Italian Economic Journal
https://doi.org/10.1007/s40797-026-00411-3

RESEARCH PAPER

Where Digitalisation Supports Sustainability: Environmental Gains in the Agrifood Sector

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Received: 6 October 2025 / Accepted: 7 September 2026
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Abstract
This paper investigates the role of digital technologies in enhancing environmental sustainability in the agricultural sector. Using microdata from the Italian Farm Accountancy Data Network (FADN) and counterfactual methods for policy evaluation, we find that digitalised farms exhibit lower GHG emissions. By contrast, we find no significant effects on water use. The potential impact on non-digitalised farms, had they been treated, is estimated to be even larger. The digitalisation of agricultural systems, therefore, holds significant potential for reducing emissions while promoting more effective, sustainable strategies. The paper offers novel and significant policy insights into promoting digitalisation to enhance environmental sustainability across the sector and to support economic actors in making more sustainable decisions.

Keywords Digital transformation · Innovation diffusion · Agriculture · Information systems · Internet economics · Policy evaluation

JEL Classification Q16 · O13 · O31 · C21

1 Introduction

The promotion of innovation and digitalisation has been proposed as a cross-cutting objective to bolster the sustainability of the agrifood systems by the current Common Agricultural Policy (CAP) (EC 2025a, b). The post-2027 Vision has confirmed this trend and the need, in the future, to continue in "*investing and leveraging the transformative power that research, knowledge, skills and innovation offer*" (EC 2025b, p. 6),

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Published online: 16 November 2026

by proposing to "*launch an EU digital strategy for agriculture to enable the transition to a digital-ready and future-oriented farming and food sector while avoiding possible pitfalls*" (EC 2025b, p. 25). Advances in digitalisation may offer, in fact, significant opportunities for environmental sustainability in agriculture, making the transition a win–win for both economic actors and nature, while supporting competitiveness (EC 2024). Nevertheless, the diffusion of innovative and digital technologies is as desirable as it is complex due to structural characteristics of EU farms and the link with the historical tradition of agrifood production (Brunori 2022).

On the one hand, the agrifood is characterised by family farming, small-medium holdings with scarce generation renewal, and heterogenous territorial contexts, which have been highlighted by the literature as frictions to innovate (Cattani et al. 2023; Bottai et al. 2024; FAO 2019; Domenech et al. 2014): "*in 2021, only 55% of SMEs reached at least a basic level of adoption of digital technologies*" (EC 2023, p. 135). On the other hand, the EU agrifood sector is still anchored at traditional production processes along which using innovative and digital technologies could be difficult (Vaquero-Piñeiro and Pierucci 2025), and it will remain in this pathway given the objective of "*going back to the 'roots' and re-establishing the link between food, territory, seasonality, cultures and local traditions*" proposed by the EU Vision for the agricultural system for 2040, and beyond (EC 2025b, p. 22).

As a result, agriculture is one of the least innovative and digitalised sectors (Birner et al. 2021; Triguero et al. 2013). For instance, according to the last Agricultural Census conducted by ISTAT, only 12% of the total number of farms surveyed declared to have introduced innovation over the last five years, with production optimisation as the main benefit achieved (ISTAT 2026). Larger farms and Northern regions are more prone to adopt innovation compared with small farms and Southern areas. Despite such a territorial imbalance, policy choices supporting innovation are fragmented, lacking specific differentiation in response to local criticalities (Vagnozzi and Giarè 2025).

At the same time, agriculture mostly impacts environmental systems by exploiting many natural resources, like soil and water, and producing a huge amount of greenhouse gas (GHG) emissions (FAO 2025; Olper and Curzi 2022; EEA 2019). In this scenario, the evaluation of whether digital technologies are viable strategies to improve the environmental sustainability of the agriculture sector becomes crucial.

Existing literature laid out conceptual foundations for understanding how digital technologies can contribute to more sustainable agricultural systems. In his paper, Finger (2023) highlighted the potential benefits of digitalisation and provided concrete examples of how digitalisation can support the implementation of more sustainable agricultural systems. However, the analysis remains at the theoretical level, debating the benefits, costs and challenges of digitalisation and providing some policy reflection. Publications on the environmental role of digital technologies in agriculture are constantly increasing over time (Parra-López et al. 2024), but most existing papers adopted qualitative approaches and focused on specific case studies (Panero et al. 2025; Mao et al. 2024; Mancini et al. 2019; Läpple and Thorne 2019), leaving the literature without comprehensive empirical analysis.

This paper tries to provide a blueprint for future research by empirically investigating the role of digitalisation for environmental sustainability in the agricultural sector, in the form of GHG and water use, using a new variable capturing the status of being

a digitalised farm. Data were released in 2025 within the Italian Farm Accountancy Data Network (FADN), which is the official and unique annual harmonised dataset available with structural and accountancy data at the micro-level. The variable is a dummy assigned a value of 1 for farms that use at least one digital technology in the year of the survey, and 0 for those that do not.

The analysis is conducted at the farm level over the 2017–2022 period. Methodologically, we first adopt propensity score matching (PSM) to estimate the average effect on digitalised farms. Second, with regression adjusted models, we disentangle the potential percentage size of the effect of digitalisation on non-digitalised farms, i.e., what the effects would have been if farms that had not used digitalisation had used it (Cerulli 2014).

Findings indicate that digitalisation reduces emissions, while it does not significantly affect water use. Potential benefits in terms of emissions reduction also emerge in the case of non-digitalised farms, which would experience a lower level of emissions if they used digital technologies.

The paper is structured as follows: Sect. 2 introduces the background, with a conceptual focus on the link between digitalisation and environmental sustainability; Sect. 3 illustrates data and the empirical setting, while Sect. 4 illustrates the results. Section 5 concludes.

2 Background

2.1 Digitalisation and Environmental Sustainability

Digitalisation has been recognised by the economic literature as a beneficial channel through which improved economic performance can be achieved from different perspectives, such as reducing production costs, increasing productivity and supporting efficiency. By looking at the case of farmers located in Garfagnana (Tuscany, Italy), Metta and Mazzocchi (2020) demonstrated that digital tools can contribute to farm economic resilience.

At the same time, a virtuous link between digitalisation and environmental sustainability has been posited (Pacciani et al. 2025). Digital technologies have, in fact, been defined as potential strategic drivers of environmental sustainability, working as a generator of intangible value creation and environmental upgrading at both micro- (e.g., emissions production) (Miranda et al. 2024; Lee and Roh 2023; Frank et al. 2019) and meso-levels (e.g., biodiversity, ecosystem services) (Rueda et al. 2023; Zhang and Du 2023). Recent studies further suggest that agricultural digitalisation may reduce carbon emissions both directly (Chang 2025) and indirectly, through the optimisation of input use and the reduction of waste (Lepore et al. 2025).

At the micro level, digitalisation technologies have the potential to advance sustainability by enabling actors to integrate environmentally friendly practices into their business models (Di Vaio et al. 2020; Gebler et al. 2014; Saberi et al. 2019). In the long term, the literature demonstrated that the use of digital technologies, aligned with circular economy principles, can lead to economic competitive advantages, while reaching environmental achievements (Del Río Castro et al. 2021; Díaz-Chao et al.

2016). By integrating digital tools with sustainability objectives, producers can spur economic performance while simultaneously contributing to environmental sustainability (Copestake et al. 2024; Guo et al. 2023; Curzi et al. 2023). However, such environmental benefits are still not really perceived by economic actors, who associate the green transition with higher costs and lower production capacity. As a result, the adoption of digital technologies for environmental purposes is often guided by social commitments or public support (Aksin-Sivrikaya and Bhattacharya 2017) and, consequently, the involvement in digital transition varies among economic systems and, within them, across sectors (Lange and Santarius 2020). For instance, while the manufacturing sector began its digital transition decades ago, achieving significant economic and environmental benefits, the agricultural sector remains largely reliant on traditional production processes, characterised by low levels of digitalisation and a high environmental impact.

2.2 Why Can Using Digital Technologies Affect the Environmental Sustainability of Farms?

As in the case of other economic sectors, digital technologies can also reduce the environmental footprint of agricultural systems (McFadden et al. 2022; Sidhoum et al. 2023; Stetter et al. 2022) and support sustainable rural development (Brunori 2022). Literature demonstrated that a win–win linkage between digital technologies and environmental sustainability exists and proposed their adoption as an effective strategy to face the challenge of increasing agrifood production to ensure food security, while reducing emissions and input use (Vaquero-Piñeiro et al. 2025a, b; Mao et al. 2024; Cerutti et al. 2023; EC 2022a, b).

There are several ways in which the digitalisation and environmental sustainability of the agricultural sector are conceptually interrelated, as mainly summarised by Finger (2023). First, digitalisation can enable a reduction in footprints by optimising inputs, increasing efficiency and cutting waste. Precision farming, for instance, can help to optimise agricultural inputs (e.g., water and fertilisers) (Finger et al. 2019; Bwambale et al. 2022), to avoid inefficient operations (Gasso et al. 2013) and, consequently, to reduce GHG emissions (EC 2025a, b). For instance, Banerjee et al. (2024) show that the use of AI can help in predicting groundwater availability and help in planning water use.

Second, digital technologies can contribute to substituting original inputs with more environmentally friendly ones within a circular economy perspective (FAO 2022). Agriculture is not only one of the key drivers of emissions, but also a major consumer of natural resources (Rosa and Gabrielli 2023; Cerutti et al. 2023). Lastly, digitalisation can redesign farming systems, reducing the need for external inputs (e.g., agroecology) (Abbasi et al. 2022). The use of data-driven decision-making, information systems and big data analytics (Hussein et al. 2025; Coble et al. 2018) can, in fact, alleviate the stress of agriculture on environmental habitats. In line with this, Ouro-Salim et al. (2023) and Siddique et al. (2025) stated that smart technologies and integrating data analytics, especially big data, can provide transformative capabilities throughout the agri-food sector.

At the same time, socio-economic sustainability can also benefit from the adoption of digital technologies. In particular, the use of digital technologies in agriculture can reduce production costs, thanks to production optimisation, enhance workers' conditions and social welfare (Bianchi et al. 2025), increase traceability while reducing information asymmetry (Giannini et al. 2025; Rossi et al. 2025; Cricelli et al. 2024), and spur competitiveness by creating new business and job opportunities (Lepore et al. 2025).

Even if farmers increasingly rely on digital technologies, some challenges remain, mainly due to a sort of path dependence of farmers' behaviours. Domenech et al. (2014) demonstrated, in fact, that the adoption of web technologies in agrifood is shaped by their location, economic performance and previous history of adopting innovations. At the same time, the adoption of digital technologies may be disincentivised by the time lag between the investments and their benefits, which reduces trust in digital tools (Fuglie 2018). To support the diffusion of digital technologies among farmers, policies have adopted different approaches over the years, from economic subsidies and market measures to co-creation and cooperation tools. In the EU, for example, the CAP has promoted a multi-stakeholder collaboration governance approach based on the Digital Agricultural Knowledge and Innovation Systems (DAKIS) to make agrifood actors conscious of the benefits of digitalisation and overcome the locked-in modes of production and the lack of adequate training and education (Del Puente et al. 2024; Mouratiadou et al. 2023; EC 2021). Among others, several projects aiming to spur digital adoption have been financed.[1] However, as recently demonstrated by Soma et al. (2026), digitalisation may not necessarily lead to increased sustainability, and the effects are challenging to predict (Ferrari et al. 2022).

3 Data and Empirical Setting

The objective of the paper is to empirically investigate the effects of digitalisation on the environmental sustainability of the agricultural sector. With this aim, this study uses a farm-level dataset over the 2017–2022 period and exploits policy evaluation methods for binary treatments: propensity score matching (PSM) and regression adjustment (RA) (Rosenbaum and Rubin 1983; Wooldridge 2010; Cerulli 2014).

Data come from FADN, which are collected yearly by Liaison Agencies (CREA for Italy) through a special entry book (EC 2020c). The variable accounting for digitalisation is a dummy variable coded 1 for farms that use digital technologies, and 0 otherwise.

The information on digital technologies has been collected since 2017, and it has been included as a new variable in the dataset only in the last release (accounting year 2022, first released in 2025). Indeed, before 2017, the FADN survey respondents

[1] Examples of projects financed by the European innovation partnership for agricultural productivity and sustainability (EIP-AGRI): "Innovazioni per il miglioramento della competitività e sostenibilità della filiera vitivinicola toscana" (CRA-Unità di Ricerca per la Viticoltura, Toscana); "Realizzazione di un sistema di supporto alle decisioni dedicato alle aziende agricole per l'elaborazione, operando via web, di piani di trattamento fitosanitari sostenibili" (Ente Regionale per i Servizi all'Agricoltura e alle Foreste—ERSAF, Lombardia).

More information available at: https://www.innovarurale.it/it/italia/bancadati-ricerca.

were not asked to declare whether they used digital techniques. It is self-declared, and we do not know if it is a new adoption or not. At the same time, in the current FADN survey, there is no distinction between participation in digital innovation activities (i.e., European Innovation Partnerships), use or new adoption. According to the guidelines, farmers can indicate the presence of technologies referring to several cases, such as farm management information systems and/or precision agriculture systems (such as robotics for crop production and precision crop monitoring), as well as livestock farming machinery (such as monitoring of animal welfare and health, automatic feeding systems, and milking robots). However, given that data do not reveal which technology is used, we cannot distinguish between basic (e.g., smart services) and advanced (e.g., robotic and blockchain) digital technologies. The treatment is, therefore, a binary measure of digital technology. As a coarse variable, it may mask heterogeneity across forms of digitalisation, producing average associations potentially attenuated by measurement limitations. Even if this is a limitation for this study, it also suggests a potential extension of the analysis, given that it will be possible to address it from 2027, when the results of the new Farm Sustainability Data Network survey will be accessible.[2]

By using data from 2017 to 2022, this paper thus looks at the longest period available and captures, for the first time, the farms' digitalisation phenomenon with an ad hoc survey variable. The survey registers the use of digital techniques yearly. Our sample is composed of around 11,000 farms per year (65,254 observations in total). By construction, the sample includes only actors with a standard output of a minimum of 8,000 EUR, and the stratification relies on three dimensions: NUTS2, year and production specialisation (*Orientamento Tecnico Produttivo*). Among them, only 109 actors use at least one digital technology along their production processes (Table 5).

On this sample, we performed a PSM pooled estimation using the K-nearest-neighbour algorithm (with $K = 10$) and the logit specification for the selection equation (Cerulli 2014; Rosenbaum and Rubin 1983).[3] The treated units are those farms with digital techniques, while controls are those farms without digital techniques.

The outcome variables, which proxy the impact on a farm's environmental sustainability, are the following: (i) GHG emissions produced, both in total and per hectare; and (ii) water used, also both in total and per hectare. According to the FADN data collection strategy: emissions are not self-declared but estimated by the EU office responsible for the FADN survey based on farms' characteristics; water use is self-declared as it is considered a production factor; Utilised Agricultural Area (UAA) is self-declared.

See Table 1 for outcome variables, detailed definitions and units of measurement.

The matching variables were carefully selected to obtain a set of farm-level covariates proxying for key dimensions of entrepreneurial ability, strategic orientation, and

[2] COMMISSION IMPLEMENTING REGULATION (EU) 2024/2746 of 25 October 2024 laying down rules for the application of Council Regulation (EC) No 1217/2009 setting up the Farm Sustainability Data Network and repealing Commission Implementing Regulation (EU) 2015/220.

[3] The logit specification is the best model specification for binary treatments as it adequately captures the relationship between covariates and treatment assignment. The number of neighbours, which could seem particularly high, has been selected to guarantee a representative sample given the small number of treated units.

Table 1 Outcome variables

Variable	Definition	Unit of measurement
GHG emissions (total)	The total amount of emissions (estimated)	Quintals of CO_2 equivalents (IPCC guidelines)
GHG emissions per hectare	Emissions per hectare are defined as the total amount of emissions divided by utilised agricultural area (estimated)	Quintals of CO_2 equivalents (IPCC guidelines)
Water (total)	Total amount of water used (self-declared)	Cubic meters
Water per hectare	Amount of water per hectare defined as the total amount of water used divided by the utilised agricultural area (self-declared)	Cubic meters

Note: the source of all these variables is the Italian FADN database. The variables do not distinguish the emissions' source and the water destination along the supply chain

resilience, dimensions that are most likely to drive both treatment selection and performance outcomes. By conditioning on these observables, we aim to reduce the scope for residual unobserved heterogeneity that would be both relevant and strongly unbalanced across groups.

First, we control for the *share of owned UAA* (rather than rent) as the literature demonstrates that owned enterprises are more sustainability-conscious and prone to innovate (Pagliacci et al. 2020). Secondly, we include the *share of family workers*, as a high level of family engagement may affect farms' strategies based on personal behaviours, being also an index of financial constraints and, therefore, lower propensity to adopt new technologies and invest in environmentally friendly practices. Family farmers are also more likely to preserve traditional production processes and to be less market-oriented.

The *presence of diversification strategies* allows us to capture the engagement in other economic sectors (e.g., agritourism, energy production), which suggests farmers are more prone to investing, assuming entrepreneurship risks and shifting towards new paradigms (Vaquero-Piñeiro et al. 2025a).

We also consider the *altitude,* which could be particularly relevant in affecting agricultural sustainability and economic resilience. Overall, in fact, farmers located in lowland areas are more market-oriented, rely on economies of scale and account for higher levels of production and innovation adoption. Conversely, farmers in mountain areas are likely to be smaller, both in terms of economic and physical size, less prone to diversify and anchored in traditional production processes (Grilli et al. 2026).

Moreover, we control for two fixed effects specifically related to farms' size: *Utilised Agricultural Area size* and *economic size*. This allows us to compare units with similar physical and economic size, which are both proxies of production levels and characteristics that influence the acceptance of digital technologies and innovations (Reissig and Siegrist 2025).

Table 2 Estimated average treatment effect on the treated—propensity score matching

	Emissions (total)	Emissions per hectare	Water (total)	Water per hectare
	(1)	(2)	(3)	(4)
Digitalisation	−0.125***	−0.002***	0.011	0.001
	(0.021)	(0.001)	(0.009)	(0.001)
Constant	0.188***	0.003***	0.017***	0.004***
	(0.017)	(0.001)	(0.002)	(0.001)
Obs.	680	680	359	359
Treated	62	62	37	37

Note: ***p < 0.01, **p < 0.05, *p < 0.1. Emissions and emissions per hectare are expressed in million quintals of CO_2 equivalents (IPCC guidelines). Water and water per hectare are expressed in million cubic meters

Table 3 Estimated average treatment effect on the treated—DDML

	Emissions (total)	Emissions per hectare	Water (total)	Water per hectare
	(1)	(2)	(3)	(4)
Digitalisation	−0.092***	−0.002**	0.006	0.001
	(0.024)	(0.001)	(0.007)	(0.001)
Obs.	65,254	65,254	65,254	65,254

Note: ***p < 0.01, **p < 0.05, *p < 0.1. Emissions and emissions per hectare are expressed in million quintals of CO_2 equivalents (IPCC guidelines). Water and water per hectare are expressed in million cubic meters

Lastly, we account for *organic production*, as this type of production could itself affect environmental sustainability performance, but may also require more advanced digital technologies (Schnebelin 2022). In addition, farmers who decide to adopt organic production processes are likely to better respond to market dynamics (e.g., demand for sustainable production), change their usual business and adopt new production practices.

Given that the sample is composed only of economic actors operating in the agricultural sector, we do not include sector-fixed effects, but *year fixed effects,* to account for potential invariant unobserved confounders at the time level.

All controls are considered at the farm level and lagged by one year to minimise any simultaneity bias (full description of control variables and descriptive statistics of the model in Tables 6 and 7). We cannot claim that the selected variables fully resolve endogeneity concerns related to unobservables, nor do we present the estimates as causal in a strict experimental sense. Rather, we view the PSM framework as a transparency-enhancing tool that allows us to improve comparability between treated and non-treated farms.

The quality of the matching has been assessed by comparing the degree of overlap of the propensity score distributions for treated and untreated observations before and

Table 4 Treatment effect estimates—regression adjustment model

	(1) ATE	(2) ATET	(3) ATENT
Emissions (total)			
Digitalisation	−0.061*** (0.013)	−0.113*** (0.019)	−0.061** (0.024)
Rate of return of the treatment (ρ), percentage	−51.17	−61.16	−51.15
Observations: 46,925			
Emissions per hectare			
Digitalisation	−0.001*** (0.000)	−0.002*** (0.000)	−0.001*** (0.000)
Rate of return of the treatment (ρ), percentage	−38.79	−61.04	−38.77
Observations: 46,925			
Water (total)			
Digitalisation	−0.009 (0.009)	−0.005 (0.005)	−0.009 (0.023)
Rate of return of the treatment (ρ), percentage	−8.05	−20.68	−8.02
Observations: 25,364			
Water per hectare			
Digitalisation	0.005** (0.002)	−0.001 (0.001)	0.004 (0.003)
Rate of return of the treatment (ρ), percentage	126.24	−26.42	126.49
Observations: 25,364			

Note: ***p < 0.01, **p < 0.05, *p < 0.1. Emissions and emissions per hectare are expressed in million quintals of CO_2 equivalents (IPCC guidelines). Water and water per hectare are expressed in million cubic meters. The rate of return of the treatment (ρ) in percentage terms is estimated as the average treatment effect divided by the potential outcome mean without treatment (multiplied by 100). The ρ captures the relative impact of the treatment compared to a non-treatment status

after matching (Fig. 2), and the balancing test (difference-in-mean) over the predetermined chosen covariates (from Tables 8, 9, 10, 11). We assessed the sensitivity of the results to potential violations of the conditional mean independence assumption using Rosenbaum bounds, which evaluate the robustness of treatment effect estimates to the potential presence of unobserved confounders (DiPrete and Gangl 2004). Table 12 shows that, even when assuming the presence of an unobserved factor capable of generating a substantial departure ($\Gamma = 1.6$ or even 2.0) from the ex-post randomisation achieved by PSM, the results remain consistent with the assumption of no unobserved selection bias. Therefore, our matching results can be considered sufficiently robust.

Due to the large number of untreated observations, we decide to explore the farm-level idiosyncratic effects, focusing on the potential impact of our treatment (i.e., *digitalisation*) on the untreated units (Cerulli 2014). To do that, we apply the regression adjustment (RA) approach, which is a parametric alternative to matching when one aims at measuring the impact of a treatment on an outcome. RA is based on a treatment random coefficient model as outlined in Wooldridge (2010, pp. 945–51). This model

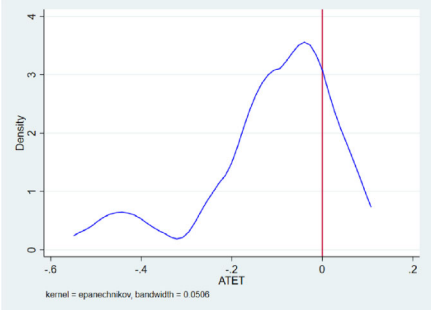
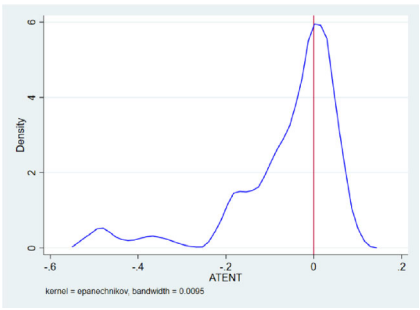
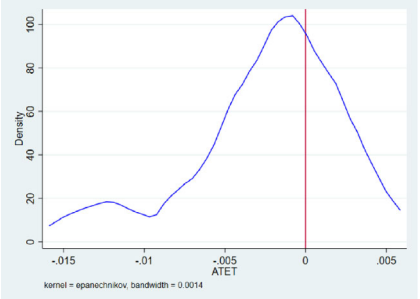
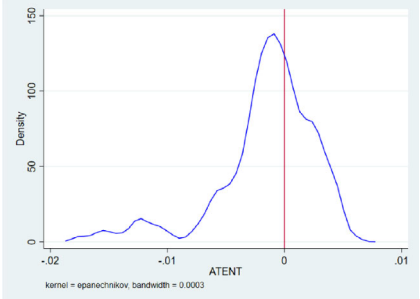
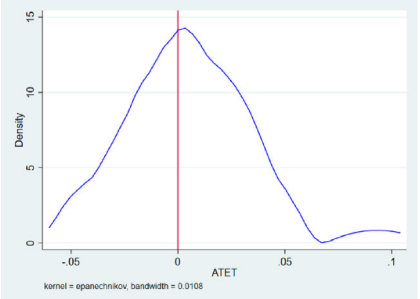
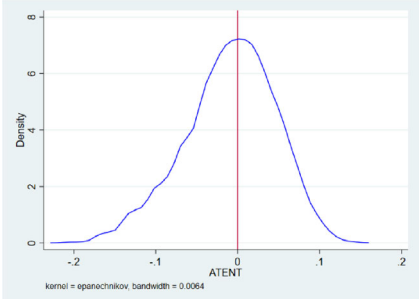
ATET (1)	ATENT (2)
Panel a	
Emissions (total)	
	
79% of farms with a reduction in GHG emissions	63% of farms with a potential reduction in GHG emissions
Emissions per hectare	
	
69% of farms with a reduction in GHG emissions	62 % of farms with a potential reduction in GHG emissions
Panel b	
Water (total)	
	
43% of farms with a reduction in water use	54 % of farms with a potential reduction in water use

Fig. 1 ATET and ATENT—Kernel density estimation. Source: Authors' elaboration on Italian FADN data. Note: Emissions and emissions per hectare are expressed in million quintals of CO_2 equivalents (IPCC guidelines). Water and water per hectare are expressed in million cubic meters

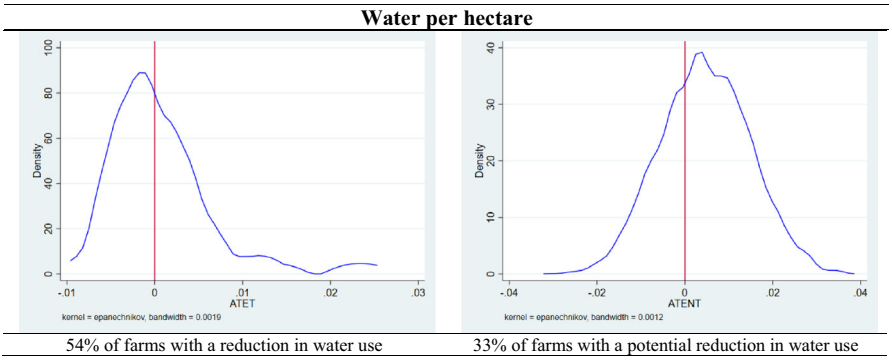


Fig. 1 continued

allows us to estimate, for each farm, an idiosyncratic effect of the treatment (i.e., being a farm that uses *digital technologies*), formally defined as the Average Treatment Effect conditional on a vector of covariates **x** (i.e., ATE(**x**)). On the contrary, in standard regression models, this effect cannot be estimated individually but only as a common (and thus singleton) parameter (typically, the ATE). See the Appendix for the model's description.

4 Results

4.1 The Impact of Digital Technologies

Starting from emissions, our findings show that digitalisation alleviates environmental impacts by slightly reducing GHG emissions.

Digitalisation is associated with a statistically significant, albeit modest, reduction in GHG emissions (see Table 2). Farms using digital technologies emit, on average, 0.125 million quintals of CO_2 equivalents less in terms of total emissions than non-digitalised farms (*Column 1*), and 0.002 million quintals of CO_2 equivalents less per hectare compared to non-digitalised farms (*Column 2*). Although the magnitude of the effect is relatively limited (particularly for emissions per hectare), these results provide clear evidence that digitalisation is associated with lower agricultural emissions. This evidence is in line with the existing literature (Pacciani et al. 2025; Chang 2025; Lepore et al. 2025).

Conversely, no statistically significant effects are detected for water use. Even if estimates for water-related outcomes should be interpreted with particular caution due to limited treated observations, results show that being a digitalised farm does not significantly affect either total water consumption (*Column 3*) or water use per hectare (*Column 4*). While the estimated coefficients are small and not statistically different from zero, indicating no evidence of adverse effects, digital technologies alone do not appear sufficient to significantly address water-related environmental issues.

Such a non-significant effect can be mainly explained by water being a necessary input for the sector, thus difficult to substitute, especially in the context of growing temperatures and climate change (EU 2021). While irrigated water-intensive crops require more water (e.g., *actinidia*), non-irrigated crops are also starting to suffer from water scarcity and need supplemental and emergency irrigation (e.g., *vines and olive oil*) (Vaquero-Piñeiro et al. 2025a, b; Mozell and Thach 2014). As stated by Girotto et al. (2022), even in viticulture, which was one of the first sectors to implement smart and precision farming activities, water consumption along the supply chain still remains a black box, with path dependence that is difficult to change or influence.

In the future, the resilience of agricultural systems will likely depend heavily on water availability and the adoption of new water management models and irrigation strategies (EC 2025a; EC 2020a; Berbel et al. 2018). Digitalisation can support this shift, but it seems that, at this stage, its contribution is not large enough to significantly impact water consumption.

To test the robustness of our findings, we replicate the analysis by adopting a Double/Debiased Machine Learning (DDML) interactive model with cross-fitting for binary treatment (Chernozhukov et al. 2018). Compared to partially-linear models, the interactive DDML relaxes the assumption that the confounders and the treatment variable of the model are separable. To estimate the nuisance parameters, this approach uses machine learning (ML) methods. In this DDML application, we use 5 folds and 5 resampling, meaning that the model is estimated 25 times using randomly chosen folds, and apply this procedure: for the selection equation, we use stacked logit and gradient-boosted trees, whereas for the outcome equation, we use stacked linear regression and gradient-boosted trees (Ahrens et al. 2024).

The results (reported in Table 3) are in line with the PSM ones, confirming the positive effect of using digital technologies on emission outcomes. Regarding emissions, the estimated ATET is negative and statistically significant, suggesting that treated units exhibit, on average, a lower carbon footprint compared to untreated units. The negative coefficient indicates that the treatment is associated with a reduction in the carbon footprint for treated farms, both in total (ATET: -0.092) and per hectare (ATET: -0.002). Conversely, the effect on water use is not statistically significant.

4.2 The Potential Impact of Digital Technologies

Table 4 presents the average treatment effect of digitalisation on environmental performance estimated by regression adjustment models. The effects are reported on average (*Column 1*), for treated units (*Column 2*) and untreated units (*Column 3*).

The results reveal a clear and robust negative effect of digitalisation on emissions, both in total and per hectare. The ATE is statistically significant and economically meaningful, while the larger magnitude of the ATET relative to the ATE suggests the presence of positive treatment effect heterogeneity, with treated units benefiting more than the average. The corresponding rates of return (ρ) indicate substantial reductions relative to the counterfactual scenario without treatment. The rate of return of a policy or treatment is defined as the selected average treatment effect (ATE, ATET, or ATENT) divided by the estimated mean untreated potential outcome. This has to be interpreted

as a "gross" return, as it does not account for treatment costs. Importantly, this pattern is also confirmed for non-digitalised farms (*Column* 3), which have not yet used digital technologies: the estimated rate of return (ρ) amounts to −51.15% for total emissions and −38.77% for emissions per hectare, indicating that these farms would have experienced sizeable reductions in emissions had they used digital practices. In contrast, no statistically significant effects are detected for total water use, pointing to the absence of a systematic relationship between digitalisation and aggregate water consumption. However, a positive and statistically significant ATE emerges for water use per hectare, suggesting that digitalisation may increase water intensity, although this effect is not robust across ATET and ATENT estimates. Taken together, these findings point to a potential environmental trade-off: while digitalisation appears to enhance efficiency in terms of emissions reduction, its impact on water use is more ambiguous and may reflect increased production intensity.

To measure the farm-specific (average) effect of digital use on the outcome variables, we then look at the kernel density distribution of the estimated effects (Fig. 1). Overall, the distributions are bell-shaped across all outcome variables.[4]

Starting from emissions (*Panel a,* Fig. 1), the distributions of both ATET(x) and ATENT(x) are skewed toward negative values, indicating reductions in GHG emissions.

Among treated farms (*Column 1*), the proportion of farms experiencing a reduction in agricultural emissions ranges from 79% for total emissions to 69% for emissions per hectare. For non-treated farms (*Column 2*), the estimated ATENT(x) deviates substantially from zero, indicating that farms which have not used digital technologies would have experienced significant environmental gains in terms of GHG reductions had they done so. Specifically, a majority of non-treated farms—63% for total GHG emissions and 62% for emissions per hectare—would have benefited from a reduction in emissions.[5]

The distributions for water use reflect the non-significant impact of the treatment (*Panel b,* Fig. 1). Among treated farms (*Column 1*), the values are approximately evenly distributed between positive and negative changes: 43% of farms would experience a reduction in total water use, and 54% in water use per hectare. For non-treated farms (*Column 2*), these proportions are 54% for total water use and only 33% for water use per hectare. Accordingly, a majority of non-treated farms would likely have increased rather than decreased their water consumption had they adopted digital technologies—particularly in terms of water use per hectare.

To sum up, the first part of the analysis provides preliminary evidence of the effects of using digital techniques in terms of environmental outcomes, highlighting a benefit in terms of emission reduction and a non-significant effect in terms of water use.

The second part of the analysis reveals that the largest part of farms that have not used digital technologies would experience reductions in emissions if they were to use

[4] Based on the law of iterated expectations, ATET(**x**) distributions are centred at ATET, and can be interpreted as the distributions of farm-specific idiosyncratic (average) effects. The same applies to the ATENT(**x**).

[5] As reflected in the left-skewed tail of the distributions, the experienced reduction would be strong, especially for the group of farms included in the area between −0.2 and −0.01.

digital technologies. Even untreated units would benefit, therefore, from digitalisation in terms of reducing emissions.

This evidence confirms the importance of digital tools to create a more sustainable environment for local actors and citizens (Barabanova and Krzysztofowicz 2023) and reinforces the policy rationale for encouraging the diffusion of digital technologies among currently non-adopters to lower the environmental footprint and foster green transition (EC 2022a, b).

This objective could benefit from more tailored interventions based on communities' and farms' characteristics. So far, in fact, the digitalisation strategies have been mainly conducted through a one-size-fits-all approach tailored to the characteristics of each country, without considering local actors' heterogeneity.

4.3 Limitations and Potential Extensions

The limitations of this paper mainly depend on the level of detail of the available data.

First, the FADN data structure makes a before-and-after treatment analysis, such as the Difference-in-Differences, unsuitable. In Italy, every year the sample includes around 11,000 respondents with a 20–25% annual turnover. This structural rotation, unfortunately, prevented the construction of a consistent balanced panel at the micro-level (Vaquero-Piñeiro et al. 2025a, b). In our case, adjusting the sample to include only farms observed throughout the entire period would lead to a significant reduction in observations (from 109 to 6 before the matching). Moreover, all farms are potentially eligible for the treatment, so we cannot exclude any group a priori as structurally untreated. Even within a repeated cross-section framework, the data do not display a clear and exogenous time variation in treatment assignment at the group level, which is required to implement a DiD design. As a consequence, the construction of a valid control group and the plausibility of the parallel trends assumption required for DiD are not supported by the data. More structured data might allow for dynamic analysis and the assessment of the time lag between treatment and effect.

Second, the analysis highlighted the need to collect more accurate data on digitalisation techniques. While no single variable can exhaustively capture all the various dimensions of digitalisation, a wider range of variables may, in fact, increase the robustness of studies on the effects of the use of digital techniques (Copestake et al. 2024). Even if slowly, the EU is making some steps forward in this direction. First, the EU proposed the *AgridataSpace* action aiming at paving the way for facilitating data sharing, processing, and analysis. Second, since the 2025 accounting year (deliverable in 2027), the FADN will shift to the Farm Sustainability Data Network (FSDN) (see Footnote 2). The new EU survey will include a specific set of questions related to innovation and digital technologies, thanks to which we will be able to distinguish among technology types and between participation and adoption (CREA 2025). So far, therefore, the evidence provided by this study is limited to a preliminary stage due to data accuracy.

Lastly, even if technically feasible, the analysis cannot be extended at the EU level as the collection of data on digital technologies is not mandatory, but rather the intention of collecting data is deferred to national authorities.

Future research avenues include the extension of the analysis on other sustainability outcomes (e.g., social and economic, Sardone et al. 2023), which might be, at least theoretically, affected by the digital technologies. FSDN will, in fact, register not only economic and business outcomes, but also data on environmental and social sustainability performance. In addition, we aim at collecting unconventional data on digitalisation from internet sources (e.g., websites) to have a more detailed and vast variety of indicators on sustainability practices as well as on innovation adoption.

5 Discussion and Conclusions

Although the green transition may not be completely achieved in the short run, digitalisation appears to be a promising lever to accelerate the process and the EU decarbonisation strategy (Draghi 2024), while also promoting emission reductions within the agricultural sector (EC 2020a, b). By looking at the case of the Italian agricultural sector, using quantitative analysis and relying on completely new data, this paper provided first preliminary evidence in support of this thesis. Even with some clear limitations, the analysis conducted suggests, in fact, not only that farmers using digital techniques have reduced total emissions and their intensity, but also that most of the farmers who are currently not using digital technologies would have experienced reductions in emissions if they used digital technologies.

Beyond its substantive findings, this study also speaks to the broader value of data-driven approaches for evidence-based economic policymaking. By combining novel, granular farm-level data with a counterfactual, policy-evaluation strategy, the analysis moves beyond descriptive or case-based accounts of digitalisation's environmental effects, offering policymakers a more transparent and replicable evidence base on which to ground intervention design. This is particularly relevant in a policy context, such as the one outlined by the EU's R&I strategy (EC 2025b), that increasingly calls for interventions to be informed by rigorous, data-driven evidence rather than by broad policy priors alone. In this sense, the methodological approach adopted here may serve as a possible starting point for future research aiming to inform targeted, evidence-based agricultural and environmental policy.

This study contributes to the policy debate by providing cutting-edge evidence for reflecting on the need to continue promoting digitalisation to address environmental challenges in the agricultural sector by implementing "*a new [*political*] EU strategic approach to R&I*" (EC 2025b, p. 25). Digitalisation, given its role as a catalyst for environmental sustainability, appears, in fact, as a R&I channel through which to face environmental issues, overcoming the difficulties in emission reduction, mainly due to legislative (Verschuuren 2022; Laborde et al. 2021; Coderoni and Esposti 2018) and managerial (Garnett 2011) frictions.

From the policy perspective, this means that the diffusion of digitalisation should be encouraged, especially among currently non-adopters (EC 2022a, b; 2023). To achieve this objective, tailored interventions facilitating actors' interactions and based on communities' and farms' characteristics could help in reconciling productivity with environmental goals (Hermans et al. 2015).

The EU Action for Smart Villages, launched in 2017 as a pilot case, goes in this direction. It aims at fostering and sharing knowledge, innovation and digitalisation by relying on local actors' engagement and cooperation networks. This approach ensures that interventions are tailored to specific local needs while also allowing actors facing structural challenges, such as small farms, to become familiar with the potential benefits of digitalisation.

This pathway has synergies with the European Economic and Social Committee's recommendations on establishing an Agri-food Just Transition Fund to support small and medium-sized agri-food enterprises (EESC 2024).

Regarding environmental sustainability performance, our findings also highlight the need for more incisive strategies for reducing water consumption, suggesting that, so far, most of the digital technologies have emission-related outcomes. In the water management context, regulatory instruments are probably the most urgent interventions that the government should put in force to increase the sustainability of agricultural production. Although the last EU and national water strategies have already prioritised a "*fit for purpose*" approach, rather than a "*fit-for-all*" one, most of the interventions still, in fact, regard the adoption of digitalisation in the upstream part of the supply chain (i.e., irrigation), leaving space for tailoring interventions also in other parts of the process. This evidence is fully supported by the EU's awareness of the need for an updated EU water strategy and the policy debate on the proposal for a directive amending the EU Water Framework Directive.[6]

Appendix

Model Description

Under the assumption of selection on firm's observable characteristics $\mathbf{x}_i$, company *i's* idiosyncratic average treatment effect for the outcome Y_i is:

$$\mathrm{ATE}(\mathbf{x}_i) = m_1(\mathbf{x}_i) - m_0(\mathbf{x}_i) \tag{1}$$

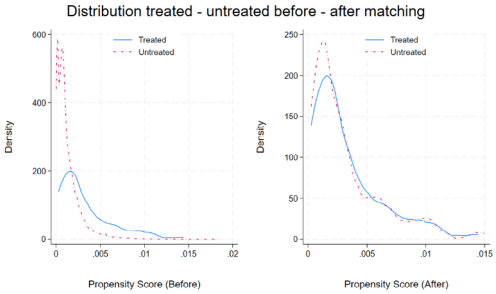
where $m_1(\mathbf{x}_i) = \mathrm{E}(Y_i \mid \mathbf{x}_i, D_i = 1)$ and $m_0(\mathbf{x}_i) = \mathrm{E}(Y_i \mid \mathbf{x}_i, D_i = 0)$, with D_i equal to the binary treatment variable taking either value 1 or 0. In our case, $D_i = 1$ for firms that have introduced digital technology and zero otherwise. The average effects (i.e., the average treatment effect, ATE; the average treatment effect on the treated, ATET; and the average treatment effect on the non-treated, ATENT) are estimated as follows:

$$\widehat{\mathrm{ATE}} = \frac{1}{N} \sum_{i=1}^{N} \left[\hat{m}_1(\mathbf{x}_i) - \hat{m}_0(\mathbf{x}_i) \right] \tag{2}$$

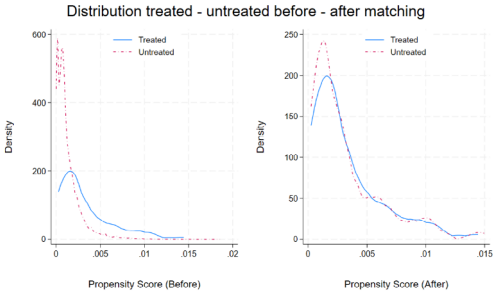
$$\widehat{\mathrm{ATET}} = \frac{1}{N_1} \sum_{i=1}^{N} D_i \cdot \left[\hat{m}_1(\mathbf{x}_i) - \hat{m}_0(\mathbf{x}_i) \right] \tag{3}$$

[6] Directorate-General for Environment. Proposal for a Directive amending the Water Framework Directive, the Groundwater Directive and the Environmental Quality Standards Directive. 26 October 2022.

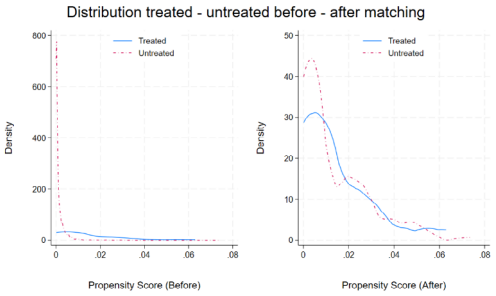
Emissions (total)



Emissions per hectare



Water (total)



Water per hectare

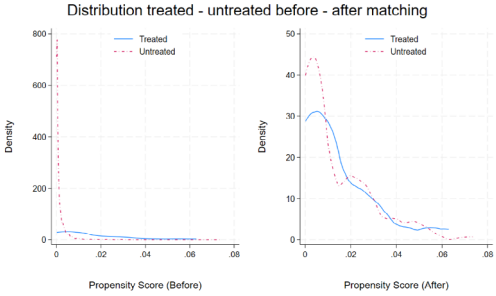


Fig. 2 Before-and-after distribution of the propensity score between treated and untreated

Table 5 Digital innovation among firms

No. of digital innovations	No. of firms
1	46
2	15
3	9
4	16
5	5
6	9
7	7
8	1
9	1
	109

Source: Authors' elaboration on FADN data

$$\widehat{\text{ATENT}} = \frac{1}{N_0} \sum_{i=1}^{N} (1 - D_i) \cdot \left[\hat{m}_1(\mathbf{x}_i) - \hat{m}_0(\mathbf{x}_i) \right] \tag{4}$$

where the "hat" refers to a consistent estimator of $m_1(\mathbf{x})$ and $m_0(\mathbf{x})$, and N_1 and N_0 are respectively the number of treated and untreated units.

Both $m_1(\mathbf{x})$ and $m_0(\mathbf{x})$ can be estimated either parametrically or non-parametrically, and the use of a parametric model (as a linear one) corresponds to the regression adjustment approach.

Regression adjustment is well-suited to obtain the idiosyncratic (i.e., firm-specific) effect of the treatment as it directly estimates the conditional average treatment effect on the treated ATET($\mathbf{x}$) as well as the average treatment effect on the untreated ATENT($\mathbf{x}$). We are interested in the analysis of the ATENT($\mathbf{x}$) that allows us to investigate the impact that digitalisation would have had on those actors that had not adopted it.

The models are estimated on the entire sample and on the same outcome variables considered for the PSM. The control variables are also equal to the variables used as controls in the PSM (Table 6).

The size of the effect is also calculated in percentage terms (%) and it corresponds to the rate of return of the treatment (ρ). It is estimated as the average treatment effect divided by the potential outcome mean without treatment (also, multiplied by 100). The ρ captures the relative impact of the treatment compared to a non-treatment status.

Table 6 Definition of control variables

Variable	Definition
Share of utilised agricultural area owned	The ratio of the owned utilised agricultural area to total utilised agricultural area—ha
Family holding	Share of family employees
Diversification	Dummy =1 for the presence of diversification practices (engagement in other economic sectors)
Altitude	Categorical variable classifying municipalities according to the level of altitude: low, moderate and high altitude
Physical dimension	Categorical variable classifying farms according to four levels of physical dimensions: <5, 5–15, 15–40, >40 ha
Economic dimension	Categorical variable classifying farms according to five levels of economic dimension: small, medium-small, medium, medium-big, big
Organic	Dummy = 1 for the presence of organic farming practices

Note: the source of all these variables is the Italian FADN database

Table 7 Descriptive statistics

Control variables	Mean	Sd	Min	Max
Share of utilised agricultural area owned	0.485	0.420	0	1
Family holding	0.838	0.255	0	1
Diversification	0.132	0.339	0	1
Altitude—hill	0.455	0.498	0	1
Altitude—mountain	0.226	0.418	0	1
Altitude—land	0.318	0.465	0	1
Physical size <5 ha	0.172	0.377	0	1
Physical size 5–15 ha	0.331	0.470	0	1
Physical size 15–40 ha	0.266	0.442	0	1
Physical size >40 ha	0.230	0.421	0	1
Economic size—small	0.205	0.404	0	1
Economic size—medium small	0.225	0.418	0	1
Economic size—medium	0.228	0.419	0	1
Economic size—medium big	0.268	0.443	0	1
Economic size—big	0.071	0.258	0	1
Organic	0.203	0.402	0	1
Outcome variables				
Emissions	0.108	0.398	−0.482	25.741

Table 7 (continued)

Control variables	Mean	Sd	Min	Max
Emissions per hectare	0.004	0.019	−0.009	1.777
Water	0.017	0.058	0	2.530
Water per hectare	0.004	0.007	0	0.411

Note: Emissions and emissions per hectare are expressed in million quintals of CO_2 equivalents (IPCC guidelines). Water and water per hectare are expressed in millions cubic meters

Table 8 Balancing test—emissions (total)

	Mean		t-test		Reduced bias
	Treated	Control (matched)	t	p > t	%
Share of the utilised agricultural area owned	0.48	0.52	−0.52	0.60	−2796.0
Family holding	0.75	0.75	0.05	0.95	96.7
Diversification	0.14	0.15	−0.13	0.90	47.6
Altitude—hill	0.35	0.36	−0.15	0.88	87.3
Altitude—land	0.25	0.26	0.16	0.87	77.2
Physical size 5–15 ha	0.27	0.32	−0.58	0.56	9.8
Physical size 15–40 ha	0.29	0.24	−0.65	0.52	−109
Physical size >40 ha	0.41	0.42	−0.05	0.95	97.4
Organic	0.27	0.32	−0.66	0.51	30.5
Economic size—medium small	0.24	0.22	0.38	0.70	−163.8
Economic size—medium	0.40	0.37	0.40	0.68	73.1
Economic size—medium big	0.17	0.20	−0.41	0.68	37.8
Economic size—big	0.06	0.08	−0.41	0.68	85.9
Year 2018	0.09	0.07	0.55	0.58	71.6
Year 2019	0.14	0.15	−0.20	0.84	75.1
Year 2020	0.14	0.16	−0.30	0.73	69.2
Year 2021	0.43	0.42	0.20	0.84	92.1

Table 9 Balancing test—emissions per hectare

	Mean		t-test		Reduced bias
	Treated	Control (matched)	t	p > t	%
Share of the utilised agricultural area owned	0.48	0.52	−0.52	0.60	−2796.0
Family holding	0.75	0.75	0.05	0.95	96.7
Diversification	0.15	0.15	−0.13	0.90	47.6
Altitude—hill	0.35	0.37	−0.15	0.88	87.3
Altitude—land	0.25	0.25	−0.15	0.88	85.8
Physical size 5–15 ha	0.27	0.32	−0.58	0.56	9.8
Physical size 15–40 ha	0.29	0.24	0.65	0.52	−109.0
Physical size >40 ha	0.41	0.42	−0.05	0.95	97.4
Organic	0.27	0.33	−0.66	0.51	30.5
Economic size—medium small	0.24	0.22	0.38	0.70	−163.8
Economic size—medium	0.40	0.37	0.40	0.69	73.1
Economic size—medium big	0.17	0.20	−0.41	0.68	37.8
Economic size—big	0.06	0.08	−0.41	0.68	85.9
Year 2018	0.09	0.07	0.55	0.58	71.6
Year 2019	0.14	0.15	−0.20	0.83	75.1
Year 2020	0.14	0.16	−0.30	0.77	69.2
Year 2021	0.44	0.42	0.20	0.84	92.1

Table 10 Balancing test—water (total)

	Mean		t-test		Reduced bias
	Treated	Control (matched)	t	p > t	%
Share of the utilised agricultural area owned	0.49	0.51	−0.12	0.91	67.0
Family holding	0.66	0.67	−0.16	0.87	86.5
Diversification	0.15	0.08	0.78	0.43	−467.7
Altitude—hill	0.16	0.20	−0.42	0.67	74.9
Altitude—land	0.32	0.23	0.82	0.41	45.2
Physical size 5–15 ha	0.35	0.39	−0.36	0.73	−33.8
Physical size 15–40 ha	0.35	0.35	−0.07	0.94	91.1
Physical size >40 ha	0.29	0.25	0.46	0.64	16.7
Organic	0.16	0.19	−0.36	0.72	−189.4
Economic size—medium small	0.14	0.13	0.03	0.97	98.1
Economic size—medium	0.57	0.52	0.44	0.66	73.4

Table 10 (continued)

	Mean		t-test		Reduced bias
	Treated	Control (matched)	t	p > t	%
Economic size—medium big	0.08	0.13	−0.67	0.51	67.0
Year 2018	0.03	0.03	−0.14	0.89	95.9
Year 2019	0.05	0.09	−0.66	0.52	88.5
Year 2020	0.48	0.48	0.09	0.93	96.5
Year 2021	0.16	0.14	0.26	0.79	−60.4

Table 11 Balancing test—water per hectare

	Mean		t-test		Reduced bias
	Treated	Control (matched)	t	p > t	%
Share of the utilised agricultural area owned	0.50	0.59	−0.12	0.90	67.0
Family holding	0.66	0.67	−0.16	0.87	86.5
Diversification	0.13	0.07	0.78	0.43	−462.7
Altitude—hill	0.16	0.20	−0.42	0.68	74.9
Altitude—land	0.32	0.24	0.82	0.42	45.2
Physical size 5–15 ha	0.35	0.39	−0.36	0.73	−33.8
Physical size 15–40 ha	0.35	0.35	−0.07	0.94	91.1
Physical size >40 ha	0.29	0.25	0.46	0.64	16.7
Organic	0.16	0.19	−0.36	0.72	−189.4
Economic size—medium small	0.13	0.13	0.03	0.97	98.1
Economic size—medium	0.57	0.52	0.44	0.66	10.4
Economic size—medium big	0.08	0.13	−0.67	0.50	67.0
Year 2018	0.02	0.03	−0.14	0.89	95.9
Year 2019	0.05	0.09	−0.66	0.51	62.6
Year 2020	0.48	0.47	0.09	0.93	96.5
Year 2021	0.16	0.14	0.26	0.79	−60.4

Table 12 Rosenbaum bounds test

Gamma	Sig+	Sig−	T-hat+	T-hat−	CI+	CI−
Emissions (total)						
1	1.0e−08	1.0e−08	−0.082549	−0.082549	−0.13717	−0.052869
1.6	7.6e−14	0.000018	−0.1244	−0.0583	−0.18822	−0.034813
2	0	0.000212	−0.14765	−0.0481	−0.212012	−0.02557
Emissions per hectare						
1	1.0e−08	1.0e−08	−0.082549	−0.08254	−0.13717	−0.052869
1.6	7.6e−14	0.000018	– 0.12444	−0.058319	−0.18822	−0.034813
2	0	0.000212	−0.14765	−0.048129	−0.21201	−0.025579
Water (total)						
1	0.437068	0.437068	0.000506	0.000506	−0.00621	0.00973
1.6	0.863215	0.077734	−0.00436	0.0064	−0.009974	0.016783
2	0.956072	0.020534	−0.005829	0.008892	−0.011406	0.020827
Water per hectare						
1	0.270602	0.270602	0.00032	0.00032	−0.000857	0.001652
1.6	0.735565	0.029673	−0.000457	0.00110	−0.001627	0.002662
2	0.890047	0.00582	−0.000744	0.001495	−0.001856	0.003326

Note: rbounds delta, gamma (1 (0.01) 2)

Acknowledgements The authors thank the participants of the 2025 AIEAA Conference and the 2025 CARMA Conference for their comments and suggestions on the working paper.

Funding Open access funding provided by Università degli Studi Roma Tre within the CRUI-CARE Agreement. This research has benefited from funding from the EU Horizon Europe project "ACT4CAP27—Advancing capacity and analytic Tools for supporting Common Agricultural Policies post 2027" (Grant Agreement No. 101134874), which is gratefully acknowledged. Views and opinions expressed are those of the authors only and do not necessarily reflect those of the European Union or the European Commission. This research has benefited from Potion: PRIN PNRR 2022 POTION—Policies for Transition: Impact and Governance CUP: F53D23009400001.

Data Availability The data that support the findings of this study are available from the FADN database, but restrictions apply to the availability of these data, which are not publicly available. The data are, however, available with the permission of the EC.

Declarations

Conflict of interest The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Disclaimer During the preparation of this work, the author used Claude and ChatGPT for grammar checking and proofreading. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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