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Environmental LCA of Precision Agriculture for Stone Fruit Production

Pablo Núñez-Cárdenas ^{1,2} , Belén Diezma ¹ , Guillermo San Miguel ³ , Constantino Valero ¹ and Eva C. Correa ^{1,*}

- ¹ Laboratorio de Propiedades Físicas y Técnicas Avanzadas en Agroalimentación, Escuela Técnica Superior de Ingeniería Agronómica, Alimentaria y de Biosistemas (ETSIAAB), Universidad Politécnica de Madrid, Avenida Puerta de Hierro 2-4, 28040 Madrid, Spain; pm.nunez@alumnos.upm.es or pablo.nunez@umag.cl (P.N.-C.); belen.diezma@upm.es (B.D.); constantino.valero@upm.es (C.V.)
- ² Centro de Horticultura y Floricultura, Instituto de la Patagonia, Universidad de Magallanes, Avenida Manuel Bulnes 01890, 6213029 Punta Arenas, Chile
- ³ Grupo de Agroenergética, Departamento de Química e Ingeniería Medioambiental, Escuela Técnica Superior de Ingenieros Industriales (ETSI), Universidad Politécnica de Madrid, Calle José Gutiérrez Abascal 2, 28006 Madrid, Spain; g.sanmiguel@upm.es
- * Correspondence: evacristina.correa@upm.es

Abstract: Precision agriculture is a concept that encompasses various technologies aimed at optimizing the management of agricultural activities. The main aim of this investigation is to evaluate the environmental and economic performance of precision agriculture practices on the production of a stone fruit crop (nectarine) using a life cycle approach and to consider a *cradle-to-farm gate* scope. The results have been compared against the traditional uniform application (UA). The analysis considers five impact categories, including climate change, photochemical ozone formation, acidification, eutrophication, and water use. The foreground inventory data was provided by a local producer in Southern Spain, and the background information was sourced from commercial Life Cycle Inventory (LCI) databases. The results show that the manufacturing of crop inputs (mainly fertilizers, but also crop management inputs) is responsible for most of the damage generated in all the impact categories, except for water use. The reduced input requirements associated with the application of VA techniques resulted in significantly lower economic costs and environmental savings throughout the life cycle of the production system, which ranged on average between 12–26%.

Keywords: life cycle analysis; variable application of inputs; stone fruit; nectarine



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1. Introduction

Precision agriculture (PA) is currently a powerful solution for mitigating the environmental impact of agricultural systems [1]. It contributes to the precise and optimized use of cultivation inputs, resulting in reduced costs and environmental savings [2]. The variable application (VA) of inputs is the basic technique of PA, whose main objective is to carry out a precise management of inputs (such as fertilizers, phytosanitaries, and water) according to the specific requirements of each cultivation area and even of each plant. The economic and ecological performances in agriculture can potentially be improved through specific field management [3]. This requires strong and temporally coherent relationships between the management areas, and the underlying physical, chemical, and biological parameters of the soil and crop yields.

The PA techniques typically encompass three different areas: *guidance systems* (i.e., the hardware and software that guide tractors and pieces of equipment over a field); *recording technologies* (i.e., the sensors mounted on ground-based stations, rolling, airborne or satellite platforms, and gathering spatial information, which elaborate maps of spatial variability in key agricultural parameters, such as yield, soil fertility, moisture content,

and the physiological state of the plant); and *reacting technologies* (i.e., implements, such as the hardware and software that together can vary the placement of agricultural inputs in the field) [4].

Concerning the use of PA to optimize the fertilization stage, several authors described a reduction in the consumption of cultivation inputs through the use of VA techniques, while maintaining similar yields per ha⁻¹ year⁻¹. Thus, Colaço (2017) [5] compared the VA and UA fertilizations in orange trees (Table 1), estimating the VA requirements (P and K) as a function of the soil fertility indicators and leaf nutritional conditions, along with the surface production maps. The results showed an average reduction in the input requirements by 39% per ha⁻¹ year⁻¹. Aggelopoulou et al. (2010) [6] with apple trees, and Vatsanidou et al. (2017) [7] with pear trees, both estimated nitrogen's VA by considering the production map of the plantation in the previous year and estimating the amount of N extracted from the soil by each plant and orchard area. The VA application of N resulted in up to 38% of N savings in apple, and 53% in pear production for a similar crop yield. Liakos et al. (2020) [8] used the same methodology to generate the map of variable applications of N with apple trees in two campaigns. The fertilization dose was reduced, on average, by 62% in the VA compared to the UA that Zaman et al. (2005) [9] analyzed with orange trees. The VA of nitrogen fertilizers following the prescription maps generated from the volume of the canopy of the trees were scanned using ultrasound technology. VA reduced the fertilizer dose on average by 39% with the same yield compared to the producer's uniform application of 270 kg of N ha⁻¹ year⁻¹.

Regarding the VA of phytosanitary products, the literature presents several studies with fruit trees (Table 1). Nackley et al. (2021) [10] used a sprayer with a LiDAR sensor to determine the canopy density and define the application of the phytosanitary products on apple trees and vineyards. The spray volume was reduced by an average of 71% while reaching a comparable product yield. Chen et al. (2020) [11] used a spray system similar to the previous one to perform a VA on apple and peach trees. The intelligent application of spraying reduced the phytosanitary requirements by 59% and 31%, respectively, to reach similar yields. Roman et al. (2021) [12] calculated the pesticide doses in real-time for the two previous works and used phytosanitary prescription maps to estimate the VA of phytosanitary products in vineyards. To assess the spatial variability in each vineyard, aerial multispectral images were taken, which allowed to differentiate between the areas of higher and lower agricultural vigor. The reduction in the doses in the areas of higher vigor allowed an average savings of 21% to be achieved with the same yield, compared to the treatment of UA.

Relating to the use of VA to optimize irrigation, Bellvert et al. (2020) [13] evaluated the performance of an integrated methodology based on a model of water consumption and remote sensing data. This was used to optimize the watering of a commercial vineyard with three grape varieties in two seasons. Each irrigation sector was classified according to the normalized difference vegetation index (NDVI) map. Irrigation prescriptions were carried out independently in each irrigation sector according to the results of the model. The non-precision irrigation (NPI) strategy consisted of simulating the irrigation prescriptions according to the evapotranspiration of the entire canopy. The average reduction in water consumption in the precision irrigation (PI) program was about 11% in the Cabernet Sauvignon and Tempranillo vineyards.

Ortuani et al. (2019) [14] also created irrigation prescription maps using vineyards. They identified two homogeneous soil types based on electrical resistivity and texture and considered the total water available for each field using sensors, and estimated the evapotranspiration using the NDVI model. The implementation of this PI system achieved water savings of 18% compared to the NPI strategy that was used in accordance with the farmer's experience. Modina D. et al. (2021) [15], with pear trees, compared a PI drip system with a traditional NPI drip system. The infield variability was detected using soil electrical conductivity and soil profile analyses. The irrigation sectors were defined, optimizing in each sector's flow rate and the distance between drippers. During the season, the sensors

monitored the soil's moisture and irrigation water. Using the PI strategy, the amount of irrigation water was reduced by 50% in the pear orchard compared to the NPI system.

Table 1. Literature review on the percentage of difference in the use of inputs per ha^{−1} year^{−1} between uniform and variable application.

Ref.	Crop	Input	Method for Variable Application	Inputs Difference (%)
[5]	Orange	Fertilizer (N, P, K)	Prescription maps based on soil fertility (for P and K application) and leaf nutritional conditions (for N application), combined with yield maps.	−39
[6]	Apple	Fertilizer (N)	Prescription maps based on the yield map of the previous year's data and on the estimation of the amount of N extracted by the crop	−38
[7]	Pear	Fertilizer (N)	Prescription maps based on the yield map of the previous year's data and on the estimation of the amount of N extracted by the crop	−53
[8]	Apple	Fertilizer (N)	Prescription maps based on the yield map of the previous year's data and on the estimation of the amount of N extracted by the crop	−62
[9]	Orange	Fertilizer (N)	Prescription maps based on the sizes of ultrasonically scanned trees	−39
Average fertilizers				−46
[10]	Apple	Phytosanitary	Laser sensor to calculate the volume of foliage in the tree canopy from which the volume of spray liquid for each nozzle was calculated in real-time	−71
	Vineyard		Laser sensor to calculate the volume of foliage in the tree canopy from which the volume of spray liquid for each nozzle was calculated in real-time	−71
[11]	Apple	Phytosanitary	Prescription maps based on multispectral images to calculate the vegetative vigor and define maps with two classes of high and low vigor	−59
	Peach		Prescription maps based on multispectral images to calculate the vegetative vigor and define maps with two classes of high and low vigor	−31
[12]	Vineyard	Phytosanitary	Prescription maps based on multispectral images to calculate the vegetative vigor and define maps with two classes of high and low vigor	−21
Average phytosanitaries				−51
[13]	Vineyard	Water	Prescription map based on a vine water consumption model and remote sensing data (NDVI map)	−11
[14]	Vineyard	Water	Prescription map based on soil characteristics, soil-water content determined by sensors, and crop water needs using NDVI map.	−18
[15]	Pear	Water	Prescription map based on soil characteristics and soil-water content determined by sensors	−50
[16]	Nectarine	Water	Soil water sensors to monitor water content by establishing an automated irrigation protocol in real-time	−43
[17]	Peach	Water	Soil water sensors to monitor water content by establishing an automated irrigation protocol in real-time	−18
Average irrigation				−28

Conesa et al. (2021) [16] conducted a field experiment in a nectarine orchard using PI. In the treatment control, the irrigation dose was based on the crop's evapotranspiration, while the PI system was based on soil-water sensors to monitor the volumetric soil–water content using multi-depth capacitance sensors. In the PI scenario, 43% of the water was saved compared with conventional irrigation. Mounzer et al. (2008) [17] Using a similar procedure in peach trees, the same researchers reported 18% in PI water savings compared to the NPI irrigation treatment.

The life cycle assessment (LCA) is a management tool that is widely used to determine the environmental performance of agricultural product systems throughout their entire value chain, from primary production, processing, distribution, and consumption to *end-of-life* treatment [18]. In the fruit sector, most LCA studies have been carried out, giving

preference to the evaluation of the field phase, which primarily considers the production of crop inputs, the diffusion of such inputs into different environmental receivers (atmosphere, soil, water) and the energy requirements associated with the agricultural practices [19–22]. Canals, M. et al. (2006) [23] conducted an analysis of the agricultural practices in an apple crop, identifying which agricultural processes contributed the most to the environmental impact of the product. The results revealed that fertilization and the use of agricultural machinery were the most important contributors to total greenhouse gas (GHG) emissions. Balafoutis et al. (2017) [4] obtained similar results when carrying out the LCA of vineyards following a VA of fertilizers and water. Compared to the traditional UA strategy, they found that the production and distribution of fertilizers (direct) and their application (indirect) were the stages that benefited the most from the reduced GHG emissions, with 17.2%, followed by energy use (8.8%).

Variable-rate irrigation also caused environmental savings compared to the traditional treatment, but to a lesser degree than the variable-rate fertilization. Vatsanidou et al. (2020) [24] performed an LCA in a small pear orchard to identify the environmental effects of a VA in nitrogen fertilization, compared to the conventional UA. The results showed higher crop yields combined with a reduced N fertilization rates when using the VA technique, resulting in a significant reduction in air emissions. In addition, the results showed that climate change, water scarcity, fossil fuels, and particle formation were the impact categories that contributed the most to the overall environmental performance of the product. Canaj et al. (2021) [25] conducted a study where they assessed the environmental and economic sustainability of PI zucchini production using environmental LCA and life cycle costing (LCC) analyses. The PI practices, based on the soil moisture sensors and cloud-based decision support systems, resulted in a 38.2% average water savings. The results determined, by using the aggregated single-point indicator, showed a 13% reduction in environmental burdens throughout the product's life cycle. The LCC results showed that although the implementation of PI imposes upfront investments, the water and energy savings associated with these practices offset these costs. While most PA studies are on cereals and vegetables, very little information is available on the sustainability benefits of this technology on stone fruit crops. The combination of environmental and economic assessments in stone fruit production has not been reported in the literature.

Hence, the main objective of this study is to investigate, comparatively, the environmental and economic benefits associated with the production of nectarines using conventional and precision agriculture practices.

2. Materials and Methods

This investigation describes the life cycle environmental and economic assessment of nectarine production using inventory data from an orchard (*Prunus persica* var. *nucipersica*) located in the town of Abarán (Murcia) in southeast Spain. This plot extends over 405 ha, contains 667 individual plants per ha and yields, on average, 35 t ha⁻¹ year⁻¹ of fresh fruit, considering a productive period of 15 years and 3 years of crop establishment. The LCA was carried out following the standardized structure proposed in ISO 14040 and 14044 [26,27], which was adapted to the layout and format of the journal. Hence, the analysis was articulated in four stages: goal and scope definition, life cycle inventory (LCI), life cycle impact assessment (LCIA), and the interpretation of the results (Results and Discussion).

2.1. Definition of Goal and Scope

The main objective is to evaluate, comparatively, the environmental and economic benefits associated with the production of nectarines using either conventional UA techniques or precision agriculture VA techniques. The secondary objectives relate to estimating the contribution of individual life cycle stages and processes and defining the environmental categories most significantly affected.

2.1.1. System Boundaries

The study considers the life cycle stages of nectarine production using a *cradle-to-farm gate* approach, as shown in Figure 1.

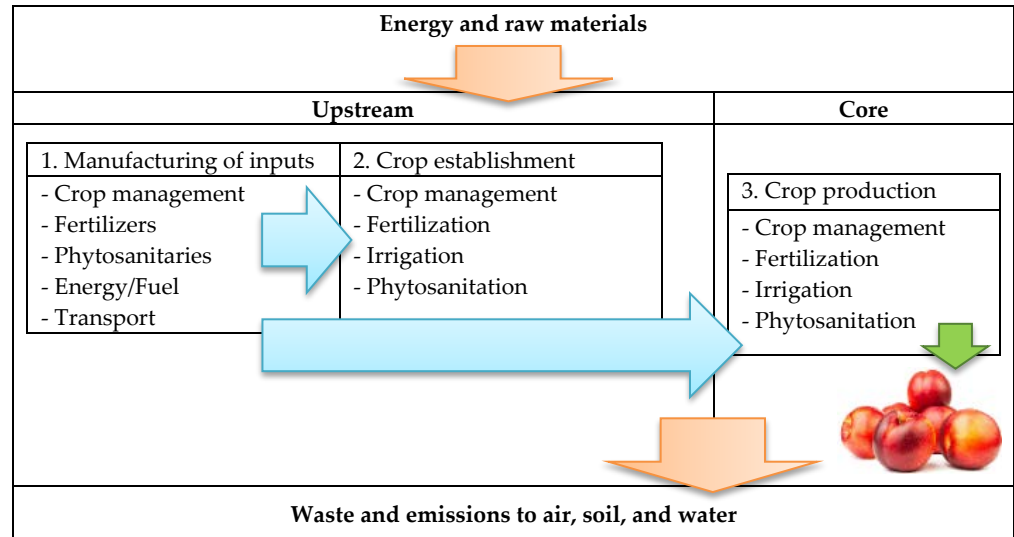


Figure 1. Life cycle diagram and system boundaries of the nectarine product system using the *cradle-to-farm gate* approach.

2.1.2. Functional Unit (FU)

The FU was defined as 1 kg of nectarines, unpackaged (in bulk), at the farm gate [28].

2.1.3. Methodological Decisions and Tools

The analysis was carried out using the Simapro v9.1 software [29], following the product category rules (PCR) for fruits and nuts published by ENVIRONDEC [28] and using the Environment Footprint 3.0 (adapted) as the environmental impact assessment method, as per the recommended European Commission in its Product Environmental Footprint (PEF) guidelines [30]. The impact categories considered included the carbon footprint (CF), photochemical ozone formation (POF), acidification (A), freshwater eutrophication (FE) and water use (W). The single-score normalized and weighted indicators were also used to evaluate the overall environmental performance of the system and to determine the relative importance of each impact category.

The air emissions of ammonia, nitrous oxide, and nitric oxide (direct emission) and nitrous oxide (indirect emission), and the nitrate and phosphorus emissions to water were calculated according to the methodology outlined in the IPCC guidelines [31]. The emissions from pesticide use in the air, surface water, and groundwater were calculated using the PestLCI 2.0 model [32]. The economic input inventory of a fruit company was used as a reference to evaluate the differences in the input costs between UAs and VAs.

2.1.4. Stages of the Life Cycle System

- **Upstream:** includes two substages: (1) **Manufacturing of inputs** (including transport) used throughout the product's life cycle (including fertilizers, phytosanitaries, and irrigation systems) and for crop management (trellis systems, seedlings of fruit trees, and fuel); (2) **crop establishment** includes the soil preparation, installation of the trellis and irrigation systems, planting, fertilization (inputs and electricity), phytosanitation (including fungicides, insecticides and herbicides, machinery and fuel) and irrigation (water and electricity) during the three years corresponding to the crop establishment.
- **Core:** addresses the agricultural substage of (3) **crop production**, which includes irrigation (including water and electricity) and fertilization (including inputs and machinery), phytosanitation for pest and disease control (including fungicides, insecticides, and herbicides).

ticides and herbicides, machinery and fuel), and crop management (including soil preparation, pruning, thinning, and harvesting and the related use of machinery and fuel). Both the upstream and core processes incorporate the production, distribution, and consumption of fuel for transport, and the construction of machinery and electricity use.

2.2. Life Cycle Inventory

Table 2 shows the foreground life cycle inventory for the nectarines referred to as FU, as described in Section 2.1.2. Primary data for the UA scenario were sourced directly from the producer, while the VA data was calculated considering the input reductions reported in the literature for similar crops (see Table 1) as follows: −46% in fertilizers, −51% in phytosanitaries and −28% in irrigation, for similar yields. The background secondary data assumptions reported below were sourced from the Ecoinvent v3. 7.1 database [33].

Data Assumptions: The Following Premises Were Assumed for the Analysis of Generic Processes

- Transport of cultivation inputs: transport was assumed to be carried out using 32 t EURO5 trucks, assuming a 500 km distance from the fabrication plant to the place of sale and 30 km from the place of sale to the cultivation site.
- Electricity: high-voltage production, the transformation from a medium voltage and the distribution of electricity were estimated using information from the Ecoinvent database, according to the Spanish medium-voltage electricity mix of the year 2020 [33].
- Machinery: the fabrication of machinery and diesel emissions during operations [33].
- Fuel: the oil extraction, and the refining and distribution to the final consumer in Europe [33].
- Irrigation water: the crop used a drip irrigation system that consumed well water and used electric pumps [33].
- Fertilizers: from the extraction of raw materials to the manufacturing of the final product [33].
- Phytosanitaries: the production of active ingredients for fungicides, insecticides, and herbicides (generic database parameters) [33].

Table 2. Life cycle inventory analysis related to a FU in scenario UA and VA.

UPSTREAM				CORE			
1. Manufacturing of inputs	unit	UA	VA	3. Crop production	unit	UA	VA
Fuel	l	4.46×10^{-3}	3.04×10^{-3}	Fertilizers (N-P-K)	kg	3.66×10^{-2}	1.98×10^{-2}
Transport	t km	2.70×10^{-2}	1.84×10^{-2}	13-0-46	kg	1.57×10^{-2}	8.50×10^{-3}
2. Crop establishment				15-0-0-26.5 Ca	kg	8.42×10^{-3}	8.42×10^{-3}
Fertilizers (N-P-K)	kg	2.44×10^{-3}	1.32×10^{-3}	21-0-0-60 SO ₃	kg	7.32×10^{-3}	3.96×10^{-3}
13-0-46	kg	1.05×10^{-3}	5.67×10^{-4}	0-53-0	kg	5.13×10^{-3}	2.77×10^{-3}
15-0-0-26.5 Ca	kg	5.62×10^{-4}	3.03×10^{-4}	Phytosanitaries *	kg	6.69×10^{-4}	3.28×10^{-4}
21-0-0-60 SO ₃	kg	4.88×10^{-4}	2.64×10^{-4}	Fungicides	kg	2.67×10^{-5}	1.31×10^{-5}
0-53-0	kg	3.42×10^{-4}	1.85×10^{-4}	Insecticides	kg	1.87×10^{-4}	9.15×10^{-5}
Phytosanitaries *	kg	4.46×10^{-5}	2.18×10^{-5}	Herbicides	kg	4.54×10^{-4}	2.22×10^{-4}
Fungicides	kg	1.78×10^{-6}	8.72×10^{-7}	Irrigation			
Insecticides	kg	1.25×10^{-5}	6.10×10^{-6}	Water	m ³	1.29×10^{-1}	9.26×10^{-2}
Herbicides	kg	3.02×10^{-5}	1.48×10^{-5}	Others			
Irrigation				Electricity	kWh	4.24×10^{-2}	3.05×10^{-2}
Water	m ³	8.57×10^{-3}	6.17×10^{-3}	Machinery	kg	1.10×10^{-3}	1.10×10^{-3}
Others				Fuel	l	1.54×10^{-3}	1.46×10^{-3}
Electricity	kWh	2.83×10^{-3}	2.04×10^{-3}	Transport	t km	1.12×10^{-3}	6.03×10^{-4}
Machinery	kg	1.14×10^{-4}	1.14×10^{-4}				
Fuel	l	1.01×10^{-4}	9.06×10^{-5}				
Transport	t km	1.08×10^{-4}	4.69×10^{-5}				

* Active ingredients.

3. Results

3.1. Economic Assessment

The market prices of phytosanitaries and fertilizers for 2020 were sourced from a local fruit producer operating in the region of Murcia (Spain) [34]. The price of water was that reported by the local irrigation association of Cartagena (Murcia, Spain) [35]. The electricity tariff considered the value of the national mix [36]. The price of fuel was obtained from the Spanish confederation of freight transport [37].

Table 3 illustrates the average economic savings in the consumption of cultivation inputs between -51% for phytosanitaries and -28% for water use. This results in the overall energy and transport savings were between -25% and -32% . The largest net savings (EUR 665 ha $^{-1}$ year $^{-1}$) were related to the consumption of phytosanitaries. Table 4 shows a detailed inventory of the cultivation input costs per FU, as used in the different substages of the production of stone fruits.

Table 3. Inputs cost summary of UA and VA scenarios (FU).

Item	EUR/unit	Units/ FU	UA (EUR/FU)	VA (EUR/FU)	Input Savings (%)
Fertilizers (kg) [34]	1.22	3.91×10^{-2}	0.048	0.026	-46^*
Phytosanitaries (kg) [34]	53.03	7.13×10^{-4}	0.038	0.019	-51^*
Water (m 3) [35]	0.33	1.37×10^{-1}	0.045	0.033	-28^*
Electricity (kW) [36]	0.37	4.53×10^{-2}	0.017	0.012	-28
Fuel (L) [37]	1.60	6.10×10^{-3}	0.008	0.006	-25
Transport (t·km) [38]	1.1	2.83×10^{-2}	0.031	0.021	-32
Total			0.187	0.116	-38

* Reduction in average inputs applied according to the data presented in Table 1.

Table 4. Life cycle inventory of nectarines per FU (1 kg of fruit), in the UA and VA scenarios.

Stages	Substages	Inputs	Unit	EUR UA	EUR VA	Inputs Difference (%)
Upstream	(1) Manufacturing of inputs	Fuel	L	6.20×10^{-3}	4.23×10^{-3}	-25
		Transport	t·km	2.97×10^{-2}	2.03×10^{-2}	-32
	(2) Crop establishment	Fertilizers	kg	2.97×10^{-3}	1.60×10^{-3}	-46^*
		Phytosanitaries	kg	2.36×10^{-3}	1.16×10^{-3}	-51^*
		Water	m 3	2.83×10^{-3}	2.04×10^{-3}	-28^*
		Electricity	kW	1.05×10^{-3}	7.54×10^{-3}	-28
		Fuel	L	1.40×10^{-4}	1.26×10^{-4}	-10
		Transport	t·km	1.19×10^{-4}	5.16×10^{-5}	-57
Core	(3) Crop production	Fertilizers	kg	4.46×10^{-2}	2.41×10^{-2}	-46^*
		Phytosanitaries	kg	3.55×10^{-2}	1.74×10^{-2}	-51^*
		Water	m 3	4.24×10^{-2}	3.05×10^{-2}	-28^*
		Electricity	kW	1.57×10^{-2}	1.13×10^{-2}	-28
		Fuel	L	2.14×10^{-3}	2.02×10^{-3}	-6
		Transport	t·km	1.23×10^{-3}	6.63×10^{-3}	-46

* Reduction in average inputs applied according to the data presented in Table 1.

3.2. Environmental Life Cycle Impact Assessment

Table 5 illustrates the characterized impacts associated with the life cycle of nectarines produced when using the precision VA agriculture and traditional UA practices.

- Carbon footprint (CF).

The impact on the climate change category was calculated at 5.32×10^{-1} kg of CO $_2$ eq per FU for the UA and 4.24×10^{-1} kg of CO $_2$ eq per FU for the VA, which represents a 20% reduction in favor of the precision agriculture. Figure 2a,b illustrates that the manufacturing

of cultivation inputs (1) is responsible for most of the greenhouse gas (GHG) emissions (87% in UA and 88% in VA). Of these cultivation inputs, the manufacturing of fertilizers (substage 1) is the main contributor in both scenarios (41% in UA and 30.7% in VA). Crop production (3) is the second-largest contributor, with 12% in UA and 11% in VA.

Table 5. Characterized impacts of nectarine production using traditional UA and precision practices VA (per FU = 1 kg of fruit). (Dif %: percentage reduction when comparing UA vs. VA scenarios).

Impact Category	Unit	(1) Manufacturing of Inputs			(2) Crop Establishment			(3) Crop Production			Total		
		UA	VA	Dif %	UA	VA	Dif %	UA	VA	Dif %	UA	VA	Dif %
Carbon footprint	kg CO ₂ eq	4.65×10^{-1}	3.75×10^{-1}	−19	4.44×10^{-3}	3.48×10^{-3}	−21	6.18×10^{-2}	4.55×10^{-2}	−26	5.32×10^{-1}	4.24×10^{-1}	−20
Photochemical Ozone formation	kg NMVOC eq	2.40×10^{-3}	2.18×10^{-3}	−9	2.75×10^{-5}	2.16×10^{-5}	−21	3.77×10^{-4}	2.65×10^{-4}	−30	2.80×10^{-3}	2.46×10^{-3}	−12
Acidification	mol H ⁺ eq	2.85×10^{-3}	2.27×10^{-3}	−20	4.08×10^{-5}	3.20×10^{-5}	−21	5.70×10^{-4}	4.12×10^{-4}	−28	3.46×10^{-3}	2.72×10^{-3}	−22
Eutrophication	kg P eq	1.70×10^{-5}	1.44×10^{-5}	−15	8.86×10^{-7}	6.07×10^{-7}	−31	1.44×10^{-5}	9.00×10^{-6}	−37	3.23×10^{-5}	2.40×10^{-5}	−26
Water use	m ³ depriv.	1.85×10^{-2}	1.45×10^{-2}	−21	8.57×10^{-3}	6.34×10^{-3}	−26	1.29×10^{-1}	9.51×10^{-2}	−26	1.56×10^{-1}	1.16×10^{-1}	−25

- Photochemical ozone formation (POF).

Table 5 describes the emissions of 2.80×10^{-3} and 2.46×10^{-3} kg of volatile organic compounds other than methane (NMVOC) eq per FU for the UA and VA, respectively, which represents a 12% reduction in this impact category when using precision agriculture. As shown in Figure 2a,b, the largest contribution, with 86% in the UA and 88% in the VA, comes from the manufacturing of inputs (1). Crop production (3) is the second most important life cycle stage, contributing to 13% in the UA and 11% in the VA. The same figure also shows the manufacturing of cultivation inputs (substage 1) as the main contributor in the UA with 49.6% and in the VA with 56.4%.

- Acidification (A).

Table 5 describes the emissions of 3.46×10^{-3} and 2.72×10^{-3} mol H⁺ eq per FU for the UA and VA, respectively, which represent a 22% savings due to the application of precision agriculture practices. As shown in Figure 2a,b, the manufacturing of inputs (1) is the main contributor, with 82% in the UA and 84% in the VA. Crop production (3) is the second most important life cycle stage, with 17% and 15% for the UA and VA, respectively. More specifically, the manufacturing of fertilizers is the main process in this category, contributing to 39.3% of the acidification impact in the UA scenario. The manufacturing of crop management inputs (substage 1) contributes to 31.3% in the VA scenario (Figure 2).

- Freshwater eutrophication (E).

The results show 3.23×10^{-5} and 2.40×10^{-5} kg of P eq per FU for the UA and VA, respectively, representing a 26% reduction in this category as a result of using precision agriculture practices. As shown in Figure 2a,b, the manufacturing of inputs (1) is the main contributor, with 52% in the UA and 60% in the VA. Crop production (3) contributes second with 45% and 38% for the UA and VA, respectively. The same figure shows the fertilization in crop production (3) with the greatest contribution to this impact in the UA with 36.5%, and in the VA, the manufacturing of crop management inputs (substage 1) is 29.4%.

- Water use (W).

The water use category describes 1.56×10^{-1} and 1.16×10^{-1} m³ per FU for the UA and VA, respectively, with a water-saving of 25% in the precision agriculture scenario. Crop production (3) represents a contribution of 83% for the UA and 81% for the VA (Figure 2), and the manufacturing of inputs (1) is the second-largest contributing stage with 12% and 13% for the UA and VA, respectively.



Figure 2. Percentage contribution by substage and process on each impact category considering conventional UA (a) and precision agriculture VA practices (b). (1) Manufacturing of inputs, (2) crop establishment, (3) crop production.

The analysis of the characterized impacts (Figure 2) describes that the manufacturing of cultivation inputs (1) is responsible for most of the environmental burdens in all the environmental categories, except for water use. This refers to both the conventional and precision agriculture scenarios. The results identify the manufacturing of fertilizers, production of irrigation systems and crop management as the processes contributing the most to the overall environmental burdens of the nectarine. Owing to its predominant contribution, the manufacturing of the crop inputs (1) process has been analyzed separately in Figure 3 using the single-score normalized and weighted approaches from the EF3.0

environmental impact assessment methodology. The results illustrate a –17% difference between the traditional UA and the precision agriculture VA practices. According to this methodology, climate change (carbon footprint) is the category generating the strongest environmental burden in this substage.

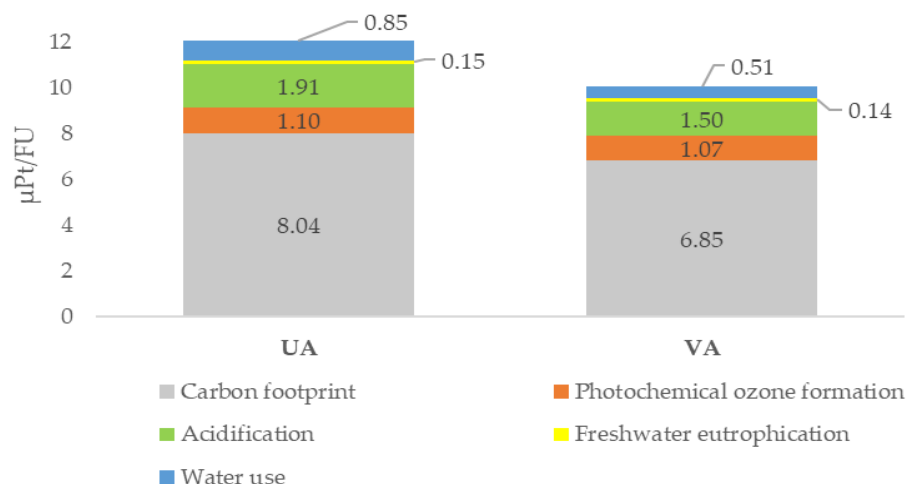


Figure 3. EF3.0 single-score environmental impact of the manufacturing of cultivation inputs substage in the production of nectarines using conventional UA and precision agriculture VA practices.

4. Discussion

Vinyes et al. 2017 [20] reported a life cycle carbon footprint for peach production in Spain using a *cradle-to-grave* approach of 0.38 kg of CO₂ eq per kg of fruit, with the highest contribution corresponding to the crop production stage. A similar analysis, but using a *cradle-to-gate* approach, was carried out by Ingrao et al. (2015) [21] for peach production in Italy. This investigation describes a comparatively lower carbon footprint of 0.22 kg of CO₂ eq per kg of fruit and reports irrigation and the use of agricultural machinery as the largest contributors. Frankowska et al. (2019) [22] calculated 2.0 kg of CO₂ eq per kg of fruit in a *cradle-to-grave* system, considering the production of peaches and their transportation to the United Kingdom. In this case, the greatest environmental contributions came from air transport and storage, due to the large distances and cooling times. Our results describe comparatively higher greenhouse gas emissions (0.53 kg of CO₂ eq per FU for the conventional UA and 0.42 kg of CO₂ eq per FU for the precision VA) than those reported in the literature for local consumption, but they were lower than the stone fruits intended for export. The other differences may be associated with the methodological decisions applied in each investigation, which are primarily related to the consideration of biogenic CO₂ emissions, system boundaries, and the use of updated inventories describing the most recent energy mixes and material production datasets.

Regarding the environmental consequences of implementing precision VA agriculture techniques, Vatsanidou (2020) [24] reported that the strongest contributions to climate change come from irrigation (by groundwater pumping), machinery use and crop production. Their results coincide with Ingrao et al. (2015) [21] and Vinyes et al. (2015) [19], regarding the dominant contribution of irrigation, land use, and the manufacturing of fertilizers and pesticides in the LCA of peach production. These results are also in line with ours, which describe the prevalence of irrigation, fertilization, and phytosanitation (all of which belong to a substage three-crop production), which are directly benefited by the precision agriculture practices. Based on these results, it would be appropriate to investigate the environmental and economic benefits associated with optimizing the efficiency in the use of fossil fuels and their substitution by renewable energies, primarily in the irrigation, machinery use, and transport stages.

In relation to the economic analysis of fruit systems, Liakos et al. (2020) [8] reported that the implementation of a variable fertilization system reduces the input costs by an

average of 5% in two years for similar fruit qualities and yields. Bellvert et al. (2020) [13] analyzed the economic savings in electricity and water use resulting from the utilization of an intelligent irrigation system in vineyards. These authors reported a 59% gross benefit rise from EUR 20 ha⁻¹ year⁻¹ to EUR 48.7 ha⁻¹ year⁻¹. This shows a similar but more optimistic trend than that calculated in our investigation, which describes a 26% reduction in cultivation input expenditures (fertilizers, phytosanitaries, and water). These differences may be associated with the temporal and geographical variability in the market prices of agriculture inputs.

When comparing the economic and environmental life cycle profile of the nectarine, it is worth noting the prevalence of cultivation input manufacturing (substage 1) in the environmental dimension, and crop production (substage 3) in the economic dimension. This indicates a higher environmental intensity per unit of expenditure in the cultivation inputs employed in both conventional and precision agriculture practices.

5. Conclusions

- This investigation describes that the carbon footprint of nectarine production, using conventional UA practices, amounts to 0.53 kg CO₂ eq per kg of fresh fruit at the farm's gate. This value may be reduced to 0.42 kg CO₂ eq through the application of precision agriculture practices based on the variable application of cultivation inputs.
- The results show that the manufacturing of cultivation inputs (upstream) is the life cycle stage that contributes the most to four of the five impact categories considered (except for water use). These inputs refer primarily to fertilizers and crop management inputs.
- Significant savings may be achieved in all impact categories as a result of implementing precision agriculture variable application practices, which involve savings in the use of fertilizers, phytosanitaries, and irrigation water. These savings are as follows: carbon footprint emissions −20%, photochemical formation of ozone −12%, acidification −22%, eutrophication of fresh water −26% and water use −25%.
- In economic terms, a 38% cost reduction may be associated with the use of precision agriculture practices, mainly due to the reduced fertilizer needs (46% and 51% savings in fertilizer in phytosanitaries expenses, respectively).
- The results from this investigation confirm and quantify the potential economic and environmental benefits of precision agriculture practices. These findings may be used to support policies and make a decision toward more sustainable agricultural practices.
- Additional work is required to expand the life cycle boundaries of this economic and environmental analysis to incorporate the construction of infrastructures required to carry out the PA practices.

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