
Fine Particulate Matter Formation AM	$1.25 \cdot 10^{-3}$	25.7%	$8.76 \cdot 10^{-4}$	$1.67 \cdot 10^{-3}$
Photochemical Ozone Formation, Ecosystems BM	$4.00 \cdot 10^{-3}$	38.8%	$2.10 \cdot 10^{-3}$	$6.13 \cdot 10^{-3}$
Photochemical Ozone Formation, Ecosystems AM	$1.62 \cdot 10^{-3}$	33.6%	$9.86 \cdot 10^{-4}$	$2.37 \cdot 10^{-3}$
Photochemical Ozone Formation, Human Health BM	$3.99 \cdot 10^{-3}$	39.0%	$2.09 \cdot 10^{-3}$	$6.12 \cdot 10^{-3}$
Photochemical Ozone Formation, Human Health AM	$1.61 \cdot 10^{-3}$	33.9%	$9.71 \cdot 10^{-4}$	$2.36 \cdot 10^{-3}$
Stratospheric Ozone Depletion BM	$5.20 \cdot 10^{-6}$	51.7%	$1.92 \cdot 10^{-6}$	$8.73 \cdot 10^{-6}$
Stratospheric Ozone Depletion AM	$3.41 \cdot 10^{-6}$	45.7%	$1.62 \cdot 10^{-6}$	$5.44 \cdot 10^{-6}$
Terrestrial Acidification BM	$6.71 \cdot 10^{-3}$	29.4%	$4.24 \cdot 10^{-3}$	$9.31 \cdot 10^{-3}$
Terrestrial Acidification AM	$6.55 \cdot 10^{-3}$	40.2%	$3.41 \cdot 10^{-3}$	$1.00 \cdot 10^{-2}$

AM: baseline modelling; BM: alternative modelling.

Table A3.5. Results of the Monte Carlo simulations of organic system, with goblet spur pruning, rainfed, Bobal variety (ORB)

Impact categories	Mean	Variation coefficient	10%	90%
Climate change, default, excl biogenic carbon BM	$1.36 \cdot 10^{-1}$	38.0%	$7.52 \cdot 10^{-2}$	$2.06 \cdot 10^{-1}$
Climate change, default, excl biogenic carbon AM	$6.80 \cdot 10^{-2}$	28.7%	$4.80 \cdot 10^{-2}$	$9.44 \cdot 10^{-2}$
Fine Particulate Matter Formation BM	$9.38 \cdot 10^{-4}$	31.5%	$5.72 \cdot 10^{-4}$	$1.31 \cdot 10^{-3}$
Fine Particulate Matter Formation AM	$6.16 \cdot 10^{-4}$	26.7%	$4.22 \cdot 10^{-4}$	$8.50 \cdot 10^{-4}$
Photochemical Ozone Formation, Ecosystems BM	$2.89 \cdot 10^{-3}$	60.7%	$9.17 \cdot 10^{-4}$	$5.28 \cdot 10^{-3}$
Photochemical Ozone Formation, Ecosystems AM	$9.87 \cdot 10^{-4}$	35.3%	$5.59 \cdot 10^{-4}$	$1.45 \cdot 10^{-3}$
Photochemical Ozone Formation, Human Health BM	$2.89 \cdot 10^{-3}$	60.8%	$9.12 \cdot 10^{-4}$	$5.28 \cdot 10^{-3}$
Photochemical Ozone Formation, Human Health AM	$9.81 \cdot 10^{-4}$	35.5%	$5.53 \cdot 10^{-4}$	$1.45 \cdot 10^{-3}$
Stratospheric Ozone Depletion BM	$3.52 \cdot 10^{-6}$	54.0%	$1.29 \cdot 10^{-6}$	$6.14 \cdot 10^{-6}$
Stratospheric Ozone Depletion AM	$1.02 \cdot 10^{-6}$	70.4%	$2.86 \cdot 10^{-7}$	$2.00 \cdot 10^{-6}$
Terrestrial Acidification BM	$4.77 \cdot 10^{-3}$	45.0%	$2.12 \cdot 10^{-3}$	$7.66 \cdot 10^{-3}$
Terrestrial Acidification AM	$3.16 \cdot 10^{-3}$	42.3%	$1.62 \cdot 10^{-3}$	$5.09 \cdot 10^{-3}$

AM: baseline modelling; BM: alternative modelling.

Table A3.6. Results of the Monte Carlo simulations of organic system, with goblet spur pruning, rainfed, Tempranillo variety (ORT)

Impact categories	Mean	Variation coefficient	10%	90%
Climate change, default, excl biogenic carbon BM	$1.64 \cdot 10^{-1}$	38.2%	$8.75 \cdot 10^{-2}$	$2.50 \cdot 10^{-1}$
Climate change, default, excl biogenic carbon AM	$8.76 \cdot 10^{-2}$	27.6%	$6.30 \cdot 10^{-2}$	$1.20 \cdot 10^{-1}$
Fine Particulate Matter Formation BM	$1.16 \cdot 10^{-3}$	31.3%	$6.90 \cdot 10^{-4}$	$1.64 \cdot 10^{-3}$
Fine Particulate Matter Formation AM	$7.48 \cdot 10^{-4}$	27.6%	$5.05 \cdot 10^{-4}$	$1.03 \cdot 10^{-3}$
Photochemical Ozone Formation, Ecosystems BM	$3.59 \cdot 10^{-3}$	59.1%	$1.11 \cdot 10^{-3}$	$6.70 \cdot 10^{-3}$
Photochemical Ozone Formation, Ecosystems AM	$1.20 \cdot 10^{-3}$	37.6%	$6.43 \cdot 10^{-4}$	$1.82 \cdot 10^{-3}$
Photochemical Ozone Formation, Human Health BM	$3.59 \cdot 10^{-3}$	59.2%	$1.10 \cdot 10^{-3}$	$6.69 \cdot 10^{-3}$
Photochemical Ozone Formation, Human Health AM	$1.20 \cdot 10^{-3}$	37.8%	$6.36 \cdot 10^{-4}$	$1.81 \cdot 10^{-3}$
Stratospheric Ozone Depletion BM	$4.23 \cdot 10^{-6}$	54.6%	$1.42 \cdot 10^{-6}$	$7.40 \cdot 10^{-6}$
Stratospheric Ozone Depletion AM	$1.42 \cdot 10^{-6}$	62.7%	$5.13 \cdot 10^{-7}$	$2.60 \cdot 10^{-6}$
Terrestrial Acidification BM	$5.90 \cdot 10^{-3}$	45.0%	$2.59 \cdot 10^{-3}$	$9.58 \cdot 10^{-3}$
Terrestrial Acidification AM	$3.83 \cdot 10^{-3}$	43.3%	$1.91 \cdot 10^{-3}$	$6.08 \cdot 10^{-3}$

AM: baseline modelling; BM: alternative modelling.

Table A3.7. Results of the Monte Carlo simulations of organic system, double guyot cane pruning with trellis, irrigated, Bobal variety (OIB)

Impact categories	Mean	Variation coefficient	10%	90%
Climate change, default, excl biogenic carbon BM	$1.32 \cdot 10^{-1}$	27.9%	$8.83 \cdot 10^{-2}$	$1.80 \cdot 10^{-1}$
Climate change, default, excl biogenic carbon AM	$9.04 \cdot 10^{-2}$	16.0%	$7.48 \cdot 10^{-2}$	$1.07 \cdot 10^{-1}$
Fine Particulate Matter Formation BM	$7.19 \cdot 10^{-4}$	28.9%	$4.70 \cdot 10^{-4}$	$9.93 \cdot 10^{-4}$
Fine Particulate Matter Formation AM	$4.85 \cdot 10^{-4}$	25.6%	$3.40 \cdot 10^{-4}$	$6.45 \cdot 10^{-4}$
Photochemical Ozone Formation, Ecosystems BM	$2.24 \cdot 10^{-3}$	56.1%	$7.66 \cdot 10^{-4}$	$3.92 \cdot 10^{-3}$
Photochemical Ozone Formation, Ecosystems AM	$8.70 \cdot 10^{-4}$	30.0%	$5.74 \cdot 10^{-4}$	$1.23 \cdot 10^{-3}$
Photochemical Ozone Formation, Human Health BM	$2.23 \cdot 10^{-3}$	56.2%	$7.61 \cdot 10^{-4}$	$3.91 \cdot 10^{-3}$
Photochemical Ozone Formation, Human Health AM	$8.65 \cdot 10^{-4}$	30.2%	$5.69 \cdot 10^{-4}$	$1.22 \cdot 10^{-3}$
Stratospheric Ozone Depletion BM	$2.51 \cdot 10^{-6}$	54.1%	$8.97 \cdot 10^{-7}$	$4.27 \cdot 10^{-6}$
Stratospheric Ozone Depletion AM	$9.74 \cdot 10^{-7}$	54.8%	$3.98 \cdot 10^{-7}$	$1.60 \cdot 10^{-6}$
Terrestrial Acidification BM	$3.57 \cdot 10^{-3}$	43.1%	$1.73 \cdot 10^{-3}$	$5.62 \cdot 10^{-3}$
Terrestrial Acidification AM	$2.40 \cdot 10^{-3}$	41.6%	$1.23 \cdot 10^{-3}$	$3.75 \cdot 10^{-3}$

AM: baseline modelling; BM: alternative modelling.

Table A3.8. Results of the Monte Carlo simulations of organic system, double guyot cane pruning with trellis, irrigated, Tempranillo variety (OIT)

Impact categories	Mean	Variation coefficient	10%	90%
Climate change, default, excl biogenic carbon BM	$1.83 \cdot 10^{-1}$	27.7%	$1.22 \cdot 10^{-1}$	$2.54 \cdot 10^{-1}$
Climate change, default, excl biogenic carbon AM	$1.23 \cdot 10^{-1}$	16.3%	$1.02 \cdot 10^{-1}$	$1.48 \cdot 10^{-1}$
Fine Particulate Matter Formation BM	$9.83 \cdot 10^{-4}$	31.4%	$5.93 \cdot 10^{-4}$	$1.40 \cdot 10^{-3}$
Fine Particulate Matter Formation AM	$6.61 \cdot 10^{-4}$	25.7%	$4.57 \cdot 10^{-4}$	$8.90 \cdot 10^{-4}$
Photochemical Ozone Formation, Ecosystems BM	$3.05 \cdot 10^{-3}$	55.8%	$1.01 \cdot 10^{-3}$	$5.39 \cdot 10^{-3}$
Photochemical Ozone Formation, Ecosystems AM	$1.18 \cdot 10^{-3}$	30.8%	$7.55 \cdot 10^{-4}$	$1.64 \cdot 10^{-3}$
Photochemical Ozone Formation, Human Health BM	$3.05 \cdot 10^{-3}$	55.9%	$1.00 \cdot 10^{-3}$	$5.39 \cdot 10^{-3}$
Photochemical Ozone Formation, Human Health AM	$1.17 \cdot 10^{-3}$	31.0%	$7.48 \cdot 10^{-4}$	$1.63 \cdot 10^{-3}$
Stratospheric Ozone Depletion BM	$3.55 \cdot 10^{-6}$	52.8%	$1.30 \cdot 10^{-6}$	$6.17 \cdot 10^{-6}$
Stratospheric Ozone Depletion AM	$1.31 \cdot 10^{-6}$	56.3%	$5.26 \cdot 10^{-7}$	$2.25 \cdot 10^{-6}$
Terrestrial Acidification BM	$4.89 \cdot 10^{-3}$	45.7%	$2.19 \cdot 10^{-3}$	$7.81 \cdot 10^{-3}$
Terrestrial Acidification AM	$3.27 \cdot 10^{-3}$	42.3%	$1.64 \cdot 10^{-3}$	$5.17 \cdot 10^{-3}$

AM: baseline modelling; BM: alternative modelling.

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Annex B. Supplementary material for section 2.2

B.1. ECREA database limited to orange and tomato crops

Available at B.1.xlsx

B.2. Supplementary material for irrigation

B.2.1. Freshwater irrigation requirement

The amount of freshwater used for irrigation is estimated as the crop's water requirements under standard conditions, following Allen et al. (1998). Fresh water use for irrigation is estimated from the soil water balance in the root zone, considering the evapotranspiration under water stress conditions (Allen et al., 1998). Fig. 1 represents the root zone as a container where the capillary rise (CR) of groundwater towards the root zone, rainfall (P) and irrigation (I) are water inputs, which decrease the water depletion in the root zone. At the same time, evapotranspiration ($\mathrm{ET_c}$, soil evaporation plus crop transpiration), surface runoff, and percolation losses remove water from the root zone, increasing water depletion.

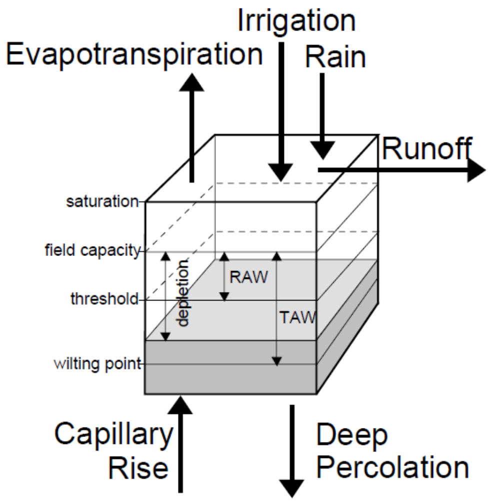

Fig. B2.1. Water balance at the root zone (From Allen et al., 1998).

Field capacity is the amount of water that the soil, depending on its properties, can hold after deep percolation (DP). In contrast, saturation refers to the water poured on the soil from rainfall or irrigation above the field capacity. Water available at field capacity loses potential energy as it is depleted, depending on both the type of soil and the crop rooting depth (Z_r). Consequently, only a part of the water at field capacity is available for the crop, since from a depletion level onwards the water extracted by the crop is relatively null, which corresponds to the wilting point. Therefore, the total water available at the root zone (TAW) can be estimated as:

$$TAW = 1000 \cdot (\theta_{FC} - \theta_{WP}) \cdot Z_r \quad \text{(B2.1)}$$

Where, TAW is the total available soil water at the root zone (mm), θ_{FC} the water content at field capacity (m^3m^{-3}), θ_{WP} the water content at the wilting point (m^3m^{-3}) and Z_r is the rooting depth (m).

Crops can efficiently use only a fraction of the TAW without suffering water stress, this fraction corresponds to the readily available soil water in the root zone (RAW). RAW (Eq. B2.2) depends on both crop features and the evaporation power of the atmosphere, and from a TAW threshold onwards, water availability cannot satisfy the needs of water evaporation from the soil and water transpiration by the crop:

$$RAW = p \cdot TAW \tag{B2.2}$$

Where, RAW is the readily available soil water in the root zone (mm), and p is the average TAW fraction that can be depleted from the root zone before moisture stress.

TAW, θ_{FC} and θ_{WP}, are estimated as a function of the type of soil by using the Soil Water Characteristics software (v. 6.02.74) of the Agricultural Research Service of the United States (USDA) (ESDAC, 2020).The data on the clay, sand, and silt content in the soil have been obtained from LUCAS 2015 topsoil database (ESDAC, 2020; Jones et al., 2020). Then the weighted average is computed, considering the share of each type of soil in a specific NUTS 2 as the weight variable. The values corresponding to Z_r, for TAW calculation, and p, for RAW calculation, are taken from FAO (Allen et al., 1998).

The irrigation water requirement in a specific period (I_i, mm), is calculated from an iterative process (Eq. B2.3).

$$D_{r,i} = D_{r,i-1} - (P_i - RO_i) + DP_i - CR_i + ET_{c,i} - I_i \tag{B2.3}$$

I_i represents the net irrigation depth during period i that infiltrates the soil (mm), calculated assuming that irrigation water is efficiently applied when rainfall cannot supply enough water to prevent crop water stress. Thus, taking into account that $D_{r,i}$ and $D_{r,i-1}$ represent the root zone depletion at the end of period i and after the previous period $i-1$ (mm), respectively, and considering that rainfall (P_i, mm) and irrigation happen at the beginning of each period, water irrigation should be applied if $D_{r,i-1} \leq RAW_{i-1}$, where $I_i \leq D_{r,i-1}$ to prevent deep percolation losses. Although Allen et al. (1998) use daily periods to estimate I_i, for the sake of simplicity monthly periods are considered in this study. Values of P_i, lower than 20% of the reference evapotranspiration (ET_0, mm) are not considered, because a small amount of precipitation water is normally entirely evaporated (Allen et al., 1998) and for greenhouse systems P_i is assumed as zero. RO_i is the runoff from the soil surface during period i (mm), which depends on the soil slope, soil type, its hydraulic conditions and previous moisture content, and land use and cover. Following Allen et al. (1998) RO_i is assumed to be zero in this case study. DP_i represents the water loss outside the root zone by deep percolation during period i (mm). For simplification purposes, and following Allen et al. (1998), DP_i is estimated from Eq. B2.3: assuming that the soil water content is θ_{FC} within the same period i, of the wetting event, it means $D_{r,i} = 0$ whereas if $D_{r,i} > 0, DP_i = 0$. CR_i is the amount of water transported upwards by capillary rise from the water table to the root zone during period i (mm). This depends on the soil type, the depth of the water table and the moisture content at the root zone. CR_i is also null because the average water table in Spain is around 1 m below the bottom of the root zone (Allen et al., 1998; Espinosa-Tasón et al., 2020). $ET_{c,i}$ is the crop evapotranspiration during period i (mm); it is estimated using Eq. B2.4, where $K_{c,i}$ is the crop coefficient in the period i (dimensionless).

$$ET_{c,i} = ET_{o,i} \cdot K_{c,i} \tag{B2.4}$$

To apply Eqs. B2.3 and (6.4), data on P_i, ET_o, K_c, are obtained from the Agroclimatic Information System for Irrigation (SIAR, 2022). $K_{c,i}$ varies according to the crop growth stage. To simplify calculations, a global $K_{c,i}$ for every i period is calculated as the weighted average, considering the frequency of each $K_{c,i}$ value during the years studied for each crop as the weight variable.

Considering that the years evaluated are consecutive and assuming that the precipitation does not change significantly from one year to another, it is assumed for the sake of simplicity that the first i period of the crop season corresponds to the first month of the year in which irrigation is carried out, and similarly for the final i period. Consequently, the net water irrigation requirement (I_{net}, $m^3 \cdot FU^{-1}$) is estimated using Eq. B2.5 by adding every periodic I_i calculated for each year divided by the yield (Y) of the reference holdings. The months corresponding to each crop season are obtained from (MAPA, 2021). To calculate I_{net}, additional assumptions regarding the parameters of Eq. B2.3 are considered. Specifically, it is assumed that during the initial period of the year, due to heavy rain or irrigation, the soil is at field capacity and the initial root zone depletion is zero. Therefore, if there is not enough rain during the last period to leave the soil at field capacity, the irrigation in the last period of the year is equal to $D_{r,i}$, without taking into account that $D_{r,i-1} \leq RAW_{i-1}$.

$$I_{net} = \frac{10 \cdot \sum I_i}{Y} \tag{B2.5}$$

B.2.2. Freshwater consumption

Society values freshwater as an economic good because it is considered as a limited natural resource, whereas seawater is not. Thus, freshwater consumption is the basis with which to evaluate the water scarcity footprint (ISO, 2014; SPHERA, 2022). In agricultural systems, the consumptive use of water is mainly associated with freshwater losses at the watershed level caused by evapotranspiration from the crops (SPHERA, 2022). Freshwater is defined as water with a low concentration of dissolved solids (ISO, 2014) and it is basically made up of the freshwater available on surfaces and in underground bodies of water (blue water) and by the precipitation on land that does not runoff or that restocks the groundwater which can be used by the crops (green water). Following Sphera (2022), it is assumed that rainwater does not contribute to blue water scarcity; hence, only irrigation water is considered when estimating blue water consumption (m^3) (Eq. B2.6):

$$Blue\ water\ consumption = \left(\frac{\sum ET_{c,i}}{\sum ET_{0,i}}\right) \cdot I_{net} \quad \text{(B2.6)}$$

B.2.3. Energy consumption for irrigation

Following Daccache et al. (2014) and Espinosa-Tasón et al. (2020), the energy needed for irrigating the crops (E, kWh·m3 of water-1) is estimated as the energy required for water abstraction (pumping), by using Eq. B2.7; this relates the efficiency and pressure needed to pump water according to the irrigation method (furrow, sprinkler or drip). The source of each parameter used to estimate the energy consumption for irrigation following the methodology described below is detailed in Table 1.

$$E = \frac{TH}{367 \cdot \mu_{pump} \cdot \mu_{motor}} \quad \text{(B2.7)}$$

Where TH (m) is the head pressure required for pumping, and μ_{pump} and μ_{motor} are the pump and motor efficiencies, respectively. Taking into account that the water for irrigation considered in this study could come from surface freshwater, groundwater, desalinated water or reclaimed water, Eq. B2.7 is adapted to include the energy consumed to treat the water (E_{treat}, kWh·m3 of treated water-1) when using desalinated or reclaimed water, thus giving Eq. B2.8.

$$E = \frac{TH}{367 \cdot \mu_{pump} \cdot \mu_{motor}} + E_{treat} \quad \text{(B2.8)}$$

TH is calculated as the sum of the standard operating pressure (p_m, m), plus the friction losses (p_l, m) within the piped distribution system of the irrigation method (Eq. B2.9). Moreover, for furrow irrigation, it is assumed that only surface water is used. Thus, the pressure required to transport the water from the source because of gravity energy (p_{W_s}, m) is also added. The weighted mean pressure associated with the water sources (p_{md_pump}) is added for sprinkler and drip irrigation.

$$TH_i = \begin{cases} [p_m \cdot (1 + p_l)] + p_{W_s} & if\ i = furrow\ method, \\ [p_m \cdot (1 + p_l)] + p_{md\_pump} & if\ i = sprinkler\ or\ drip\ method \end{cases} \quad \text{(B2.9)}$$

p_{md_pump} is calculated using Eq. B2.10, which considers the share of surface (W_s) and underground (W_g) water in the total water sources of each NUTS 2, and the pressure required to lift both surface water (l_{W_s}, m) and ground water (l_{W_g}, m).

$$p_{md\_pump} = \left[\frac{W_s}{(W_s+W_g)} \cdot l_{W_s}\right] + \left[\frac{W_g}{(W_s+W_g)} \cdot l_{W_g}\right] \quad \text{(B2.10)}$$

The efficiency of the pump (μ_{pump}) is taken from Daccache et al. (2014). The efficiency of the motor (μ_{motor}) is estimated using Eq. B2.11 as the weighted average of the standard efficiency of a diesel motor (μ_{Dm}) and an electricity motor (μ_{Em}), with the share of the total number of diesel and electricity motors used in Spanish agriculture, P_{Dm} (Eq. B2.12) and P_{Em}, (Eq. B2.13) respectively, as weighting variables.

$$\mu_{motor} = [(P_{Dm} \cdot \mu_{Dm}) + (P_{Em} \cdot \mu_{Em})] \quad \text{(B2.11)}$$

$$P_{Dm} = \frac{Diesel\_motors}{(Diesel\_motors + Electric\_motors)} \quad \text{(B2.12)}$$

$$P_{Em} = \frac{Electric\_motors}{(Diesel\_motors + Electric\_motors)} \quad \text{(B2.13)}$$

E_{treat} is estimated as the energy consumption from desalinated and reclaimed water:

$$E_{treat} = (E_d \cdot P_{Wd}) + (E_r \cdot P_{Wr}) \quad \text{(B2.14)}$$

$$P_{wd} = \frac{W_d}{(W_d + W_r)} \quad \text{(B2.15)}$$

$$P_{wr} = \frac{W_r}{(W_d + W_r)} \quad \text{(B2.16)}$$

Where E_d and E_r represent the amount of energy (kWh) required to desalinate or reclaim 1 m3 of water; and P_{wd} and P_{wr} are the share of desalinated and reclaimed water, respectively. W_d and W_r are the volume (m3) of desalinated and reclaimed water used in agriculture.

As this study does not consider a specific irrigation method for the reference holdings, the energy for each reference holding (E_{rh}, kWh· m3 of water supplied-1) is estimated as the weighted average of the E estimated for the irrigation methods used in the NUTS 2 (Eq. B2.7) weighted by the quantity of water irrigated with each method (furrow, sprinkler, and drip irrigation methods), plus the proportional energy from the desalinated or reclaimed water used in each NUTS 2:

$$E_{rh} = \left(\frac{[(E_{fm} \cdot W_{fm}) + (E_{sm} \cdot W_{sm}) + (E_{dm} \cdot W_{dm})]}{W_{tm}}\right) + \left(E_{treat} \cdot \frac{W_{treat}}{W_{total\_sources}}\right) \quad \text{(B2.17)}$$

Where E_{fm}, E_{sm}, E_{dm} represent the energy consumption in furrow, sprinkler, and drip irrigation methods, respectively, and are obtained by applying Eq. B2.7 to each irrigation method. W_{fm}, W_{sm}, W_{dm} and W_{treat} are the volume (m3) of water irrigated with furrow, sprinkler and drip methods and the desalinated and reclaimed water used, respectively. W_{tm} is the total water irrigated (m3) and $W_{total\_sources}$ is the total water availability (m^3).

To calculate the irrigation energy consumption per FU (E_{FU}, kWh·FU-1), Eq. B2.18 is applied. I_{gross} (m3 of water·FU-1) represents the gross water use for irrigation.

$$E_{FU} = I_{gross} \cdot E_{rh} \quad \text{(B2.18)}$$

I_{gross} is calculated as the ratio between I_{net}, calculated above in the Freshwater irrigation requirement section, and the efficiency of the irrigation system (μ_{system}) (B2.20):

$$I_{gross} = \frac{I_{net}}{\mu_{system}} \quad \text{(B2.19)}$$

μ_{system} is dimensionless. It is obtained as the weighted average of the efficiencies of conveyance and distribution of water for irrigation (μ_{dis_conv}) and the application efficiency (μ_{app}), using the share of water from surface source (W_s, m3) as weight of μ_{dis_conv} and the share of water from ground source (W_g, m3) as weight of μ_{app}:

$$\mu_{system} = \left[\frac{W_s}{(W_s+W_g)} \cdot \ \mu_{dis\_conv}\right] + \left[\frac{W_g}{(W_s+W_g)} \cdot \ \mu_{app}\right] \tag{B2.20}$$

μ_{app} is estimated as the weighted average of the efficiencies of the different irrigation methods used, considering the area irrigated with each irrigation method:

$$\mu_{app} = \frac{[(A_{fm} \cdot \mu_{fm}) + (A_{sm} \cdot \mu_{sm}) + (A_{dm} \cdot \mu_{dm})]}{A_{total}} \tag{B2.21}$$

Where μ_{fm}, μ_{sm} and μ_{dm} are the efficiencies of furrow, sprinkler, and drip irrigation methods, respectively, and A_{fm}, A_{sm} and A_{dm}, represent the area (ha) irrigated with furrow, sprinkler and drip methods in each NUTS 2, respectively. A_{total} is the total irrigated area (ha) in each NUTS 2.

The value of μ_{dis_conv} from Eq B2.20 is estimated by multiplying the application (μ_{app}),, conveyance (μ_{conv}), and distribution (μ_{dis}), efficiencies:

$$\mu_{dis\_conv} = \mu_{app} \cdot \mu_{conv} \cdot \mu_{dis} \tag{B2.22}$$

Additionally, statistics on the type of irrigation pump used in Spanish agriculture have been considered, to estimate the E_{FU} corresponding to diesel and electricity (Espinosa-Tasón et al., 2020). For inventory purposes, quantifying the fuel consumed by diesel pumps is of relevance (Eq. B2.23) as it is to quantify the electricity consumed by electric pumps (Eq. B2.24).

$$F_{ir} = \frac{(E_{FU} \cdot P_{Dm})}{11.97} \tag{B2.23}$$

Where, F_{ir} is the diesel consumed for irrigation (kg), P_{Dm} and E_{FU} are taken from Eq. B2.12 and Eq. B2.18, respectively, and the fraction, 11.97, represents the power generation (kWh) of 1 kg of diesel.

$$E_{ir} = E_{FU} \cdot P_{Em} \tag{B2.24}$$

Where, E_{ir} is the electricity consumption for irrigation (kWh·FU-1), P_{Em} and E_{FU} are taken from Eq. B2.13 and Eq. B2.18, respectively.

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B.3. Upstream processes used in the LCAs

Available at B.3.xlsx

B.4. Activity data data for orange and tomato cropping in Spain

Available at B.4.xlsx

B.5. Environmental midpoint impacts from orange and tomato crops in Spain

Available at B.5.xlsx

Annex C. Supplementary material for section 2.4

C.1. Features of the sample and production of the assessed crops

Available at C.1.xlsx

C.2. Activity data for the Spanish reference holdings at the NUTS 2 farm-level

Available at C.2.xlsx

C.3. Environmental impacts of the Spanish refecence holdings at the NUTS 2 farm-level

Available at C.3.xlsx

Annex D. Supplementary Material for section 2.5.

D.1. Raw data, some partial results and statistics of validation

Available at D.1.xlsx

D.2. Guidelines for the survey to gather preferences of decision-makers on the sustainability of Spanish agriculture.

D.2.1. Survey goal

To obtain the preference scores of the decision-makers on the sustainability attributes, applying pairwise comparisons

D.2.2. Study goal

In a previous study, we have obtained some social, economic, and natural environmental attributes for Spanish agriculture at the farm level. To this aim, we assessed reference holdings of the most representative crops at a regional level using data from the annual reports on costs and incomes of agricultural holdings published by the Spanish Ministry of Agriculture Fisheries and Food (MAPA, 2022) and other official Spanish sources.

From these results, we are now attempting to estimate a composite sustainability indicator to represent holistically the sustainability profile of the reference holdings following the traditional triple bottom line (TBL) framework. According to the TBL, the sustainability concept is represented by three base pillars (Bahadur et al., 2013), namely economic viability, social equity and natural environment (ecological integrity). The indicator to be developed will be based on decision-maker preferences and will be calculated as the weighted sum of the scores of the attributes of the reference holdings, using as a weighted variable the importance that the decision-makers give to each attribute in sustainability terms. This weighted variable will be obtained from the pairwise comparison of the sustainability attributes and represents how important is for a decisionmaker an attribute with respect to the others. The composite indicator is a relative indicator that, due to data availability, only considers some sustainability aspects. The scores obtained by applying the indicator do not aim to be used as absolute values. Instead, the sustainability scores will be only used to rank the sustainability profile of the reference holdings analysed. Table D2.1 shows the description and the sources of the sustainability attributes considered.

Table D2.1: Sustainability attributes considered for the reference holdings of the main crops

Attribute	Description	Source
Economic:		
Gross value added	Attribute to be maximised. It is calculated as the differences between the incomes from the sales and the costs of intermediate goods (€·ha^{-1}·yr^{-1}). It represents the economic value that the activity adds to the final product, available to remunerate the labour, taking into account the depreciation of capital goods, taxes, and generating a profit of the farmers.	ECREA reports
Social:		
Labour gender equity	Attributed to be targeted. It is calculated as the fraction between female full-time equivalent employment and male full-time equivalent employment (Female Annual work unit or AWU· Male AWU^{-1}·ha^{-1}·yr^{1}). This approximation represents the level of female employment with respect to the male one.	EUROSTAT
Human health	Attribute to be minimised. It is calculated from the LCAs carried out on crops at a regional level. It represents the damage to human health due to the agricultural practices in the reference holdings assessed (DALY· ha^{-1}·yr^{-1}).	Our study through an LCA approach
Natural environment:		
Quality of the terrestrial ecosystem (species·yr^{-1}·ha^{-1})	Attribute to be minimised. It is calculated from the LCAs carried out on crops at a regional level. It represents the damage to the terrestrial ecosystem due to the agricultural practices in the reference holdings assessed (species·yr^{-1}·ha^{-1})	Our study through an LCA approach
Quality of the freshwater ecosystem (species·yr^{-1}·ha^{-1})	Attribute to be minimised. It is calculated from the LCAs carried out on crops at a regional level. It represents the damage to the freshwater ecosystem due to the agricultural practices in the reference holdings assessed (species·yr^{-1}·ha^{-1})	Our study through an LCA approach
Quality of the marine water ecosystem (species·yr^{-1}·ha^{-1})	Attribute to be minimised. It is calculated from the LCAs carried out on crops at a regional level. It represents the damage to the marine water ecosystem due to the agricultural practices in the reference holdings assessed (species·yr^{-1}·ha^{-1})	Our study through an LCA approach
Natural resources availability (US_2013·ha^{-1})	Attribute to be minimised. It is calculated from the LCAs carried out on crops at a regional level. It represents the natural resource depletion due to the agricultural practices in the reference holdings assessed (US_2013·yr^{-1}·ha^{-1})	Our study through an LCA approach

Following Saaty and Vargas (2006), we want to apply a pairwise comparison to obtain the preference scores of the decision-makers on the sustainability attributes by considering a five-level scale (extreme importance, very strong importance, strong importance, moderate importance, and equal importance). Table 2 shows three examples of how important is a sustainability attribute with respect to another. Example 1 shows that for the decision-maker, attributes 1 and 2 have similar importance when estimating sustainability. In the second one, the decision-maker considers that attribute 1 is strongly more important than attribute 2. In the third example, attribute 2 is moderately more important than attribute 1.

Table D2.2. Examples of pairwise question

Example	**Item 1**	**Extreme importance**	**Very strong importance**	**Strong importance**	**Moderate importance**	**Equal importance**	**Moderate importance**	**Strong importance**	**Very strong importance**	**Extreme importance**	**Item 2**
1	Attribute 1					1					Attribute 2
2	Attribute 1			1							Attribute 2
3	Attribute 1						1				Attribute 2

It would be very useful for our study to know your opinion; thus, we kindly ask you to answer the following questions related to the sustainability attributes and their relationship. Please keep in mind that we aim to evaluate the sustainability of Spanish crops.

Note: To answer, either you can fill the tables below or the ones detailed in the Excel file that accompanies this document. The difference between the options is that in the Excel file you can verify that your answers meet the required level of consistency.

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D.3. Complementary tables and figures of the results

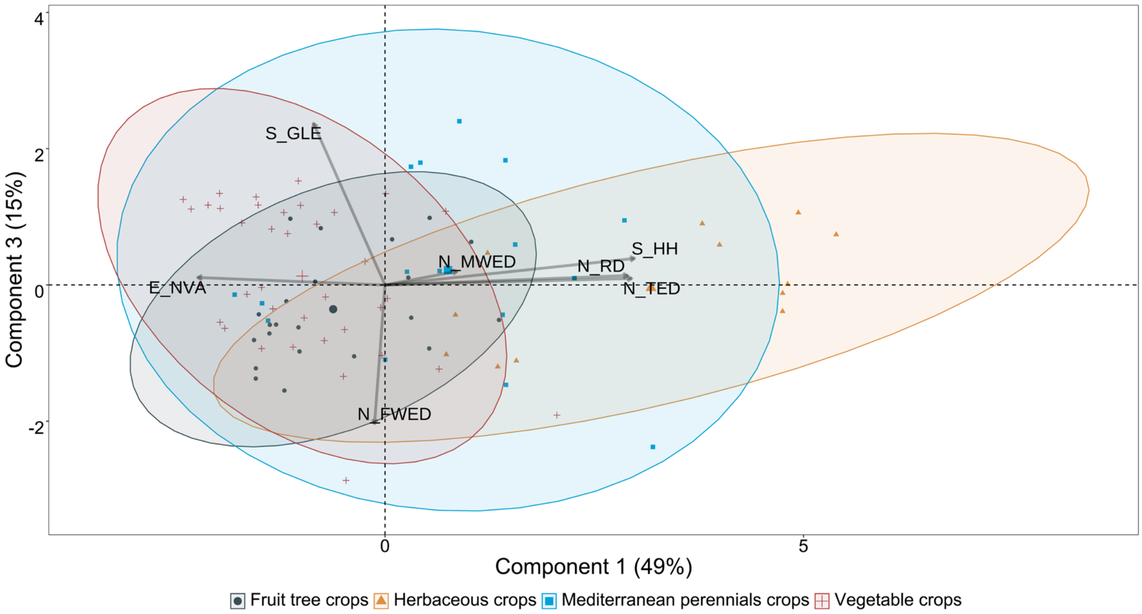

Fig. D3.1. PCA-Biplot of the orthogonal subset component 1 vs component 3 of the sustainability attributes of reference holdings at the Spanish NUTS 2 level

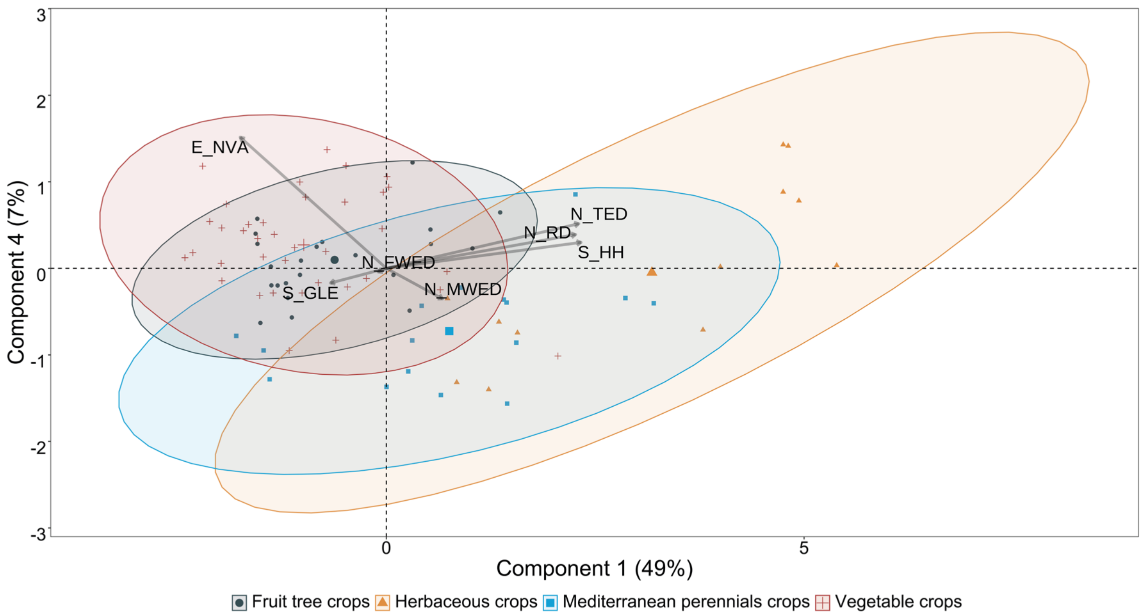

Fig. D3.2. PCA-Biplot of the orthogonal subset component 1 vs component 4 of the sustainability attributes of reference holdings at the Spanish NUTS 2 level

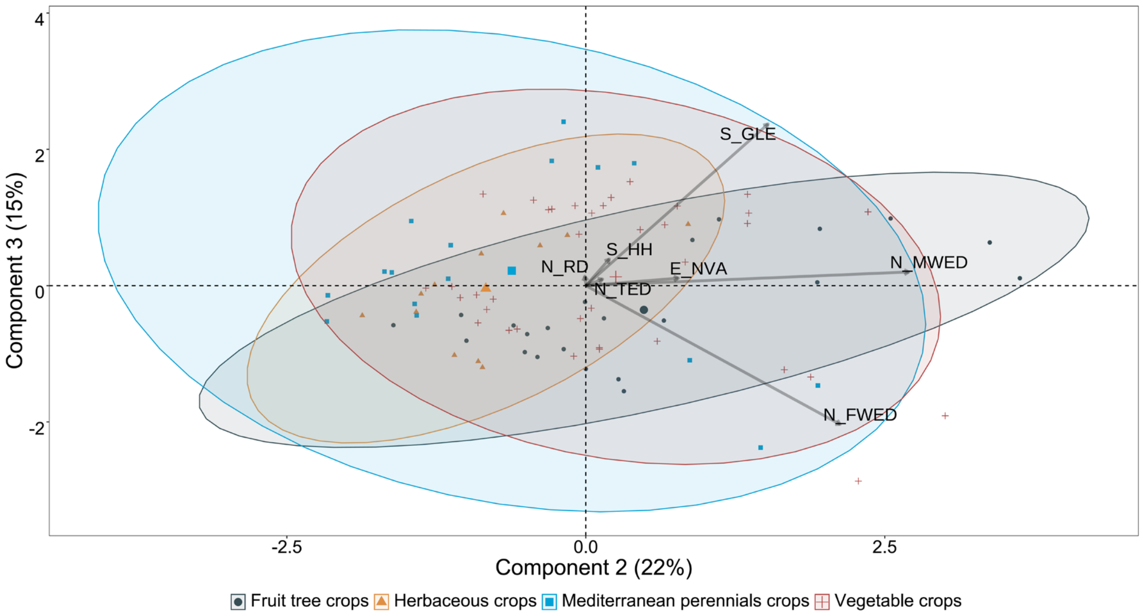

Fig. D3.3. PCA-Biplot of the orthogonal subset component 2 vs component 3 of the sustainability attributes of reference holdings at the Spanish NUTS 2 level

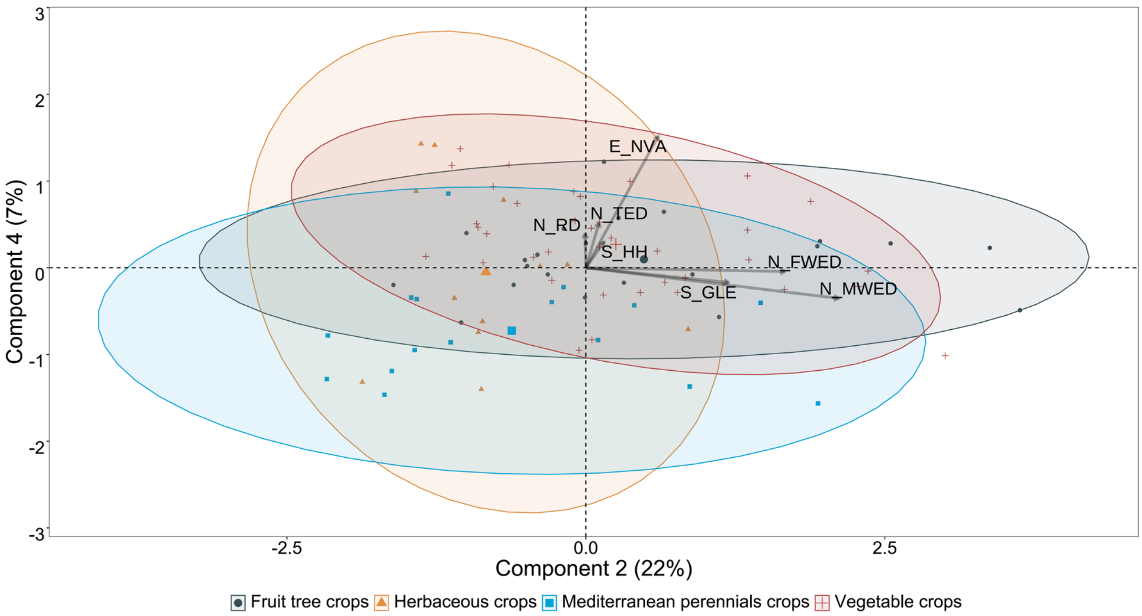

Fig. D3.4. PCA-Biplot of the orthogonal subset component 2 vs component 4 of the sustainability attributes of reference holdings at the Spanish NUTS 2 level

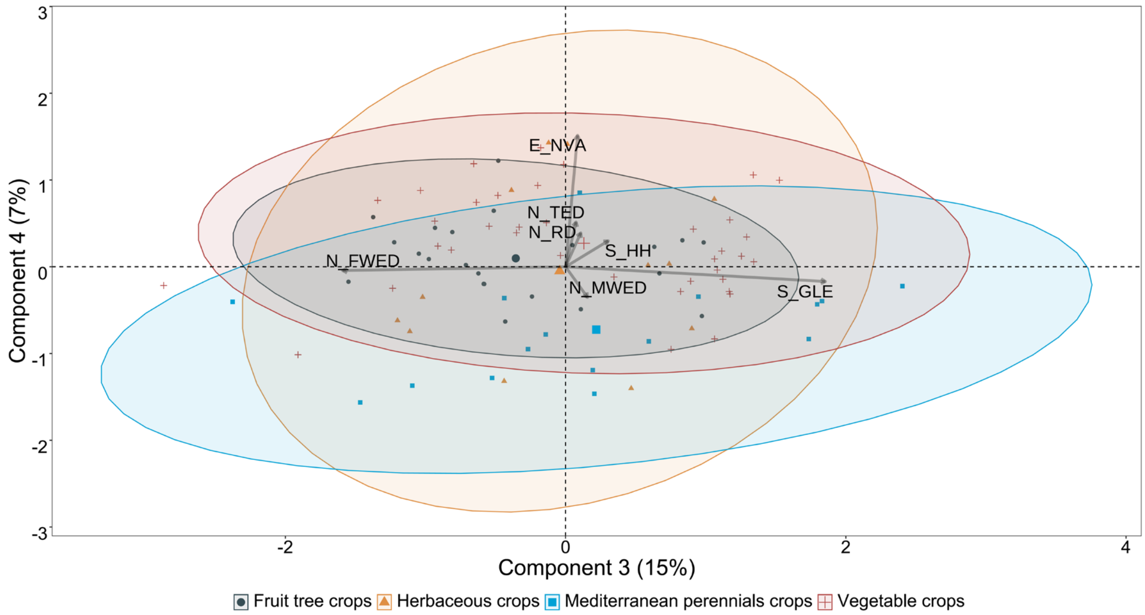

Fig. D3.5. PCA-Biplot of the orthogonal subset component 3 vs component 4 of the sustainability attributes of reference holdings at the Spanish NUTS 2 level

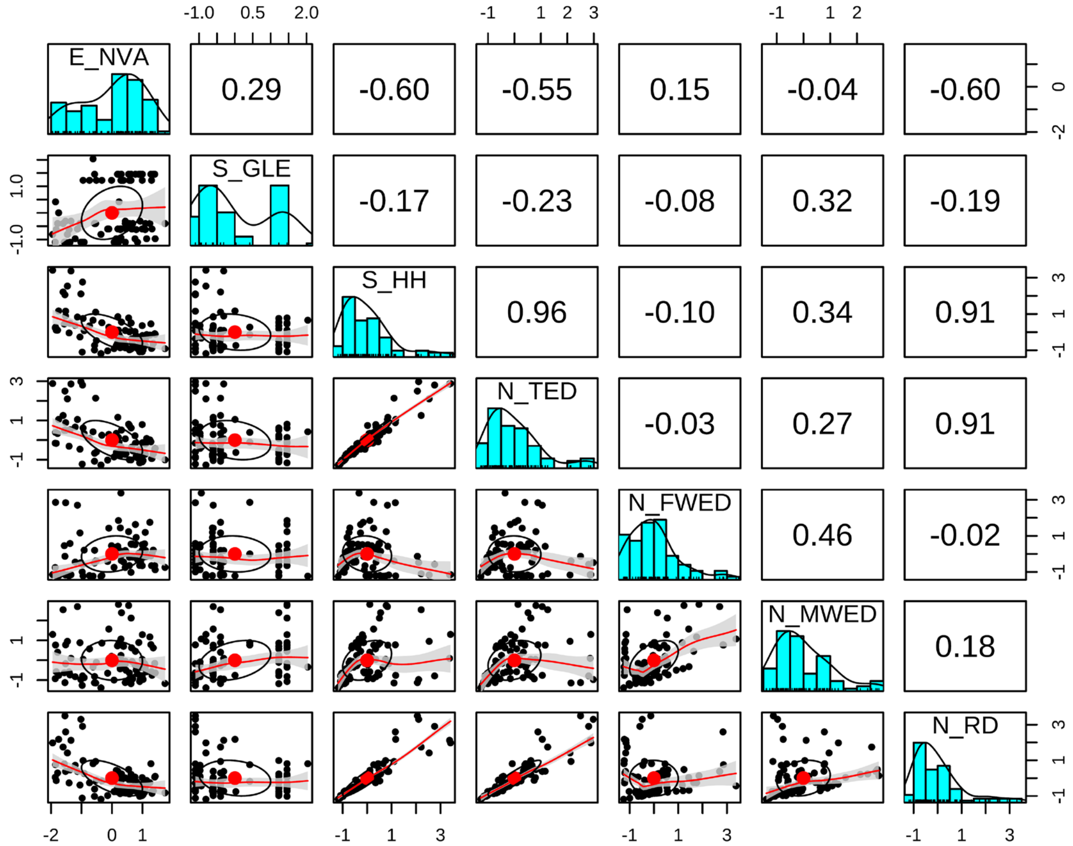

Fig. D3.6. Pearson correlation of the sustainability attributes of reference holdings at the Spanish NUTS 2 level

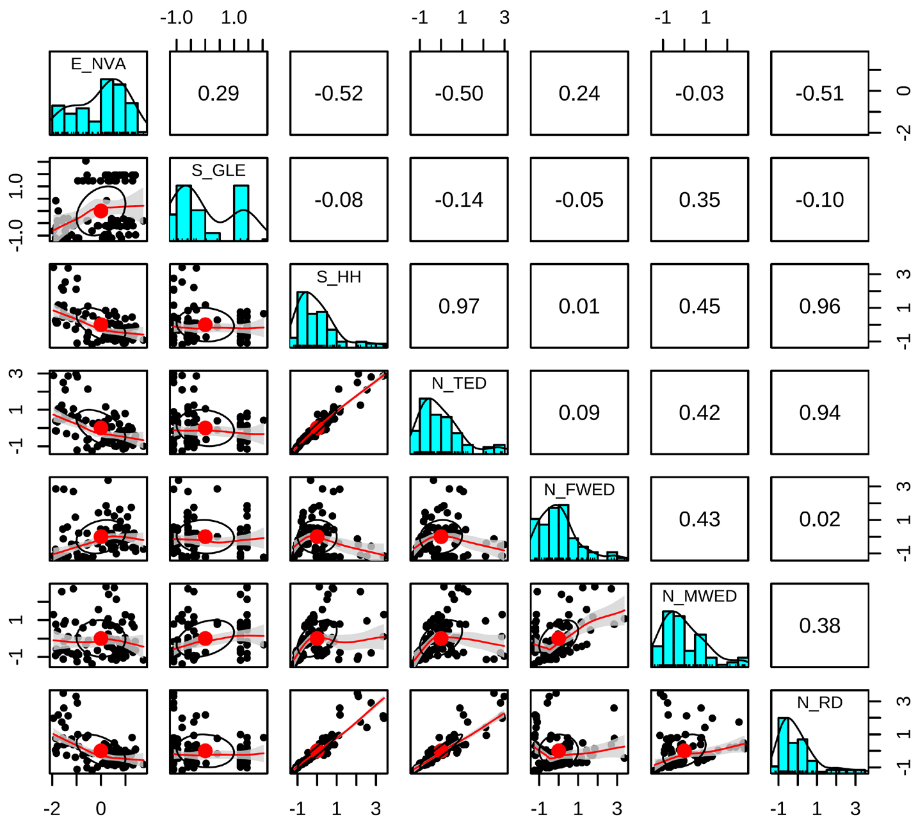

Fig. D3.7. Spearman correlation of the sustainability attributes of reference holdings at the Spanish NUTS 2 level

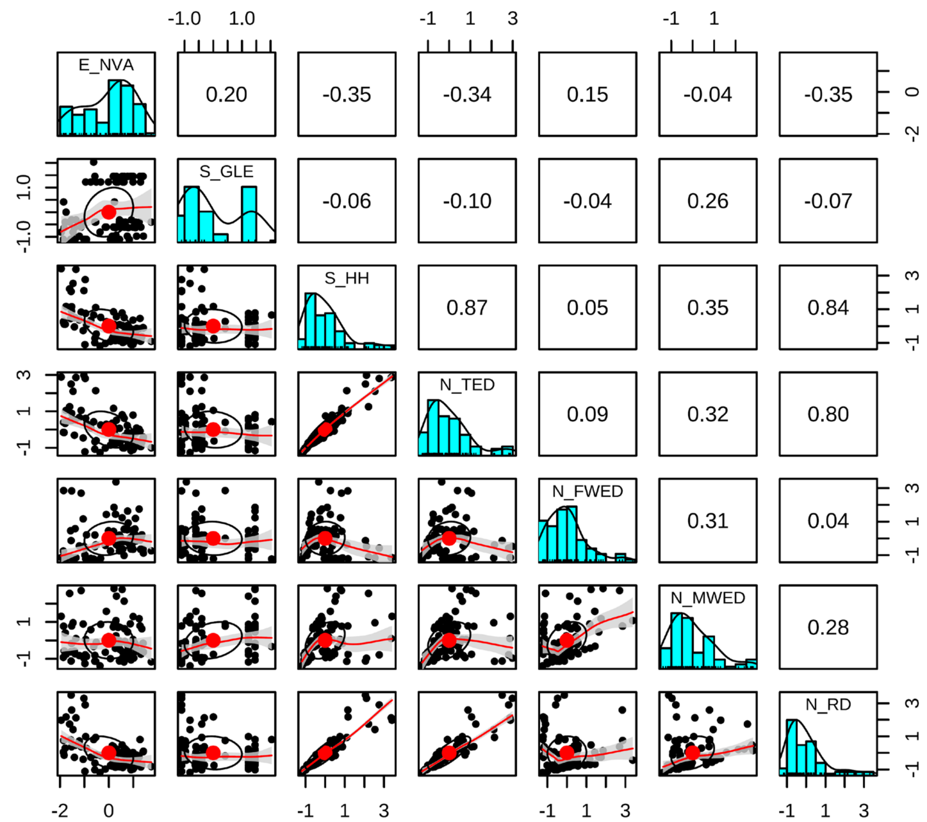

Fig. D3.8. Kendall correlation of the sustainability attributes of reference holdings at the Spanish NUTS 2 level

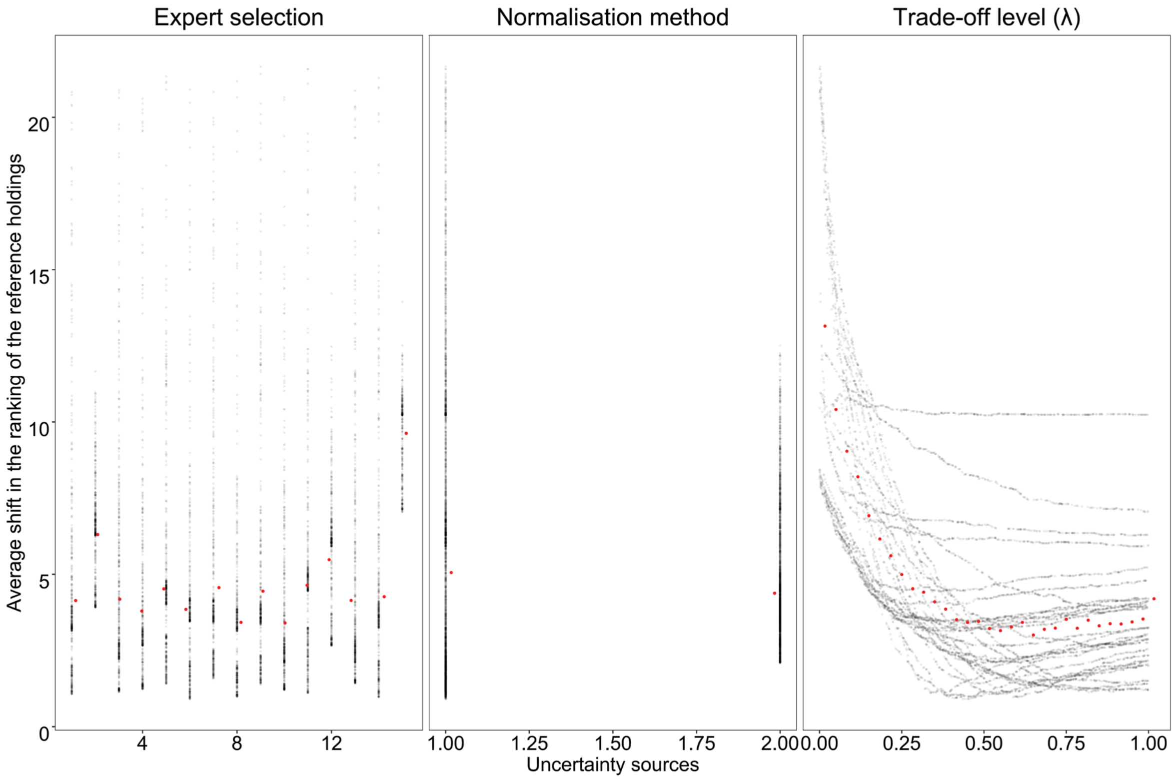

Fig. D3.9. Local uncertainty of the average shift reference holdings rankings ($\bar{R}_{SCI}$). Trade-off level = 0.58

Table D3.1. Sensitivity estimator for $\bar{R}_{ASI}$. First-order estimator: Azzini|Total-order estimator: Azzini| Total number of models run: 160,000.

sensitivity	parameters	original	bias	std.error	low.ci	high.ci
First-order	Expert selection	$2.35 \cdot 10^{-1}$	$2.34 \cdot 10^{-5}$	$6.92 \cdot 10^{-3}$	$2.21 \cdot 10^{-1}$	$2.49 \cdot 10^{-1}$
	Normalisation method	$2.62 \cdot 10^{-2}$	$5.26 \cdot 10^{-5}$	$2.91 \cdot 10^{-3}$	$2.08 \cdot 10^{-2}$	$3.21 \cdot 10^{-2}$
	λ	$5.24 \cdot 10^{-1}$	$-5.02 \cdot 10^{-5}$	$7.36 \cdot 10^{-3}$	$5.08 \cdot 10^{-1}$	$5.38 \cdot 10^{-1}$
Total-order	Expert selection	$3.60 \cdot 10^{-1}$	$1.69 \cdot 10^{-5}$	$7.82 \cdot 10^{-3}$	$3.45 \cdot 10^{-1}$	$3.76 \cdot 10^{-1}$
	Normalisation method	$1.88 \cdot 10^{-1}$	$3.38 \cdot 10^{-5}$	$4.37 \cdot 10^{-3}$	$1.79 \cdot 10^{-1}$	$1.97 \cdot 10^{-1}$
	λ	$7.22 \cdot 10^{-1}$	$-1.39 \cdot 10^{-4}$	$7.55 \cdot 10^{-3}$	$7.07 \cdot 10^{-1}$	$7.36 \cdot 10^{-1}$
Second-order	Expert selection. Normalisation method	$1.48 \cdot 10^{-2}$	$-4.62 \cdot 10^{-5}$	$3.44 \cdot 10^{-3}$	$7.53 \cdot 10^{-3}$	$2.11 \cdot 10^{-2}$
	Expert selection. λ	$5.24 \cdot 10^{-2}$	$-3.75 \cdot 10^{-5}$	$6.06 \cdot 10^{-3}$	$3.97 \cdot 10^{-2}$	$6.39 \cdot 10^{-2}$
	Normalisation method. λ	$9.51 \cdot 10^{-2}$	$2.34 \cdot 10^{-4}$	$8.08 \cdot 10^{-3}$	$7.90 \cdot 10^{-2}$	$1.11 \cdot 10^{-1}$
Third-order	Expert selection. Normalisation method. λ	$6.41 \cdot 10^{-2}$	$1.85 \cdot 10^{-4}$	$7.01 \cdot 10^{-3}$	$5.07 \cdot 10^{-2}$	$7.89 \cdot 10^{-2}$

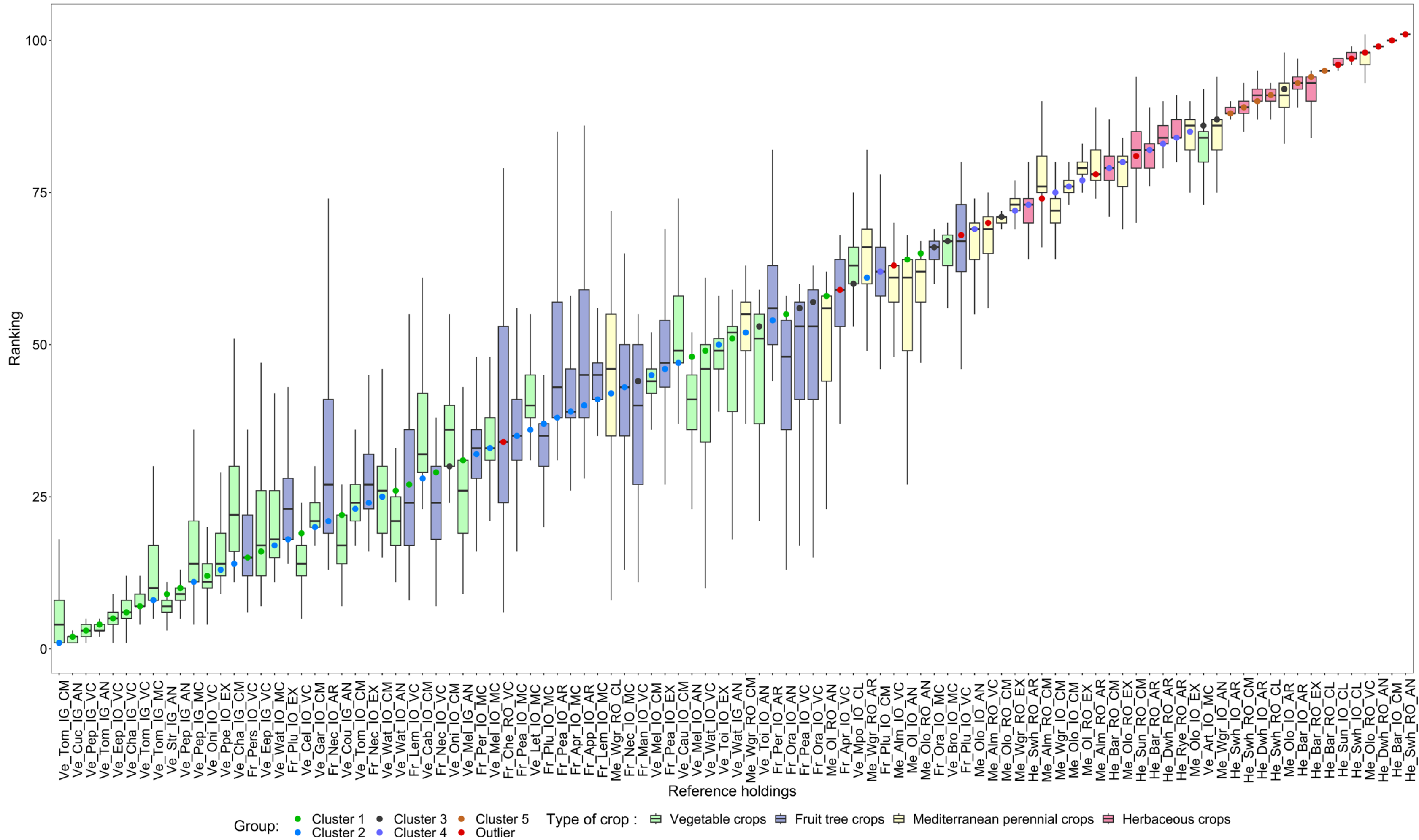

Fig. D3.10. Ranking in descending order of the sustainability composite (SCI) indicator for the Spanish reference holdings at the NUTS 2 level. Trade-off level = 1

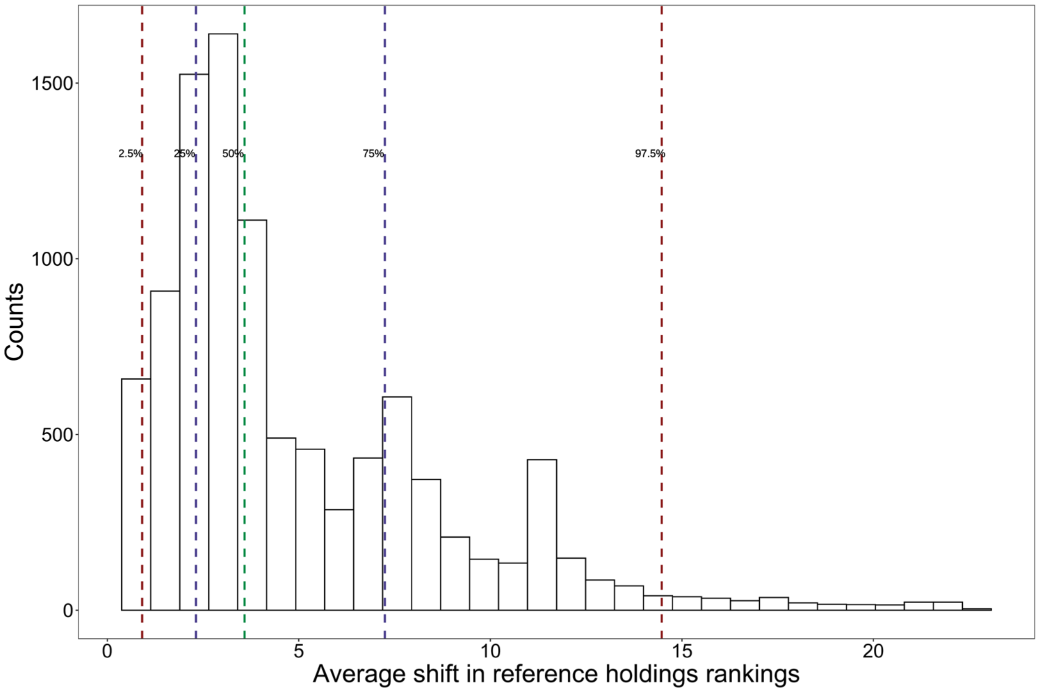

Fig. D3.11. Histogram of the simulation of the average shift reference holdings ranking ($\bar{R}_{ASI}$). Trade-off level = 1

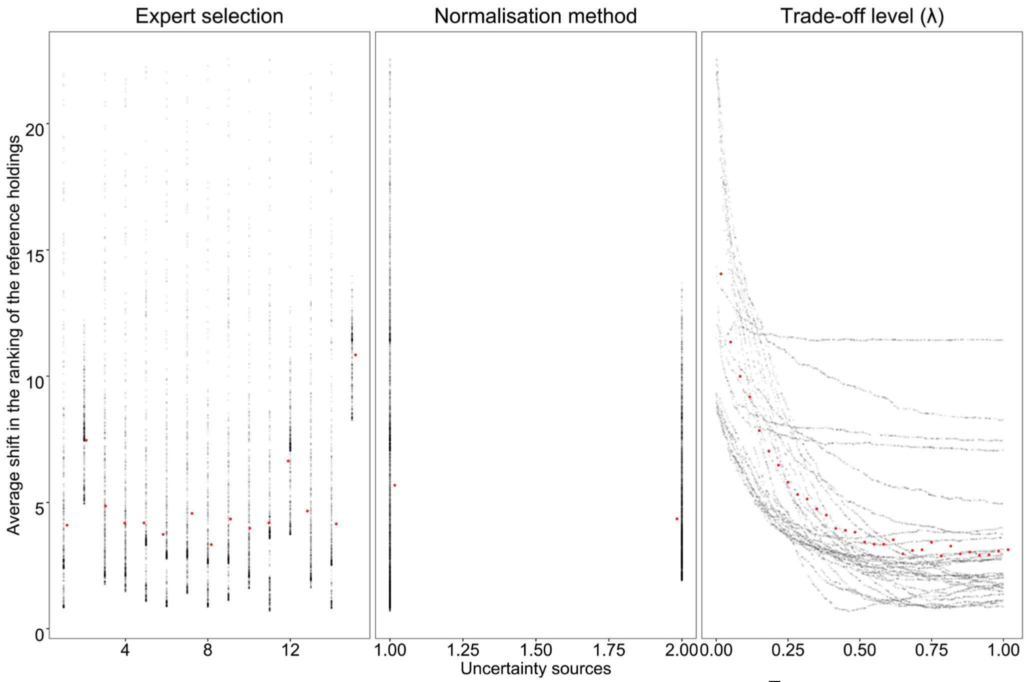

Fig. D3.12. Local uncertainty of the average shift reference holdings rankings ($\bar{R}_{ASI}$). Trade-off level = 1

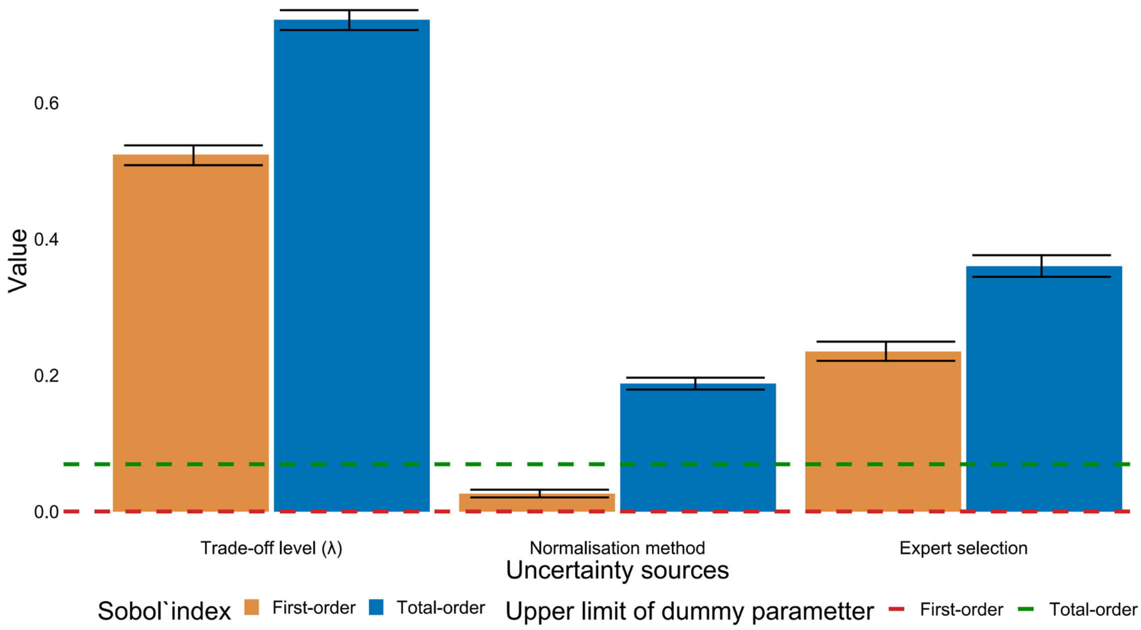

Fig. D3.13. Sobol' first-order and total-order estimators for sensitivity analysis of the $\bar{R}_{ASI}$. Trade-off level = 1

Table D3.2. Sensitivity estimator for $\bar{R}_{ASI}$. First-order estimator: Azzini|Total-order estimator: Azzini| Total number of models run: 160,000.

sensitivity	**parameters**	**original**	**bias**	**std.error**	**low.ci**	**high.ci**
First-order	Expert selection	$3.45\cdot10^{-1}$	$1.52\cdot10^{-4}$	$6.96\cdot10^{-3}$	$3.31\cdot10^{-1}$	$3.59\cdot10^{-1}$
	Normalisation method	$1.16\cdot10^{-1}$	$3.19\cdot10^{-5}$	$2.97\cdot10^{-3}$	$1.10\cdot10^{-1}$	$1.22\cdot10^{-1}$
	λ	$3.84\cdot10^{-1}$	$-2.56\cdot10^{-4}$	$5.47\cdot10^{-3}$	$3.73\cdot10^{-1}$	$3.95\cdot10^{-1}$
Total-order	Expert selection	$4.80\cdot10^{-1}$	$1.61\cdot10^{-4}$	$6.97\cdot10^{-3}$	$4.66\cdot10^{-1}$	$4.93\cdot10^{-1}$
	Normalisation method	$2.16\cdot10^{-1}$	$2.83\cdot10^{-5}$	$4.14\cdot10^{-3}$	$2.08\cdot10^{-1}$	$2.25\cdot10^{-1}$
	λ	$4.87\cdot10^{-1}$	$-3.86\cdot10^{-4}$	$6.01\cdot10^{-3}$	$4.75\cdot10^{-1}$	$4.99\cdot10^{-1}$
Second-order	Expert selection. Normalisation method	$5.16\cdot10^{-2}$	$9.21\cdot10^{-5}$	$4.66\cdot10^{-3}$	$4.21\cdot10^{-2}$	$6.06\cdot10^{-2}$
	Expert selection. λ	$5.64\cdot10^{-2}$	$-1.35\cdot10^{-4}$	$6.70\cdot10^{-3}$	$4.34\cdot10^{-2}$	$6.94\cdot10^{-2}$
	Normalisation method. λ	$2.10\cdot10^{-2}$	$2.51\cdot10^{-4}$	$6.98\cdot10^{-3}$	$8.38\cdot10^{-3}$	$3.59\cdot10^{-2}$
Third-order	Expert selection. Normalisation method. λ	$3.41\cdot10^{-2}$	$-4.64\cdot10^{-5}$	$5.21\cdot10^{-3}$	$2.41\cdot10^{-2}$	$4.46\cdot10^{-2}$

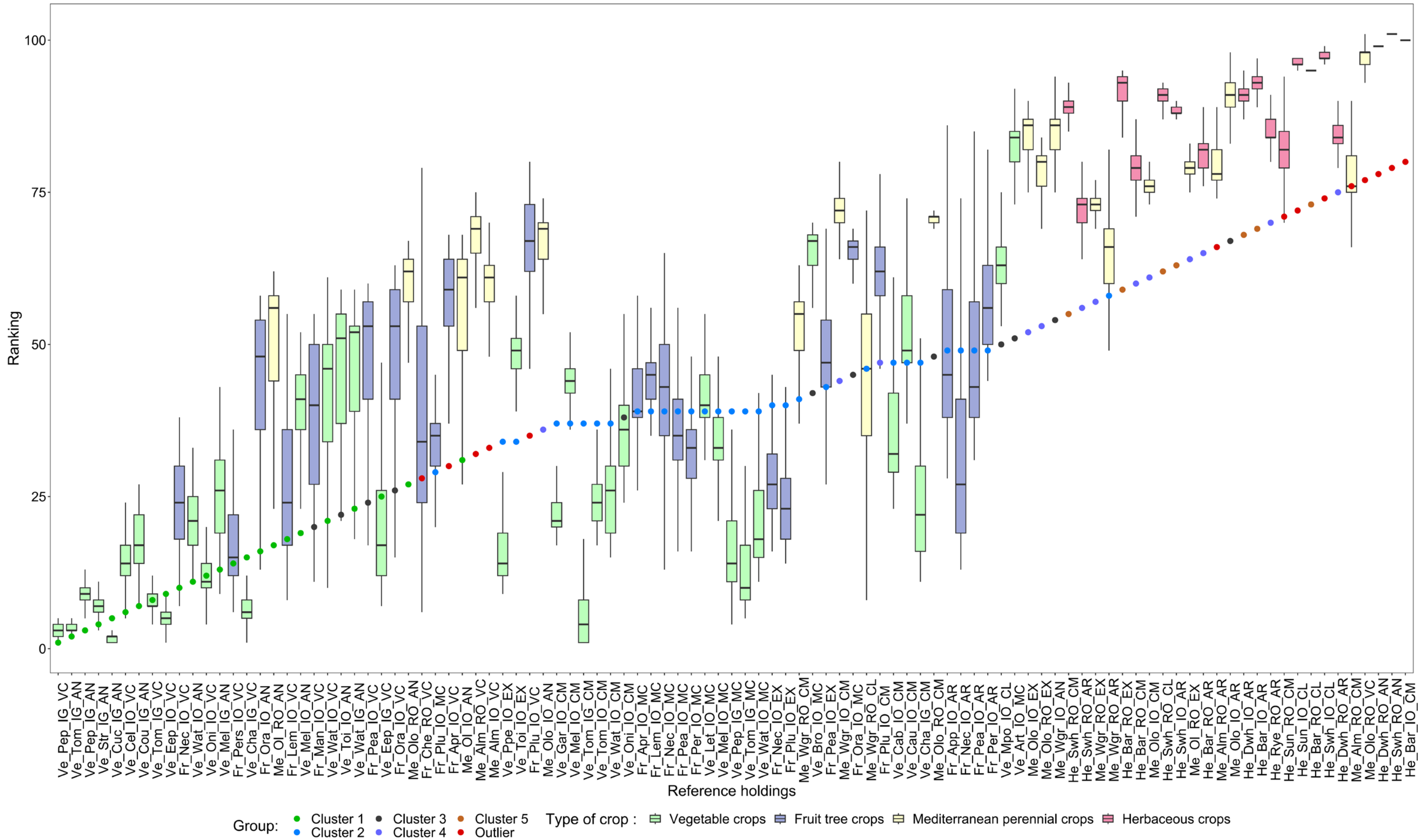

Fig. D3.14. Ranking in descending order of the sustainability composite (SCI) indicator for the Spanish reference holdings at the NUTS 2 level. Trade-off level = 0

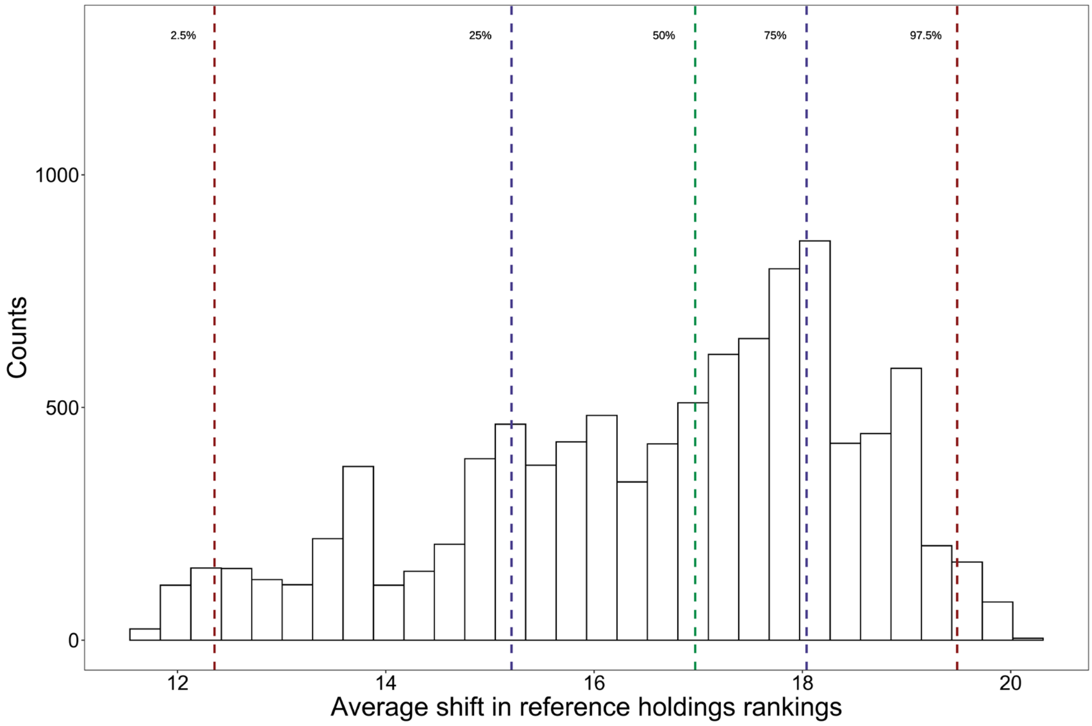

Fig. D3.15. Histogram of the simulation of the average shift reference holdings rankings ($\bar{R}_{ASI}$). Trade-off level = 0

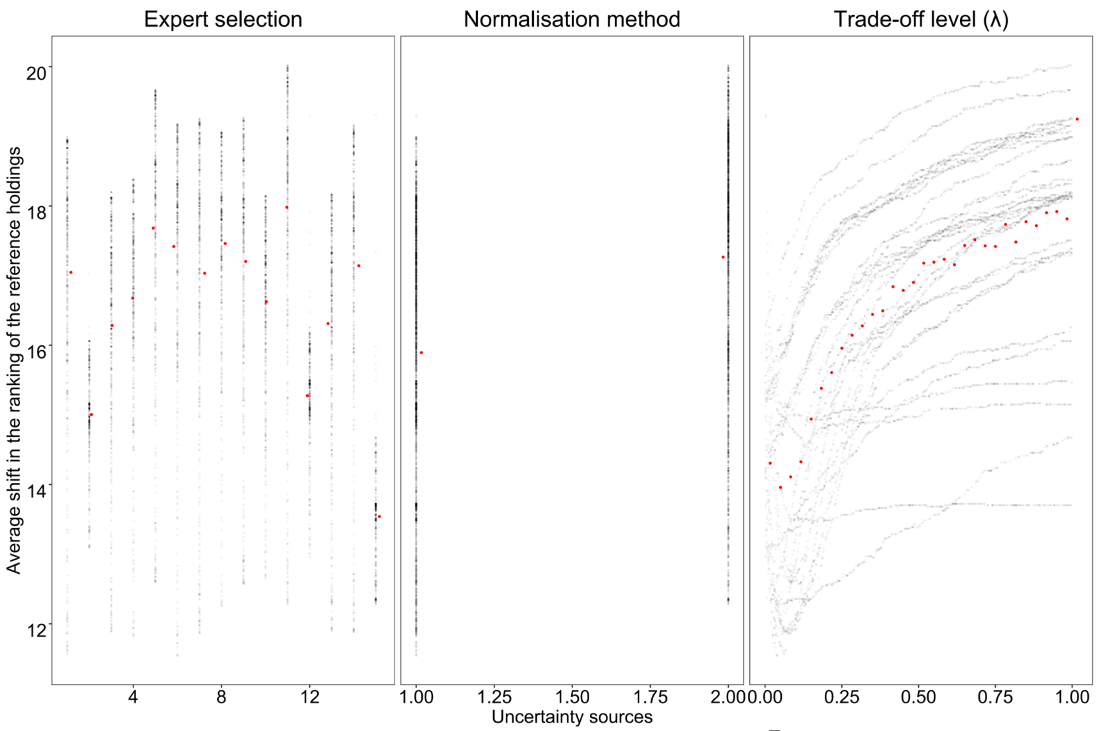

Fig. D3.16. Local uncertainty of the average shift reference holdings rankings ($\bar{R}_{ASI}$). Trade-off level = 0

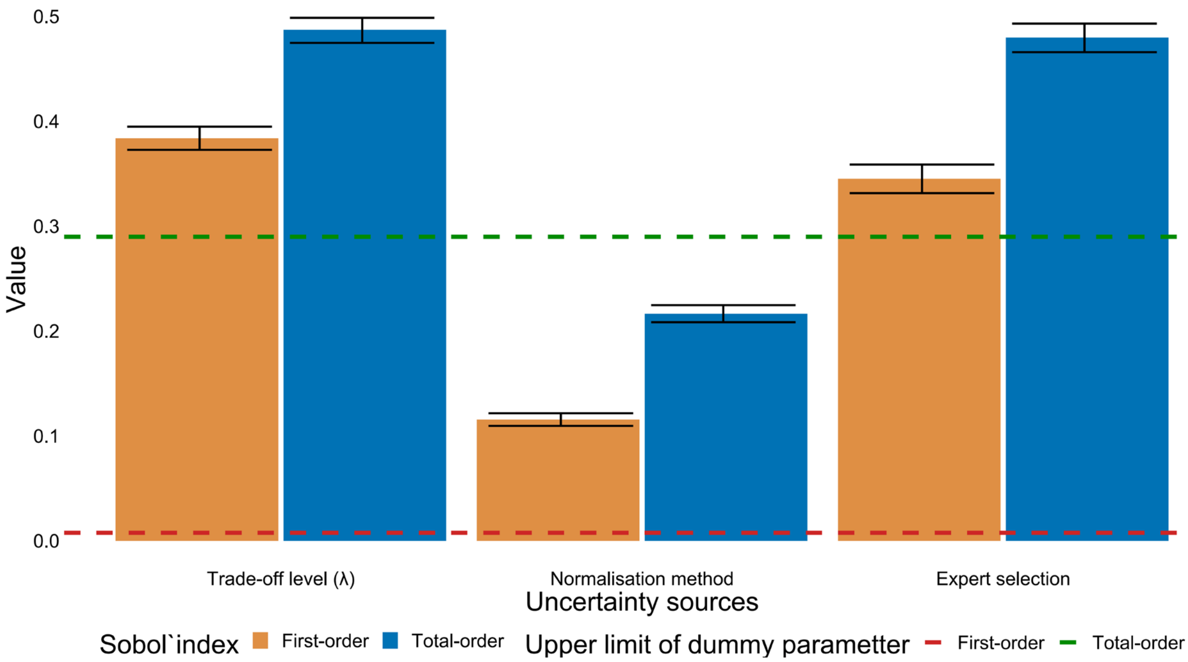

Fig. D3.17. Sobol' first-order and total-order estimators for sensitivity analysis of the $\bar{R}_{ASI}$. Trade-off level = 0.

Annex E. Supplementary material for the general discussion

E.1. Raw data and results of the eco-efficiency analysis

Available at E.1.xlsx

DOCTORAL THESIS 2024

Departamento de Economía y Ciencias Sociales

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