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Comparative Assessment of Environmental/Energy Performance under Conventional Labor and Collaborative Robot Scenarios in Greek Viticulture

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Abstract: The viticultural sector is facing a significant maturation phase, dealing with environmental challenges to reduce agrochemical application and energy consumption, while labor shortages are increasing throughout Europe and beyond. Autonomous collaborative robots are an emerging technology and an alternative to the scarcity of human labor in agriculture. Additionally, collaborative robots could provide sustainable solutions to the growing energy demand of the sector due to their skillful precision and continuous labor. This study presents an impact assessment regarding energy consumption and greenhouse gas emissions of collaborative robots in four Greek vineyards implementing a life cycle assessment approach. Eight scenarios were developed in order to assess the annual production of four Vitis vinifera L. cultivars, namely, Asyrtiko, Cabernet Sauvignon, Merlot, and Tempranillo, integrating data from two wineries for 3 consecutive years. For each conventional cultivation scenario, an alternative was developed, substituting conventional viticultural practices with collaborative robots. The results showed that collaborative robots' scenarios could achieve a positive environmental and energy impact compared with conventional strategies. The major reason for lower impacts is fossil fuel consumption and the efficiency of the selected robots, though there are limitations regarding their functionality, lifetime, and production. The alternative scenarios have varying energy demand and environmental impact, potentially impacting agrochemical usage and requiring new policy adjustments, leading to increased complexity and potential controversy in farm management. In this context, this study shows the benefits of collaborative robots intended to replace conventional practices in a number of viticultural operations in order to cope with climate change impacts and excessive energy consumption.

Keywords: collaborative robots; energy efficiency; GHG emissions; farm management; life cycle assessment; viticulture

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1. Introduction

Climate change is one of the main global challenges for viticulture, since direct (e.g., temperature, rainfall distribution, and CO_2 concentration) and indirect impacts (e.g., pests' population, energy efficiency, and invasive species availability of food) affect an assortment of production factors (yield, quality, etc.). Early flowering and maturity of grapes are already a worldwide problem [1], while wine-producing regions may face issues related to land suitability for growing grapevines [2]. Predictions of climate change scenarios have depicted significant raises in average growing season temperature in several wine-growing regions over the past 50 years [3], though recent studies have indicated that the barrier is surpassed in specific areas in Europe and in the USA [4]. Apart from the abovementioned, budbreak, flowering, and véraison dates of different grapevine varieties are expected to differ significantly due to climate change impacts in the 21st century [5].

Spain, France, and Italy are major producers of viticulture, accounting for over 50% of the wine production worldwide while covering about one-third of the global area under vines [6]. According to the latest Eurostat data [7], Spain has the largest agricultural areas under vines in Europe, whereas France is second. Nevertheless, Italy produces more wine than either Spain or France, holding the lead in Europe since 2017 [8]. The importance of grape production in the European area is enhanced by an assortment of studies implementing life cycle assessment (LCA) to evaluate the environmental, societal, and economic performance of manifold locations and objectives. In this context, the investigation of energy consumption and environmental sustainability in viticulture is more crucial than ever.

The energy and environmental evaluation of the current industry should follow a strict protocol and a credible methodological framework to ensure the homogeneity of results. LCA is an established tool, integrating the ISO 14040 and 14044 guidelines [9,10] and defining a standardized methodological framework for the life cycle of a product or a procedure. Nevertheless, the results' legitimacy is questionable, since the standards do not detail a step-by-step procedure, but rather, they describe a broader range of choices that could lead to dubious assumptions [11].

One the one hand, LCA has been included in environmental legislation around the world, while recognizing process issues related to recent developments [12], system boundaries set by researchers [13], consequences of the appropriate impact assessment method [14], and translation of the functional unit to the real world [15]. On the other hand, LCA is an integrated methodological framework for the evaluation of the environmental performance of a system (product or procedure), taking into account all the relevant inputs and outputs throughout its lifetime [16]. Furthermore, LCA is considered a competent decision support system incorporating scientific data [17] and a policy decision-making tool [18]. Consequently, the LCA methodological framework could be used with other quantitative methods for better data management and validation of results especially to assess agricultural sustainability [19,20]. The evolution of LCA incorporates an interdisciplinary framework with economic, social, and environmental aspects, formulating an integrated approach, namely, life cycle sustainability analysis (LCSA) [21]. In this context, the life cycle methodological framework consists of four interrelated stages, namely, (i) goal and scope definition, (ii) life cycle inventory (LCI), iii) life cycle impact assessment, and (iv) interpretation [22].

LCA has also been implemented to assess the environmental impacts of irrigation systems for vineyard cropping systems in southern Italy [23] and in southern France [24]. In addition, freshwater scarcity and footprint profile for the production of a Portuguese wine (vinho verde) have been evaluated following four freshwater use LCA methods [25]. Furthermore, water-focused LCA has been used to assess the impacts on water resources for the production of a typical red Italian wine [26]. Identifying critical life cycle stages and comparing environmental performance among wine production is another domain of several LCA studies in Spain [27–29], in Italy [30,31], and in Portugal [32,33]. Roselli et al. [34] assessed the environmental impacts of three table grape production schemes related to harvesting dates in Italy. Moreover, the environmental sustainability of four vineyard production scenarios, mixing cultivation techniques (conventional and organic) with training systems (gobelet and espalier), in a protected designation of origin (PDO) wine-growing area in Calabria (southern Italy) was investigated by Falcone et al. [35] and extended with the integration of multicriteria analysis to rank the scenarios' environmental and economic sustainability in the same area [36]. In a similar manner, two viticultural management techniques (integrated and organic) were assessed via LCA in Loire Valley, France [37].

In Greece, the estimation of environmental performance for the wine production industry is relatively recent and limited to PDO and protected geographical indication

(PGI) red and white varieties in several areas [38,39]. Greek viticulture is changing and aligning with EU directives for quality products over quantity, and LCA is considered a methodological tool for identifying environmental performance and environmental and energy weak points throughout the production process. Furthermore, Greek viticulture is characterized by the production of (i) PDO wines, (ii) PGI wines, and (iii) currants. According to environmental impact assessment studies in the area, Corinthian currant cultivation is a human-labor-intensive production procedure, and the relevant impacts are mainly caused by processing [40]. On the other hand, Balafoutis et al. [41] identified field energy (tractor fuel use and electricity for irrigation) as the most significant activity related to greenhouse gas (GHG) emissions between conventional and precision viticulture techniques in the region of Eastern Macedonia and Thrace, Greece. In this context, viticulture management and, more importantly, production techniques related to on-field agricultural activities play one of the most significant roles in environmental performance in viticulture.

Robots are increasingly being used in the viticulture industry to improve efficiency and accuracy in tasks, such as vineyard mapping, pruning, and harvesting. The use of robots in vineyards can provide several advantages, such as continuous work day and night, reduced labor costs, and task precision, especially in areas where human labor is scarce or expensive. Replacing conventional labor with robots in order to cope with labor shortages, especially when the demand for human labor cannot be satisfied, is a promising solution, though agricultural robots for commercial use focus mainly on weeding and harvesting operations [42]. The "VineRobot" is another example of a robotic system used in viticulture, which is equipped with cameras and sensors that allow it to map the vineyard and identify individual vines. This information is used to prune the vines with high precision, while also collecting data on the health and growth of the vines [43]. Therefore, farmers take rational decisions on when and how to prune their vines, which can lead to improved yields and higher-quality grapes. A similar project is the "FLEXIGROBOTS", which integrates precision agriculture operations based on intelligent automation. Nevertheless, this is an ongoing project, and the first trial regarding harvesting operations was positive [44]. Robotic systems such as these can also help to reduce the environmental impact of viticulture. This was the case in studies by the University of California–Davis (UC Davis), where a robot could simultaneously collect soil moisture samples and adjust irrigation emitters [45,46]. Furthermore, the use of robots can reduce the need for pesticides, herbicides, and fungicides, which can be harmful to the environment [47,48].

Consequences to the environment, GHG emissions, and energy consumption of an integrated robotic system for agricultural operations are difficult to quantify, and very few studies have reported on those issues. In particular, some studies address the impact of autonomous weeding systems [49,50] and autonomous electric tractors [51] or focus on economic impacts [52]. Therefore, the main aim of the current study is a holistic environmental and energy assessment of conventional and collaborative robots [53] (cobot) scenarios in Northeastern Greece following a LCA framework. In particular, on-field activities during grapevine production by human labor are compared with activities by cobots regarding energy consumption and overall efficiency in two private vineyards in the region of Eastern Macedonia and Thrace, Greece. The study highlights for the first time the potential of cobots in an assortment of agricultural operations against climate change impacts and excessive energy consumption.

The paper is structured as follows: The methodology section (Section 2) includes eight subsections describing the methodological framework, the case study area, and the cobot description. Section 3 includes the results of the study regarding the impacts of cobots on the environment and the relevant indices. Finally, Sections 4 and 5 summarize the contribution of this work, including discussions, conclusions, and potential future work.

2. Materials and Methods

2.1. Case Study Area and Selected Vineyards' Description

The wine-producing vineyards assessed herein during the 2019–2021 vintages are located in Northern Greece, regional unit of Drama in the region of Eastern Macedonia and Thrace, at two different locations that are approximately 30 km apart, with similar terroir parameters. Note that the wider area of Drama hosts a plethora of wineries and vineyards producing several PGI-labelled wines. The first location of the current study, denoted as LOC1, namely, Ktima Pavlidis winery (41.200400 N, 23.953084 E, 200 m elevation), includes *Vitis vinifera* L. cvs Tempranillo (grafted onto *Berlandieri* X *Rupestris* 110R rootstock) and Asyrtiko (grafted onto *Berlandieri* X *Rupestris* 1103P rootstock), whereas the second location, denoted as LOC2, namely, Nico Lazaridi winery (41.127832 N, 24.275972 E, 190 m elevation), includes *Vitis vinifera* L. cvs Cabernet Sauvignon and Merlot (both grafted onto *Berlandieri* X *Riparia* SO4 rootstock).

The cultivars Tempranillo and Asyrtiko in LOC1 are part of a 40 ha vineyard under conventional crop management. The planting distance is 2.2 m between rows and 1.2 m along each row (3780 vines/ha) with planting in both cultivars being NE to SW orientated following the low slope of the terroir. Likewise, the cultivars Cabernet Sauvignon and Merlot in LOC2 are part of a 35 ha vineyard under conventional crop management. The planting distance is 2.5 m between rows and 1.2 m along each row (3330 vines/ha) with planting for Cabernet Sauvignon being NW to SE and for Merlot N to S orientated (Table 1). All cultivars in both locations are managed under very similar conventional management schemes employed by most wineries in the wider area. Those include composite winter pruning following the bilateral cordon training of the vines, followed by summer pruning operations, including budding, topping, defoliation, and crop load reduction. All vegetation and crop load management operations follow the course of the phenological stages of the vines that may differ between years targeting a relatively low final crop load for optimum crop quality (in the order of ≈10 t/ha). In addition, the vegetation between rows is managed mechanically, implementing plant protection practices via targeted sprays for pests and diseases.

Table 1. Location, cultivars, and vineyard details of the two assessed case studies.

Cultivar/Rootstock	Tempranillo/110 Richter	Asyrtiko/1103 Paulsen	Cabernet Sauvignon/SO_4	Merlot/SO_4
Winery	LOC1 Ktima Pavlidis winery	LOC1 Ktima Pavlidis winery	LOC2 Nico Lazaridi winery	LOC2 Nico Lazaridi winery
Coordinates (HGRS87/EGSA87) (Lat, Lon)	41.200400 N, 23.953084 E		41.127832 N, 24.275972 E	
Elevation	200 m		190 m	
Planting distance/orientation	2.2 X 1.2/NE–SW		2.2 X 1.2/NW–SE	2.2 X 1.2/N–S
Vines/ha	3780		3330	

2.2. Collaborative Robots in Agriculture

Cobots in agriculture integrate specific equipment and technology, which may include drones and wheel robots, in order to be effective [54]. Before activating the robots, the area of interest was mapped by a drone. In particular, the drone captures geographic data (digital images of the vineyard) and feeds them to the computing base station to calculate the optimal path for the ground robots within the vineyard [55]. The robots communicate through the base station, as illustrated by the autonomous mobile robot "VINBOT" [56]. The novelty of the SVtech project is based on the collaboration among master and slave robots, as well as on the enhanced number of viticultural operations by cobots. Each master robot has at least one robotic arm equipped with a robotic hand attached to it and various electronic sensing instruments, including cameras, while the slave robot has up to one robotic arm equipped with a gripper. Note that a gripper is much less dexterous than a robotic hand, but typically, a gripper can lift more than 2 kg. A master robot carries out viticultural tasks either alone or cooperatively with the other master robot in selected viticultural tasks, such as in vine tying, whereas the slave robot is used to transport materials produced by the master robot, such as grapes (during harvest). In addition, a master robot can direct the slave robot as needed. The cobot's technology is based on the interaction and coordination between robots and humans during production.

A robotic hand can handle a manual viticultural tool per operation, such as pruning/spraying/ tying, thus significantly reducing the cost of using an expensive specialized robotic arm per operation. Furthermore, a robotic hand can replace the human hand, such as during harvest. The effective use of robotic hands will be pursued by innovative artificial intelligence (AI) techniques tackling embodiment issues [57]. The pilot project SVtech of autonomous cooperative robots is focusing on the following basic viticultural operations: (i) cutting (see defoliation, pruning, and harvesting), (ii) spraying (precautionary), and (iii) tying. The aforementioned multiple operations and innovations are also supported using a new AI technology, called "lattice computing" [58–60], toward making the robots autonomous.

2.3. Selected Cobots' Description

The current project uses two types of robots: an expert-type robot and a helper-type robot; both are supplied by Robotnik Automation S.L.L. company in Valencia, Spain RB-EKEN (helper) is a ragged robot with a weight of 270 kg and a payload of 300 kg, equipped with a UR10e robotic arm and a payload of 16 kg (Figure 1). The robot moves with 4 motors (each has a maximum power of 1.2 kW). It can reach a maximum speed of 2 m/s. RB-EKEN is powered by LiFePO4 (48 V, 60 Ah) batteries with a maximum autonomy of 4 h of continuous motion. The maximum reachable slope of RB-EKEN is 60%.

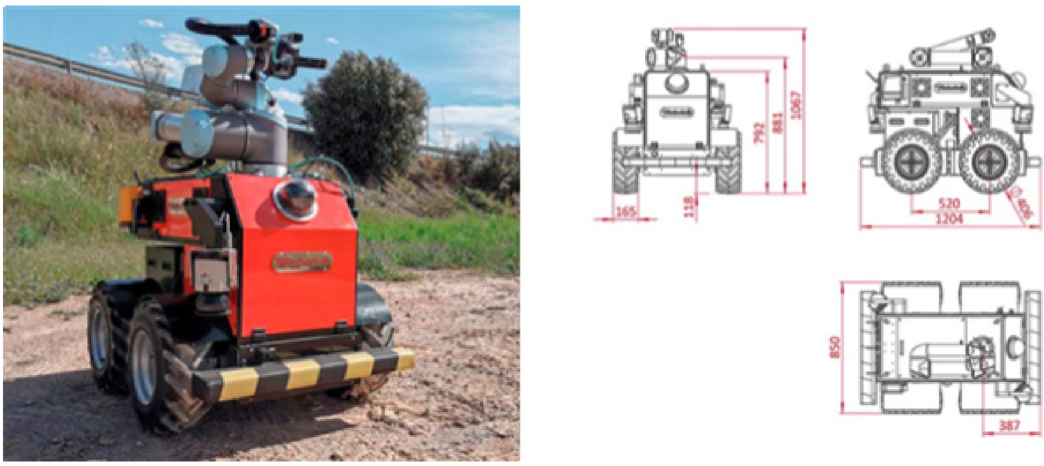

Figure 1. RB-EKEN blueprints (source: [61]).

RB-VOGUI (expert) is an autonomous base robot with a weight of 165 kg and a payload of 150 kg (Figure 2). The robot moves with four traction motors (each has a maximum power of 500 W) and 2 or 4 steering motors (each has a maximum power of 100 W). It can reach a maximum speed of 2.5 m/s. RB-VOGUI is powered by LiFePO4 (48 V, 30 Ah) batteries with a maximum autonomy of 8 h of continuous motion.

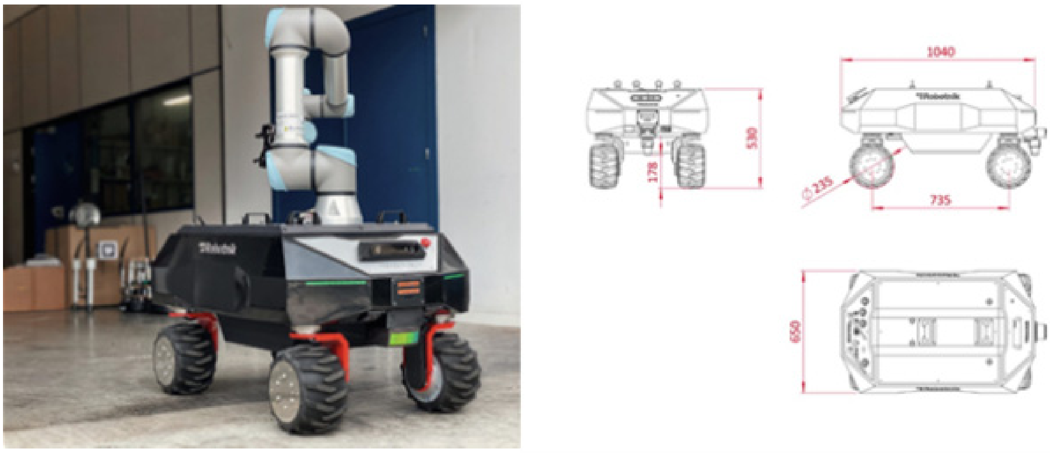

Figure 2. RB-VOGUI blueprints (source: [62]).

2.4. Goal and Scope Definition

The main goal of the current study is a holistic environmental assessment and the comparison of environmental performances between conventional and cobot labor scenarios of four vineyards in the region of Eastern Macedonia and Thrace, Greece. The process includes an assortment of operations, namely, harvesting, pruning, spraying, tying, weed control, and defoliation performed either conventionally or by cobots. More attention is paid to farming activities and machinery operations in order to highlight core differences between conventional and cobot labor. System boundaries are depicted in Figure 3, including all the relevant phases and the respective actions and inputs from annual grape production, while the transportation of products to the wine processing plant is also included.

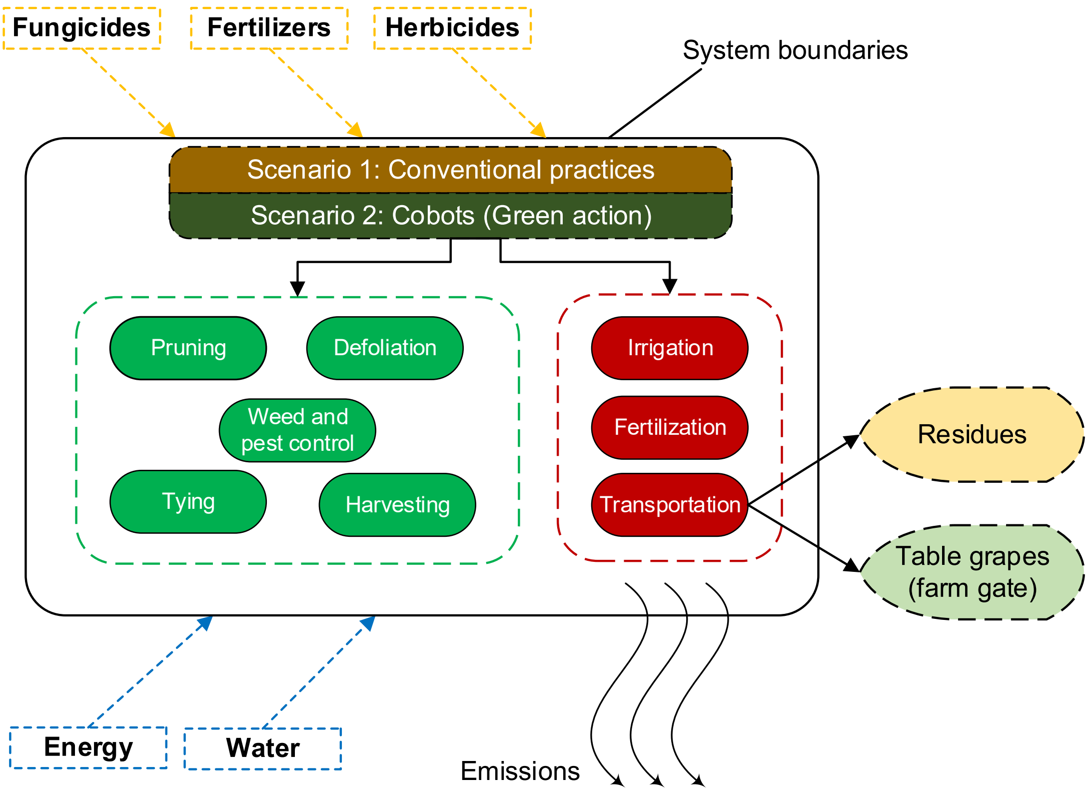

Figure 3. System boundaries.

A cradle-to-factory gate variation is selected since the study focuses on the on-field activities and the integration of robotic labor in the production phase, neglecting the planting and disposal phase. A 3-year framework is proposed as a minimum timeline for GHG accounting, as suggested by the International Organisation of Vine and Wine (OIV), to minimize uncertainty [63]. Therefore, data from 3 consecutive years were collected, and the functional unit was set to 1 ha of agricultural land in order to minimize deviations among grapevine varieties. Furthermore, it is a commonly used functional unit that is easily transmuted to 1 metric ton of table grapes produced on 1 ha if needed [34,64].

Transportation of all the inputs necessary for the table grapes' cultivation was set on trucks for a distance of 200 km. Biomass produced by the pruning and defoliation activities involved the transportation of grapes to a specified storage area in order to continue to the processing stage, while biomass residues were used again as fertilizers, as stated by the two firms. Therefore, four management cultivation schemes were thoroughly analyzed, comparing GHG emissions, performances, and labor substitutions by cobots toward sustainable wine growing grape cultivation.

The collected data for the environmental/energy assessment included fertilizers (kg/ha), fungicides (kg/ha), herbicides (kg/ha), machinery usage (h/ha), human labor (h/ha), electrical energy (kWh/ha), irrigation needs (m^3/ha), other inputs (kg/ha), diesel, and petrol (l/ha) per management cultivation scheme.

2.5. Inventory Analysis

Formulating an LCI is a crucial stage that involves the development of a directory for input and output flows for the relevant system [65]. Flows include inputs of agrochemicals, energy and raw materials, emissions, and primary energy consumption. The inventory is based on literature analysis, and all the relevant parameters for calculating GHGs and consumption of primary energy for grapes' cultivation are given in Table 2. Emissions from land use change are excluded, and the remarks are focused on the cultivation phase, since the major goal of the study is the assessment of conventional and cobot's labor. Data related to harvested yield, growing area, agrochemical application, number of pesticide applications, transportation of supplies, and biomass are equal for the respective cobot's scenarios. The robots have built-in LiFePO4 technology batteries inside their shell to meet their needs, namely, the movement in the field, the use of sensors, computing systems, and the powering of the telecommunication systems with the base station. If batteries reach a low energy state, the robot should reach the location of recharge in a protected area with a sufficient supply of energy, ideally within walking distance of the field of work.

Quality and consistency are considered major factors for the inventory analysis, especially in the primary sector and, hence, in sustainable agricultural production toward lower GHG emissions. The connection between LCA and agricultural production systems has grown stronger over the past years [66] and has generated a number of public and private inventories [67]. The reference system of the present study is based mainly on the BioGrace-II greenhouse gas (GHG) standard values [68] following European Directive 2018/2001 [69]. The Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) integrates the latest radiative efficiencies and metrics, meaning that global warming potential (GWP_{100}) in CO_2 equivalents has been calculated as follows: CO_2 = 1, CH_4 = 27.9, and N_2O = 273. The time horizon of 100 years was selected considering short-term and mid-term implications of agricultural production systems and wide application in relevant studies as well [6]. Lubricants, biomass, and supplies transportation are estimated as well, and more specifically, lubricants represent 0.7% of the consumed diesel fuel [70], while the assumption for the distance travelled in order to acquire the required materials (lubricants, fertilizers, pesticides, etc.) is set to 200 km. Furthermore, indirect emissions from nitrogen fertilization are considered as 1% of the N_2O direct emissions [71].

Table 2. Inventory for GHGs and primary energy consumption.

Inputs	Unit	Energy Content	GHG Unit	GHGs	Remarks
Agrochemicals					
N	MJ/kg	48.99	gCO_2eq/kg	4524.41	[68]
P	MJ/kg	15.23	gCO_2eq/kg	541.67	[68]
K	MJ/kg	9.68	gCO_2eq/kg	416.67	[68]
Olive pomace res	MJ/kg	20.75	gCO_2eq/kg	67.00	[72–74]
Poultry manure	MJ/kg	8.40	gCO_2eq/kg	148.62	[73,75,76]
Fungicides	MJ/kg	99.00	gCO_2eq/kg	3,900.00	[77,78]
Herbicides	MJ/kg	418.00	gCO_2eq/kg	9,100.00	[77,79]
Energy					
Lubricants	MJ/kg	53.28	gCO_2eq/kg	947.00	[68]
Diesel	MJ/kg	56.80	gCO_2eq/MJ	95.10	[68,80]
Petrol	MJ/kg	60.20	gCO_2eq/MJ	93.30	[68,80]
Electricity	MJ/MJ	2.73	gCO_2eq/MJ	243.49	[68]
Operations, maintenance, and manufacturing					
Tractor	MJ/h	16.42	gCO_2eq/h	9800	[81,82]
Human	MJ/h	1.80	gCO_2eq	-	[81]
Machinery	MJ/h	0.10–35.05	gCO_2eq/h	0.10–190	[73,83,84]
RB-EKEN	MJ/h	2.59	gCO_2eq	-	-
RB-VOGUI	MJ/h	0.65	gCO_2eq	-	-
Irrigation system	MJ/ha	373.7	gCO_2eq	-	[85]
Use of diesel	MJ	-	gCO_2eq/MJ	0.9	[68]
Transportation					
Supplies	MJ/t.km	0.87	$gCO_2eq/t.km$	71	[68,86]
Biomass	MJ/t.km	0.81	$gCO_2eq/t.km$	71	[68,86]

2.6. Carbon Footprint and Energy Consumption Impact Assessment

Differences among conventional and cobot practices were assessed in terms of GHG emissions following the approach of "emission factors" [87]. Although this approach has been criticized for deficiency of field measurements and background datasets, comparing similar systems and quantifying GHG fluxes as a function of farming activity could illustrate trade-offs among them. The formulation of one unified indicator converting climate pollutants into CO_2 equivalents is based on two factors, namely, the conversion factor and the respective quantity of each pollutant, as follows [88]:

$$CF_i = \sum_{n=1}^{i} EM_{i,j} \times GWP_{100} \tag{1}$$

where CF_i is the carbon footprint in CO_2 equivalents for each scenario i, $EM_{j,i}$ is the emissions of each pollutant j related to each scenario i, and GWP_{100} is the global warming potential conversion factor of each pollutant for a specified time horizon (100 years). Furthermore, the calculation of consumed energy for each scenario is based on the multiplication of a primary energy factor with the quantity of energy consumed per functional unit, which is based on the following equation:

$$EC_i = \sum_{n=1}^{i} PE_{i,j} \times PEF_j \tag{2}$$

where EC_i is the consumed energy for each scenario i, $PE_{j,i}$ is the primary energy of each action j related to each scenario i, and PEF_j is the primary energy factor of each input to the system. The parameters considered for calculating energy and environmental impacts include the agricultural practices as described in the goal and scope definition section. Furthermore, energy used to produce every piece of machinery, including mining, manufacture, and transport, is calculated according to embodied energy (*EI*) equation [83]:

$$EI = \sum \frac{w_i \times ec_i}{Li_i} \times Hop_i \quad (3)$$

where w_i represents the machinery's weight in kilograms, *ec* is the respective energy coefficient, Li_i is the total hours of each machinery's lifetime in hours, and Hop_i is the hours of agricultural operations for the on-field cultivation practices. Consequently, indirect impacts from the machinery used in the agricultural operations are calculated.

2.7. Energy Efficiency and Emission Intensity of the Investigated System

Energy efficiency is of the utmost importance in agriculture, as the primary sector is vulnerable to energy cost fluctuations, and the depiction of energy consumption per production unit could elicit important conclusions for farm management strategies [89]. Nevertheless, the concept of energy efficiency is considered a ratio between a sum of outputs (energy or not) per sum of energy inputs of a process as well [90]. Whichever energy efficiency indicator is chosen, the energy content of all the relevant inputs should be determined following a robust protocol. The EU highlights the importance of a life cycle approach in order to cover gaps toward energy efficiency [91]. As a result, the energy efficiency (EF_i) of the relevant scenarios is calculated as follows:

$$EF_{i,j} = \frac{EN_i}{CY_j} \quad (4)$$

where *EN* is the consumed energy per scenario *i* in MJ, and *CY* is the crop yield for each cultivar *j* in kg. A similar indicator presenting the efficiency of new technologies and their impact on the reduction of emissions and costs is GHG emission intensity [92]. Emission intensity is a parameter that represents the impact of innovative technologies on agricultural production and their respective effect on climate change. Emission intensity is calculated by the amount of CO_2 equivalents emitted in kg per produce in kg, which could be used for a broader spectrum of production systems [93]. Nevertheless, for the selected vineyards, the GHG emission intensity indicator (EI_i) is measured as follows:

$$EI_{i,j} = \frac{GHG\ emissions_i}{CY_j} \quad (5)$$

Calculations for data analysis and illustrations presented in the Results section were elaborated via RStudio 2022.07.1+554 [94].

3. Results

In the context of our study, the calculation of GHG emissions for each scenario was carried out based on the inventory and the provided data from the wineries. The two firms integrate different management strategies for the selected vineyards in relation to the amount and type of applied agrochemicals, hours of labor, and energy consumption. A brief description of the management schemes per hectare for the four cultivars is presented in Table 3.

Table 3. Management scheme for the selected vineyards.

Inputs	Unit	Asyrtiko	Tempranillo	Cabernet Sauvignon	Merlot
Acreage	ha	2.9	2.2	2.4	1.9
Crop yield	t/ha	9.63	8.02	5.32	5.05
Irrigation (energy)	MJ/ha	884.52	884.52	442.26	442.26
Borehole depth	m	180	180	90	90
N-based fertilizers	kg/ha	33	3	15	10.5
P-based fertilizers	kg/ha	3	3	15	10.5
K-based fertilizers	kg/ha	3	3	21.5	14.88
Poultry manure	kg/ha	-	-	244	940
Olive pomace res	kg/ha	-	-	1100	-
Fungicides	kg/ha	25	25	15.44	8
Herbicides	kg/ha	-	-	-	3.5
Diesel	lt/ha	255	238	111.8	142
Petrol	lt/ha	40	40	20	20
Residues	t/ha	4.2	3.9	1.5	1.5
Human labor	h/ha	447.5	450	308.66	401.25
Tractor	h/ha	32.5	30	23.7	32.75

Factors that significantly alter the GHG totals, expressed in CO_2 equivalents, are classified in separate categories, indicating critical hotspots of each management system. In this context, five subcategories are created: (i) agrochemicals (fertilizers, fungicides, and herbicides, (ii) electrical energy, (iii) fossil fuels (petrol and diesel), (iv) machinery (direct and indirect), and (v) other (transportation of inputs, indirect N_2O, lubricants, etc.). Electrical energy is a discrete category since the cobots are powered by rechargeable batteries, thus lowering the usage of human and agricultural machinery labor.

All agricultural activities, such as pruning, tying, and harvesting, are connected to an assortment of impacts and energy consumption, alternating the total needs of energy and emissions per management scheme. The abbreviations of the scenarios use the first letter of the respective cultivar (e.g., for Asyrtiko, it is A), followed by the letter C if the operations are performed conventionally or CB if the operations are performed by cobots (e.g., AC for conventional practices and ACB for cobot simulation for the Asyrtiko cultivar). All the relevant scenarios integrating cobots illustrate lower energy consumption in comparison with their respective conventional scenarios. In Figure 4, a dual Y-axis bar chart is presented, depicting the consumed energy in MJ ha^{-1} and the total GHG emissions in kg CO_2-eq ha^{-1} for each scenario. Verifying the abovementioned, all the scenarios integrating cobots (namely, ACB, CCB, MCB, and TCB) are less energy demanding in comparison with their corresponding conventional scenarios(AC, CC, MC, and TC, respectively). On the one hand, regarding only the conventional scenarios, AC consumes the highest amount of energy (27,281.79 MJ ha^{-1}), while MC is the least energy intensive scenario (25,014.93 MJ ha^{-1}). Nevertheless, agricultural activities adopted in CC and TC systems do not deviate significantly from the lowest energy consumption scenario (+2.51% and +2.53%, respectively).

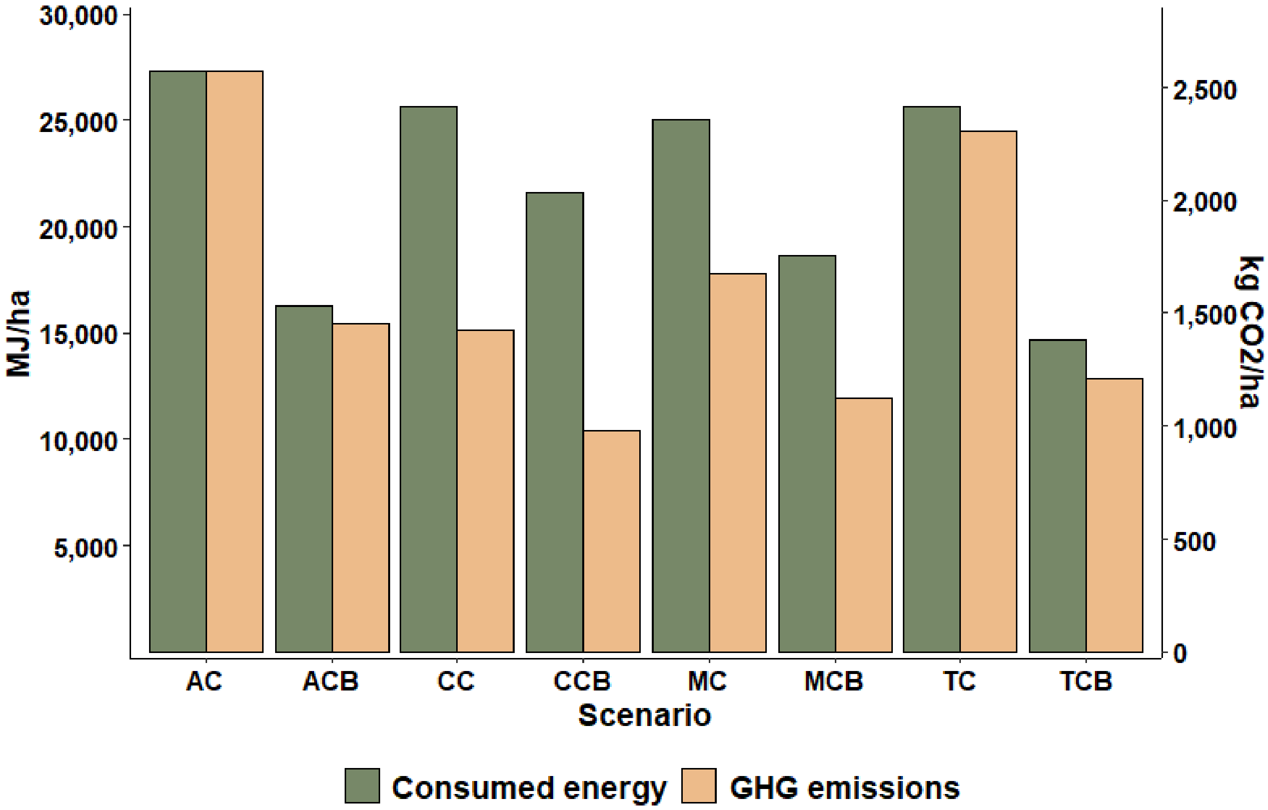

Figure 4. GHG emissions and consumed energy per hectare for each scenario.

On the other hand, TCB is the least energy-demanding system with 14,703.07 MJ ha^{-1}, followed by ACB with 16,304.33 MJ ha^{-1}, illustrating the potential positive impact of cobots in vine-growing systems. Regarding GHG emissions, scenarios under conventional practices form two groups, one group exceeding the threshold of 2,000 kg CO_2eq ha^{-1} and the other one below this threshold (Table 4). More specifically, CC and MC emit lower levels of GHGs with 1,428.75 and 1,678.68 kg CO_2eq ha^{-1}, respectively, while the results for AC and TC are 2,570.57 and 2,308.90 kg CO_2eq ha^{-1}, respectively. Cobots performing agricultural activities could lower the carbon footprint of agriculture, since the results show GHG emissions under 1,500 kg CO_2eq ha^{-1} for all the relevant scenarios. More specifically, CCB accounts for only 980.16 kg CO_2eq ha^{-1}, which is the lowest value, while ACB emits 1,465.57 kg CO_2eq ha^{-1}, which is the highest value among the cobots' scenarios.

Table 4. Analytical presentations of GHG emissions and consumed energy per hectare.

Scenario	Unit	AC	ACB	CC	CCB	MC	MCB	TC	TCB
Consumed energy	MJ ha^{-1}	27,281.80	16,304.33	25,643.95	21,642.95	25,014.93	18,633.65	25,648.47	14,703.07
GHG emissions	kg CO_2-eq ha^{-1}	2570.57	1456.57	1428.74	980.16	1678.68	1125.43	2308.90	1210.23

The differences among the four cultivars are due to the different management practices implemented by the two wineries. In fact, the main difference is the fossil fuel consumption, which is higher for the Asyrtiko and Tempranillo cultivars, since the agricultural activities are performed by the same winery (Figure 4).

Indeed, conventional agricultural practices highlight significant environmental impacts due to fossil fuel consumption ranging from 50.13% for CC to 69.39% for TC, as shown in Figure 5. The substitution of conventional with cobot's labor reduces the share of fossil fuels for the cobot's scenarios, especially for the Merlot management scheme in which the percentage is cut in half (MC—52.38% and MCB—26.64%) (Table 5). Conventional labor techniques consume more fossil fuels due to machinery usage (e.g., tractor) for some viticultural operations, whereas cobots consume only electrical energy much more efficiently.

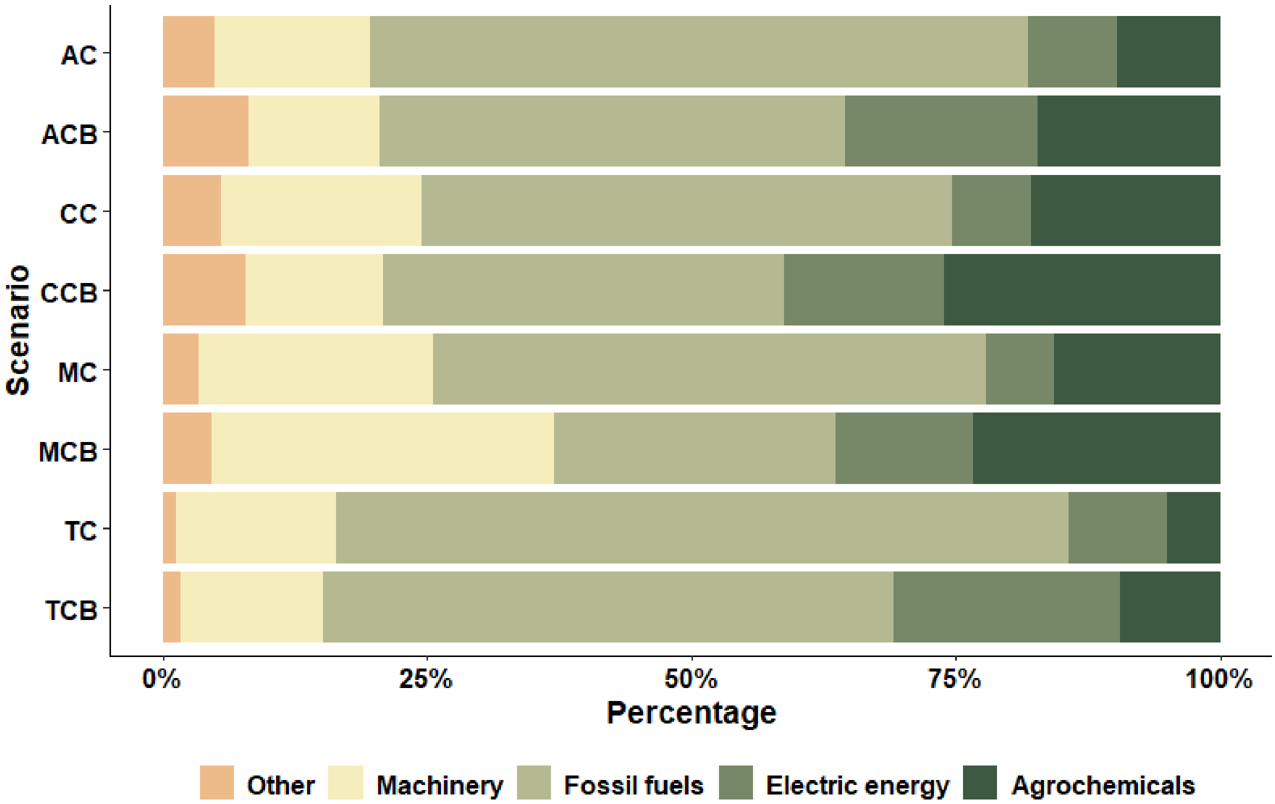

Figure 5. Stacked bars comparing the shares of GHG emissions.

Table 5. Shares of GHG emissions per scenario.

Scenario	Agrochemicals	Electric Energy	Fossil Fuels	Machinery	Other
AC	9.71%	8.38%	62.32%	14.60%	4.98%
ACB	17.14%	18.21%	44.13%	12.35%	8.18%
CC	17.85%	7.54%	50.13%	18.87%	5.62%
CCB	26.02%	15.17%	37.97%	12.94%	7.90%
MC	15.62%	6.41%	52.38%	22.15%	3.43%
MCB	23.29%	13.02%	26.64%	32.44%	4.61%
TC	4.94%	9.33%	69.39%	15.05%	1.29%
TCB	9.42%	21.38%	54.01%	13.46%	1.74%

Although the replacement of conventional labor by robots increases the share of impacts due to the constant need for charging the batteries of the cobots. Electrical energy accounts for lower GHG emissions since the cobots' energy consumption is low, though the share of electrical energy emissions for TCB and ACB is quite significant (21.38% and 18.21%, respectively). On the other hand, the "Other" category, integrating transportation of inputs, indirect N_2O, and lubricants illustrate minimum impact on the environment with percentages below 10% for each scenario.

Consumed energy is yet another aspect creating an uneven situation and complicating the decision making between efficiency and environmental protection. The impact of each category, as a share for each scenario, is depicted in Figure 6. As a matter of fact, agrochemicals are of the upmost importance especially for the Cabernet Sauvignon and the

Merlot cultivars, presenting a range of percentages between 43.85% for MC and 64.63% for CCB (Table 6). Nevertheless, the impact of fossil fuels is approximately the same for AC and TC in comparison with the shares of GHG emissions (61.92% and 65.86%, respectively). Regarding the electric energy consumed, the major difference apparently hinges on the usage of cobots, which is responsible for the high shares of the respective impact category in the relevant scenarios. Following the same pattern with Figure 5, Machinery and Other categories illustrate a very low energy impact, under 15%.

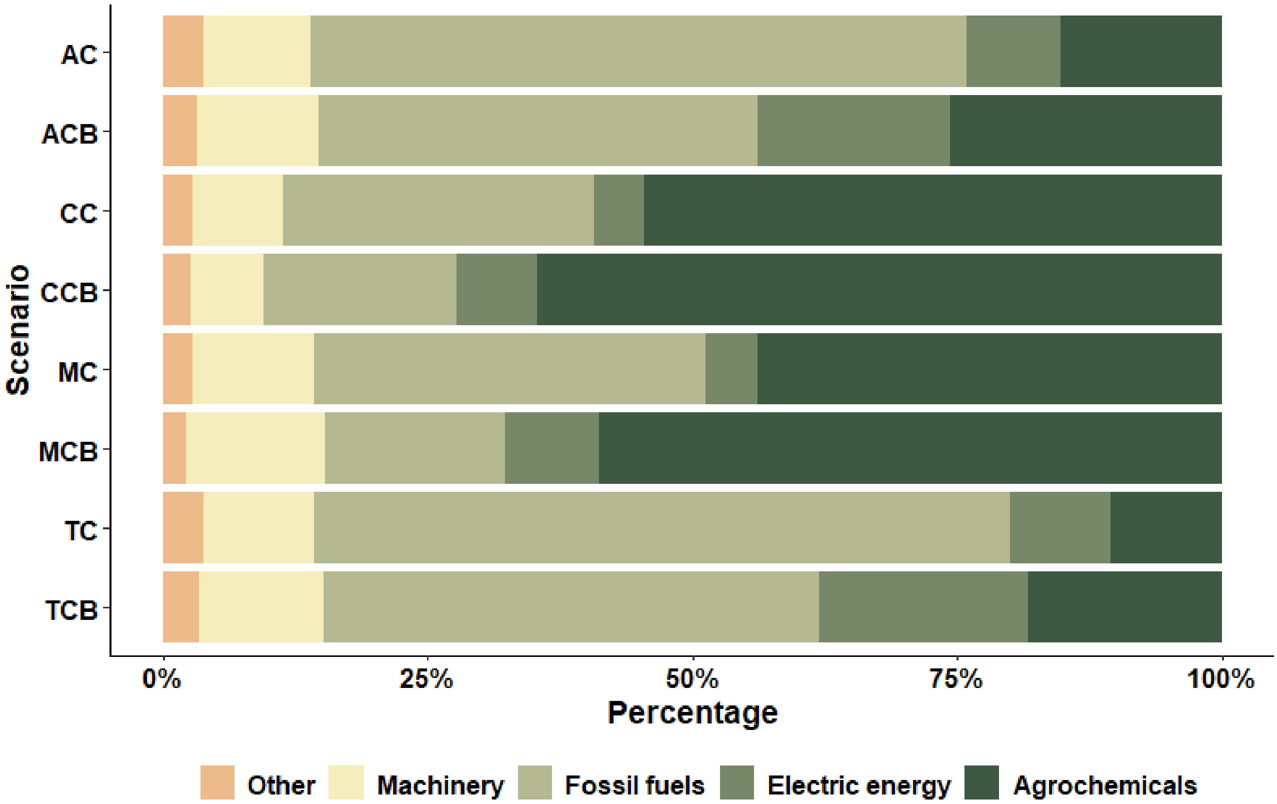

Figure 6. Stacked bars comparing the shares of consumed energy.

Table 6. Shares of consumed energy per scenario.

Scenario	Agrochemicals	Electric Energy	Fossil Fuels	Machinery	Other
AC	15.27%	8.85%	61.92%	10.14%	3.82%
ACB	25.55%	18.24%	41.46%	11.48%	3.28%
CC	54.54%	4.71%	29.46%	8.43%	2.86%
CCB	64.63%	7.70%	18.08%	6.94%	2.65%
MC	43.85%	4.83%	37.06%	11.40%	2.86%
MCB	58.87%	8.82%	16.92%	13.28%	2.11%
TC	10.51%	9.41%	65.86%	10.34%	3.87%
TCB	18.34%	19.73%	46.74%	11.83%	3.36%

The results of the research indicate that agricultural activities performed by cobots alter the total GHG and energy consumption pattern, reducing the impact of fossil fuels. Nevertheless, the impact of agrochemicals and electric energy differentiate the critical points between the conventional and the cobot's scenarios. Especially in the ACB and TCB scenarios, the proportion of electric energy consumed has increased by over 10% in comparison with conventional scenarios.

The estimation of energy efficiency and GHG emissions per kg of production could illustrate the real potential of cobots in agriculture. In particular, Table 7 depicts deviations between the selected vine-growing systems, indicating the positive impact of cobots regarding energy consumption, as well as GHG emissions. More specifically, the CO_2 eq per kg of produce indicator could approach a value of 0.151 kg CO_2-eq kg^{-1}, achieving 47.58% less emissions to the environment. Deviations for the Asyrtiko, Merlot, and Cabernet Sauvignon cultivars are −43.34%, −32.96%, and −31.40%, respectively. Furthermore, deviations in energy efficiency are effective to a higher degree for the Asyrtiko and Tempranillo cultivars (−40.24% and −42.67%, respectively) and to a lesser degree for the Merlot and Cabernet Sauvignon cultivars (−25.51% and −15.60%, respectively).

Table 7. Energy efficiency and GHG emission intensity per vine-growing scenario.

Scenario	kg CO_2 eq kg^{-1}	Deviation (%)	MJ kg^{-1}	Deviation (%)
AC ACB	0.267 0.151	−43.34%	2.833 1.693	−40.24%
CC CCB	0.269 0.184	−31.40%	4.820 4.068	−15.60%
MC MCB	0.332 0.223	−32.96%	4.953 3.690	−25.51%
TC TCB	0.288 0.151	−47.58%	3.198 1.833	−42.67%

In comparison with the Asyrtiko and Tempranillo cultivars, Merlot and Cabernet Sauvignon present minor discrepancies (especially for energy efficiency). The latter is explained by the more intensive usage of agrochemicals and particularly by the poultry manure and olive pomace residue application. As depicted in Figure 6, the shares of agrochemicals for the two cultivars have a significant impact on the total mixture of energy needed; thus the cobot scenarios could not alter the efficiency aspect to the same degree as in the Asyrtiko and Tempranillo scenarios. The same pattern applies for the GHG emission per kg of produce for the cobot scenarios, although the impact is more meaningful in comparison with energy efficiency.

4. Discussion

The integration of cobots performing viticultural tasks on the field is not an energy and environmentally impact-free step toward agricultural sustainability. An LCA approach has been implemented to investigate the environmental and energy impact of various real-life and simulated agricultural management scenarios. Furthermore, energy efficiency and GHG emission intensity indicators have been calculated as well to highlight deviations between conventional practices and the cobot's integration to the agricultural practices. Vineyard planting and disposal stages were neglected in order to focus on the impacts of annual production and the respective pros and cons of cobots, which could substitute conventional viticultural practices. Merlot and Cabernet Sauvignon scenarios during the production phase are heavily affected by the amount and nature of specific inputs (e.g., poultry manure and olive pomace residues), which usually cause considerable impacts on the environment [95].

The Merlot and Cabernet Sauvignon cultivars illustrate a better environmental profile in absolute terms than the Asyrtiko and Tempranillo cultivars, though these latter had higher yields, better energy efficiency, and GHG emissions intensity. The results for MJ per hectare fall into the range of Steenwerth et al. [96] with average values of 20,000 MJ. Human-induced emissions mainly due to soil management and diesel consumption accounted for 0.26 kg CO_2-eq kg^{-1} per kg of grape yield in the south of Sardinia in Italy [97]. This value is quite similar to the respective emission intensity indicator for the conventional practices applied to the Asyrtiko, Cabernet Sauvignon, and Tempranillo cultivars of the current study. Nevertheless, Gierling and Blanke [98] presented higher GHG emissions per hectare, investigating the difference between steep and flat terrains of vineyards. Their findings for steeper terrains (2990 kg CO_2 ha^{-1}), in which human labor is preferred over mechanical labor, match to a certain degree with the findings of the GHG emission of AC and TC scenarios. In addition, Gierling and Blanke [98] highlight the relationship between lower emissions due to human labor in steep terrains, though lower productivity of human labor in comparison with mechanical labor along with scarcity of manual labor when needed, developing a paradox stalemate for sustainable viticulture.

In relation to fossil fuel production and consumption as the main source of GHG emissions in viticulture, the findings of the current study are consistent with other surveys [96–99], while this is the case as well for a table grape variety named Soultanina in Cyprus [100]. Moreover, Balafoutis et al. [41] reported field energy use as the main factor of GHG emissions for two different cultivars in Greece, while fertilizers are the second most important factor. Nevertheless, other studies present fertilizer production as the major contributor to the carbon footprint shares among management practices and more specifically the Xynisteri and Cabernet Sauvignon varieties in Cyprus [100]. Indeed, GHG emissions associated with annual production of multiple grape training systems in North Tajikistan have been linked to impacts mainly due to ammonium nitrate application [101]. Roselli et al. [34] reported agrochemicals as factors of significant environmental impact as well, especially regarding the cultivation phase, while the same perspective applies for Gazzula et al. [27].

Inventory parameters, estimation methods for impact assessment, and methodological options complicate the comparability of the results among LCA studies [32]. Extending the system boundaries of the cultivation phase in vineyards, by including cobots performing agricultural operations and substituting human and mechanical labor, is an innovative approach that should be assessed. Nonetheless, significant hotspots have been identified, which would not be taken into account otherwise, though there are few available cobot-related LCA studies focusing on autonomous weed mowing. Weeding management strategies were assessed by Pradel et al. [49], concluding to overall lower environmental impacts in comparison with conventional solutions. Autonomous lawn mowing has illustrated even better performance when the path planning is optimized [50].

However, the implementation of these technologies comes with maintenance costs, which can include regular check-ups, repairs, and replacement of parts. Despite the potential benefits, the high cost of purchasing and maintaining agricultural robots remains a major barrier to their widespread adoption [102]. The investment and annual costs of real-time kinematics Global Positioning Systems along with the small battery capacity of robots hinder the economic viability to a significant degree [103]. Autonomy is also a concern for agricultural robots. These machines are often required to operate in unstructured environments, which can make it difficult for them to navigate and perform complicated tasks [104]. Additionally, the use of robots in agriculture often requires them to work in close proximity to humans, animals, and other equipment, which can increase the risk of accidents and injuries, creating gray areas in autonomy regulations [105].

Furthermore, the use of robots in agriculture has the potential of significantly impacting the job market, both positively and negatively. On the one hand, the use of robots can lead to job losses as they automate tasks that were previously performed by human workers, creating key ethical debates [106]. On the other hand, the use of robots can also create new jobs as they increase productivity and efficiency, leading to growth in the agriculture industry [107]. Nevertheless, these new jobs could include positions in areas such as robot design, programming, maintenance, and data analysis. Software maintenance and updates are crucial for the proper functioning of robots in agriculture. A key aspect of software maintenance is troubleshooting and resolving any issues that arise, especially for robots in agriculture [108], thus meaning that the cost of software maintenance and updates can be another aspect of troubleshooting for farmers and other agricultural operators.

Nonetheless, the present study focuses on the environmental performance and energy consumption of an assortment of agricultural activities performed for the first time by cobots [109]; thus the concluding remarks focus on the key parameters never published before and on suggestions for future research.

5. Conclusions

This paper examined the energy consumption and GHG emissions of conventional and cobot agricultural practices of selected vineyards in Northern Greece. The methodological framework of LCA is implemented to identify main hotspots of four different cultivars and to highlight the most sustainable and environmentally friendly scenarios. The study implies that the use of cobots for several agricultural operations in vineyards emits lower GHG emissions than conventional practices performed by human and conventional mechanical labor. The reduction of GHG emissions is mainly due to the fossil fuel consumption, which is significantly decreased when the cobots are used. Furthermore, GHG emission intensity deviations between scenarios present a greater environmental impact, achieving reductions of kg CO_2 eq kg^{-1} of grapes from 31.40% to 47.58%. However, the implementation of cobots' labor in agriculture changes the potential energy and environmental shares of inputs used, which develops a new mixture of energy demand and GHG emissions. Specifically, all the cobot's scenarios demonstrate higher shares of impacts due to agrochemical application and machinery usage.

Although cobots decrease impacts in absolute terms, at the same time, a new mixture of energy needs and environmental impacts alternates the perspective of hotspots in viticultural systems. Therefore, the functionality of cobots should be further investigated, integrating an actual lifetime period for cobots, as well as all impacts connected to the manufacturing of electronic components, cables, and motors. Additionally, while cobots consume less energy than other agricultural machines (e.g., tractors), the results should be viewed with optimism as the study assumes ideal conditions (e.g., flat terrain, exposure to fungicides/climatic conditions, and a lack of data on cobot failures). Finally, the results were evaluated regarding the cultivation phase, neglecting on purpose the planting, training, and disposal phase; thus impacts regarding these phases could alter the magnitude of the total positive impacts of cobots.

Future research should integrate economic data to highlight the eco-efficiency management philosophy, mitigating simultaneously climate change and economic impacts. Furthermore, additional data for the whole lifecycle of vineyards could be integrated, including the planting, training, and disposal stages of viticultural operations performed by cobots, since the environmental impacts of batteries' production, use, and recycling/disposal could be significant [110].

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References

1. Porter, J.; Xie, L.; Challinor, A.; Cochrane, K.; Howden, M.; Iqbal, M.; Lobell, D.; Travasso, M. Food Security and Food Production Systems. In *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects*; Cambridge University Press: New York, NY, USA, 2014.
2. FAO. *Climate Change and Food Security: Risks and Responses*; FAO: Rome, Italy, 2015; ISBN 978-92-5-108998-9.
3. Jones, G.V.; White, M.A.; Cooper, O.R.; Storchmann, K. Climate Change and Global Wine Quality. *Clim. Change* **2005**, *73*, 319–343. [CrossRef]
4. Kurtural, S.K.; Gambetta, G.A. Global Warming and Wine Quality: Are We Close to the Tipping Point? *Oeno One* **2021**, *55*, 353–361. [CrossRef]
5. Duchêne, E.; Huard, F.; Dumas, V.; Schneider, C.; Merdinoglu, D. The Challenge of Adapting Grapevine Varieties to Climate Change. *Clim. Res.* **2010**, *41*, 193–204. [CrossRef]
6. Ferrara, C.; De Feo, G. Life Cycle Assessment Application to the Wine Sector: A Critical Review. *Sustainability* **2018**, *10*, 395. [CrossRef]
7. Eurostat Wine-Grower Holdings by Production. Total Area under Vines (in/Not yet in Production). Available online: https://ec.europa.eu/eurostat/databrowser/view/vit_t1/default/table?lang=en (accessed on 28 July 2022).
8. OIV. *World Wine Production Outlook—OIV First Estimates—31.10.2022*; OIV: Dijon, France, 2022.
9. ISO 14040 International Standard. *Environmental Management—Life Cycle Assessment—Principles and Framework*; International Organization for Standardization (ISO): Geneva. Switzerland, 2006.
10. *ISO 14044: Environmental Management—Life Cycle Assessment—Requirements and Guidelines*; International Organization for Standardization: Geneva, Switzerland, 2006.
11. European Commission—Joint Research Centre—Institute for Environment and Sustainability. International Reference Life Cycle Data System (ILCD) Handbook: Analysing of Existing Environmental Impact Assessment Methodologies for Use in Life Cycle Assessment. *European Commission* **2010**, 115. [CrossRef]
12. Finnveden, G.; Hauschild, M.Z.; Ekvall, T.; Guinée, J.; Heijungs, R.; Hellweg, S.; Koehler, A.; Pennington, D.; Suh, S. Recent Developments in Life Cycle Assessment. *J. Environ. Manag.* **2009**, *91*, 1–21. [CrossRef]
13. Matthews, H.S.; Hendrickson, C.T.; Weber, C.L. The Importance of Carbon Footprint Estimation Boundaries. *Environ. Sci. Technol.* **2008**, *42*, 5839–5842. [CrossRef]
14. Guinée, J.B.; Heijungs, R.; Van Der Voet, E. A Greenhouse Gas Indicator for Bioenergy: Some Theoretical Issues with Practical Implications. *Int. J. Life Cycle Assess.* **2009**, *14*, 328–339. [CrossRef]
15. Sheehan, J.J. Biofuels and the Conundrum of Sustainability. *Curr. Opin. Biotechnol.* **2009**, *20*, 318–324. [CrossRef]
16. Rebitzer, G.; Ekvall, T.; Frischknecht, R.; Hunkeler, D.; Norris, G.; Rydberg, T.; Schmidt, W.-P.; Suh, S.; Weidema, B.P.; Pennington, D.W. Life Cycle Assessment: Part 1: Framework, Goal and Scope Definition, Inventory Analysis, and Applications. *Environ. Int.* **2004**, *30*, 701–720. [CrossRef]
17. Jensen, A.; J., E.; Christiansen, K.; Hoffman, L.; Moller, B.T.; Schmidt, A. Life Cycle Assessment (LCA)—A Guide to Approaches. *Exp. Inf. Sources* **1998**.
18. Sala, S.; Reale, F.; Cristobal-Garcia, J.; Marelli, L.; Pant, R. *Life Cycle Assessment for the Impact Assessment of Policies*; Publications Office of the European Union: Luxemburg, 2016.
19. De Luca, A.I.; Iofrida, N.; Leskinen, P.; Stillitano, T.; Falcone, G.; Strano, A.; Gulisano, G. Life Cycle Tools Combined with Multi-Criteria and Participatory Methods for Agricultural Sustainability: Insights from a Systematic and Critical Review. *Sci. Total Environ.* **2017**, *595*, 352–370. [CrossRef] [PubMed]
20. Tziolas, E.; Bournaris, T.; Manos, B.; Nastis, S. *Life Cycle Assessment and Multi-Criteria Analysis in Agriculture: Synergies and Insights BT—Multicriteria Analysis in Agriculture: Current Trends and Recent Applications*; Berbel, J., Bournaris, T., Manos, B., Matsatsinis, N., Viaggi, D., Eds.; Springer International Publishing: Cham, Switzerland, 2018; pp. 289–321. ISBN 978-3-319-76929-5.
21. Guinée, J.B.; Heijungs, R.; Huppes, G.; Zamagni, A.; Masoni, P.; Buonamici, R.; Ekvall, T.; Rydberg, T. Life Cycle Assessment: Past, Present, and Future. *Environ. Sci. Technol.* **2011**, *45*, 90–96. [CrossRef] [PubMed]
22. Muralikrishna, I.V.; Manickam, V. Chapter Five—Life Cycle Assessment. In *Environmental Management*; Muralikrishna, I.V., Manickam, V., Eds.; Butterworth-Heinemann: Oxford, UK, 2017; ISBN 978-0-12-811989-1.
23. Canaj, K.; Morrone, D.; Roma, R.; Boari, F.; Cantore, V.; Todorovic, M. Reclaimedwater for Vineyard Irrigation in a Mediterranean Context: Life Cycle Environmental Impacts, Life Cycle Costs, and Eco-Efficiency. *Water* **2021**, *13*, 2242. [CrossRef]
24. Kalboussi, N.; Biard, Y.; Pradeleix, L.; Rapaport, A.; Sinfort, C.; Ait-mouheb, N. Life Cycle Assessment as Decision Support Tool for Water Reuse in Agriculture Irrigation. *Sci. Total Environ.* **2022**, *836*, 155486. [CrossRef]
25. Quinteiro, P.; Dias, A.C.; Pina, L.; Neto, B.; Ridoutt, B.G.; Arroja, L. Addressing the Freshwater Use of a Portuguese Wine ('vinho Verde') Using Different LCA Methods. *J. Clean. Prod.* **2014**, *68*, 46–55. [CrossRef]
26. Borsato, E.; Giubilato, E.; Zabeo, A.; Lamastra, L.; Criscione, P.; Tarolli, P.; Marinello, F.; Pizzol, L. Comparison of Water-Focused Life Cycle Assessment and Water Footprint Assessment: The Case of an Italian Wine. *Sci. Total Environ.* **2019**, *666*, 1220–1231. [CrossRef]
27. Gazulla, C.; Raugei, M.; Fullana-I-Palmer, P. Taking a Life Cycle Look at Crianza Wine Production in Spain: Where Are the Bottlenecks? *Int. J. Life Cycle Assess.* **2010**, *15*, 330–337. [CrossRef]

28. Vázquez-Rowe, I.; Villanueva-Rey, P.; Moreira, M.T.; Feijoo, G. Environmental Analysis of Ribeiro Wine from a Timeline Perspective: Harvest Year Matters When Reporting Environmental Impacts. *J. Environ. Manag.* **2012**, *98*, 73–83. [CrossRef]
29. Laca, A.; Gancedo, S.; Laca, A.; Díaz, M. Assessment of the Environmental Impacts Associated with Vineyards and Winemaking. A Case Study in Mountain Areas. *Environ. Sci. Pollut. Res.* **2021**, *28*, 1204–1223. [CrossRef]
30. Masotti, P.; Zattera, A.; Malagoli, M.; Bogoni, P. Environmental Impacts of Organic and Biodynamic Wine Produced in Northeast Italy. *Sustainability* **2022**, *14*, 6281. [CrossRef]
31. Chiriacò, M.V.; Belli, C.; Chiti, T.; Trotta, C.; Sabbatini, S. The Potential Carbon Neutrality of Sustainable Viticulture Showed through a Comprehensive Assessment of the Greenhouse Gas (GHG) Budget of Wine Production. *J. Clean. Prod.* **2019**, *225*, 435–450. [CrossRef]
32. Neto, B.; Dias, A.C.; Machado, M. Life Cycle Assessment of the Supply Chain of a Portuguese Wine: From Viticulture to Distribution. *Int. J. Life Cycle Assess.* **2013**, *18*, 590–602. [CrossRef]
33. Martins, A.A.; Araújo, A.R.; Graça, A.; Caetano, N.S.; Mata, T.M. Towards Sustainable Wine: Comparison of Two Portuguese Wines. *J. Clean. Prod.* **2018**, *183*, 662–676. [CrossRef]
34. Roselli, L.; Casieri, A.; de Gennaro, B.C.; Sardaro, R.; Russo, G. Environmental and Economic Sustainability of Table Grape Production in Italy. *Sustainability* **2020**, *12*, 3670. [CrossRef]
35. Falcone, G.; Strano, A.; Stillitano, T.; De Luca, A.I.; Iofrida, N.; Gulisano, G. Integrated Sustainability Appraisal of Wine-Growing Management Systems through LCA and LCC Methodologies. *Chem. Eng. Trans.* **2015**, *44*, 223–228. [CrossRef]
36. Falcone, G.; De Luca, A.I.; Stillitano, T.; Strano, A.; Romeo, G.; Gulisano, G. Assessment of Environmental and Economic Impacts of Vine-Growing Combining Life Cycle Assessment, Life Cycle Costing and Multicriterial Analysis. *Sustainability* **2016**, *8*, 793. [CrossRef]
37. Rouault, A.; Beauchet, S.; Renaud-Gentie, C.; Jourjon, F. Life Cycle Assessment of Viticultural Technical Management Routes (TMRs): Comparison between an Organic and an Integrated Management Route. *Journal International des Sciences de la Vigne et du Vin* **2016**, *50*. [CrossRef]
38. Tsangas, M.; Gavriel, I.; Doula, M.; Xeni, F.; Zorpas, A.A. Life Cycle Analysis in the Framework of Agricultural Strategic Development Planning in the Balkan Region. *Sustainability* **2020**, *12*, 1813. [CrossRef]
39. Dede, D.; Didaskalou, E.; Bersimis, S.; Georgakellos, D. A Statistical Framework for Assessing Environmental Performance of Quality Wine Production. *Sustainability* **2020**, *12*, 10246. [CrossRef]
40. Vantarakis, G.C.; Abeliotis, K.; Karathanos, V.T. Environmental Impact Assessment of Protected Designation of Origin (PDO) Foods: The Case of Vostizza Corinthian Currants in Greece. *Euro-Mediterr. J. Environ. Integr.* **2022**, *7*, 131–140. [CrossRef]
41. Balafoutis, A.T.; Koundouras, S.; Anastasiou, E.; Fountas, S.; Arvanitis, K. Life Cycle Assessment of Two Vineyards after the Application of Precision Viticulture Techniques: A Case Study. *Sustainability* **2017**, *9*, 997. [CrossRef]
42. Fountas, S.; Mylonas, N.; Malounas, I.; Rodias, E.; Santos, C.H.; Pekkeriet, E. Agricultural Robotics for Field Operations. *Sensors* **2020**, *20*, 2672. [CrossRef] [PubMed]
43. VINEROBOT Deliverable 2.3: First Field Demonstration. Basic Mobility and Navigation of the Robot. Available online: https://www.vinerobot.eu/wp-content/uploads/2015/12/Deliverable-2_3_First-demo-report.pdf (accessed on 15 January 2023).
44. Álvarez Fernández, S.; Prieto López, D.; Nistal Freije, V.; González Cueva, M.; Ribeiro, Á.; Bengochea, J.M.; Todeschini, M.; Andujar, D.; Valente, J.; Ariza Sentís, M.; et al. *D4.1 Pilot 1 Objectives, Requirements and Design*. 2021. Available online: https://flexigrobots-h2020.eu/sites/flexig/files/public/content-files/deliverables/FLEXIGROBOTS_D4.1.%20Pilot%201%20objectives%2C%20requirements%20and%20design_v1.0.pdf (accessed on 19 January 2023).
45. Thayer, T.C.; Vougioukas, S.; Goldberg, K.; Carpin, S. Multi-Robot Routing Algorithms for Robots Operating in Vineyards. In Proceedings of the IEEE International Conference on Automation Science and Engineering, Munich, Germany, 20–24 August 2018.
46. Thayer, T.C.; Vougioukas, S.; Goldberg, K.; Carpin, S. Bi-Objective Routing for Robotic Irrigation and Sampling in Vineyards. In Proceedings of the IEEE International Conference on Automation Science and Engineering, Vancouver, BC, Canada, 22–26 August 2019.
47. Lacotte, V.; NGuyen, T.; Sempere, J.D.; Novales, V.; Dufour, V.; Moreau, R.; Pham, M.T.; Rabenorosoa, K.; Peignier, S.; Feugier, F.G.; et al. Pesticide-Free Robotic Control of Aphids as Crop Pests. *AgriEngineering* **2022**, *4*, 903–921. [CrossRef]
48. Urdal, F.; Utstumo, T.; Vatne, J.K.; Ellingsen, S.A.A.; Gravdahl, J.T. Design and Control of Precision Drop-on-Demand Herbicide Application in Agricultural Robotics. In Proceedings of the 2014 13th International Conference on Control Automation Robotics and Vision, ICARCV, Singapore, 10–12 December 2014.
49. Pradel, M.; de Fays, M.; Séguineau, C. Comparative Life Cycle Assessment of Intra-Row and Inter-Rows Weeding Practices Using Autonomous Robot Systems in French Vineyards. *SSRN Electron. J.* **2022**, *838*, 156441. [CrossRef]
50. Saidani, M.; Pan, Z.; Kim, H.; Wattonville, J.; Greenlee, A.; Shannon, T.; Yannou, B.; Leroy, Y.; Cluzel, F. Comparative Life Cycle Assessment and Costing of an Autonomous Lawn Mowing System with Human-Operated Alternatives: Implication for Sustainable Design Improvements. *Int. J. Sustain. Eng.* **2021**, *14*, 704–724. [CrossRef]
51. Lagnelöv, O.; Larsson, G.; Larsolle, A.; Hansson, P.A. Life Cycle Assessment of Autonomous Electric Field Tractors in Swedish Agriculture. *Sustainability* **2021**, *13*, 11285. [CrossRef]
52. Lowenberg-DeBoer, J.; Huang, I.Y.; Grigoriadis, V.; Blackmore, S. Economics of Robots and Automation in Field Crop Production. *Precis. Agric.* **2020**, *21*, 278–299. [CrossRef]
53. Lytridis, C.; Kaburlasos, V.G.; Pachidis, T.; Manios, M.; Vrochidou, E.; Kalampokas, T.; Chatzistamatis, S. An Overview of Cooperative Robotics in Agriculture. *Agronomy* **2021**, *11*, 1818. [CrossRef]

54. Choset, H.; Lynch, M.K.; Hutchinson, S.; Kantor, A.G.; Burgard, W.; Kavraki, E.L.; Thrun, S. *Principles of Robot Motion Theory, Algorithms, and Implementations*; MIT Press: Cambridge, MA, USA, 2005; ISBN 9780262033275.
55. Delmerico, J.; Mueggler, E.; Nitsch, J.; Scaramuzza, D. Active Autonomous Aerial Exploration for Ground Robot Path Planning. *IEEE Robot. Autom. Lett.* **2017**, *2*, 664–671. [CrossRef]
56. Guzman, R.; Arino, J.; Navarro, R.; Lopes, C.; Graça, J.; Reyes, M.; Barriguinha, A.; Braga, R. *Autonomous Hybrid Gps/Reactive Navigation of an Unmanned Ground Vehicle for Precision Viticulture—VINBOT*; University of Lisbon: Lisbon, Portugal, 2016.
57. Duffy, B.; Joue, G. Intelligent Robots: The Question of Embodiment. In *Proceedings of BRAIN-MACHINE 2000 Workshop*; University College Dublin: Dublin, Ireland, 2000.
58. Kaburlasos, V.G.; Pachidis, T. A Lattice-Computing Ensemble for Reasoning Based on Formal Fusion of Disparate Data Types, and an Industrial Dispensing Application. *Inf. Fusion* **2014**, *16*, 68–83. [CrossRef]
59. Kaburlasos, V.G. Lattice Computing: A Mathematical Modelling Paradigm for Cyber-Physical System Applications. *Mathematics* **2022**, *10*, 271. [CrossRef]
60. Kaburlasos, V.G. The Lattice Computing (LC) Paradigm. In *CEUR Workshop Proceedings*; International Hellenic University: Kavala, Greece, 2020.
61. Robotnik RB-EKEN 5 Technical Specifications Datasheet. Available online: https://robotnik.eu/wp-content/uploads/2022/02/Robotnik-DATASHEET-RB-EKEN-5-EN-220209.pdf (accessed on 30 December 2022).
62. Robotnik RB-VOGUI MOBILE ROBOT Technical Specifications Datasheet. Available online: https://robotnik.eu/wp-content/uploads/2022/02/Robotnik-RB-VOGUIDatasheet-211212-EN.pdf (accessed on 30 December 2022).
63. Svinartchuk, T.; Hunziker, P.; Novello, V.; Tonni, M.; Corbet-Milward, J.; de la Fuente, M.; Costa, D. Methodological Recommendations for Accounting for GHG Balance in the Vitivinicultural Sector. Available online: https://www.oiv.int/public/medias/5519/methodological-ghg-balance.pdf (accessed on 8 December 2022).
64. Tziolas, E.; Ispikoudis, S.; Mantzanas, K.; Koutsoulis, D.; Pantera, A. Economic and Environmental Assessment of Olive Agroforestry Practices in Northern Greece. *Agriculture* **2022**, *12*, 851. [CrossRef]
65. Vaskan, P.; Pachón, E.R.; Gnansounou, E. Life Cycle Assessment of Sugar Crops and Starch-Based Integrated Biorefineries. In *Life-Cycle Assessment of Biorefineries*; Elsevier: Amsterdam, The Netherlands, 2017; ISBN 9780444635860.
66. Brentrup, F.; Küsters, J.; Kuhlmann, H.; Lammel, J. Environmental Impact Assessment of Agricultural Production Systems Using the Life Cycle Assessment Methodology: I. Theoretical Concept of a LCA Method Tailored to Crop Production. *Eur. J. Agron.* **2004**, *20*, 247–264. [CrossRef]
67. Corrado, S.; Castellani, V.; Zampori, L.; Sala, S. Systematic Analysis of Secondary Life Cycle Inventories When Modelling Agricultural Production: A Case Study for Arable Crops. *J. Clean. Prod.* **2018**, *172*, 3990–4000. [CrossRef] [PubMed]
68. *Biograce II Harmonised Greenhouse Gas Calculations for Electricity, Heating and Cooling from Biomass, Calculation Rules 4a*; Biograce: Delhi, India, 2021.
69. EC Directive (EU) 2018/2001 of the European Parliament and of the Council of 11 December 2018 on the Promotion of the Use of Energy from Renewable Sources. Official Journal of the European Union. 2018. Available online: https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=&cad=rja&uact=8&ved=2ahUKEwjqrtu1wfb8AhWDrVYBHT8qAFsQFnoECBgQAQ&url=https%3A%2F%2Feur-lex.europa.eu%2Flegal-content%2FEN%2FTXT%2FPDF%2F%3Furi%3DCELEX%3A32018L2001&usg=AOvVaw28E3vJb4j-I3mDMed04_C (accessed on 21 December 2018).
70. ASAE American Society of Agricultural and Biological Engineers. D497.7 MAR2011 Agricultural Machinery Management Data. *Test* **2011**, *9*.
71. Rozakis, S.; Haque, M.I.; Natsis, A.; Borzecka-Walker, M.; Mizak, K. Cost-Effectiveness of Bioethanol Policies to Reduce Carbon Dioxide Emissions in Greece. *Int. J. Life Cycle Assess.* **2013**, *18*, 306–318. [CrossRef]
72. Diacono, M.; Persiani, A.; Testani, E.; Montemurro, F.; Ciaccia, C. Recycling Agricultural Wastes and By-Products in Organic Farming: Biofertilizer Production, Yield Performance and Carbon Footprint Analysis. *Sustainability* **2019**, *11*, 3824. [CrossRef]
73. Taxidis, E.T.; Menexes, G.C.; Mamolos, A.P.; Tsatsarelis, C.A.; Anagnostopoulos, C.D.; Kalburtji, K.L. Comparing Organic and Conventional Olive Groves Relative to Energy Use and Greenhouse Gas Emissions Associated with the Cultivation of Two Varieties. *Appl. Energy* **2015**, *149*, 117–124. [CrossRef]
74. Genitsariotis, M.; Chlioumis, G.; Tsarouhas, B.; Tsatsarelis, K.; Sfakiotakis, E. Energy and Nutrient Inputs and Outputs of a Typical Olive Orchard in Northern Greece. *Acta Hortic.* **2000**, *525*, 455–458. [CrossRef]
75. White, R.; Taiganides, E. Pyrolysis of Livestock Manure, Livestock Manure Management. In *Proceedings of the 2nd International Symposium on Livestock Manure*; American Society of Agricultural Engineers: St. Joseph, MI, USA, 1971; pp. 190–191.
76. Zhu, Z.; Li, L.; Dong, H.; Wang, Y. Ammonia and Greenhouse Gas Emissions of Different Types of Livestock and Poultry Manure during Storage. *Trans. ASABE* **2020**, *63*, 1723–1733. [CrossRef]
77. Cech, R.; Leisch, F.; Zaller, J.G. Pesticide Use and Associated Greenhouse Gas Emissions in Sugar Beet, Apples, and Viticulture in Austria from 2000 to 2019. *Agriculture* **2022**, *12*, 879. [CrossRef]
78. Kaltsas, A.M.; Mamolos, A.P.; Tsatsarelis, C.A.; Nanos, G.D.; Kalburtji, K.L. Energy Budget in Organic and Conventional Olive Groves. *Agric. Ecosyst. Environ.* **2007**, *122*, 243–251. [CrossRef]
79. Kavargiris, S.E.; Mamolos, A.P.; Tsatsarelis, C.A.; Nikolaidou, A.E.; Kalburtji, K.L. Energy Resources' Utilization in Organic and Conventional Vineyards: Energy Flow, Greenhouse Gas Emissions and Biofuel Production. *Biomass Bioenergy* **2009**, *33*, 1239–1250. [CrossRef]

80. Havrysh, V.; Kalinichenko, A.; Brzozowska, A.; Stebila, J. Life Cycle Energy Consumption and Carbon Dioxide Emissions of Agricultural Residue Feedstock for Bioenergy. *Appl. Sci.* **2021**, *11*, 2009. [CrossRef]
81. Soni, P.; Sinha, R.; Perret, S.R. Energy Use and Efficiency in Selected Rice-Based Cropping Systems of the Middle-Indo Gangetic Plains in India. *Energy Rep.* **2018**, *4*, 554–564. [CrossRef]
82. Janulevičius, A.; Juostas, A.; Čipliene, A. Estimation of Carbon-Oxide Emissions of Tractors during Operation and Correlation with the Not-to-Exceed Zone. *Biosyst. Eng.* **2016**, *147*, 117–129. [CrossRef]
83. Sørensen, C.G.; Halberg, N.; Oudshoorn, F.W.; Petersen, B.M.; Dalgaard, R. Energy Inputs and GHG Emissions of Tillage Systems. *Biosyst. Eng.* **2014**, *120*, 2–14. [CrossRef]
84. Mantoam, E.J.; Romanelli, T.L.; Gimenez, L.M. Energy Demand and Greenhouse Gases Emissions in the Life Cycle of Tractors. *Biosyst. Eng.* **2016**, *151*, 158–170. [CrossRef]
85. Gemtos, T.A.; Cavalaris, C.; Karamoutis, C.; Tagarakis, A.; Fountas, S. Energy Analysis of Three Energy Crops in Greece. *Agric. Eng. Int. CIGR J.* **2013**, *15*, 52–66.
86. Smart Freight Centre. *Cefic Calculating GHG Transport and Logistics Emissions for the European Chemical Industry*; Smart Freight Center: Amsterdam, The Netherlands, 2021.
87. World Resources Institute GHG Protocol Agricultural Guidance Interpreting the Corporate Accounting and Reporting Standard for the Agricultural Sector. Available online: https://ghgprotocol.org/sites/default/files/standards/GHG%20Protocol%20Agricultural%20Guidance%20%28April%2026%29_0.pdf (accessed on 15 August 2022).
88. Lynch, J.; Cain, M.; Pierrehumbert, R.; Allen, M. Demonstrating GWP: A Means of Reporting Warming-Equivalent Emissions That Captures the Contrasting Impacts of Short—A Nd Long-Lived Climate Pollutants. *Environ. Res. Lett.* **2020**, *15*, 044023. [CrossRef] [PubMed]
89. Blancard, S.; Martin, E. Energy Efficiency Measurement in Agriculture with Imprecise Energy Content Information. *Energy Policy* **2014**, *66*, 198–208. [CrossRef]
90. Patterson, M.G. What Is Energy Efficiency? Concepts, Indicators and Methodological Issues. *Energy Policy* **1996**, *24*, 377–390. [CrossRef]
91. Mahmoud, M.; Cheikh, N.; Cerny, O.; Gerard, F.; Lemoin, P. The Road to Energy Efficiency. Available online: https://www.europarl.europa.eu/RegData/etudes/STUD/2021/695480/IPOL_STU(2021)695480_EN.pdf (accessed on 15 August 2022).
92. Laborde, D.; Mamun, A.; Martin, W.; Piñeiro, V.; Vos, R. Agricultural Subsidies and Global Greenhouse Gas Emissions. *Nat. Commun.* **2021**, *12*, 1–9. [CrossRef] [PubMed]
93. Mrówczyńska-Kamińska, A.; Bajan, B.; Pawłowski, K.P.; Genstwa, N.; Zmyślona, J. Greenhouse Gas Emissions Intensity of Food Production Systems and Its Determinants. *PLoS ONE* **2021**, *16*, e0250995. [CrossRef]
94. RStudio Team RStudio: Integrated Development Environment for R 2020. Available online: https://www.r-project.org/conferences/useR-2011/abstracts/180111-allairejj.pdf (accessed on 15 August 2022).
95. Petti, L.; Arzoumanidis, I.; Benedetto, G.; Bosco, S.; Cellura, M.; De Camillis, C.; Fantin, V.; Masotti, P.; Pattara, C.; Raggi, A.; et al. Life Cycle Assessment in the Wine Sector. In *Life Cycle Assessment in the Agri-food Sector*; Springer: Berlin/Heidelberg, Germany, 2015.
96. Steenwerth, K.L.; Strong, E.B.; Greenhut, R.F.; Williams, L.; Kendall, A. Life Cycle Greenhouse Gas, Energy, and Water Assessment of Wine Grape Production in California. *Int. J. Life Cycle Assess.* **2015**, *20*, 1243–1253. [CrossRef]
97. Marras, S.; Masia, S.; Duce, P.; Spano, D.; Sirca, C. Carbon Footprint Assessment on a Mature Vineyard. *Agric. For. Meteorol.* **2015**, *214–215*, 350–356. [CrossRef]
98. Gierling, F.; Blanke, M. Lower Carbon Footprint from Grapevine Cultivation on Steep Slopes Compared with Flat Terrain? A Case Study. *Acta Hortic.* **2021**, *1327*, 703–706. [CrossRef]
99. Villanueva-Rey, P.; Vázquez-Rowe, I.; Moreira, M.T.; Feijoo, G. Comparative Life Cycle Assessment in the Wine Sector: Biodynamic vs. Conventional Viticulture Activities in NW Spain. *J. Clean. Prod.* **2014**, *65*, 330–341. [CrossRef]
100. Litskas, V.D.; Irakleous, T.; Tzortzakis, N.; Stavrinides, M.C. Determining the Carbon Footprint of Indigenous and Introduced Grape Varieties through Life Cycle Assessment Using the Island of Cyprus as a Case Study. *J. Clean. Prod.* **2017**, *156*, 418–425. [CrossRef]
101. Rashidov, N.; Chowaniak, M.; Niemiec, M.; Mamurovich, G.S.; Gufronovich, M.J.; Gródek-Szostak, Z.; Szeląg-Sikora, A.; Sikora, J.; Kuboń, M.; Komorowska, M. Assessment of the Multiannual Impact of the Grape Training System on GHG Emissions in North Tajikistan. *Energies* **2021**, *14*, 6160. [CrossRef]
102. Pedersen, S.M.; Fountas, S.; Blackmore, S. Agricultural Robots—Applications and Economic Perspectives. In *Service Robot Applications*; InTech: Houston, TX, USA, 2008; p. 16.
103. Pedersen, S.M.; Fountas, S.; Have, H.; Blackmore, B.S. Agricultural Robots—System Analysis and Economic Feasibility. *Precis. Agric.* **2006**, *7*, 295–308. [CrossRef]
104. Romero Schmidt, J.; Auat Cheein, F. Assessment of Power Consumption of Electric Machinery in Agricultural Tasks for Enhancing the Route Planning Problem. *Comput. Electron. Agric.* **2019**, *163*, 104868. [CrossRef]
105. Gil, G.; Casagrande, D.E.; Cortés, L.P.; Verschae, R. Why the Low Adoption of Robotics in the Farms? Challenges for the Establishment of Commercial Agricultural Robots. *Smart Agric. Technol.* **2023**, *3*, 100069. [CrossRef]
106. Ryan, M.; van der Burg, S.; Bogaardt, M.-J. Identifying Key Ethical Debates for Autonomous Robots in Agri-Food: A Research Agenda. *AI Ethics* **2022**, *2*, 493–507. [CrossRef]
107. FAO. *Brief to The State of Food and Agriculture 2022*; FAO: Rome, Italy, 2022; ISBN 978-92-5-137005-6.

108. Vrochidou, E.; Pachidis, T.; Manios, M.; Papakostas, G.A.; Kaburlasos, V.G.; Theocharis, S.; Koundouras, S.; Karabatea, K.; Bouloumpasi, E.; Pavlidis, S.; et al. Identifying the Technological Needs for Developing a Grapes Harvesting Robot: Operations and Systems. In *CEUR Workshop Proceedings*; International Hellenic University: Kavala, Greece, 2020.
109. Vrochidou, E.; Bazinas, C.; Mavridou, E.; Pachidis, T.; Mamalis, S.; Koundouras, S.; Gkrimpizis, T.; Kaburlasos, V.G. Considerations for a Multi-Purpose Agrobot Design toward Automating Skillful Viticultural Tasks: A Study in Northern Greece Vineyards. In Proceedings of the 10th International Conference on Information and Communication Technologies in Agriculture, Food & Environment (HAICTA 2022), Athens, Greece, 22–25 September 2022; p. 7.
110. Notter, D.A.; Gauch, M.; Widmer, R.; Wäger, P.; Stamp, A.; Zah, R.; Althaus, H.J. Contribution of Li-Ion Batteries to the Environmental Impact of Electric Vehicles. *Environ. Sci. Technol.* **2010**, *44*, 6550–6556. [CrossRef]