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LCA FOR AGRICULTURE

On the relevance of site specificity and temporal variability in agricultural LCA: a case study on mandarin in North Uruguay

María Inés Cabot[1,2] · Joanna Lado[2] · Inmaculada Bautista[3] · Javier Ribal[4] · Neus Sanjuán[1]

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Abstract

Purpose Mandarin is a relevant citrus crop in Uruguay both in terms of yield and area. This study is aimed at assessing the environmental impacts of mandarin cultivation in the country to identify the environmental hotspots. Temporal variability is assessed by considering six harvest seasons and site specificity by developing a regionalized inventory using a Tier 3 to estimate nitrogen on-field emissions. Also, the effect of regionalizing specific impact categories is analyzed.

Methods A cradle-to-farm gate assessment was carried out based on mass and area functional units. Primary data was gathered from a representative orchard of the region for the seasons 2016 to 2022. Nitrogen on-field emissions were modeled using LEACHN, a Tier 3 model that considers site-specific climatic and soil parameters as well as water and fertilizer applications at a daily scale. In addition, other modeling approaches were tested following the Environmental Product Declarations (EPD), Product Environmental Footprint (PEF), World Food LCA Database guidelines (WFLDB), and the updated IPCC and EMEP/EEA guidelines. The EN 15804 + A2 standard was followed to assess the environmental impacts, except for the categories concerning acidification, where IMPACT 2002 + v2.1 was used. In addition, to analyze the variations in the results when regionalizing impacts of on-field emissions, IMPACT World + was used.

Results The main hotspots detected are on-field emissions, machinery operations, pesticides, and fertilizer production. Irrigation is the main hotspot in blue water scarcity. As for the models tested to estimate nitrogen emissions, significant differences were detected in marine eutrophication between LEACHN and WFLDB, regardless of the functional unit, and in terrestrial acidification, terrestrial eutrophication, and aquatic acidification per ha between LEACHN and PEF. Significant reductions in the results were observed by regionalizing the environmental impacts caused by the on-field emissions.

Conclusions The development of site-specific inventories and impact assessment methods with spatial resolution is encouraged, although more research is needed to draw general conclusions about the convenience of mechanistic models to estimate nitrogen emissions in Uruguayan citriculture. The high variation coefficients obtained reaffirm the importance of considering temporal variability. Moreover, the relevance of considering different functional units is highlighted since different influencing variables are observed throughout the seasons depending on the functional unit used.

Keywords Life cycle assessment · Citrus fruit · On-field emissions modeling · Inter-seasonal variability · Environmental impacts · Regionalized impacts

1 Introduction

Mandarin is a representative crop in Uruguayan citriculture, both in terms of tonnes produced (99,736 tonnes in 2021) and area occupied (5,712 hectares in 2021), exhibiting a 28%

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✉ María Inés Cabot
macalu7@upv.edu.es

[1] Grup ASPA, Departament de Tecnologia d'Aliments, Edifici 3F, Universitat Politècnica de València, Camí de Vera S/N, 46022 València, Spain

[2] Instituto Nacional de Investigación Agropecuaria, Salto Grande, Camino a la Represa s/n, Salto, Uruguay

[3] Research Group in Forest Science and Technology (Re-ForeST), Research Institute of Water and Environmental Engineering (IIAMA), Universitat Politècnica de València, Camí de Vera s/n, 46022 València, Spain

[4] Departament d'Economia i Ciències Socials, Edifici 3P, Universitat Politècnica de València, Camí de Vera s/n, 46022 València, Spain

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increase in production from 2020 to 2021 (MGAP 2022). Nearly 95% of the mandarin production is located in the north of the country due to favorable weather conditions, with a high heliophany and alternating high and low temperatures that favor an earlier maturation. Uruguayan citrus fruits are mainly exported, reaching 55% of the total production of mandarins in 2021. The United States is the leading destination, with 57% of exported mandarins (Uruguay XXI 2022). In recent years, Afourer mandarin has gained ground in the citrus sector due to its high yield and outstanding fruit quality (despite its tendency to alternating bearing), being the second variety in the country in terms of tonnes produced (17% of mandarin production) and area (10% of total mandarin surface area) (MGAP 2022).

Life cycle assessment (LCA) is a broadly accepted and used methodology for assessing the impacts of agriculture by quantifying all the emissions and resource consumption along the product life cycle. The use of this methodology is in line with the proposals of the UN through the SDGs (UN 2022), specifically the SGD-12 "Ensure sustainable consumption and production patterns". In particular, the 12.2 target aims to achieve, by 2030, a sustainable management and efficient use of natural resources and proposes as an indicator the "material footprint, material footprint per capita, and material footprint per gross domestic product". LCA has been used to determine the environmental profile of citrus in different countries. Specifically, mandarin production has been studied in Morocco (Bessou et al. 2016), Italy (Nicoló et al. 2015), and Spain (Nicoló et al. 2015; Martin-Gorriz et al. 2020). As for the Southern Cone, the published research on citrus LCAs focuses on oranges in Brazil (Knudsen et al. 2011) and lemons in Argentina (Machin Ferrero et al. 2021, 2022) and Uruguay (Cabot et al. 2023).

The estimation of the environmental impacts of agricultural systems through LCA entails difficulties. Among others, those concerning the system variability are especially relevant in perennial fruit crops (Cabot et al. 2022). On the one hand, this variability is associated with temporal issues related to agroclimatic factors that affect annual crop productivity (Cerutti et al. 2014; Bessou et al. 2016), which is more evident in those perennial crops affected by alternating bearing (Bessou et al. 2016), such as some citrus varieties. As well, as pointed out by Lee et al. (2020), the magnitude of on-field emissions released into the environment also depends on time-varying factors such as farm management practices (i.e., fertilization rate and irrigation) and climatic ones (temperature and pluviometry). Along these lines, to increase the temporal representativeness of the inventory data, Cerutti et al. (2014) recommend collecting field data in an even number of years (at least four) to assess the impacts of perennial crops in their full production phase (i.e., highest yield). In addition, Cabot et al. (2023) highlight inter-seasonal variability as an issue to be considered when gathering inventory data for the highly productive years, even when agricultural practices remain the same with time. Despite this, a previous literature review on the LCA of citrus fruits (Cabot et al. 2022) shows that only Bessou et al. (2016) consider more than one productive year of the high production stage.

Spatial considerations also play a relevant role when performing agricultural LCAs. Traditionally, LCAs have relied on global or country-level inventory data, even when literature has raised the potential risks it may entail, mainly inaccurately representing a product's environmental impacts at regional or local levels (Potting and Hauschild 2006). Regional LCAs, which involve the collection of specific inventories, allow for more accurate and relevant results. Specifically, the model used to estimate on-field emissions is crucial to obtaining representative inventory data, as they are responsible for many environmental impacts in agricultural LCAs (Bessou et al. 2016; Cabot et al. 2023; Machin Ferrero et al. 2022). However, in the LCA literature of agri-food systems, different approaches with varying complexity are used to estimate these emissions and, depending on the guidelines followed (e.g., EPD, PEF, and WFDB), the recommended approaches to estimate these emissions differ. Mechanistic Tier 3 models have been proposed to quantify N on-field emissions as they are both site and time-dependent, although they require many input data (Andrade et al. 2021; Cabot et al. 2023). Spatial issues should also be considered in the impact assessment since, among the relevant impact categories in the LCAs of agri-food products, regional ones, such as eutrophication and acidification, stand out (Cabot et al. 2022). Along these lines, the regionalization of the impact calculation accounts for the spatial variability of the impact scores as a function of the characteristics of the receiving environment (Patouillard et al. 2018). To this aim, the use of characterization factors at the regional level is recommended. Notwithstanding the importance of this aspect, to the best of the author's knowledge, previous LCAs of citrus fruits have not considered spatial aspects when modeling on-field emissions or quantifying some environmental impacts.

Built upon spatially and temporally explicit life cycle data, further analyses capable of capturing the relative influences of weather, soil, and farming practices on life cycle environmental impacts are needed. Bearing all this in mind, this study is aimed at performing an environmental assessment of Uruguayan mandarin production and identifying the environmental hotspots in the farming stage by addressing the temporal and spatial issues of LCAs of perennial crops. In particular, six harvest seasons with different farm management practices and climatology are analyzed to account for the temporal variability during the full production phase of the trees. In addition, temporal differentiation is made, as N emissions are modeled per day. This daily differentiation is also applied to estimate water consumption, whereas the remaining processes are assessed per crop season. Site specificity is also addressed, as the inventory is composed mainly of primary data, and the Tier 3 LEACHN model (Hutson and Wagenet 1992) is applied for modeling reactive N on-field emissions using specific soil and agroclimatic data of the region. Finally, the influence of the modeling of N emissions due to fertilizer application is studied by comparing the results using this Tier 3 model and alternative Tier 1 and Tier 2 methods proposed in published guidelines. To assess the relevance of the regional specificity of the impacts, the ImpactWorld + method (Bulle et al. 2019) is used to analyze the differences between regionalized and non-regionalized impact scores for the on-field emissions stage.

2 Methods

This study follows the LCA methodology based on ISO standards (ISO 2006a, b, 2017, 2020a, b) using GaBi software v10 (Sphera Solutions GmbH, Leinfelden-Echterdingen, Germany).

2.1 System description

A representative conventional orchard of Uruguayan mandarin production located in Quebracho, Paysandú department, northwest of Uruguay, was selected for the case study. It has an effective surface of 272 ha with mandarin and orange trees; of these, a plot of 2.71 ha. with 1,509 trees in full production corresponding to the "Afourer" mandarin cultivar and planted in the same year (2006) was assessed.

The geographical representativeness of the studied orchard is accounted for by following the recommendations proposed by Cabot et al. (2022). The selected orchard can be considered representative in several aspects; it is located in the north of the country, where the production of Uruguayan mandarins is concentrated with 95% of total mandarin production (MGAP 2022). In addition, the Afourer cultivar is the second most important in the country in terms of production (17% of total mandarin production) and area (10% of the area destinated to mandarin production) (MGAP 2022). Likewise, the selected plot has an average yield of 35.8 tonnes ha^{-1} and a plant density of 557 trees·ha^{-1}, similar to the average values in the country (36 tonnes·ha^{-1} for this variety and 543 trees·ha^{-1} for mandarins in general) (MGAP 2022). It must also be highlighted that the orchard belongs to one of the eight companies that concentrate 67% of citrus production in Uruguay (MGAP 2022), and the agricultural practices follow the Global GAP certification system for exportation (GLOBALG.A.P. 2022), widely used by citrus exporting companies in the country.

According to IPCC (2006a) and FAO (2001), Uruguay has a warm temperate moist climate, which corresponds to a subtropical humid zone. Based on data from the nearest weather station (INIA Salto Grande), the average annual rainfall for the studied seasons (from 2016 to 2022) was 1348.9 mm, and the average temperature was 19.6 °C. A minimum temperature of -3.6 °C was recorded in July 2019, and a maximum of 41.8 °C in January 2022 (INIA-GRAS 2022a). As to soil characteristics, according to CONEAT classification, the orchard has a 9.3 soil, whose geological material corresponds to sandstones with clayey cement, frequently with pink tones, sometimes reddish or grayish white (INIA-GESIR 2022). In the USDA classification, the soil is Planosol/Argisol corresponding to an Argiabol (Argialboll), and Planosol Dístrico Ocrico in the DSA-MGAP classification (INIA-SIGRAS 2022).

In this study, the term "cropping season" has been used to define the period beginning immediately after the previous harvest (usually August) and ending with the next harvest (July), as it does not correspond to a calendar year. During each cropping season, different operations are performed. Fertilization is generally carried out from September to March via fertigation, foliar application, and direct application to the soil. The 2018–2019 season constitutes an exception, in which fertigation was not applied for economic reasons. Throughout the year, pesticides are applied via foliar to combat different pests, mainly anthracnose, melanosis, scabies, mites, citrus leaf miner, and cochineal. A tractor (48.5 kW and 1700 rpm) is used for shredding pruning debris, transporting harvested mandarin bins and foliar input application, for which a fumigator is attached. Superficial drip irrigation is mainly concentrated from September to February, coinciding with the most significant water demand in spring–summer although, depending on the climatology, it can be extended until April. Irrigation water is withdrawn from a nearby lake, property of the company, by using an electric pump. As mentioned above, Afourer mandarins for export are harvested in July; they are picked by hand and then quickly transported to packinghouses, where the fruit is packaged according to the quality requirements at the destination.

2.2 Life cycle assessment

2.2.1 Functional unit and system boundaries

Two functional units (FUs) are adopted to observe the sensitivity of the impacts to this variable. A mass FU (1-tonne mandarin) is used to account for the function of food provision. In addition, taking into account that agricultural systems do not only rely on ecosystem services provided by natural ecosystems but they also produce a variety of ecosystem services (Swinton et al. 2007; Power 2010), an area FU (namely, 1 ha) has also been considered.

The system boundaries are set from cradle to farm gate, and the stages considered are the production, transportation, and application of inputs (fertilizers and pesticides), the use of machinery, which involves the production and combustion of diesel, as well as the irrigation, which implies the production of electricity for water pumping (Fig. 1). Following Frischknecht et al. (2007), the impacts related to the production of capital goods for agriculture were not quantified since, except for resource use (mineral and metals) and land use impact categories, they do not significantly contribute to environmental impacts. Nevertheless, two issues should also be considered in this respect. First, the assessment method used by Frischknecht et al. (2007), CML 2001, does not account for phosphorus and potassium, two relevant mineral resources in the production of fertilizers that, if considered, could reduce the relative contribution of capital goods to this impact category. These two mineral resources are included in the impact assessment method applied in the present study. As well, as reported in Sect. 2.1., the studied plot is part of a large orchard. Hence, farm machinery is not only used where Afourer mandarins are grown, for which the impacts of its manufacture should be divided among all the agricultural activities in which it participates, causing these impacts to be reduced. Regarding the temporal scope, one farming season is considered and, given the relevance of inter-season variability, which is a critical issue in LCAs of perennial crops (Cerutti et al. 2014; Bessou et al. 2016; Cabot et al. 2023), data from 6 seasons corresponding to trees in full production phase are used, namely, from 2016 to 2022.

2.2.2 Life cycle inventory (LCI)

As described below, several data sources and models were used to carry out the life cycle inventory (LCI). Relevant background processes were taken from commercial databases to develop reference LCI datasets for the LCA model, which are also explained in the following paragraphs. Background processes following the “allocation cut-off by classification” were retrieved from Ecoinvent 3.8. database (Wernet et al. 2016; Moreno Ruiz et al. 2021); nevertheless, to get more reliable results concerning the case study, GaBi database v.10 (Sphera Solutions GmbH 2022) was also used for a selected number of processes. Inventory data for the mandarin farming stage is shown in Table 1 and more detailed in Table S1, whereas the metadata for the reference LCIs is described in Table S2.

Agricultural practices Information on the farming practices, yields, the type and dose of inputs applied, their origin, the amount of water for irrigation, and fuel for machinery is primary data obtained from direct interviews with the agronomist responsible for the orchard.

Irrigation and blue water consumption The amounts of irrigated water and the irrigation hours are primary data from the orchard. Values for each season are shown in Table 1. The blue water consumption for irrigation was calculated by performing a water balance in the soil using the LEACHM model (Hutson and Wagenet 1992). The water consumed by the crop, defined as the water withdrawn from a watershed

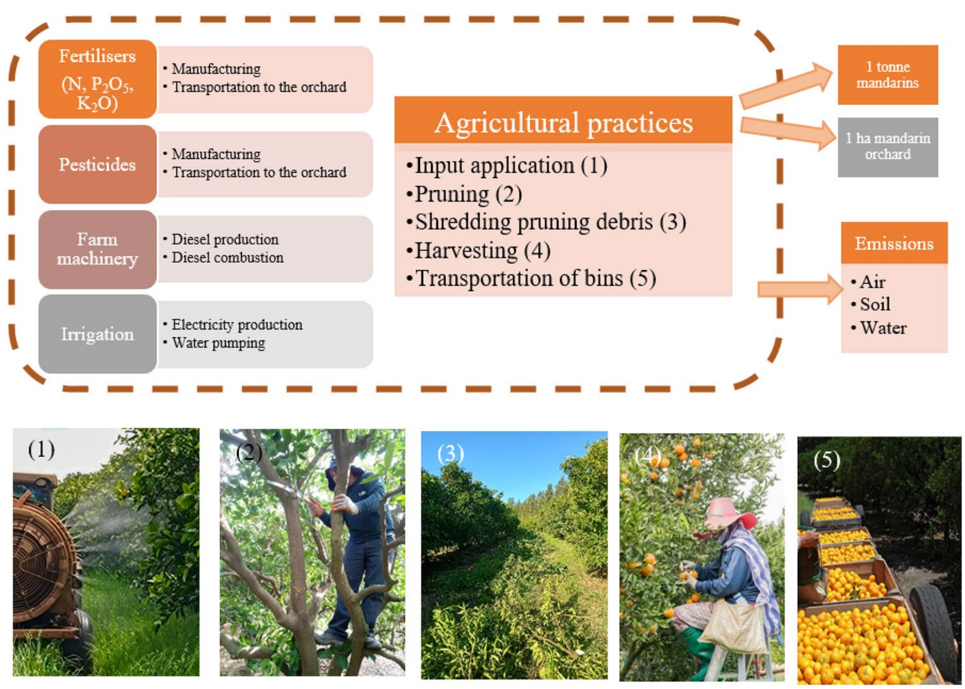

Fig. 1 System boundaries showing the life cycle stages included in the LCA of Uruguayan mandarins. Pictures were taken and provided by technicians of the studied orchard

Table 1 Main inventory data for the mandarin cultivation stage

LCI data	Unit	2016/17	2017/18	2018/19	2019/20	2020/21	2021/22	Average	Standard deviation
Yield	tonne·ha^{-1}	49.3	21.4	34.8	31.3	54.0	24.0	35.8	13.3
Electricity for irrigation	kWh·ha^{-1}	70.7	114.3	23.1	38.8	52.4	91.7	65.2	34.0
Water withdrawal for irrigation	mm·season^{-1}	211.0	341.0	68.8	115.7	156.5	273.7	194.5	101.5
Rainfall	mm·season^{-1}	1716.0	1388.0	1695.0	1364.0	1119.0	1053.0	1389.2	278.2
Rainfall + irrigation	mm·season^{-1}	1927.0	1729.0	1763.8	1479.7	1275.5	1326.7	1583.6	262.0
Machinery use (input application)	h·ha^{-1}	17.7	17.4	12.2	15.1	12.9	13.5	14.8	2.3
Machinery use (harvest and transport of bins)	h·ha^{-1}	11.8	2.8	29.0	11.1	22.0	12.4	14.8	9.2
Diesel for machinery operations									
Application of foliar fertilizers and pesticides	L·ha^{-1}	141.7	139.1	97.8	121.0	103.3	108.1	118.5	18.6
Harvest and transport of bins	L·ha^{-1}	23.6	5.5	57.9	22.1	43.9	24.7	29.6	18.4
Fertilizers									
N	kg·ha^{-1}	41.3	68.1	3.3	93.7	89.4	114.0	68.3	40.3
P_2O_5	kg·ha^{-1}	0.0	3.3	0.2	2.3	1.7	3.4	1.8	1.5
K_2O	kg·ha^{-1}	28.4	41.4	0.5	51.3	77.2	87.5	47.7	31.9
Pesticides									
Fungicides	kg·ha^{-1}	19.0	25.1	11.3	17.2	14.8	19.9	17.9	4.7
Herbicides	kg·ha^{-1}	3.5	3.7	1.1	3.3	0.7	2.9	2.5	1.3
Insecticides	kg·ha^{-1}	29.1	5.3	0.9	30.6	16.6	16.9	16.6	12.1
Growth regulators	kg·ha^{-1}	$1.9·10^{-2}$	$3.0·10^{-2}$	0.0	0.0	$3.0·10^{-2}$	$6.2·10^{-2}$	$2.3·10^{-2}$	$2.3·10^{-2}$
Dispersants	kg·ha^{-1}	0.5	0.5	0.5	0.7	0.6	0.8	0.6	0.1
On-field emissions									
Direct N_2O	kg·ha^{-1}	$6.3·10^{-2}$	$1.3·10^{-1}$	0.0	$1.3·10^{-1}$	$2.5·10^{-1}$	$5.0·10^{-1}$	$1.8·10^{-1}$	$2.0·10^{-1}$
Indirect N_2O (from NO_3^-)	kg·ha^{-1}	$2.2·10^{-1}$	$3.0·10^{-1}$	$8.0·10^{-3}$	$1.9·10^{-1}$	$2.0·10^{-1}$	$6.6·10^{-1}$	$2.6·10^{-1}$	$2.0·10^{-1}$
Indirect N_2O (from NH_3)	kg·ha^{-1}	$2.6·10^{-1}$	$3.8·10^{-1}$	$6.8·10^{-2}$	$5.1·10^{-1}$	$4.9·10^{-1}$	$5.8·10^{-1}$	$3.8·10^{-1}$	$2.0·10^{-1}$
NH_3 volatilized	kg·ha^{-1}	$1.4·10^{1}$	$2.0·10^{1}$	3.7	$2.7·10^{1}$	$2.6·10^{1}$	$3.1·10^{1}$	$2.0·10^{1}$	$1.0·10^{1}$
NO_2 volatilized	kg·ha^{-1}	1.7	2.7	$1.3·10^{-1}$	3.7	3.6	4.6	2.7	1.6
NO_3^- leached	kg·ha^{-1}	$5.6·10^{1}$	$7.7·10^{1}$	2.0	$4.8·10^{1}$	$5.1·10^{1}$	$1.7·10^{2}$	$6.7·10^{1}$	$5.6·10^{1}$
PO_4^{3-} run-off	kg·ha^{-1}	1.1	1.1	1.1	1.1	1.1	1.1	1.1	0.0

but not returned to it (ISO 2014), was estimated by adding the values for water evaporation and water absorption from the water balance. The climatic parameters used in the water balance were retrieved from INIA agroclimatic data bank (INIA-GRAS 2022a), namely, maximum, minimum, and average temperatures. Weekly reference evapotranspiration was calculated using the Penman–Monteith equation (Allen et al. 1998), with climate data for the studied seasons retrieved from the same meteorological station used as inputs (SM S1). As for precipitation, the amount of water accumulated was recorded every morning in the orchard using a pluviometer. Since the exact moment of the precipitation is not registered, the rain pattern recorded at the closest station, INIA Salto Grande, was thus followed. This station reports hourly values for precipitation (INIA-GRAS 2022b) and is located 90 km north of the orchard.

The electricity consumption for irrigation was estimated from the GaBi process "Irrigation pump generic" (Table S2), with the amount of water irrigated for each season as an input and considering that water is withdrawn from a lake. For the parameters "nominal operating pressure," "power unit efficiency," "pumping efficiency," and "irrigation efficiency," default values were used, which correspond to 3 bar, 0.9, 0.8, and 1.0, respectively.

On-field emissions from fertilizer application For the estimation of NH_3 and direct N_2O emissions to air, and NO_3^- leached to groundwater, the LEACHN model, the N module of the LEACHM model (Hutson and Wagenet 1992), was used. This is a mechanistic, one-dimensional, and dynamic method in line with the Tier 3 approach proposed by the IPCC (2006b) that simulates water and solute movement, as well as chemical and biological processes in the unsaturated soil. It estimates NH_4^+, urea and NO_3^- lixiviation, NH_3 volatilization, and NO_3^- losses by denitrification. To estimate water and nutrient fluxes, the model uses the numerical integration of Richards' equation and the convection–dispersion equation for solute transport (SM S2). Specifically, N fluxes among compartments are simulated with first-order kinetics (Hutson and Wagenet 1991). LEACHN offers advantages over IPCC's Tier 1 approach, as it accounts for not only N fertilizer management but also for the influence of soil and climate conditions and water management. The input data corresponds to N added through irrigation (considering that the irrigation water has an $N\text{-}NO_3^-$ concentration of 2.8 mg/L) and fertilization. Three organic N pools (manure, litter, and a relatively stable humus fraction) and three mineral N pools (urea, ammonium, and nitrate) are considered. To estimate N fluxes in drip irrigation, the soil was divided into fertigated/irrigated soil area, which occupies 40% of the surface, and non-fertigated/irrigated soil area, where irrigation or fertigation was not applied. LEACHN was run twice for each harvest season to obtain the emissions in both soil areas, and on-field emissions were estimated as the weighted mean from the two simulations. Potential N uptake by the citrus trees and monthly uptake pattern were obtained from a study for Spanish citrus (Quiñones et al. 2010), adapted to Uruguay's climatic seasons, and incorporated into the model. The use of a specific N uptake pattern to calibrate N balance is encouraged in future studies, as the Uruguayan climate is subtropical, and the growth pattern of the tree, and therefore its N extraction, may differ. Nitrification, volatilization, and denitrification rates specific to citrus soils were taken from Paramasivam et al. (2002). These authors compare measured values of soil nitrogen in a citrus orchard with the same type of soil as the one in this study with values obtained using the LEACHN model and highlight this modeling approach's usefulness in estimating the N leaching losses and predicting other mass balance components of N and water simultaneously and accurately for the entire crop season. The hydraulic parameters of the model were estimated from the SPAW software (Saxton and Rawls 2006) by using data on soil texture and organic carbon content from the soil (INIA-SIGRAS 2022). The water balance of the LEACHN model was calibrated by adjusting the sum of plant uptake and soil evaporation to crop evapotranspiration using experimental crop coefficients (García Petillo and Castel 2007). The calibrated model was then applied to the remaining scenarios by considering data of the successive seasons as to climatic parameters, water, and fertilizer applications. From the NH_3 and NO_3^- emissions estimated with LEACHN, the indirect N_2O emissions were modeled following the IPCC Guidelines (IPCC 2006b) and the subsequent refinement (IPCC 2019). NO_x emissions were modeled using the Tier 1 EMEP/EEA guidebook (EEA 2019), as no Tier 2 emission factor is proposed. In addition to N emissions, CO_2 emissions from urea application were calculated under the Tier 1 approach of the IPCC (2006b) guidelines. Emissions from phosphorus application, namely, phosphate (PO_4^{3-}) run-off to surface water, were estimated with the SALCA-P model (Nemecek et al. 2019) considering the P_2O_5 content of each fertilizer used and the average quantity of P lost through run-off for arable land.

In addition to the former modeling (i.e., "LEACHN"), nitrogen emissions have been estimated using four different approaches to compare their influence on the impact scores. Briefly, the guidelines proposed in the Environmental Product Declarations—"EPD" (EPD 2019), the Product Environmental Footprint—"PEF" (EC 2018), and the World Food LCA Database—"WFLDB" (Nemecek et al. 2019), which combine Tier 1 and Tier 2 methods, have been used. Furthermore, an additional combination of Tier 1 and Tier 2 methods using the most up-to-date coefficients of the IPCC (2019) and the EEA (2019), named the "updated method," has also been assessed. The literature sources used for modeling each emission and the inputs needed for each method are detailed in Table S3. A statistical analysis was carried out using R software (R Core Team 2022) to assess whether there are significant differences between the results of the N on-field emissions (N_2O, NH_3, NO_3^-, and NO_x) estimated with the above-described methods and also between the scores of five impact categories influenced by N on-field emissions (CC, MEu, TEu, AqAc, and TAc). A Kruskal–Wallis test (Hollander and Wolfe 1973) was performed to determine the existence of differences at a general level, followed by non-parametric comparisons in pairs, by performing a Dunn's test.

On-field emissions from pesticide application PestLCI Consensus V.1.0 (Fantke et al. 2017) was used to calculate primary emissions from pesticide application. It estimates the fraction of pesticide that goes to air, field soil surface, crop leaf surface, freshwater, and natural soil by considering parameters of the orchard and input application.

Production of agricultural inputs A total of 10 fertilizer compounds were modeled for the seasons studied using default processes from Ecoinvent 3.8. database (Wernet et al. 2016; Moreno Ruiz et al. 2021). Those fertilizers unavailable in the database were modeled as standard NPK fertilizers, considering their respective fertilizer units, as N, P_2O_5, and K_2O. The production of gibberellic acid (a growth regulator) was not modeled due to a lack of data, although it must be noted that the dose applied is low, with a maximum application rate of $3.3 \cdot 10^{-2}$ kg·ha^{-1} on 2021–2022.

Ecoinvent 3.8. (Wernet et al. 2016; Moreno Ruiz et al. 2021) was used to model pesticide manufacturing. First, the production process corresponding to the active principle of the pesticide was searched for. If it was not available in the database, the production of the corresponding chemical group was searched for. In the ultimate case that this production was not found either, the pesticide production was modeled as generic ("pesticide production" on Ecoinvent 3.8). Compounds with the same active ingredient but different commercial denominations were modeled separately, as seen in Table S1, to differentiate the contribution of each one to the environmental impacts. To model the production of Spinosad and copper oxychloride, which are also used in organic farming, the recommendations of Montemayor et al. (2022) were followed. The former was modeled considering glucose and electricity production in the country of origin, and the second as copper oxide. The productions of the three compounds that stimulate the plant defenses against molds, and whose active principle is potassium phosphite, were modeled as NPK compound productions using their NPK composition since potassium phosphite production is not available in the databases used. As for the remaining compounds, only copper sulfate, cuprous oxide, glyphosate, mancozeb, paraffinic oil, and polyether silicone copolymer could be modeled directly (Table S2). 2,4-D dimethyl amine salt, 2,4-D isopropyl ester, diuron, flumioxazin, paraquat, phosmet, and pyriproxyfen were modeled considering their corresponding chemical group and the rest as generic pesticides. A total of 43 pesticides were modeled.

Input transportation All agricultural inputs were transported by truck or ship and truck, as seen in Table S4, where the distances shown were retrieved from Searates (2022). Transportation was modeled as one-way transport using the corresponding processes from Ecoinvent 3.8 (Wernet et al. 2016; Moreno Ruiz et al. 2021) and the GaBi v10 database (Sphera Solutions GmbH 2022), as shown in Table S2.

2.2.3 Impact categories and impact assessment methods

To carry out the impact assessment, the default list of environmental performance indicators recommended by the PCRs for fruits (EPD 2019) was accounted for, considering the latest update (EPD 2022). Specifically, the EN 15804 + A2 standard was follows (Tables 2 and 3), except for the categories of aquatic acidification and terrestrial acidification that were assessed according to IMPACT 2002 + v2.1 (Humbert et al. 2012) to discern among those two compartments. As well, USEtox 2.12 (Rosenbaum et al. 2008) was applied to assess freshwater and human toxicity (Tables 2 and 3), as they constitute relevant impact categories in agricultural LCAs (Cabot et al. 2022).

To calculate BWS at the farming stage, monthly characterization factors (CFs) from AWARE (Boulay et al. 2018) for the corresponding Uruguayan basin were retrieved from the Google Earth layer (Google Earth 2022a), whereas for BWS due to indirect water consumption (i.e., inputs manufacturing, irrigation, electricity production, and diesel production and combustion), AWARE CFs for non-agricultural activities for the corresponding country were retrieved from WULCA (2022). Regarding toxicity impacts, and since no CFs are available in USEtox 2.12 for paraffinic oil, pyraclostrobin, polyether silicone copolymer, saflufenacil, and spinosad, a search in scientific articles was performed. CFs for paraffinic oil and spinosad were retrieved from Juraske and Sanjuán (2011), those for acetamiprid from Steingrímsdóttir et al. (2018), and those for pyraclostrobin from Fantke and Jolliet (2016) and Bennet (2012). As regards 2,4-D isopropyl ester, abamectin, and copper oxychloride, the CFs for substances with similar characteristics were used, namely, 2-(2,4-dichlorophenoxy) acetic acid, avermectin B1A, and copper (II), respectively. No CF was found in the literature for polyether silicone copolymer and saflufenacil.

Regionalization of impacts In order to assess the influence of the regionalization of environmental impacts, IMPACT World + (Bulle et al. 2019), a regionalized impact calculation method that proposes characterization factors at different resolution scales, was applied to estimate the impact of on-field emissions. The impact categories assessed were those for which the environmental impacts of agricultural activities are relevant and midpoint CFs are available, namely, marine eutrophication (MEu), freshwater eutrophication (FEu), terrestrial acidification (TAc), and freshwater acidification (FWAc). The impacts of the emitted flows were regionalized at the native resolution scale, retrieving the CFs from the corresponding Google Earth layer (Google Earth 2022b) and compared to those quantified using the global resolution CFs from IMPACT World + (2022).

3 Results and discussion

3.1 Environmental impacts and contribution analysis

The scores for all the impact categories assessed per both FU for the six seasons evaluated, as well as their average value and coefficient of variation (CV, %), are shown in Tables 2 and 3. Figure 2 shows the average contribution of the life cycle stages to the total life cycle impact of the mandarins for each environmental impact category. The average contribution values of each stage and their standard deviation for both FUs are shown in Tables S5a and b.

When analyzing the relative contribution of the cradle-to-farm gate stages, fertilizer production and machinery operations represent a significant share of CC (both 32% on average), with the production of urea ammonium nitrate and diesel combustion for the tractor as main hotspots. Regarding eutrophication, the main contributors to FEu

Table 2 Impact scores per cropping season, average values, and coefficient of variation (CV) of cradle-to-farm gate mandarin cultivation in Uruguay. FU = 1 ha

Impact category	Impact assessment method	2016/17	2017/18	2018/19	2019/20	2020/21	2021/22	Average	CV (%)
CC (kg CO_2 eq.·ha $^{-1}$)	EN 15804 + A2	1237.8	1445.5	611.1	1561.8	1562.3	2014.3	1405.5	28
FEu (kg P eq.·ha $^{-1}$)	EN 15804 + A2	$8.8{\cdot}10^{-1}$	$9.6{\cdot}10^{-1}$	$5.4{\cdot}10^{-1}$	1.0	$7.9{\cdot}10^{-1}$	$9.5{\cdot}10^{-1}$	$8.6{\cdot}10^{-1}$	20
MEu (kg N eq.·ha^{-1})	EN 15804 + A2	17.7	23.5	3.3	18.2	18.7	46.4	21.3	66
TEu (mole of N eq.·ha $^{-1}$)	EN 15804 + A2	225.5	321.4	76.6	418.8	403.4	472.3	319.7	46
AqAc (kg SO_2 eq.·ha $^{-1}$)	Impact 2002 + v2.1	32.3	47.2	9.3	60.4	56.9	67.6	45.6	47
TAc (kg SO_2 eq.·ha $^{-1}$)	Impact 2002 + v2.1	262.5	370.9	91.7	479.4	460.7	558.6	370.6	46
BWS (m^3eq.·ha $^{-1}$)	AWARE	3849.6	3107.4	3227.9	4071.1	3579.4	4102.5	3656.3	12
ET (CTUe·ha $^{-1}$)	USEtox 2.12	$3.4{\cdot}10^{7}$	$3.9{\cdot}10^{7}$	$1.2{\cdot}10^{7}$	$4.2{\cdot}10^{7}$	$2.6{\cdot}10^{7}$	$3.4{\cdot}10^{7}$	$3.1{\cdot}10^{7}$	35
HTc (CTUh·ha $^{-1}$)	USEtox 2.12	$8.2{\cdot}10^{-5}$	$1.0{\cdot}10^{-4}$	$2.7{\cdot}10^{-5}$	$1.2{\cdot}10^{-4}$	$9.4{\cdot}10^{-5}$	$1.2{\cdot}10^{-4}$	$9.0{\cdot}10^{-5}$	37
HTnc (CTUh·ha $^{-1}$)	USEtox 2.12	$1.5{\cdot}10^{-3}$	$1.5{\cdot}10^{-3}$	$7.3{\cdot}10^{-4}$	$1.5{\cdot}10^{-3}$	$1.2{\cdot}10^{-3}$	$1.1{\cdot}10^{-3}$	$1.2{\cdot}10^{-3}$	26
RUm (kg Sb eq.·ha $^{-1}$)	EN 15804 + A2	$1.3{\cdot}10^{-1}$	$1.5{\cdot}10^{-1}$	$4.7{\cdot}10^{-2}$	$1.6{\cdot}10^{-1}$	$9.8{\cdot}10^{-2}$	$1.3{\cdot}10^{-1}$	$1.2{\cdot}10^{-1}$	34
RUf (MJ·ha $^{-1}$)	EN 15804 + A2	$1.6{\cdot}10^{4}$	$1.6{\cdot}10^{4}$	$7.8{\cdot}10^{3}$	$1.8{\cdot}10^{4}$	$1.7{\cdot}10^{4}$	$2.0{\cdot}10^{4}$	$1.6{\cdot}10^{4}$	27
POFhh (kg NMVOC eq.·ha $^{-1}$)	EN 15804 + A2	10.8	11.9	7.0	13.1	12.7	14.2	11.6	22
Ozone depletion (kg CFC-11 eq.·ha $^{-1}$)	EN 15804 + A2	$5.2{\cdot}10^{-5}$	$9.0{\cdot}10^{-5}$	$2.4{\cdot}10^{-5}$	$7.1{\cdot}10^{-5}$	$8.8{\cdot}10^{-5}$	$1.2{\cdot}10^{-4}$	$7.4{\cdot}10^{-5}$	44

CC climate change, *FEu* freshwater eutrophication, *MEu* marine eutrophication, *TEu* terrestrial eutrophication, *AqAc* aquatic acidification, *TAc* terrestrial acidification, *BWS* blue water scarcity, *ET* ecotoxicity, *HTc* human toxicity – cancer, *HTnc* human toxicity—non-cancer, *RUm* resource use—minerals and metals, *RUf* resource use – fossils, *POFhh* photochemical ozone formation impacts on human health, OD ozone depletion, *CV*, coefficient of variation

are pesticide production (45% on average), mainly due to copper compounds production, and on-field emissions (41% on average) due to PO_4^{3-} run-off. On-field emissions lead MEu (85% average contribution) due, to a large extent, to NO_3^- leaching, followed by tractor use (10% on average). On-field emissions also dominate TEu, AqAc, and TAc (89%, 87%, and 86% on average, respectively), mainly due to NH_3 volatilization. Blue water consumption for irrigation is the main cause of BWS, with an average of 90%, ranging from 84 to 97%, depending on the season. When analyzing the results of toxicity-related categories, pesticide production stands out as the main hotspot (91% of total ET,

Table 3 Impact scores per cropping season, average values, and coefficient of variation (CV) of cradle-to-farm gate mandarin cultivation in Uruguay. FU = 1 tonne

Impact category	Impact assessment method	2016/17	2017/18	2018/19	2019/20	2020/21	2021/22	Average	CV (%)
CC (kg CO_2 eq.·tonne^{-1})	EN 15804 + A2	25.1	67.6	17.5	49.8	28.9	83.8	45.5	45
FEu (kg P eq.·tonne $^{-1}$)	EN 15804 + A2	$1.8{\cdot}10^{-2}$	$4.5{\cdot}10^{-2}$	$1.5{\cdot}10^{-2}$	$3.2{\cdot}10^{-2}$	$1.5{\cdot}10^{-2}$	$3.9{\cdot}10^{-2}$	$2.7{\cdot}10^{-2}$	48
MEu (kg N eq.·tonne $^{-1}$)	EN 15804 + A2	0.4	1.1	0.1	0.6	0.3	1.9	0.7	92
TEu (mole of N eq.·tonne $^{-1}$)	EN 15804 + A2	4.6	15.0	2.2	13.4	7.5	19.6	10.4	65
AqAc (kg SO_2 eq.·tonne $^{-1}$)	Impact 2002 + v2.1	0.7	2.2	0.3	1.9	1.1	2.8	1.5	66
TAc (kg SO_2 eq.·tonne $^{-1}$)	Impact 2002 + v2.1	5.3	17.3	2.6	15.3	8.5	22.4	11.9	64
BWS (m^3eq.·tonne $^{-1}$)	AWARE	78.1	145.3	92.8	130.0	66.2	170.7	113.9	36
ET (CTUe·tonne $^{-1}$)	USEtox 2.12	$6.8{\cdot}10^{5}$	$1.8{\cdot}10^{6}$	$3.5{\cdot}10^{5}$	$1.3{\cdot}10^{6}$	$4.8{\cdot}10^{5}$	$1.4{\cdot}10^{6}$	$1.0{\cdot}10^{6}$	59
HTc (CTUh·tonne $^{-1}$)	USEtox 2.12	$1.7{\cdot}10^{-6}$	$4.9{\cdot}10^{-6}$	$7.8{\cdot}10^{-7}$	$3.7{\cdot}10^{-6}$	$1.7{\cdot}10^{-6}$	$5.0{\cdot}10^{-6}$	$2.9{\cdot}10^{-6}$	61
HTnc (CTUh·tonne $^{-1}$)	USEtox 2.12	$3.1{\cdot}10^{-5}$	$6.8{\cdot}10^{-5}$	$2.1{\cdot}10^{-5}$	$4.8{\cdot}10^{-5}$	$2.1{\cdot}10^{-5}$	$4.4{\cdot}10^{-5}$	$3.9{\cdot}10^{-5}$	47
RUm (kg Sb eq.·tonne $^{-1}$)	EN 15804 + A2	$2.6{\cdot}10^{-3}$	$7.0{\cdot}10^{-3}$	$1.3{\cdot}10^{-3}$	$5.0{\cdot}10^{-3}$	$1.8{\cdot}10^{-3}$	$5.2{\cdot}10^{-3}$	$3.8{\cdot}10^{-3}$	59
RUf (MJ·tonne $^{-1}$)	EN 15804 + A2	$3.2{\cdot}10^{2}$	$7.5{\cdot}10^{2}$	$2.2{\cdot}10^{2}$	$5.9{\cdot}10^{2}$	$3.2{\cdot}10^{2}$	$8.4{\cdot}10^{2}$	$5.1{\cdot}10^{2}$	51
POFhh (kg NMVOC eq.·tonne $^{-1}$)	EN 15804 + A2	0.2	0.6	0.2	0.4	0.2	0.6	0.4	48
Ozone depletion (kg CFC-11 eq.·tonne^{-1})	EN 15804 + A2	$1.1{\cdot}10^{-6}$	$4.2{\cdot}10^{-6}$	$7.0{\cdot}10^{-7}$	$2.3{\cdot}10^{-6}$	$1.6{\cdot}10^{-6}$	$4.9{\cdot}10^{-6}$	$2.5{\cdot}10^{-6}$	70

CC climate change, *FEu* freshwater eutrophication, *MEu* marine eutrophication, *TEu* terrestrial eutrophication, *AqAc* aquatic acidification, *TAc* terrestrial acidification, *BWS* blue water scarcity, *ET* ecotoxicity, *HTc* human toxicity – cancer, *HTnc* human toxicity—non-cancer, *RUm* resource use—minerals and metals, *RUf* resource use – fossils, *POFhh* photochemical ozone formation impacts on human health, OD ozone depletion, *CV* coefficient of variation

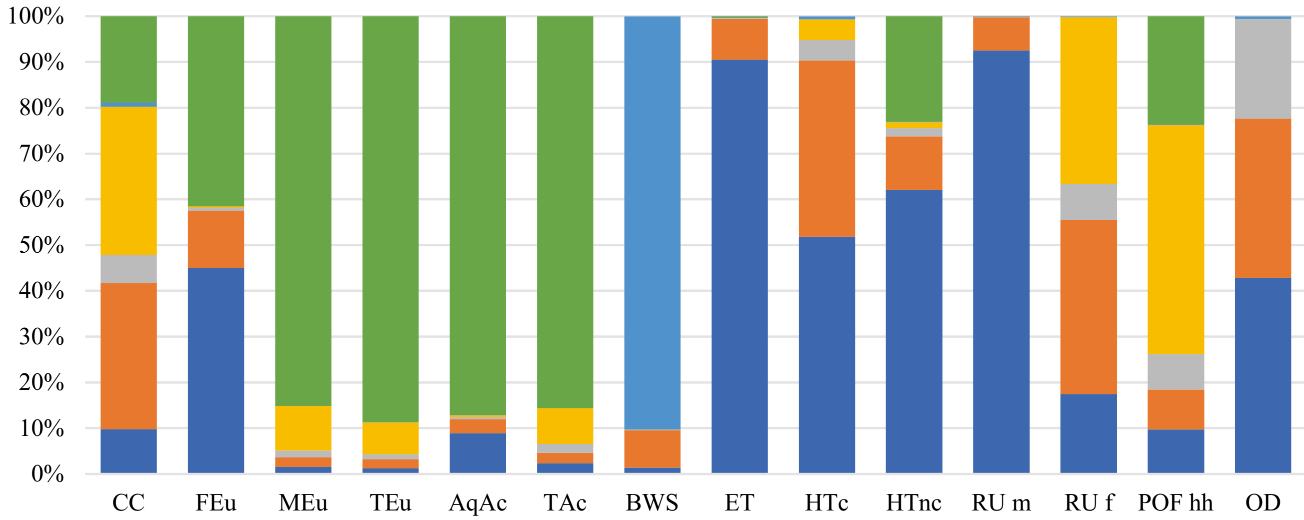

Fig. 2 Average percentual contribution of the life cycle stages to the environmental footprint of Uruguayan mandarins per tonne and ha. Blue: pesticides production, orange: fertilizers production, gray: transport, yellow: machinery operations, light blue: irrigation, green: on-field emissions. *CC* climate change, *FEu* freshwater eutrophication, *MEu* marine eutrophication, *TEu* terrestrial eutrophication, *AqAc* aquatic acidification, *TAc* terrestrial acidification, *BWS* blue water scarcity, *ET* ecotoxicity, *HTc* human toxicity – cancer, *HTnc* human toxicity—non-cancer, *RUm* resource use—minerals and metals, *RUf* resource use – fossils, *POFhh* photochemical ozone formation impacts on human health, *OD* ozone depletion

52% of HTc, and 62% of HTnc, on average). Regarding HT, fertilizer production is a relevant stage in cancer-related impacts (38% on average) and on-field pesticide emissions in non-cancer-related impacts (23% on average). Among the pesticides used, and also considering the dose applied, copper compounds—cuprous oxide, copper oxychloride, and copper sulfate—lead the three toxicity impact categories (Table S6). As to the categories related to resource depletion, the main contributors to RUf are fertilizer production (38%, on average) and machinery operations (36%, on average). Pesticide production—mostly copper compounds—is the main hotspot detected in RUm (93% on average). POFhh is dominated by machinery operations (50% on average), mainly because of diesel combustion, and by NO_2 on-field emissions (24% on average), whereas input production means a significant share of OD (43% from pesticides and 35% from fertilizers, on average). To sum up, the main hotspots in the impact categories assessed are related to on-field emissions, diesel combustion, and the production of copper and urea compounds, especially urea ammonium nitrate. In any case, it must be borne in mind that, as mentioned in Sect. 2.2.2, the production of some crop protection inputs could not be properly modeled, as they were not available in the databases used. Therefore, they were modeled considering their chemical group or, ultimately, as generic pesticides (Table S2). The development of more complete databases is a key issue for obtaining more representative LCAs.

3.2 Inter-seasonal variability of the impact scores

The inter-seasonal variability of the results for each cropping season was analyzed through the coefficient of variability (CV, %), as shown in Tables 2 and 3, and also by estimating the ratio "impact score in the season/mean impact score", which shows how the impact scores for each season and FU are distributed with respect to the mean (Fig. 3). When the impact scores are expressed per ha, the inter-seasonal variability is lower than when expressed per tonne for all the impact categories assessed (Tables 2 and 3). The impact categories that exhibit a greater variability are acidification (AqAc and TAc) and eutrophication, specifically MEu and TEu. These depend primarily on on-field emissions, specifically NO_3^- leaching and NH_3 volatilization. OD also stands out because of its high variability, which depends on the type and dose of inputs applied.

When 1 ha is used as FU, the results obtained for AqAc, TAc, MEu, and TEu follow the pattern of the respective on-field emissions affecting these impact categories, as they mean a great share of these impact categories (more than 85%). In particular, NH_3 is the emission determining AqAc, TAc, and TEu and presents a maximum in 2021–2022 and a minimum in 2018–2019 (see Table 1), corresponding to the seasons with the greatest and lowest N fertilization rates, respectively, the same as the respective scores of the impact categories (Table 2). It must be noted that the main N sources are ureic compounds and that the hydrolysis of urea releases NH_3, that subsequently volatilizes. MEu is mainly

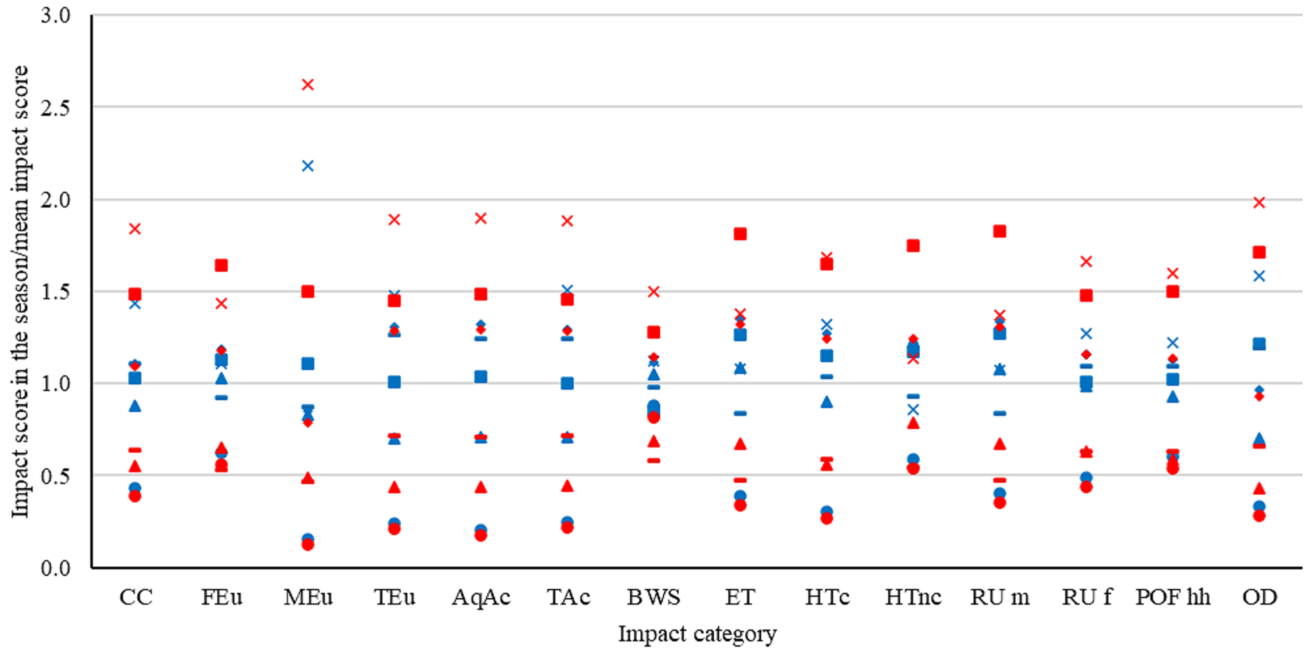

Fig. 3 Relative variability of the impact values of Uruguayan mandarins with respect to the mean for the studied seasons. Red symbols represent results per tonne of product, and blue symbols results per hectare of the orchard. ▲ 2016–2017, ■ 2017–2018, ● 2018–2019, ◆ 2019–2020, – 2020–2021, and × 2021–2022. *CC* climate change, *FEu* freshwater eutrophication, *MEu* marine eutrophication, *TEu* terrestrial eutrophication, *AqAc* aquatic acidification, *TAc* terrestrial acidification, *BWS* blue water scarcity, *ET* ecotoxicity, *HTc* human toxicity – cancer, *HTnc* human toxicity—non-cancer; *RUm*, resource use—minerals and metals; *RUf*, resource use – fossils, *POFhh* photochemical ozone formation, human health, *OD* ozone depletion

influenced by NO_3^- leaching and, according to the N fertilization rates, also exhibits a maximum in 2021–2022 and a minimum in 2018–2019, which is consistent with the impact results obtained. As concerns OD, again, the maximum and minimum scores coincide with the years in which more and fewer inputs were applied (2021–2022 and 2018–2019, respectively), as the production of fertilizers and pesticides are the stages with the highest share in this impact category. CC also exhibits the maximum and the minimum scores in the seasons with the greatest and lowest fertilization rates, as their production is a hotspot that, together with on-field emissions, sums up 50% of this category. BWS is also interesting to be discussed, given its importance in agricultural processes. It presents a minimum in 2017–2018, season with the lowest blue water consumption due to a low evaporation together with a low water absorption by the crop (Table S7), which are related to the low value of rainfall in the months of higher water demand (only 27% of the total rain fell from December to April). This low availability of water could have caused water stress, reflected in the low yield of this season (21.4 tonnes·ha^{-1}, Table 1). BWS is maximum in 2021–2022, although it is not the season with the highest water consumption. Still, the greatest water consumption in that season is mainly concentrated in the months of highest scarcity in the basin (from December to April). It must be therefore highlighted that it is not only how much blue water the crop consumes what matters in this impact category but also the moment of this consumption.

When using 1 tonne as FU, a new variable is introduced in the analysis, the crop yield, which seems to have more influence on the intermediate values of the impact scores than on the extreme ones, as explained below. Although one could expect the yield to be linked to the fertilization rates, Afourer mandarins are a variety with an alternating bearing, as commented in the introduction, and therefore, AqAc, TAc, MEu, and TEu present a maximum in 2021–2022 and a minimum in 2018–2019, which correspond to the maximum and minimum of influencing emissions (NH_3 and NO_3^-), but not to the minimum and maximum yield (Table 1). Therefore, for the extreme scores, N emissions have a greater weight in the results than the yield, whereas for intermediate impact values, the trend reverses, and the crop yield has a greater weight in the results than the emissions released. Regarding CC, the extreme scores per tonne coincide with the extreme values per ha, corresponding to seasons with the highest and lowest fertilization rates, whereas the intermediate scores respond to the yield pattern. For BWS, the results are mainly dominated by the yield; the greater the yield, the lower the impact and vice versa, except for 2021–2022, the season with the highest score because the blue water consumption is concentrated in the months of higher scarcity (54% of the consumption in the season), as mentioned above.

Table 4 Average impact scores of on-field emissions for the regionalized impact categories with and without applying the regionalization method

	FU = 1 ha		FU = 1 tonne	
	Not-regionalized	Regionalized	Not-regionalized	Regionalized
Freshwater eutrophication (kg PO_4 P-lim eq.)	$3.42{\cdot}10^{-1}$	$2.13{\cdot}10^{-2}$	$1.07{\cdot}10^{-2}$	$6.68{\cdot}10^{-4}$
Marine eutrophication (kg N N-lim eq.)	1.20	0.84	$3.91{\cdot}10^{-2}$	$2.74{\cdot}10^{-2}$
Freshwater acidification (kg SO_2 eq.)	$4.25{\cdot}10^{-5}$	$1.11{\cdot}10^{-5}$	$1.38{\cdot}10^{-6}$	$3.63{\cdot}10^{-7}$
Terrestrial acidification (kg SO_2 eq.)	$7.73{\cdot}10^{-2}$	$1.52{\cdot}10^{-2}$	$2.52{\cdot}10^{-3}$	$4.94{\cdot}10^{-4}$

3.3 Regionalized environmental impacts

The average scores of the regionalized impact categories for on-field emissions, considering global CFs (not regionalized) and native CFs (regionalized), are shown in Table 4.

To analyze these results, it must be considered that the ImpactWorld + method (Bulle et al. 2019) presents CFs for a selected group of output flows, namely, the ones with greater environmental effects. In Table S8, the native and global CFs used are shown. The environmental impacts of the on-field emissions stage were reduced when applying native CFs. In particular, FEu showed a 94% reduction, followed by an 80% reduction in TAc, a 74% reduction in FWAc, and a 30% reduction in MEu. The significant reduction percentages obtained for this stage highlight the importance of applying impact regionalization methods.

3.4 Influence of N emission modeling on the environmental impact scores

Due to the input data complexity of mechanistic models used to estimate N on-field emissions, such as LEACHN, the resulting emissions and the related impact scores have been compared with other approaches (see Sect. 2.2.2) to see if the values are comparable. Table 5 shows the average results of the N on-field emissions for both FUs, for the five methods analyzed, whereas Table 6 shows the average results for the impact categories more influenced by on-field emissions, namely, CC, MEu, TEu, AqAc, and TAc. In Fig. S1a and b, the probability distribution of N on-field emissions and environmental score results are represented in boxplots for all the seasons studied.

N_2O estimated with LEACHN shows the lowest average value (Table 5) and also the highest variability, with a CV value of 67% when considering 1 hectare as FU. Therefore, LEACHN seems to better capture the inter-season variability of farming practices and climate. As to NH_3, LEACHN applies a higher emission factor, which explains the higher average value. The values obtained present similar variability to the rest of the approaches (around 50% regardless of the method). The estimates for NO_3^- using WFLDB are two orders of magnitude greater than when using the other approaches (Table 5) and much greater than the N rate applied (68.3 kg·ha^{-1} on average). The values of this emission obtained with LEACHN are slightly lower than those obtained with the other approaches, and the estimations present high variability, with a CV of 83%, which also leads us to think that LEACHN better captures the inter-season variability. These high values of NH_3 and low values of NO_3^-obtained with LEACHN are due to the fact that this method predicts higher N volatilization and lower NO_3^-leaching losses. Therefore, urea hydrolysis and ammonium volatilization rates should be verified experimentally because, as commented in Sect. 2.2.2, the model was calibrated with data from the literature. PEF does not estimate NO_x, whereas LEACHN, WFLDB, and the "updated

Table 5 Average results and standard deviation of the N on-field emissions for 2016–2022 estimated with different modeling approaches

	Modeling approach				
Emission	LEACHN	EPD	PEF	WFLDB	Updated method*
N_2O volatilized (kg·ha^{-1})	0.8 ± 0.5	1.5 ± 0.8	1.5 ± 0.9	2.7 ± 1.6	2.2 ± 1.3
N_2O volatilized (kg·tonne^{-1})	$2.8{\cdot}10^{-2} \pm 2.5{\cdot}10^{-2}$	$4.9{\cdot}10^{-2} \pm 3.6{\cdot}10^{-2}$	$5.0{\cdot}10^{-2} \pm 3.8{\cdot}10^{-2}$	$9.0{\cdot}10^{-2} \pm 6.8{\cdot}10^{-2}$	$7.1{\cdot}10^{-2} \pm 5.4{\cdot}10^{-2}$
NH_3 volatilized (kg·ha^{-1})	20.1 ± 10.0	11.9 ± 5.9	3.4 ± 1.9	6.8 ± 3.4	7.5 ± 3.9
NH_3 volatilized (kg·tonne^{-1})	$6.6{\cdot}10^{-1} \pm 4.4{\cdot}10^{-1}$	$3.9{\cdot}10^{-1} \pm 2.6{\cdot}10^{-1}$	$1.0{\cdot}10^{-1} \pm 5.9{\cdot}10^{-2}$	$2.2{\cdot}10^{-1} \pm 1.5{\cdot}10^{-1}$	$2.4{\cdot}10^{-1} \pm 1.7{\cdot}10^{-1}$
NO_3^- leached (kg·ha^{-1})	67.2 ± 55.8	90.7 ± 53.6	30.1 ± 17.7	4184.7 ± 592.1	72.6 ± 42.9
NO_3^- leached (kg·tonne^{-1})	$2.4{\cdot}10 \pm 2.6{\cdot}10$	$3.0{\cdot}10 \pm 2.3{\cdot}10$	$9.9{\cdot}10^{-1} \pm 7.5{\cdot}10^{-1}$	$1.3{\cdot}10^{2} \pm 5.0{\cdot}10^{1}$	$2.4{\cdot}10 \pm 1.8{\cdot}10$
NO_x volatilized (kg·ha^{-1})	2.7 ± 1.6	1.0 ± 0.6	*n.e*	2.7 ± 1.6	2.7 ± 1.6
NO_x volatilized (kg·tonne^{-1})	$9.0{\cdot}10^{-2} \pm 6.8{\cdot}10^{-2}$	$3.4{\cdot}10^{-2} \pm 2.6{\cdot}10^{-2}$	*n.e*	$9.0{\cdot}10^{-2} \pm 6.8{\cdot}10^{-2}$	$9.0{\cdot}10^{-2} \pm 6.8{\cdot}10^{-2}$

*Emission factors from the updated IPCC (2019) and EEA (2019), *n.e.*, not estimated

Table 6 Average impact scores and standard deviation for 2016–2022 of the impact categories analyzed affected by the modeling approaches to estimate on-field emissions

	Modeling approach				
Impact category	LEACHN	EPD	PEF	WFLDB	Updated method*
CC (kg CO_2 eq.·ha^{-1})	1405.5 ± 464.8	1602.9 ± 560.9	1607.7 ± 571.9	1974.1 ± 786.9	1802.0 ± 683.1
CC (kg CO_2 eq.·tonne^{-1})	45.5 ± 26.2	51.7 ± 29.7	51.9 ± 30.1	64.0 ± 39.1	58.3 ± 34.8
MEu (kg N eq.·ha^{-1})	21.3 ± 14.1	25.2 ± 13.2	10.3 ± 4.4	950.6 ± 133.1	21.3 ± 11.0
MEu (kg N eq.·tonne^{-1})	$7.3·10^{-1}$ ± $6.8·10^{-1}$	$8.2·10^{-1}$ ± $5.8·10^{-1}$	$3.3·10^{-1}$ ± $2.1·10^{-1}$	$3.0·10^{1}$ ± $1.1·10^{1}$	$7.0·10^{-1}$ ± $4.9·10^{-1}$
TEu (mole of N eq.·ha^{-1})	319.7 ± 147.0	201.7 ± 87.4	81.4 ± 28.8	139.0 ± 57.8	148.7 ± 64.6
TEu (mole of N eq.·tonne^{-1})	10.4 ± 6.7	6.5 ± 4.1	2.5 ± 1.2	4.5 ± 2.8	4.8 ± 3.1
AqAc (kg SO_2 eq.·ha^{-1})	45.6 ± 21.6	29.0 ± 13.3	12.2 ± 4.9	20.5 ± 9.2	21.8 ± 10.2
AqAc (kg SO_2 eq.·tonne^{-1})	1.5 ± $9.9·10^{-1}$	$9.4·10^{-1}$ ± $6.2·10^{-1}$	$3.9·10^{-1}$ ± $2.2·10^{-1}$	$6.7·10^{-1}$ ± $4.4·10^{-1}$	$7.1·10^{-1}$ ± $4.8·10^{-1}$
TAc (kg SO_2 eq.·ha^{-1})	370.6 ± 170.2	238.3 ± 103.5	103.9 ± 35.8	169.9 ± 71.4	180.6 ± 79.1
TAc (kg SO_2 eq.·tonne^{-1})	11.9 ± 7.7	7.6 ± 4.7	3.1 ± 1.5	5.4 ± 3.3	5.7 ± 3.6

*Emission factors from the updated IPCC (2019) and EEA (2019)

approach" use the same emission coefficient, which explains the similar values obtained. Regarding each specific impact score obtained with the approaches analyzed (Table 6), LEACHN determines consistently higher scores than the rest in TEu, AqAc, and TAc (Table 6), as these categories mainly depend on NH_3 emissions, which are higher, while the highest scores of CC and MEu are those obtained when using WFLDB (Table 6), because of the higher NO_3^- values that also determine higher indirect N_2O emissions influencing the CC score.

A summary of the results from the statistical analysis is shown in Table 7. In general, both for N emissions and environmental impacts, more differences are observed per hectare than per tonne because, as commented in Sect. 3.2., the alternating yield makes the variability per tonne to be greater, which masks potential differences. When analyzing MEu, significant differences are detected between WFLDB and the other four approaches. These are closely related to the differences observed in NO_3^- leaching, which is the emission that dominates this impact category, and as commented above, exhibits values two orders of magnitude greater when using WFLDB, which are much higher than the N applied (Tables 1 and 5). The main difference between LEACHN and WFLDB with EPD, PEF, and the so-called "updated method" is that these last three do not consider the irrigation and rainfall nor soil or crop parameters. On the other hand, the emission flows are modeled on a daily basis with LEACHN, while WFLDB considers the inputs application (N and water) in a single instance, causing the values of leached NO_3^- to increase, especially in countries with high values of precipitation like Uruguay. As for TAc, TEu, and AqAc, when considering 1 hectare as a FU, significant differences are detected between LEACHN and PEF related to the significant differences in the influencing emission, NH_3, which is higher with LEACHN, and NO_x, which is not estimated in PEF. To quantify NH_3 emissions, LEACHN considers the daily hydrolysis of urea using a rate of 0.36 kg N-NH_3·kg N-urea^{-1} day^{-1}, while in the PEF method, a lower emission factor is applied depending on the type of fertilizer applied, ranging from 0.024 to 0.18 kg NH_3·kgN^{-1}. When expressing the results per tonne, these significant differences are not detected, probably due to the effect of the yield. Regarding CC, no differences were detected between the analyzed methods, neither per tonne nor per hectare, which is explained by the absence of significant differences in the influencing emission, N_2O.

Summarizing, in this case study, no significant differences are detected in the results obtained between LEACHN and the rest of the methods tested, except with WFLDB when quantifying MEu and with PEF when quantifying TAc, TEu, and AqAc per ha. However, considering the number of parameters that mechanistic methods such as LEACHN take into account and that both the soil and the agricultural system itself are dynamic, more research is encouraged to draw general conclusions about the convenience of using this method.

3.5 Comparison with other studies

The environmental impact scores of mandarin cultivation in this study are compared with those of the literature (Table S9); in particular, with two studies on mandarin (Bessou et al. 2016; Martin-Gorriz et al. 2020), two studies on citrus fruits in general (Ribal et al. 2017; Yang et al. 2020), and a previous study carried out by the authors on lemon cultivation in Uruguay (Cabot et al. 2023). The focus is on CC, FEu, MEu, TAc, and water consumption-related impact for a mass FU.

The average CC score obtained for Uruguayan mandarins is 0.045 CO_2 eq.·kg^{-1}, lower than all the studies it is

Table 7 Results of the post hoc non-parametric paired comparisons performed using Dunn's test for N emissions and impact categories that present differences detected using the Kruskal–Wallis test

	LEACHN vs. EPD	LEACHN vs. PEF	LEACHN vs. WFLDB	LEACHN vs. "updated method"	EPD vs. PEF	EPD vs. WFLDB	EPD vs. "updated method"	PEF vs. WFLDB	PEF vs. "updated method"	WFLDB vs. "updated method"
N_2O (kg·ha^{-1})	-	-	-	-	-	-	-	-	-	-
N_2O (kg·tonne^{-1})	-	-	-	-	-	-	-	-	-	-
NH_3 (kg·ha^{-1})	-	0.01[a]	-	-	0.05[a]	-	-	-	-	-
NH_3 (kg·tonne^{-1})	-	0.04[a]	-	-	-	-	-	-	-	-
NO_3^- (kg·ha^{-1})	-	-	0.02[a]	-	-	-	-	0[a]	-	0.03[a]
NO_3^- (kg·tonne^{-1})	-	-	0.02[a]	-	-	0.05[a]	-	0[a]	-	0.02[a]
NO_x (kg·ha^{-1})	-	0[a]	-	-	-	-	-	0.01[a]	0[a]	-
NO_x (kg·tonne^{-1})	-	0[a]	-	-	-	-	-	0.01[a]	0.01[a]	-
CC (kg·ha^{-1})	-	-	-	-	-	-	-	-	-	-
CC (kg·tonne^{-1})	-	-	-	-	-	-	-	-	-	-
AqAc (kg·ha^{-1})	-	0.01[a]	-	-	-	-	-	-	-	-
AqAc (kg·tonne^{-1})	-	-	-	-	-	-	-	-	-	-
MEu (kg·ha^{-1})	-	-	0.03[a]	-	-	-	-	0[a]	-	0.03[a]
MEu (kg·tonne^{-1})	-	-	0.02[a]	-	-	0.03[a]	-	0[a]	-	0.02[a]
TAc (kg·ha^{-1})	-	0.01[a]	-	-	-	-	-	-	-	-
TAc (kg·tonne^{-1})	-	-	-	-	-	-	-	-	-	-
TEu (kg·ha^{-1})	-	0.01[a]	-	-	-	-	-	-	-	-
TEu (kg·tonne^{-1})	-	-	-	-	-	-	-	-	-	-

-: not significant; [a]: significant at 0.05 level compared with. It must be remarked that, unlike in most reviewed studies, on-field emissions from fertilizer application are not a hotspot in the present study. This could be due to the lower N rate applied compared to the reviewed studies (59 to 92% lower). Likewise, a Tier 3 approach is used for modeling N_2O emissions (the main emissions influencing CC), while the reviewed studies use the IPCC Tier 1 approach (IPCC 2006b). As can be seen in Table 6, using a Tier 1 approach in the present study (e.g., "PEF") would give a 14% higher score for this impact category. The yield is another decisive factor, especially in Martin-Gorriz et al. (2020) and Yang et al. (2020), where it is 37% and 32% lower, respectively, making their scores per mass unit higher. On the other hand, the production of fertilizers (highlighted as a hotspot in the present study) is also remarked as a critical point in Cabot et al. (2023), Ribal et al. (2017), and Yang et al. (2020). Martin-Gorriz et al. (2020) highlight machinery operations as a hotspot; in particular, the impact score for that stage is 0.11 CO_2 eq.·kg^{-1}, eight times greater than the results shown in the present study (0.01 CO_2 eq.·kg^{-1}), which can be explained by the diesel consumption (four times higher than in the present study) and the yield (37% lower).

The average score obtained for FEu in the present study is 2.8·10^{-5} kg P eq.·kg^{-1} and for MEu 5.3·10^{-4} kg N eq.·kg^{-1}. The FEu score of the present study is similar to that of Cabot et al. (2023) and half the value reported by Bessou et al. (2016), even though these studies consider a higher yield. This difference could be due to the lower amount of P_2O_5 applied in our study (5 and 36 times less, respectively), as phosphate emission to freshwater is the leading cause of this environmental impact in the on-field emissions stage. Martin-Gorriz et al. (2020), Ribal et al. (2017), and Yang et al. (2020) do not discern between MEu and FEu; thus, direct comparations cannot be made. Concerning the hotspots for FEu, Cabot et al. (2023) remark pesticide production also due to copper pesticides, as in the present study, whereas Bessou et al. (2016) highlight the role of on-field emissions in this impact. As for MEu, both Cabot et al. (2023) and Bessou et al. (2016) highlight fertilizer emissions as a hotspot, despite using different methods to estimate NO_3^- emissions. The present study uses the Tier 3 LEACHN (Hutson and Wagenet 1992), while Cabot et al. (2023) use the SQCB-NO_3 method (Emmenegger et al. 2009) and Bessou et al. (2016) follow Brentrup et al. (2000). The three methods take into account different parameters in the model. However, it is interesting to make a preliminary comparison with Cabot et al. (2023) study, also located in Uruguay, and even though the amount of N added is three times higher than in the present study and the reported yield is nearly two times greater, the MEu score is almost six times higher. In case NO_3^- had been modeled in the present study using the SQCB-NO_3 method as proposed in the "WFLDB" approach (Table 5), the MEu score would have been almost thirty times higher (see Table 6). This reaffirms what was highlighted in Cabot et al. (2023), that the SQCB-NO_3 method is not the most appropriate for modeling NO_3^- leaching, at least in the case of Uruguayan citrus production, as this emission depends on climatic factors and crop management that have a great space–time variability.

Regarding TAc, comparisons are only made with Bessou et al. (2016) since the other studies do not distinguish between terrestrial and aquatic acidification. The score obtained in the present study is 1.2·10^{-2} kg SO_2 eq.·kg^{-1}, ten times higher than that of Bessou et al. (2016), which could be influenced by the higher yield of that study (18% higher on average). On-field emissions, mainly NH_3 volatilization, is the leading cause of this impact in both studies. However, these authors use a fixed emission factor to quantify NH_3 emission from mineral fertilizers, while in the present article, dynamic modeling is carried out using LEACHN. This could explain the greater scores obtained in the current study despite adding 68% less N. In case this emission was modeled with a Tier 1 approach, as proposed in "PEF," the impact score for this category would be 74% lower ("PEF," Table 6), whereas using the Tier 2 approach of EEA (2019) like in the "updated method", a 52% reduction would be observed (Table 6).

The BWS score obtained in this study is 0.11 m^3 eq.·kg^{-1}, similar to that of Cabot et al. (2023) for Uruguayan lemons, even with half the yield and an almost four times higher blue water consumption. This is mainly due to the basin CFs, which are 58–85% lower than those of Cabot et al. (2023), depending on the month. This result reaffirms the importance of considering the monthly scarcity of the basin in the BWS calculations. Bessou et al. (2016) also assess this impact category but use the amount of water irrigated as an input. However, they emphasize that the impacts due to water use should be modeled based on a proper inventory of input and output water fluxes accounting for soil, climate, and agricultural practices. In addition, the authors use the method proposed in Recipe 2008 (Goedkoop et al. 2013), which does not distinguish the origin of the water, suggesting a characterization factor of 1 for all types of water (lake, river, well), regardless of the basin.

It must be noted that for the impact categories not included in Table S9, the scores of Cabot et al. (2023) for ET, HT, RUm, and RUf are similar to those obtained in the present study, where the production of inputs (pesticides and fertilizers) stand out as hotspot. Ribal et al. (2017) highlight pesticide emissions as a hotspot in toxicity impact-related categories. As for RUf, Martin-Gorriz et al. (2020) also emphasize machinery operations as a hotspot, obtaining ten times higher impact scores, mainly because of the higher fuel consumption (four times higher) and the 37% lower yield. Martin-Gorriz et al. (2020) also highlight pesticide production as a hotspot in RUm, obtaining similar results to the present study.

4 Conclusions

The present study is a first approach to quantify the environmental impacts of mandarin production in Uruguay, seeking to achieve a more sustainable agricultural production in line with the SDGs. The main hotspots found are on-field emissions from fertilizers, input production, and water consumption for irrigation. Therefore, actions toward their minimization are encouraged, mainly by better adjusting the applied doses. The importance of considering more than one FU is reaffirmed.

Two key issues of agricultural LCAs are addressed: temporal variability during the full production phase and site specificity. As to temporal variability, the importance of evaluating different harvest seasons, even when assessing the full production stage and especially under variable climatic conditions and agricultural practices, is emphasized. In fact, a high inter-season variability is detected for all the impact categories, particularly when using a mass-based FU, due to the yield effect. When analyzing the impact categories with more variability, the results expressed per hectare mainly respond to the most influential on-field emissions. However, when expressing the results per tonne, the environmental impacts are not always inversely proportional to the yield since the studied variety is characterized by its alternating bearing; therefore, the application of higher input rates does not always imply a greater yield. Regarding site specificity, significant reductions in the impact scores are observed when applying a global spatialized model to on-field emissions, and their use should be thus boosted. As well, when data is available, the development of site-specific inventories is encouraged. As regards the modeling of N on field emissions, LEACHN seems to better capture the inter-season variability of farming practices and climate, given the higher CV of most of the emissions per ha. The statistical test showed significant differences in the MEu impact category when modeling NO_3^- following WFLDB compared to LEACHN. This method is thus not recommended for quantifying MEu impact, at least for Uruguayan citrus. Significant differences were also observed for TAc, TEu, and AqAc per ha when modeling emissions following PEF in comparison to LEACHN; therefore, the use of the former to quantify these emissions is not recommended, at least for this case study. No significant differences were obtained for CC between the five approaches assessed. Nevertheless, more research is needed to improve the application of LEACHN to the agroclimatic characteristics of Uruguay and to draw general conclusions about the advantages of using this mechanistic model to estimate N emissions for better environmental assessment of Uruguayan citriculture.

Regarding the limitations of the present study, some crop protection inputs could not be properly modeled as they were not available in the databases used. Thus, the development of more complete databases is encouraged. As to system modeling, due to the peculiarities of perennial crops, there is a need to standardize the way in which perennial systems should be modeled when performing an LCA (e.g., in forthcoming updates of published guidelines). Along these lines, further studies are needed to assess the influence of the non-productive phases (nursery and the first years in the orchard) in citrus production in order to discuss the relevance of the allocation of their environmental impact among the fruits leaving the system in the full production years.

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Declarations

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