Ecological Economics 220 (2024) 108178

Contents lists available at ScienceDirect

Ecological Economics

journal homepage: www.elsevier.com/locate/ecolecon

Conversion to organic farming: Does it change the economic and environmental performance of fruit farms?

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ARTICLE INFO

Keywords:
Farm performance
Composite indicators
Propensity score matching
Spain

ABSTRACT

This paper compares the performance of conventional and organic fruit farms in Spain, using a set of base indicators to assess their economic and environmental performance on a per hectare basis. Composite indicators are also calculated to measure the overall economic and environmental performance of both production systems. Comparisons are made using propensity score matching to minimize the non-randomization biases caused by structural differences between the samples of conventional (n = 552) and organic (n = 127) fruit farms sourced from the Spanish Farm Accountancy Data Network (RECAN). The results based on per hectare metrics point to modest changes in the performance of farms that converted to organic farming. This is mainly because most converted farms were former conventional farms characterized by lower profitability and less intensive input use, consequently minimizing the effects of the conversion process. Nevertheless, the conversion outcomes exhibit a degree of variability depending on the specific type of fruit production. Economic gains are only discernible in the case of nut farms, whereas fruit and tropical fruit farms tend to yield the most favorable results per hectare from an environmental perspective.

1. Introduction

Business-as-usual practices implemented to increase productivity in the agricultural sector make a major contribution to the negative environmental impacts of farming on biodiversity, soil, and water resources worldwide (FAO (Food and Agriculture Organization of the United Nations), 2022). In response to the social concerns about these negative externalities generated by "conventional" agriculture, governments have promoted more eco-friendly alternative production regimes. Of these, organic farming stands out as the most popular (European Commission, 2023).

At the international level, the European Union (EU) is leading the charge on efforts to mitigate the negative environmental impacts of agriculture, fostering the development of more sustainable and resilient agricultural systems. For this purpose, as part of the European Green Deal, the EU approved two policy strategies: the Farm to Fork Strategy and the Biodiversity Strategy. Among other specific objectives to be achieved by 2030, these strategies establish the target of at least 25% of agricultural land in the EU managed under organic farming. Considering that the latest official statistics from Eurostat show that in 2021 only 9.9% of the EU utilized agricultural area (UAA) was under organic farming, meeting this objective will require the proactive involvement of policymakers to promote this agroecological production system.

Compared to conventional agriculture, organic farming relies on more extensive resource use, which offers several benefits from an environmental perspective. However, from an economic perspective, the reduced use of inputs usually results in lower yields (Meemken and Qaim, 2018). This is the reason why the new environmental objectives established for European agriculture have been criticized for lacking a necessary ex-ante impact assessment (e.g., Guyomard et al., 2020; Mérel et al., 2023), especially considering the potential high trade-offs between the environmental benefits to be achieved and the economic performance of the agricultural sector.

Previous studies have used meta-analyses to examine the environmental and economic performance of organic farming (e.g., Tuomisto et al., 2012; Reganold and Wachter, 2016; Clark and Tilman, 2017; Seufert and Ramankutty, 2017; Rosa-Schleich et al., 2019). The existing literature agrees that organic farming has a better environmental performance than conventional production systems when performance is expressed on a per hectare basis. Similarly, there is a broad consensus that conversion to organic farming leads to short-term yield decline. However, accounting for its lower yields, the environmental

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https://doi.org/10.1016/j.ecolecon.2024.108178
Received 4 September 2023; Received in revised form 8 March 2024; Accepted 11 March 2024
Available online 21 March 2024

performance of organic farming is generally found to be comparable to conventional farming when expressed on a per kg basis. On the other hand, the overall economic performance of organic farming compared to conventional agriculture is still under debate considering: (a) productivity, with the possibility of achieving comparable yields to conventional agriculture over the long term; (b) lower input costs; (c) new market opportunities (niche markets, local markets, or direct sales channels) and higher prices for farmers; and (d) lower risk exposure due to more stable yields (i.e., reduced impacts of extreme weather events) and lower volatility of prices (output and inputs) over time, leading to more resilient farms.

Considering this framework, the primary objective of this paper is to further contribute to the ongoing debate surrounding organic and conventional agriculture by comparing the economic and environmental performance of farms operating under these two production regimes on a per hectare basis. To do so, the fruit production sector in Spain is taken as the case study.

Although many previous studies have had similar objectives, this paper contributes to the existing literature in two ways. First, the economic and environmental performance of organic and conventional farms is measured using a comprehensive set of base indicators and composite indicators built by aggregating all the base indicators considered in each sustainability dimension. Second, the study employs matching methods to conduct comparative analyses of organic and conventional farms. This is the most innovative feature of the paper since this methodological option makes it possible to minimize non-randomization biases when assessing differences in base/composite indicators to measure changes in farms' environmental and economic performance (i.e., changes occurring when farms convert to organic farming). Hence, the results obtained provide more valuable information than most of the analyses found in the literature, which only measure observational differences between the two production systems without considering structural differences between conventional and organic farms.

The combination of these methodological options has allowed a thorough and innovative assessment of farms' economic and environmental performance on a per hectare basis, expanding the state-of-the-art in this field. In fact, to the best of the authors' knowledge, only two previous studies have conducted farm-level comparative analyses using matching methods to assess differences in composite indicators (Bartolini et al., 2021; Dompreh et al., 2021), but neither of them is related to organic farming or farms' overall economic and environmental performance. Moreover, the above-mentioned methodological approach has been implemented to analyze the performance of organic fruit farming in Spain, a sector which has rarely been analyzed in the literature (see the studies by Beltrán-Esteve and Reig-Martínez, 2014; Nicolò et al., 2018 as notable exceptions).

2. Case study and data source

2.1. The Spanish fruit production sector and its performance

According to the data published by the Spanish Ministry of Agriculture, Fisheries, and Food (MAPA (Ministerio de Agricultura, Pesca y Alimentación), 2022a), the fruit production sector occupies 1.41 million hectares. The largest share of this area is covered by nuts (0.87 million ha), followed by citrus fruits (0.30 million ha), fruits other than citrus, tropical, and nuts (0.19 million ha), and tropical fruits (0.05 million ha). From an economic perspective, the fruit production sector in Spain makes a substantial contribution to total crop production value, accounting for 9253 million euros in 2022, which represents 25.5% of the Spanish crop output and 28.6% of the fruit production value in the EU.

According to the last agricultural census (year 2020), the whole fruit production sector in Spain is made up of 137,359 farms. At the farm level, the Spanish fruit production sector is highly heterogeneous depending on the type of farming (TF). In this sense, according to the European farm typology, fruit farms can be classified into four TFs: fruits other than citrus, tropical, and nuts (TF 361), citrus fruits (TF 362), nuts (TF 363), and tropical fruits (TF 364). Table 1 summarizes the main descriptive variables of the fruit farms in Spain by TF, based on the data provided by the Spanish Farm Accountancy Data Network (*Red Contable Agraria Nacional,* RECAN, the Spanish branch of the European Farm Accountancy Data Network, FADN). These data show the heterogeneity pointed out above in structural, economic, and environmental (e.g., fertilizers and pesticides use) terms. This heterogeneity justifies a separate analysis for each analyzed TF, as proposed in this study.

Regarding the production system, most fruits produced in Spain are grown under a conventional system. Nonetheless, the organic fruit production sector has been experiencing substantial growth in recent years. In fact, in 2021, there were 18,583 organic fruit farms (13.5% of total fruit farms), together operating 304,144 ha (21.6% of the Spanish fruit area) (MAPA (Ministerio de Agricultura, Pesca y Alimentación), 2022b).

2.2. Data source: The Spanish farm accountancy data network (RECAN)

The FADN is the only source of harmonized and representative farm

Table 1
Main structural, economic, and environmental variables of the Spanish fruit farms by TF (average values for the year 2020).

Variable	RECAN code	Fruits (TF 361)	Citrus (TF 362)	Nuts (TF 363)	Tropical (TF 364)
RECAN sampled farms	SYS03	298	275	139	106
Structure					
Total Utilized Agricultural Area (UAA) (ha)	SE025	18.1	11.8	42.6	3.9
Total labor input (AWU)[a]	SE010	3.9	1.6	1.0	2.2
Unpaid labor input (AWU)	SE015	1.1	0.7	0.7	1.2
Paid labor input (AWU)	SE020	2.7	1.0	0.2	1.0
Revenues					
Total output (€/ha)	SE131	8649	7027	1028	17,531
Total subsidies (€/ha)	SE605	265	298	317	4339
Costs					
Total inputs (€/ha)	SE270	5621	4360	496	11,744
Specific costs (€/ha)	SE281	1068	1165	135	1954
Farming overheads (€/ha)	SE336	1328	1376	177	3880
Depreciation (€/ha)	SE360	411	231	88	935
Wages paid (€/ha)	SE370	2582	1370	83	4499
Rent paid (€/ha)	SE375	199	203	12	465
Interest paid (€/ha)	SE380	33	14	0	12
Profit					
Farm Net Income (€/ha)	SE420	3469	3028	833	10,257
Environmental performance					
Fertilizers (€/ha)	SE295	330	527	64	1179
Nitrogen (kg/ha)	SE296	70.8	136	20.2	197
Phosphorus (kg/ha)	SE297	48.5	68.0	6.7	202
Potassium (kg/ha)	SE298	89.2	97.8	9.1	265
Crop protection costs (€/ha)	SE300	605	586	58	672

Source: Own elaboration based on RECAN microdata.
[a] Annual Work Unit, equivalent to one full-time job.

Table 2
Composition of the RECAN subsamples by TF and main crops and average yields for conventional and organic farming (year 2020).

Farm/crop (observations)	Average yields		Observed difference Org.-Conv. (%)
	Organic farms (kg/ha)	Conventional farms (kg/ha)	
TF 361 Fruits (organic = 32, conventional = 213)	17,220	18,991	−9.3
Peach (organic = 14, conventional = 128)	17,678	22,868	−22.7
Pear (organic = 16, conventional = 61)	19,181	21,884	−12.4
Apple (organic = 18, conventional = 41)	27,426	29,921	−8.3
Other fruits (organic = 15, conventional = 100)	10,966	11,501	−4.7
TF 362 Citrus (organic = 18, conventional = 212)	24,701	27,552	−10.3
Orange (organic = 10, conventional = 173)	25,313	28,420	−10.9
Lemon (organic = 10, conventional = 30)	27,038	21,940	23.2
Other citrus (organic = 6, conventional = 88)	18,709	24,281	−23.0
TF 363 Nuts (organic = 63, conventional = 58)	682	752	−9.4
TF 364 Tropical fruits (organic = 14, conventional = 69)	34,257	37,772	−9.3

Source: Own elaboration based on RECAN microdata.

microdata at the EU level, making any empirical study based on these data fully reproducible elsewhere in the EU. However, using the FADN as the data source for assessing farms' sustainability performance is challenging and entails some limitations regarding the environmental information provided, which may hinder the assessment of farms' performance in this field (Kelly et al., 2018). Nevertheless, there are several FADN variables that facilitate this evaluation through environmental impact *proxies* and indicators, as demonstrated in previous studies (e.g., Petsakos et al., 2023; Robling et al., 2023).

The empirical analysis performed in this study is based on a three-year (2018–2020) panel sample of fruit farms provided by the RECAN, including 679 farms classified as TF 361 (fruits, 245 farms), TF 362 (citrus, 230 farms), TF 363 (nuts, 121 farms), or TF 364 (tropical, 83 farms). 127 out of the 679 farms in the complete sample are organic. Table 2 shows the composition of each RECAN subsample by TF considering the farms' production system (i.e., conventional and organic). As can be checked, the number of organic farms in these subsamples ranges from 14 in the TF 364 (17% of tropical fruit farms sampled) to 63 in the TF 363 (52% of nut farms sampled). Overall, organic farms represent 18.7% of the total RECAN sample used in the analysis, covering 25.2% of the sampled area. According to the sector data introduced in the previous section, it is evident that organic farms are overrepresented in the RECAN fruit farm subsamples. However, this relatively high number of organic farms in the subsamples allows for a better representation of organic fruit production, enabling a more accurate and robust comparative analysis of fruit farms' performance.

Moreover, Table 2 also shows the average yields for the main fruit crops produced under conventional and organic farming. Overall, average yield comparisons highlight the aforementioned productivity gap between these two production systems, showing the generalized lower production per hectare for organic production. However, it is worth noting that average yields and their differences must be considered just for explorative purposes for two main reasons. First, the differences observed are not randomized (i.e., these differences are influenced by other underlying variables beyond the production system); thus, any test comparing conventional and organic yield averages would make little sense. Nevertheless, the small sample sizes at the crop level preclude the implementation of matching methods to minimize the existing non-randomization biases. Second, the observed yield differences at the TF level to be analyzed in this paper (i.e., TFs 361, 362, 363, and 364) are the results of aggregating diverse crop productions (e.g., adding kilograms of peaches, apples, pears, and many other fruits in the case of TF 361). This raises doubts about the suitability of grouping them in kilogram terms for the analysis since they have different biophysical attributes (e.g., moisture levels or nutrient contents) and economic values. Both facts led us to emulate randomized comparisons of conventional and organic farms' economic performance using monetary-based metrics (e.g., profitability, viability, or resilience), considering the euro as a functional unit for the comparative analyses, circumventing any potential biases resulting from the outputs' heterogeneity.

3. Methodology

We employed a three-step methodology. In the first stage, base indicators of farms' performance in the two sustainability dimensions considered (i.e., economic and environmental) were chosen and calculated for every farm included in the three-year panel sample collected by the RECAN. The scores of these indicators were calculated as average values for the three years (2018–2020) to better reflect farm performance as a structural feature, thus minimizing potential biases due to abnormal agricultural years. In the second stage, composite indicators of farms' performance were calculated for each dimension. Lastly, in the third stage, we employed propensity score matching to estimate the Average Treatment Effect (ATE) for the sample, thus quantifying the changes in base and composite performance indicators due to farms' conversion to organic farming. These stages are explained in more detail below.

3.1. Economic performance indicators

The assessment of farms' economic performance has been addressed by multiple authors, with different theoretical and quantitative approaches used to measure its multidimensional nature (e.g., Spicka et al., 2019; Loughrey et al., 2022). Hence, following the existing literature, we calculated seven indicators capturing four of the most relevant dimensions of farms' economic performance: profitability, viability, resilience, and independence.

Profitability is calculated as the relationship between farms' profits and the investments allocated by the farmer to run the agricultural business. We chose two indicators to quantify this dimension of economic performance (see Table 3). The first one is Farm Net Income (FNI) expressed in euros per hectare, which provides information on farms' accounting profit (i.e., total revenues minus total expenses). The second indicator is Return on Assets (ROA), calculated as Earnings Before Interest and Taxes (EBIT) divided by the value of total farm assets and expressed as a percentage.

Following the existing literature (e.g., Spicka and Derenik, 2021; Gómez-Limón et al., 2023), farms can be considered economically viable only when they achieve a level of income that is enough to cover all farm operating costs while also ensuring an appropriate return to production

Table 3
Description of farms' economic performance indicators.

Indicator (acronym)	Formula	Formula based on RECAN data	Units
Profitability			
Farm Net Income (FNI)	$\frac{\text{FNI}}{\text{UAA}}$	$\frac{\text{SE420}}{\text{SE025}}$	€/ha
Return On Assets (ROA)	$\frac{\text{EBIT}}{\text{Total assets}}$	$\frac{\text{EBIT}}{\text{SE436}}$	%
Viability			
Long-term viability (LT_VB)	$\frac{\text{FNI}}{\text{Total Opportunity Costs}}$	$\frac{\text{SE420}}{\text{OC}_{\text{land}} + \text{OC}_{\text{labor}} + \text{OC}_{\text{non-land assets}}}$	Dimensionless
Short-term viability (ST_VB)	$\frac{\text{FNI}}{\text{OC}_{\text{labor}}}$	$\frac{\text{SE420}}{\text{OC}_{\text{labor}}}$	Dimensionless
Resilience			
Coeff. Variation of FNI (CV_FNI)	$\frac{\sigma_{\text{FNI}_t}}{\overline{\text{FNI}_t}}$	$\frac{\sigma_{\text{SE420}_t}}{\overline{\text{SE420}_t}}$	%
FNI resistance (RES_FNI)	$Min\left[\frac{\text{FNI}_t - \overline{\text{FNI}_t}}{\overline{\text{FNI}_t}} \forall t\right]$	$Min\left[\frac{\text{SE420}_t - \overline{\text{SE420}_t}}{\overline{\text{SE420}_t}} \forall t\right]$	%
Independence			
Revenue dependency (REV_DEP)	$\frac{\text{Total CAP subsidies}}{\text{Total revenue}}$	$\frac{\text{SE605}}{\text{SE131} + \text{SE605}}$	%

factors owned by the farmer. Thus, as proposed in previous studies based on FADN data (e.g., Coppola et al., 2022), *viability* indicators relate the FNI with the opportunity costs of the different factors provided by the farmer. We computed two indicators of farms' viability (see Table 3). For the first one, named long-term viability (LT_VB), the FNI of each farm is divided by its total opportunity costs (i.e., land, labor, and non-land assets).[1] Only farms with a value of LT_VB greater than or equal to one can be considered viable in the long term since their FNI (i.e., accounting profit) is enough to adequately remunerate all the opportunity costs of factors provided by the farmer, allowing the generation of an economic surplus (i.e., economic profit). The second indicator refers to short-term viability (ST_VB) and is calculated in the same way as the first indicator but includes only the opportunity cost of unpaid labor. Only farms scoring a value greater than or equal to one in this indicator can be considered viable in the short term, since they generate an appropriate remuneration for the unpaid labor, ensuring the short-term continuity of farming.

According to Urruty et al. (2016) and Sneessens et al. (2019), *resilience* can be understood as the structural capacity of farms to minimize the impacts and changes associated with external pressures (e.g., climate events or market shocks) over time. The assessment of farms' resilience encompasses three capacities (Meuwissen et al., 2019): robustness (stability of net income over time), adaptability (capacity to slightly change the form of production–e.g., by adjusting production factors), and transformability (capacity to significantly modify the internal production structure–e.g., by changing the production technology). Due to limitations relating to the nature of RECAN data, our analysis only focused on robustness as a single subdimension of farms' resilience performance. Thus, two indicators were calculated to measure the stability of farms' income over the three years considered (Harkness et al., 2021; Slijper et al., 2022) (see Table 3). The first one is the coefficient of variation of FNI during the period 2018–2020 (CV_FNI, expressed as a percentage).[2] Hence, the greater its value (i.e., the higher the variability of FNI over time), the lower the robustness of the farm. The second indicator, FNI resistance (RES_FNI), refers to the greatest decrease in FNI with respect to its period average (the greatest downward deviation), also expressed as a percentage.

Finally, *independence* refers to farms' autonomy in terms of their ability to generate sufficient income without relying on public subsidies (i.e., CAP dependence). The only indicator in this dimension (see Table 3) relates the amount of these public payments received to the farms' total revenue (REV_DEP).

3.2. Environmental performance indicators

Considering the limited environmental information included in the RECAN database, we conducted a comprehensive literature review of previous studies that use FADN data (e.g., Volkov et al., 2022; Robling et al., 2023) in order to identify the most suitable environmental indicators based on per hectare metrics that can be calculated using this source. As with the assessment of economic performance, we adopted a comprehensive approach for assessing the fruit farms' environmental performance, considering three dimensions drawn from the specific CAP environmental objectives: biodiversity, greenhouse gas (GHG) emissions, and pollution emissions. As a result, we selected five indicators (see Table 4).

Two indicators were chosen to quantify farms' contribution to *biodiversity* using RECAN data. The first indicator is the Shannon Diversity Index (SDI), which measures the number of crops and other land uses (e.g., grassland, non-cultivated land, or forest) on the farm, based on their shares in total farm area (p_i). This indicator accounts for the landscape heterogeneity (i.e., land use) at the farm level, which is positively related to farms' biodiversity to the extent that it generates diverse habitats for many organisms (Belfrage et al., 2015). This

[1] The opportunity cost of land (OC_{land}) was calculated by multiplying the farm's owned area by the annual regional rental fee for cropland based on official statistics from MAPA (MAPA, 2022a). The opportunity cost of unpaid labor (OC_{labor}) was estimated by multiplying this labor input by the average annual wage paid for labor in each RECAN subsample used for the analysis (i.e., TFs 361, 362, 363, and 364). To calculate the opportunity cost of non-land assets provided by the farmers ($OC_{non\text{-}land}$), the value of these assets was multiplied by the annual interest rate corresponding to the 10-year Spanish government bonds.

[2] This indicator was computed using only three observations, given the existing data constraints (increasing the length of the period considered would greatly reduce subsample sizes). The authors are aware that the relatively short period used for its calculation could make this indicator very sensitive to the presence of outliers. As a way to minimize potential biases from outliers, all FNI annual data were winsorized at the 5% level. In any case, the resulting CV_FNI estimates should be interpreted with caution.

Table 4
Description of farms' environmental performance indicators.

Indicator (acronym)	Formula	Formula based on RECAN data	Units
Biodiversity			
Shannon Diversity Index (SDI)	$-\sum p_i \times ln(p_i)$	p_i based on SE035, SE041, SE046, SE050, SE055, SE060, SE065, SE071, SE075[a]	Dimensionless
Crop protection costs (CROP_PRO)	$\frac{\text{Crop protection costs}}{\text{UAA}}$	$\frac{\text{SE300}_{\text{conv.}}}{\text{SE025}}$ or $\frac{0.5 \times \text{SE300}_{\text{org.}}}{\text{SE025}}$	€/ha
GHG emissions			
GHG emissions (GHG_EM)	$\frac{\text{GHG emissions}}{\text{UAA}}$	$\frac{\sum_i \text{Input}_i \times \text{CO2e per unit}_i}{\text{SE025}}$	kg CO2e/ha
Pollution emissions			
Nitrogen use (NITROG)	$\frac{\text{Nitrogen input quantity}}{\text{UAA}}$	$\frac{(\text{SE296} \times 100) + \text{N}_{\text{organic}}}{\text{SE025}}$	kg N/ha
Phosphorus use (PHOSP)	$\frac{\text{Phosphorus input quantity}}{\text{UAA}}$	$\frac{(\text{SE297} \times 100) + \text{P}_{\text{organic}}}{\text{SE025}}$	kg P/ha

[a] In order: cereals, other field crops, vegetables and flowers, vineyards, orchards, olive groves, other permanent crops, forage crops, and forest land.

relationship allows for a proxy assessment of farms' biodiversity through land use information provided by the RECAN (e.g., Uthes et al., 2020; Dabkiene et al., 2021), providing dimensionless values for each farm analyzed, where the higher the score, the greater the level of biodiversity on the farm.

In the EU, the Farm to Fork Strategy established the objective of a 50% reduction in the use of agrochemical pesticides by 2030 to preserve farmland biodiversity. This goal justifies the second indicator chosen to capture farms' biodiversity (CROP_PRO), which quantifies crop protection costs (i.e., use of biocide products) measured in euros per hectare (Grzelak et al., 2019). Thus, this indicator gives information on farms' potential capacity to kill living organisms. However, it should be borne in mind that the plant protection products used in conventional and organic farms are different, with the former (i.e., synthetic pesticides) being much more environmentally harmful than the latter (i.e., 'natural' protection products). Experts on organic fruit production were consulted about the biocide potential of both kinds of crop protection products, and they agreed that it is reasonable to assume that one euro spent on crop protection in organic farms causes half as much biodiversity damage as one euro spent for the same purpose in conventional farms. This justifies the inclusion of a correction weight of 0.5 for crop protection costs in the case of organic farms, as shown in Table 3. This adjustment makes the values of the CROP_PRO indicator comparable across fruit farms in terms of farms' biocide potential.

The second dimension of farms' environmental performance is linked to climate change mitigation, especially to farms' contribution to GHG emissions. The RECAN does not provide information about this environmental impact. However, these emissions can be estimated by adapting the Intergovernmental Panel on Climate Change methodology (IPCC (Intergovernmental Panel on Climate Change), 2006) and applying it to this data source, as done by Baldoni et al. (2017) or Stetter and Sauer (2022). For this purpose, system boundaries are fixed at the farm-gate. By so doing, the only emissions accounted for are those that can be directly attributed to farmers' decision-making (i.e., reflecting farms' performance). At this micro level, in the case of fruit farms, most of the GHG emissions are related to the use of energy (CO2 emissions from fuel for field operations and energy for irrigation) and fertilizers (N2O emissions) (Aguilera et al., 2015).[3] Thus, aggregate GHG emissions at the farm level can be estimated as the sum of the emissions generated by the energy and fertilizer inputs, all expressed in CO2 equivalent (CO2e). The data regarding the Global Warming Potential (GWP) updated by the IPCC Sixth Assessment Report (Smith et al., 2021) were used to convert the different GHG emissions into CO2e.

Mathematically, farm-level GHG emissions were calculated as follows:

$$GHG\ emissions = \sum_i AI_i \times EF_i = \sum_i \frac{CI_i}{p_i} \times EF_i \tag{1}$$

where AI_i is the amount used of the input i (liters of fuel, kWh of electricity, and kg of nitrogen in mineral and organic fertilizers) and EF_i is the emission factor of the input i (i.e., kg CO2e per unit). However, the data provided by the RECAN only report the input costs measured in euros (CI_i).[4] For this reason, the AI_i needs to be estimated considering the average prices paid for each input (p_i), as shown in expression (1). Specifically, the RECAN data taken for the estimation of farms' GHG emissions were: cost of fuels and lubricants (RECAN code 1040), cost of electricity (5020), amount of nitrogen in mineral fertilizers (SE296), and cost of organic fertilizers such as manure, slurry, or compost (3034). Data about input prices were obtained from MAPA (Ministerio de Agricultura, Pesca y Alimentación) (2023). Emission factors were gathered from MITECO (Ministerio para la Transición Ecológica y el Reto Demográfico) (2023) for fuels and electricity and Aguilera et al. (2015) for nitrogen in mineral and organic fertilizers under Spanish Mediterranean conditions.

Thus, the indicator chosen for assessing farms' contribution to GHG emissions (GHG_EM) is the value of the individual estimated emissions expressed in kg CO2e per hectare.

The remaining environmental indicators are associated with the pressure on natural resources, particularly on water (quality deterioration due to diffuse pollution), because of the use of fertilizers. In fact, the Farm to Fork Strategy also established the objective of a 20% reduction in fertilizer use plus a decrease in nutrient losses by at least 50% by 2030. Thus, following previous empirical approaches (e.g., Dabkiene et al., 2021), the last two indicators provide information on the physical quantity of fertilizers (i.e., nitrogen -N- and phosphorus -P) used in the farm (NITROG and PHOSP), all expressed in kilograms per hectare (see

[3] Although these authors also point to changes in soil carbon sequestration as another relevant potential source (or sink) of GHG emissions, this impact was not included in the proposed GHG emissions indicator. The reason for this omission was the lack of appropriate data at the farm level to reasonably estimate changes in soil organic carbon stocks, mainly those related to management practices such as using cover cropping and incorporating pruning residues.

[4] As exceptions, the RECAN provides data about the amount of macronutrients (N, P, and K) in mineral fertilizers. Thus, in this case, the data of the AI_i reported by this source were directly used in expression (1).

Table 3). Consequently, higher values in either of them indicate poorer environmental performance by farms, as they can be directly associated with a more significant negative impact on water quality (i.e., pollution emission leading to freshwater eutrophication). Synthetic and organic fertilizers have been considered in the calculation of these two indicators. RECAN data provide information about the amount of N and P in mineral fertilizers (RECAN codes SE296 and SE297, respectively). However, the RECAN data only report the costs of organic fertilizers (code 3034). Thus, the amount of N and P in organic fertilizers was estimated based on the average prices paid (MAPA (Ministerio de Agricultura, Pesca y Alimentación), 2023) and the content of N and P in this input.

3.3. Constructing composite indicators

The main complication when using sets of indicators to assess complex multidimensional concepts is the difficulty of interpreting them jointly. This issue, which affects analyses of the different dimensions of farms' sustainability (e.g., economic or environmental performance), can be addressed by aggregating the multidimensional sets of indicators into a single index or composite indicator (e.g., Sébastien and Bauler, 2013; Greco et al., 2019). The resulting indices are useful for public communication of complex concepts (as they are easier to understand by policymakers and mass media) and help make these concepts measurable (allowing comparability across analyzed units—for example, through ranking—and the assessment of trends over time). Consequently, composite indicators have become key informative support tools to guide policy decision-making in the agricultural sector (e.g., Gómez-Limón and Sanchez-Fernandez, 2010; Talukder et al., 2018). These advantages make composite indicators a useful tool for the present study since their calculation enables a comprehensive assessment of farms' economic and environmental performance, effectively contributing to the ongoing debate on the promotion of organic farming. The composite indicators proposed in this study were constructed following the guidelines provided for this purpose by the OECD (Organisation for Economic Co-operations and Development), JRC (Joint Research Centre) (2008).

First, it must be noted that the base indicators chosen are measured in different units. To make them comparable and mathematically operational, they must be converted into dimensionless variables using the same measurement scale before moving on to the weighting and aggregation. For this reason, the base indicator values need to be normalized, transforming them into the same dimensionless scale. We employed the "min-max" normalization procedure, as is usually done for agricultural sustainability assessment (e.g., Yildirim et al., 2022). The min-max normalization procedure is sensitive to the presence of outliers. To minimize the influence of these potential extreme values, the original values of the indicators in each subsample (i.e., TFs 361, 362, 363, and 364) were winsorized at the 5% level.

Weighting and aggregation are the most critical steps when building composite indicators, as choices directly influence the final values of the constructed indexes. The weights of the base indicators refer to their relative importance in the construction of the composite indicator, thus determining the trade-offs between them. Two groups of weighting techniques can be broadly distinguished (OECD (Organisation for Economic Co-operations and Development), JRC (Joint Research Centre), 2008). On the one hand, positive or data-driven methods are those that obtain the weights endogenously employing statistical techniques. Conversely, normative or participatory methods rely on subjective judgments (e.g., opinions from experts, stakeholders, or policymakers collected through questionnaires) to derive the weights associated with each base indicator. We implemented the Best-Worst Method (BWM) to elicit the weights of the indicators based on the opinions provided by a panel of experts in fruit farming, who were asked to answer the BWM questionnaire considering the specific context of this case study.[5] This participatory method was developed by Rezaei (2015) and has already been widely used in constructing composite indicators, as shown by Wang and Fu (2020). For the implementation of the BWM in the case study considered, 27 experts were interviewed. The expert panel was primarily composed of scholars from universities (12) and research centers (9), but also contained specialists from the Regional Administration (4) and technical services firms (2). Appendix A, included as supplementary material, provides detailed information about the implementation of this weighting method.

When aggregating base indicators into a single index, commensurability becomes a key issue (Rowley et al., 2012). This concept determines the extent to which low values in one base indicator can be compensated for by higher values in another indicator when calculating the composite indicator. After reviewing the variety of aggregation procedures available (see OECD (Organisation for Economic Co-operations and Development), JRC (Joint Research Centre), 2008; Greco et al., 2019), the weighted sum of base indicators (i.e., an additive procedure) was finally chosen. This method allows for total compensation among indicator values. Mathematically, the resulting additive Farm Performance Composite Indicator (FPCI) for farm i can be expressed as follows:

$$FPCI_i = \sum_{k=1}^{k=K} w_k \cdot x_{k,i} \tag{2}$$

where w_k represents the weight assigned to the indicator k, and $x_{k,i}$ is the normalized value of indicator k for farm i.

To assess the robustness of the proposed composite indicator, constructed using the BWM method and the additive aggregation procedure, additional economic and environmental performance indexes were computed. These additional indexes were derived using combinations of alternative methodological approaches. Appendix B in the supplementary material shows detailed information on how the Principal Component Analysis (PCA) was implemented as an alternative weighting method. Similarly, Appendix C describes the application of the multicriteria procedure proposed by Diaz-Balteiro and Romero (2004) as an alternative aggregation method. Thus, four different composite indicators (2 weighting methods × 2 aggregation procedures) were actually built to comprehensively assess farms' economic and environmental performance. The Pearson and Spearman correlation matrixes for all composite indicators calculated are shown in Appendix D in the supplementary material. In this sense, extremely high positive correlations between the proposed FPCI (i.e., constructed using the BWM weighting and additive aggregation procedure) and the alternative indexes based on different weighting and aggregation methods indicate that all these composite indicators provide similar measurements of the same multidimensional concepts (i.e., farm economic and environmental performance). Therefore, since the farm performance indexes calculated are not sensitive to the choice of weighting/aggregation procedure, the quantitative analysis reported here focuses solely on the proposed FPCI, for both the economic and environmental dimensions (ECO_FPCI and ENV_FPCI, respectively).

[5] Preferences expressed by policymakers could also be considered an alternative way to obtain normative weights. One example of this is the *Product Environmental Footprint* (PEF) method proposed by the European Commission (see European Commission, 2018), where weighting factors are proposed to homogenize Life Cycle Assessment (LCA) based on product declarations regarding the environmental impacts of the products and services sold within the EU. However, considering the objective of this research, a sector- and site-specific approach for the assessment was deemed more suitable than the general framework proposed by the PEF.

3.4. Matching and average treatment effects estimation

The main purpose of this study is to assess the impact on fruit farms' economic and environmental performance caused by their conversion to organic production. This impact is quantified by both the base and composite indicators described in the previous sections. Following the seminal work of Rubin (1974) on causal effect estimation, we can consider the conversion to organic farming as a "treatment", thus dividing our farm samples into two subsamples: the "treated" group (organic farms) and the "control" group (conventional farms). According to Rosenbaum (2010), results from a direct comparative analysis between organic and conventional farms' performance might not be exclusively caused by the farms' production system, which is actually the treatment effect we want to calculate. Hence, to address this problem raised by non-randomization, we employed a "quasi-experimental" approach by utilizing matching methods, as proposed in other farm-level comparative assessments (e.g., Froehlich et al., 2018; Hansen et al., 2021; Lambotte et al., 2023).

Matching methods are used to match similar subjects from the control and the treated group based on a set of control variables (e.g., farms' structural and productive characteristics or farmers' demographic characteristics), commonly referred to as covariates (Rosenbaum, 2010). The key objective of matching methods is to replicate a randomized study by achieving a covariate balance between groups in the final matched sample, trying to make the treatment assignment "strongly ignorable" and thus allowing the researcher to isolate the causal effect of interest (Stuart, 2010). A total of 15 covariates (see Appendix E of supplementary material) were finally chosen related to fruit growers' demographic characteristics, farms' characteristics, farms' resources, and characteristics of the region where the farms are located. Table E1 shows the average values of all covariates for organic and conventional farms by TF.

The chosen covariates were used as explanatory variables in a logistic regression to estimate the propensity score of each subject (i.e., the probability of being organic for each farm). Subsequently, we applied the full matching method (Hansen, 2004; Austin and Stuart, 2015) to each analyzed TF sample, specifying the propensity scores as the measure of the distance between farms to be matched. The weights assigned by the full matching procedure enabled us to estimate the Average Treatment Effect (ATE) (Austin and Stuart, 2017a, 2017b), allowing us to obtain accurate and unbiased estimators of the impact of conversion to organic production on fruit farms' base/composite indicators of economic and environmental performance.

The unbiasedness of the estimated effects from the matching method hinges on two factors. First, from a general perspective, there is evidence that matching techniques produce less biased results than alternative approaches applied to unmatched data, such as ordinary least squares (OLS) regressions (Vable et al., 2019). Second, a diagnostic analysis of the covariate balance between the two groups of matched farms (i.e., conventional and organic) was conducted to assess the validity of the estimated effects for our case study. Matching outcomes for each TF subsample are presented in Appendix F in the supplementary material. This information makes it possible to check the covariate and propensity score balance achieved within each matched sample (i.e., ignorability of treatment assignment), ensuring that the ATE estimates shown in Tables 7 and 8 are unbiased.

4. Results

4.1. Organic vs. conventional average performance

This section presents an overview of the fruit farms' performance based on the pre-matching values obtained for both the base and the composite indicators in each analyzed TF. These outcomes provide some insights into the heterogeneity between and within the different TFs, further justifying the separate analysis proposed for each of them. The

Table 5
Pre-matching mean differences of economic performance indicators for organic and conventional farms by TF.

Indicator	Fruits (TF 361)			Citrus (TF 362)			Nuts (TF 363)			Tropical (TF 364)		
	Organic (n = 32)	Conven. (n = 213)	Difference Org-Conv	Organic (n = 18)	Conven. (n = 212)	Difference Org-Conv	Organic (n = 63)	Conven. (n = 58)	Difference Org-Conv	Organic (n = 14)	Conven. (n = 69)	Difference Org-Conv
FNI (€/ha)	2108	3083	−975	3605	3065	540	844	437	407	14,124	14,919	−795
ROA (%)	9.46	14.54	−5.08	10.46	9.26	1.20	13.56	6.87	6.69	24.39	23.79	0.60
LT_VB (dimensionless)	1.94	1.95	−0.01	2.79	1.71	1.08	2.31	0.93	1.38	2.88	2.07	0.82
ST_VB (dimensionless)	3.43	3.12	0.31	5.35	2.97	2.38	6.48	2.03	4.45	7.15	4.36	2.79
CV_FNI (%)	65.58	46.34	19.24	45.84	34.96	10.88	37.87	47.66	−9.79	35.78	33.97	1.81
RES_FNI (%)	−97.94	−68.06	−29.88	−71.95	−47.35	−24.60	−45.39	−65.53	20.14	−39.06	−41.03	1.97
REV_DEP (%)	6.61	3.98	2.64	5.44	3.17	2.26	30.47	18.15	12.32	19.77	19.44	0.32
ECO_FPCI (0–1)	0.356	0.436	−0.080	0.508	0.460	0.048	0.462	0.306	0.155	0.451	0.424	0.027

Source: Own elaboration based on RECAN microdata.

means of each base/composite indicator calculated for organic and conventional farms in all four TF samples are shown in Table 5 (economic performance indicators) and Table 6 (environmental performance indicators).

As noted above, the descriptive statistics of the indicators shown in Table 5 give us information about the substantial heterogeneity in fruit farms' economic performance across the different TFs. In this sense, average differences between economic base indicators are striking. The tropical fruit farms (TF 364) case is particularly noteworthy, showing the highest values of profitability indicators (FNI and ROA). Conversely, nut farms (TF 363) exhibit the worst economic performance among all the analyzed TFs, as indicated by the lowest values in the FNI profitability indicator, and the highest dependency on CAP subsidies (i.e., worst values in REV_DEP). Moreover, this table also shows apparent differences between organic and conventional farms in terms of the average values of base indicators. However, the results obtained are mixed. Similar results for all four TFs are found only in the case of revenue dependency (REV_DEP), as organic farms generally receive more CAP subsidies than conventional ones.

However, the absolute differences in the economic composite indicator between TFs are not that sizeable. This can be explained by the normalization method adopted, which was implemented separately by TF, meaning that the composite indicators are measured in different metrics that cannot be directly compared. However, these results are helpful in pointing out disparities between organic and conventional farms' economic performance within each analyzed TF. In this respect, while conventional farming seems to have a better overall economic performance than organic farming in the fruit farms (TF 361), the organic farms included in the other TFs (TFs 362, 363, and 364) show apparent higher average values for the economic composite indicator than conventional farms do.

Similar to the economic dimension, the descriptive statistics of environmental base indicators shown in Table 6 also evidence heterogeneity between the TFs, especially for indicators related to input use (e.g., differences in average values for CROP_PRO, GHG_EM, NITROG, and PHOSP). Average values of base environmental performance indicators suggest that nut farms (TF 363) exhibit the best environmental performance, in contrast to having the worst economic performance, as described above. Regarding the results shown in this table, the differences in environmental performance between organic and conventional farms within each TF are also worth noting. Organic farming appears to outperform conventional agriculture in every TF in three of the base indicators assessed (CROP_PRO, NITROG, and PHOSP). However, contrary to what was expected, the results obtained are mixed for the other two indicators (SDI and GHG_EM).

Regarding the environmental composite indicator, we observe slight variability in average values between TF samples; the reason for this is the same as the one given for the economic composite indicator. Despite this, the average values obtained seem to confirm the assumption that organic farming is a more environmentally friendly production system than conventional agriculture for every TF.

In any case, all these preliminary comparisons must be taken with caution. As commented in Section 3.4, these results are not accurate enough, as they are influenced by several underlying factors that introduce non-randomization biases. Therefore, results from this pre-matching analysis regarding organic vs. conventional fruit farms' performance can be understood as initial hypotheses to be tested with the unbiased ATE estimators shown in the following section.

Table 6
Pre-matching mean differences of environmental performance indicators for organic and conventional farms by TF.

Indicator	Fruits (TF 361)			Citrus (TF 362)			Nuts (TF 363)			Tropical (TF 364)		
	Organic (n = 32)	Conven. (n = 213)	Difference Org-Conv	Organic (n = 18)	Conven. (n = 212)	Difference Org-Conv	Organic (n = 63)	Conven. (n = 58)	Difference Org-Conv	Organic (n = 14)	Conven. (n = 69)	Difference Org-Conv
SDI (dimensionless)	0.319	0.223	0.097	0.015	0.080	−0.065	0.228	0.298	−0.070	0.033	0.040	−0.007
CROP_PRO (€/ha)	255.6	628.8	−373.1	326.4	507.8	−181.4	22.1	66.4	−44.3	299.8	765.7	−465.9
GHG_EM (kg CO2e/ha)	1163	1428	−265	1867	1425	442	209	297	−88	6017	5318	699
NITROG (kg N/ha)	56.8	75.4	−18.6	94.3	146.5	−52.2	7.2	35.1	−28.0	151.6	295.2	−143.6
PHOSP (kg P/ha)	29.0	51.4	−22.5	29.6	67.9	−38.2	3.4	12.3	−8.9	126.9	332.0	−205.1
ENV_FPCI (0–1)	0.636	0.487	0.148	0.496	0.459	0.037	0.656	0.499	0.157	0.550	0.433	0.117

Source: Own elaboration based on RECAN microdata.

Table 7
Organic-conventional ATE estimates on the economic performance indicators by TF.

Indicator	Fruits[a] (TF 361)			Citrus[b] (TF 362)			Nuts[c] (TF 363)			Tropical[d] (TF 364)		
	ATE	p-value	Cohen's d[e]	ATE	p-value	Cohen's d[e]	ATE	p-value	Cohen's d[e]	ATE	p-value	Cohen's d[e]
FNI (€/ha)	−486	0.281	−0.21	−768	0.074	−0.34	188	0.013*	0.39	−385	0.871	−0.04
ROA (%)	−2.39	0.223	−0.27	−3.02	0.025*	−0.42	3.28	0.007**	0.42	0.53	0.882	0.03
LT_VB (dimensionless)	0.08	0.804	0.04	0.31	0.316	0.16	0.49	0.007**	0.42	−0.15	0.676	−0.08
ST_VB (dimensionless)	0.73	0.139	0.20	0.35	0.612	0.08	2.10	0.003**	0.38	−0.29	0.776	−0.04
CV_FNI (%)	9.10	0.332	0.16	31.4	0.000***	**0.89**	−4.33	0.474	−0.12	−2.09	0.769	−0.08
RES_FNI (%)	−16.7	0.256	−0.19	−50.6	0.000***	**−0.88**	−3.38	0.692	−0.06	8.02	0.325	0.29
REV_DEP (%)	3.89	0.000***	0.62	4.64	0.000***	**1.04**	9.69	0.000***	0.63	2.16	0.590	0.14
ECO_FPCI (0–1)	−0.044	0.197	−0.25	−0.131	0.006**	−0.47	0.062	0.017*	0.38	0.009	0.844	0.06

Source: Own elaboration based on RECAN microdata.
***, **, and * denote statistical significance at 0.1%, 1%, 5%, respectively.
[a] Matched 213 conventional farms and 32 organic farms.
[b] Matched 212 conventional farms and 18 organic farms.
[c] Matched 58 conventional farms and 63 organic farms.
[d] Matched 69 conventional farms and 14 organic farms.
[e] 'Large' or 'very large' effect sizes are shown in bold.

4.2. Fruit farms' organic conversion: Changes in economic performance

Table 7 shows the ATE estimates of the unbiased impact of organic farming adoption on each base/composite indicator of economic performance by TF, including Cohen's d to account for the effect size.[6] As can be observed, the differences in farms' economic performance between organic and conventional farming (ATE estimates) contrast with those shown in the pre-matching analysis (Table 5). This can be explained by the fact that ATE estimators effectively isolate the effect of the organic production regime on farms' economic performance, removing the impact of other underlying factors through the matching procedure.

At a glance, it can be observed that the ATE estimates shown in Table 7 are highly heterogeneous between TFs. In the case of fruit farms (TF 361), the higher CAP subsidies after converting to organic farming (+3.89% in REV_DEP) lead to the ATE estimates for the rest of the base economic performance indicators not being statistically significant. Accordingly, we can conclude that the overall economic performance of fruit farms which converted to organic farming is similar to that of conventional farms (no significant differences are found for the economic composite indicator calculated).

The implementation of the organic production in the case of citrus farms (TF 362) leads to less profitability (−3.02% in ROA indicator) and less resilience, as the variability of the FNI is higher (+31.4% in CV_FNI) and it also has worse resistance (−50.6% in RES_FNI). Moreover, the conversion of citrus farms to organic makes them 4.64% more dependent on CAP subsidies than under conventional production. In fact, Cohen's d values clearly support ATE estimates on CV_FNI, RES_FNI, and REV_DEP base indicators since their effect size can be categorized as large or very large. All these facts explain why the ATE estimator for ECO_FPCI (−0.131) reflects the worse overall economic performance of organic citrus farming compared to conventional production.

On the contrary, the conversion from conventional to organic nut farming (TF 363) improves economic performance in almost all base indicators. The ATE estimators show that nut farms are more profitable (+188 €/ha and + 3.28% in FNI and ROA, respectively) and viable (+0.49 in LT_VB and + 2.10 in ST_VB) once they convert to organic. However, organic farming adoption in nut farms also involves a statistically significant higher revenue dependency on CAP subsidies (+9.69% in REV_DEP). In sum, according to the ATE estimator for ECO_FPCI (+0.062), the conversion of nut farms to organic production leads to better overall economic performance.

Lastly, regarding tropical fruit (TF 364), no statistically significant differences in economic performance were found for farms that had converted to organic.

The heterogeneity of the results obtained across the different fruit TFs makes it challenging to report general conclusions about the economic impact of organic conversion at the farm level. However, it is worth noting that the decrease in fruit production yields because of the adoption of organic farming is usually fully compensated for by the higher prices received by organic farmers (price premiums over conventional products),[7] as revealed by the widespread good performance of organic fruit farming in terms of profitability. In this sense, ATE estimates only show a significant negative difference for the ROA indicator in citrus farms (TF 362). For all other TFs and indicators, the profitability ATE estimates are either not statistically significant or significantly positive (for example, in nut farms, TF 363). These results contradict the widespread perception that organic farming is less

[6] According to Cohen (1988), absolute Cohen's d values of around 0.20 identify a 'small' effect size, around 0.50 a 'medium' effect size, around 0.80 a 'large' effect size, and around 1.20 a 'very large' effect size.

[7] Lin et al. (2008) estimated price premiums for the organic attribute for five major fresh fruits in the USA, with these premiums found to range from 13% to 86%, depending on the product.

profitable than conventional farming (Trewavas, 2001), raising doubts about the efficiency of the subsidies granted to organic fruit farmers as a way to promote the expansion of organic farming. For instance, the results show that subsidies granted to organic nut farmers might not be justified since the conversion to organic farming does not lead to any decrease in profitability; therefore, no public compensation is needed to promote this conversion. In fact, in the case of nut farms, the additional income provided through these subsidies makes this alternative unnecessarily more profitable than conventional agriculture. Conversely, the ATE estimates indicate that subsidies received by organic citrus farmers are insufficient to compensate for their lower profitability after the conversion. Only in the case of fruit farms (TF 361) can it be concluded that subsidies are set at the appropriate level to compensate for the drop in yields after organic conversion, ensuring their economic performance is similar to that of conventional production.

4.3. *Fruit farms' organic conversion: Changes in environmental performance*

Table 8 shows the ATE estimates quantifying the impact of the conversion to organic farming on each base/composite indicator of environmental performance by TF, along with their corresponding Cohen's d values (i.e., effect size). Similar to the analysis focused on economic performance, the unbiased differences (ATE estimates) in environmental performance found between organic and conventional farms are fairly different compared to those observed in the pre-matching analysis (Table 6).

In the case of fruit farms (TF 361), implementing the organic farming production system results in a statistically significant improvement in farms' biodiversity, as shown by the ATE estimate of +0.123 in the Shannon diversity index (SDI), as well as −337.9 €/ha in crop protection costs (CROP_PRO), which ultimately reflect the use of biocide products on farms. For the latter indicator, it is worth mentioning that the Cohen's d also identified a large effect size. However, no statistically significant difference was found regarding GHG or water pollutant (i.e., N and P) emissions. When jointly considering all these performance indicators, a significant difference was identified in the environmental composite indicator (+0.120 in ENV_FPCI), indicating a positive change in the overall environmental performance per hectare after adopting organic farming, mainly due to improved biodiversity.

The implementation of organic farming in citrus farms (TF 362) implies a statistically significant improvement in biodiversity performance (−139.6 €/ha in CROP_PRO) and pollution emissions (−22.9 kg N/ha in PHOSP); the latter been identified as a large effect size. However, after adopting the organic production regime, these farms have statistically significantly higher GHG emissions (+457.4 kg CO_2e/ha in GHG_EM). Since citrus organic farms' worse performance in GHG emissions counterbalances their better performance in biodiversity and pollution emissions, the ATE estimator shows no statistically significant difference for ENV_FPCI. Thus, overall environmental performance per hectare remains similar when converting conventional citrus farms to organic farming.

Regarding nut farms (TF 363), the results reveal two statistically significant differences in environmental base indicators arising from organic adoption. These differences indicate an improvement in organic nut farms' environmental performance in terms of biodiversity compared to their conventional counterparts, spending 18.3 €/ha less on biocide products (CROP_PRO) and using lower levels of N inputs (−15.8 kg N/ha in NITROG). In light of these relatively small differences, we can conclude that nut farms which converted to organic perform similarly in the environmental dimension to conventional nut farms. Hence, the overall environmental benefit per hectare derived from the implementation of organic farming is almost negligible (i.e., the ATE estimate for ENV_FPCI is not statistically significant).

The opposite is true for the case of tropical fruit farms (TF 364), where the adoption of organic farming entails less use of biocide

Table 8
Organic-conventional ATE estimates on the environmental performance indicators by TF.

Indicator	Fruits[a] (TF 361)			Citrus[b] (TF 362)			Nuts[c] (TF 363)			Tropical[d] (TF 364)		
	ATE	p-value	Cohen's d[e]	ATE	p-value	Cohen's d[e]	ATE	p-value	Cohen's d[e]	ATE	p-value	Cohen's d[e]
SDI (dimensionless)	0.123	0.033*	0.37	−0.079	0.090	−0.54	−0.053	0.204	−0.18	−0.026	0.422	−0.21
CROP_PRO (€/ha)	−337.9	0.000***	**−1.00**	−139.6	0.030*	−0.53	−18.3	0.005**	−0.44	−610.4	0.000***	**−1.58**
GHG_EM (kg CO_2e/ha)	−52.8	0.694	−0.07	457.4	0.002**	0.63	25.6	0.113	0.19	203.8	0.768	0.06
NITROG (kg N/ha)	−10.9	0.240	−0.20	39.8	0.059	0.47	−15.8	0.000***	−0.64	−207.7	0.000***	**−1.29**
PHOSP (kg P/ha)	−2.9	0.640	−0.08	−22.9	0.016*	**−0.69**	−2.1	0.131	−0.21	−325.8	0.000***	**−1.39**
ENV_FPCI (0–1)	0.120	0.001***	0.65	−0.053	0.204	−0.34	0.046	0.089	0.23	0.182	0.000***	**1.12**

Source: Own elaboration based on RECAN microdata.
***, **, and * denote statistical significance at 0.1%, 1%, 5%, respectively.
[a] Matched 213 conventional farms and 32 organic farms.
[b] Matched 212 conventional farms and 18 organic farms.
[c] Matched 58 conventional farms and 63 organic farms.
[d] Matched 69 conventional farms and 14 organic farms.
[e] 'Large' or 'very large' effect sizes are shown in bold.

products (−610.4 €/ha in CROP_PRO), increasing farms' biodiversity. Additionally, the conversion to organic farming in tropical fruit farms involves a reduction of pollution emissions, with a substantial decrease in the use of fertilizers compared to conventional farming (−207.7 kg N/ha in NITROG, −325.8 kg P/ha in PHOSP). Hence, the ATE estimate for ENV_FPCI is positive and statistically significant (+0.182). In this case, the Cohen's d values detect large effect sizes for all significant ATE estimates, thus reinforcing the findings. Consequently, the results allow us to conclude that organic farming conversion in tropical fruit farms significantly increases the overall environmental performance per hectare compared to conventional production.

To summarize this section, it is worth noting that, contrary to what was expected (Trewavas, 2001), the conversion to organic farming does not generally lead to better overall environmental performance at the farm level. Indeed, the enhanced environmental performance observed was statistically significant in only half of the analyzed TFs (fruit and tropical fruit farms). However, it is worth noting that the observed improvement exhibited only a medium effect size. Moreover, similar to the economic performance assessment, there is considerable heterogeneity regarding the ATE estimates for the various indicators analyzed. Only the indicator measuring the use of biocide products (CROP_PRO) showed significant differences in ATE estimates across all TFs, indicating a widespread good performance of organic fruit farming in terms of biodiversity. These findings also challenge the prevailing notion that organic farming is inherently more environment-friendly than conventional farming. This raises doubts about the efficiency of subsidies provided to organic fruit farmers to compensate them for the provision of environmental public goods. Only in the fruit and tropical fruit subsectors, where the overall environmental performance on a per hectare basis of organic farming is superior to that of conventional agriculture, can these subsidies be deemed an appropriate instrument to implement the “provider gets” principle in organic farming.

5. Discussion and concluding remarks

This paper provides methodological insights and practical implications that could help to achieve the policy objective of having 25% of the EU's agricultural land under organic farming by 2030, while minimizing the trade-off between the expected environmental benefits and economic losses.

First, from a methodological point of view, the results suggest that matching methods can effectively isolate the differences in farms' performance exclusively associated with the “treatment” analyzed, such as the conversion from conventional to organic farming. This study has applied a propensity score matching procedure to successfully estimate the changes in farms' per hectare economic and environmental performance resulting from the conversion to organic farming, ensuring a comprehensive and unbiased assessment. Moreover, the study also evidences the usefulness of composite indicators for comprehensively assessing farms' economic and environmental performance. In this sense, the results obtained show that the constructed indexes are not sensitive to the choice of the weighting or aggregation procedures, confirming their robustness.

Second, from a policy point of view, the empirical results obtained have relevant implications that can support policy decision-makers in the design of instruments to facilitate the organic transition at the pace stipulated by the European Green Deal, while minimizing the adverse effects arising from the loss of production. The results show that the impact of the conversion to organic farming on farms' economic and environmental performance per hectare is widely heterogeneous across types of fruit farming. These findings are aligned with those obtained by Reganold and Wachter (2016) and Seufert and Ramankutty (2017) in their meta-analyses of numerous studies comparing the two agricultural systems. Consequently, as pointed out in several policy reports (e.g., Beckman et al., 2020; Guyomard et al., 2020; Barreiro-Hurle et al., 2021), the promotion of organic farming through agricultural policy should be handled with caution, since overlooking the impacts on farms' performance could lead to economic inefficiencies (i.e., environmental benefits lower than production losses). Furthermore, the results show that differences in fruit farms' economic and environmental performance caused by the conversion to organic farming are somewhat more modest than the expectations from non-randomized average comparisons. In this sense, the relatively small changes found suggest that the expansion of organic farming is concentrated in farms that are less profitable (i.e., poorer economic performance) and less intensive (i.e., better environmental performance per hectare) than the average conventional farm. This fact calls for political attention to efficiently promote organic agriculture, accounting for the different gains/losses in farms' performance within each production subsector.

On the one hand, the results indicate that the impact of organic farming adoption on the fruit farms' economic performance is heterogeneous between types of fruit farming: positive for nut farms, negative for citrus farms, and non-significant for other fruit and tropical fruit farms. Methodological issues could explain the differences with the mixed results reported in previous comparative assessments (e.g., Nemes, 2009; Crowder and Reganold, 2015; Hansen et al., 2021): first, we adopted a broader multidimensional conceptualization of farms' economic performance beyond profitability; and second, we applied a matching method to minimize non-randomization biases in the assessment of treatment effects, instead of the observational average differences usually reported. Thus, the proposed innovative methodological approach led to more accurate and reliable results, which can help to fine-tune the design of agri-environmental instruments to promote organic farming through compensation payments. For instance, ATE estimates indicate that converting nut farms to organic farming implies receiving more CAP subsidies while improving overall economic performance. These results suggest that organic nut farmers might be overcompensated, highlighting inefficiencies in the current flat-rate allocation of subsidies. Even for the case of organic citrus farms (TF 362), where subsidies make it possible to reduce the economic performance gap with their conventional counterparts, the efficiency of the current subsidy allocation is questionable since the conversion to organic agriculture does not provide significant environmental benefits. This evidence calls for a change in the design of subsidies to promote organic farming: rather than the current flat-rate system (i.e., a crop-specific payment per hectare converted to organic farming), it would be advisable to link the amount of these subsidies to potential productivity/profitability losses and environmental benefits resulting from conversion to organic.

On the other hand, changes in fruit farms' environmental performance per hectare resulting from organic farming conversion have also turned out to differ by type of fruit farming: changes are positive for fruits and tropical fruit farms and non-significant for all other TFs. Therefore, the results obtained do not fully support the assumption that the conversion to organic farming generally enhances farms' environmental performance. These conclusions further contribute to the ongoing debate about this topic raised by several authors (e.g., Seufert and Ramankutty, 2017; Meemken and Qaim, 2018). The expansion of organic agriculture could contribute to a more sustainable food system, as its negative impacts on the environment at the local level (i.e., pressures on the ecosystems measured on a per hectare basis) are generally lower than those exerted by the average conventional agriculture. However, as the results suggest, the contribution of organic conversion to farms' environmental performance per hectare should be carefully evaluated within each context, keeping in mind that conventional agriculture can also be done without significant negative impacts on the environment (e.g., extensive agricultural systems).

It is worth noting that this study is not free of limitations. The first one is related to the source of data employed for the analysis. In this sense, it should be pointed out that there is relatively little environmental information included in the RECAN database (Kelly et al., 2018). In fact, this study could be improved if additional relevant environmental information were available; for example, farm-level data regarding the presence of potential high natural value areas and the biocide potential of the agrochemical used (biodiversity), soil management practices (soil functionality), GHG emissions (climate change), nutrient balances (pollution emissions), or water consumption (water withdrawals). Moreover, the study could also benefit if the RECAN collected valuable data to further characterize organic and conventional production for a more precise matching between farms (e.g., covariates such as planting density or farm slope). Nonetheless, many of these data limitations might be solved by the future Farm Sustainability Data Network (FSDN), which will upgrade the current FADN.

It is also worth acknowledging that the methodological approach used to assess the environmental impacts of farming relies on area-based indicators, which give a partial view of the topic under analysis. While this approach allows the measurement of differential pressures on the environment of farming systems at the local or regional level, this kind of analysis should be complemented with other studies that use product-based indicators (e.g., on a per ton or kg basis), thus offering a broader view of the environmental impact. Such a complementary approach would allow for an assessment of the environmental impacts of the transition to organic farming at a global level, properly relating farm productivity (i.e., differentiated yields) with the pressures exerted on the environment by different farming systems. This limitation could also be addressed through further research relating food production to environmental impacts, using farm microdata to compare the total factor productivity of farms under different production systems, considering production variables measured in both monetary and physical terms. The results from such new assessments might support the design of more efficient policy instruments in the context of the organic transition of agriculture, by giving more accurate insights regarding farms' capacity to provide food under alternative production systems.

Lastly, the static nature of the analysis performed must be pointed out, as the matching procedure implemented just compared average conventional and organic farms at the current time. This could be considered another limitation of this study since it ignores the dynamics of ecological transition processes in farm performance. We thus call for new research that specifically analyzes how farms' economic and environmental performance evolve over the course of the conversion process from conventional to organic production, considering the particular case of farms that are in the process of converting to organic farming (but that still appear as conventional farms) and the learning-by-doing effect.

CRediT authorship contribution statement

Jaime Martín-García: Writing – original draft, Visualization, Methodology, Formal analysis. **José A. Gómez-Limón:** Writing – review & editing, Methodology, Funding acquisition, Conceptualization. **Manuel Arriaza:** Writing – review & editing, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

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

Data availability

The authors do not have permission to share the Spanish Farm Accountancy Data Network (RECAN) microdata provided by the Ministry of Agriculture, Fisheries, and Food (MAPA).

Acknowledgments

This work was supported by the Spanish Ministry of Science and Innovation, the Andalusian Department of Economy and Knowledge, and the European Regional Development Fund through the research projects FARMPERFORM (Grant PID2022-136239OB-I00) and TRANS-ECOag (Grant PROYEXCEL_00459). Also, the University of Córdoba supported this research by financing a predoctoral contract within the framework of its Research Plan. The authors thank MAPA for providing the microdata files from the RECAN used for the research. The authors are also grateful for the collaboration of the 23 scholars and professionals who took part in the panel of experts weighting the base indicators.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolecon.2024.108178.

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