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Are Italian farms achieving water-use efficiency in agriculture? Meta-frontier DEA analysis of efficiency gaps and farm-level disparities

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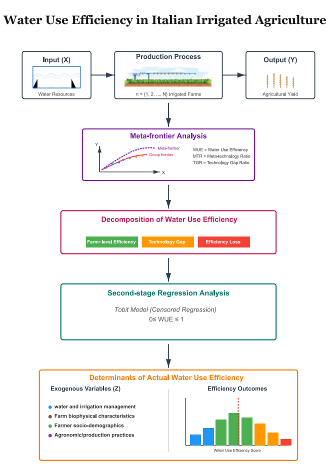
GRAPHICAL ABSTRACT



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ABSTRACT

An analysis of irrigation efficiency in Italy is essential to manage increasing water scarcity while sustaining agricultural productivity and informing targeted policy interventions. Using Farm Accountancy Data Network (FADN) data for 2018–2023 (700 farms across seven types of farming), we implement a two-step DEA framework (DEA–Tobit) with meta-frontier decomposition to estimate water-use efficiency (WUE), implied water-saving potentials, and technology gaps, and to examine farm- and context-specific determinants of WUE. Results indicate low average WUE and substantial heterogeneity across types of farming: horticulture shows the highest efficiency, whereas grazing livestock and mixed crop–livestock farms perform worst. Meta-frontier results reveal that inefficiencies reflect both technological shortfalls and managerial inefficiencies, with permanent crops exhibiting the largest technology gap. Tobit estimates suggest that higher water prices and micro-irrigation adoption are positively associated with WUE, while smaller economic scale and southern location correlate negatively. Overall, the findings support policy mixes combining demand-side instruments (e.g., volumetric

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pricing) with targeted technology diffusion and capacity building—particularly in water-stressed southern areas—and provide empirically grounded benchmarks for future modelling, scenario analysis, and policy design to improve agricultural water productivity.

1. Introduction

Global agriculture faces a dual challenge: to raise production to meet an estimated 50% increase in food demand by 2050 (FAO, 2017) while simultaneously reducing the environmental costs of intensive resource use. Irrigated systems presently consume roughly 70% of global freshwater withdrawals, and anticipated climate-driven shifts in water availability and variability are likely to intensify competition for this resource in many regions (Foley et al., 2011; Haddeland et al., 2014). Semi-arid zones are particularly exposed: seasonal water shortages and growing non-agricultural demands constrain both agricultural productivity and the provision of ecosystem services. Southern Europe illustrates these dynamics at a regional scale: a substantial proportion of the population there experiences periodic water stress (European Environment Agency (EEA, 2021). Within this context, Italy exemplifies tensions between high-value irrigated cultivation and limited water resources. In Southern Italy—some areas classified by the FAO-UNEP aridity index (Guyennon et al., 2017) —irrigation covers roughly 19% of cultivated land but accounts for the majority of agricultural water withdrawals, reflecting the region's focus on fruit and vegetable production for domestic consumption and export (Serrano et al., 2024). Declining water availability threatens aquifer depletion, soil deterioration, and elevated economic and climate risks for producers (Dalin et al., 2017; Anastasiadis et al., 2018). Heterogeneity across Italian regions—in climate, technology adoption, and policy frameworks—complicates the design and assessment of coherent, nationwide responses (Greve et al., 2018; Puy et al., 2022; Manta et al., 2024).

For high-input (irrigated) cropping systems in particular, enhancing water-use efficiency (WUE) becomes essential to reconciling yield objectives with long-term resource sustainability and resilience (Leakey et al., 2019). To investigate these challenges, this study applies Data Envelopment Analysis (DEA) combined with meta-frontier techniques (G. Wang et al., 2018; Watto and Mugera, 2019). DEA is selected over a single-step Stochastic Frontier Analysis because its non-parametric structure avoids restrictive functional-form and distributional assumptions, accommodates multiple inputs and outputs, and enables consistent comparisons across heterogeneous technologies through group-specific and meta-frontiers (Kuosmanen et al., 2015; Parman and Featherstone, 2019). These features are particularly suitable given the diversity of Italian production environments and the study's policy-oriented objective of decomposing efficiency patterns. Building on established methodological applications in agriculture (Rashidi et al., 2015; Yu et al., 2022; Zadmirzaei et al., 2024), the analysis measures input-specific technical efficiency of irrigated crop production across Italian types of farming, with particular emphasis on water, and uses medium-term microdata to assess how exogenous factors, management heterogeneity, and evolving policy contexts shape WUE dynamics.

This study is driven by a set of research questions that help frame our analysis and clarify its main focus.

1. How does water-use efficiency vary among different types of farming in Italian agriculture, and what farm-level factors drive their superior performance compared to the meta-frontier?
2. How do exogenous factors affect actual technical efficiency on farms, and what role do they have in creating disparities in efficiency among different agricultural production systems?
3. Has the expansion of production in the different Italian irrigated farms led to improvement in technical efficiency or water savings due to larger operational scales?

The main contribution of this application-oriented paper is the pioneering integration of a modified two-step DEA framework with meta-frontier analysis to represent a granular and stratified assessment of water-use efficiency in Italian irrigated agriculture, while also examining the extent to which farm-level heterogeneity in management practices and technology adoption influences WUE. Through the assimilation of micro-level farm data, the research yields original perspectives on the intermediate-term evolution of efficiency and the instrumental function of policy frameworks in influencing agricultural outcomes in Italy. These insights provide policymakers and stakeholders with evidence-based evaluations of past initiatives and potential avenues for enhancing water-use efficiency, with some tailored-strategic recommendations to promote systemic water resilience in the Italian agriculture. Consequently, the work aligns with Italy's obligations under the 2030 Agri-Food Strategy, under the broader lens of EU water resilience strategy, and advances the broader international agenda for sustainable development in the face of escalating climate variability and water resource constraints (FAO, 2023).

The rest of this article is organized as follows: The “Literature Review” section synthesises prior research in agriculture and related fields. The "Methodology" section delineates the two-step DEA-Tobit framework employed to assess water use efficiency and integrates meta-frontier analysis to elucidate efficiency gaps and farm-level disparities across agricultural systems. In the section titled “Data Source and Sample Design,” this approach is demonstrated using actual data from the Italian agricultural sector. The subsequent sections on “Results,” “Discussion,” “Policy Implication”, and “Concluding Remarks” present the findings, analyses, guidance for targeted policymaking, and final conclusion, respectively.

2. Literature Review

In agricultural economics, technical efficiency (TE) is defined as the capacity to maximise crop output while optimising resource utilisation within the confines of the prevailing technological frameworks. According to Coelli et al. (2002), TE is the ability to produce at desired levels with the least amount of inputs. These inputs are labour, fertilizers, pesticides, machinery, seeds and irrigation water (Greene, 1993). The application of frontier production function methods (Battese, 1992) to measure TE has become popular in agricultural research, as seen in studies on irrigation systems and productivity (Hong and Yabe, 2017; Khanal et al., 2018; Watto and Mugera, 2015). A key aspect of TE in water-dependent farming is water use efficiency (WUE), which is the relationship between crop yield and water consumption. Defined as a dimensionless ratio of output to water input, WUE measures how water contributes to biomass or harvestable yield in both irrigated and non-irrigated situations (Pereira et al., 2012). Agronomists commonly interpret this metric as yield per unit of water consumed, offering actionable insights for improving irrigation practices and resource allocation (Molden et al., 2010). Given water's critical role in sustainable agriculture, its efficient management has become a central focus in DEA research. DEA frameworks treat water as a foundational resource - equivalent to energy, labour, and capital - that supports multifaceted outcomes spanning economic, social, and environmental domains. This research orientation is closely aligned with global initiatives, notably Sustainable Development Goal 6.4, which emphasizes the imperative of sustainable water use. Contemporary DEA approaches, therefore, engage with water-use efficiency through diverse modelling strategies, seeking to harmonize the often-competing demands of productivity and resources conservation.

This scholarly focus is evidenced by recent literature (2020 – present), which increasingly investigates the connections between water utilisation and economic performance through various DEA approaches, as summarised in Table 1. A common feature of these studies is the incorporation of core water metrics - such as consumption volumes, total resource availability, or footprint data - as model inputs. These are subsequently evaluated against key economic outcomes, including Gross domestic product (GDP), gross value added (GVA), gross industrial output, and related indices of production.

As can be tracked, in the realm of water-use efficiency measurement, studies vary widely in how they handle time. Some, like Lozano and Borrego-Marín (2024), focus on a single period, whereas many others track multiple periods by benchmarking each observation only against contemporaries in the same time frame (André et al., 2024; Liang et al., 2021). Within this contemporaneous framework, it is common to derive Malmquist and Malmquist–Luenberger productivity change indices to gauge shifts in performance over time (Shah et al., 2022; Wei et al., 2021). Alternatively, intertemporal approaches - where each record is compared against all observations across periods - have been adopted in other works (Shi et al., 2015; Wang et al., 2019; W. Wang et al., 2018). A third avenue employs dynamic network DEA (DNDEA) methods to model multi-period water-use efficiency, capturing both carry-over effects and evolving structures (Bronner et al., 2022; Zhuang et al., 2022). Beyond the temporal dimension, DEA applications also diverge in handling sample homogeneity. When decision-making units (DMUs) are assumed to be homogeneous, a single production frontier suffices; when heterogeneity exists, meta-frontier analysis (MFA) becomes necessary (Shah et al., 2022; Zhao et al., 2022). In such cases, applied researchers also employ slacks-based measures—i.e., SBM, Super-SBM, Network SBM, and Dynamic Network SBM models—which take into consideration input and output inefficiencies (Wan et al., 2023; Zhao et al., 2022). Other extensions further include radial BCC models (Ali et al., 2022), cost-minimisation DEA (Hu et al., 2018), directional distance functions (García-Valiñas et al., 2019), cross-efficiency games (W. Zhang et al., 2022), and fixed-sum outputs models (T. Zhang et al., 2022). Of particular interest, non-radial DDF employed herein also figured in recent works (Sheng and Qiu, 2023; Zhuang et al., 2022). Furthermore, MFA has also been productive in comparing agricultural water-use efficiency in different regions. For example, Liu et al. (2022) illustrated considerable gaps among smallholder farmers in China, while Liu et al. (2021) also reported considerable provincial disparities in maize cultivation efficiency, attributing variation to irrigation aspects, moisture in soils, as well as temperatures. Comparable studies also made use of MFA in Africa and Europe, always revealing uneven technological capability and adoption.

Despite these advances, two critical gaps remain. First, few studies integrate a two-step DEA framework—where water use efficiency is first measured and then linked to underlying drivers—to provide a more nuanced decomposition of performance. Second, while meta-frontier techniques reveal technological disparities, they often stop short of translating these findings into concrete improvement pathways for underperforming farms. Therefore, our practical research aims to address both shortcomings by applying a two-step DEA to calculate water-use efficiency and then using meta-frontier analysis to quantify technological gaps. This combined approach not only offers a more detailed efficiency diagnosis but also generates tailored recommendations to guide farms managers along an evidence-based improvement trajectory.

3. Methodology

3.1. Two-step DEA framework

Conventional DEA is a linear programming technique designed to assess the performance of multiple DMUs (in our case farms) when production involves a combination of various inputs and outputs (Lin and Wang, 2014; Oral et al., 2014; Tone and Tsutsui, 2014). In DEA, each farm is evaluated relative to a best-practice frontier constructed from the observed sample. Charnes et al. (1978) developed a fundamental DEA approach, known as the CCR model (Charnes, Cooper, and Rhodes), which provides an input-oriented measure of overall (global) technical efficiency under the assumption of Constant Returns to Scale (CRS). This assumption posits that all farms can proportionally increase their output corresponding to a proportional increase in their inputs, regardless of their scale of operation (Amirteimoori et al., 2024). However, because farms may operate at different scales, Banker et al. (1984) proposed the BCC model, which allows for Variable Returns to Scale (VRS) through the inclusion of a convexity constraint to the original CCR model. The convexity of the production possibility set is a maintained hypothesis in DEA: when two or more input–output combinations are feasible, any convex combination of them is also feasible (Ray, 2004). Under VRS, the resulting efficiency score is commonly referred to as pure (local) technical efficiency (Amirteimoori et al., 2025).

Building on this standard DEA framework, we focus on water-use efficiency by estimating a sub-vector efficiency score that proportionally reduces the water input while holding other inputs and outputs constant. Consider a production system with P inputs and Q outputs for each farm j, represented by the vectors x_j and y_j, respectively. The sub-vector technical efficiency score θ_m for input m (water-use index) is calculated for each farm j by solving Equation (1):

$$\begin{aligned}
&\textit{Minimize } \theta_m, \lambda\theta_m \\
&\quad \textit{Subject to:} \\
&\quad -y_j + Y\lambda \geq 0, \\
&x_{p-m,j} + \theta_m x_{m,j} - X_m\lambda \geq 0, \\
&\quad x_{p-m,j} - X_{p-m}\lambda \geq 0, \\
&\quad\quad P1'\lambda = 1, \\
&\quad\quad \lambda \geq 0,
\end{aligned} \tag{1}$$

Here, m is reduced while keeping other inputs and outputs constant. The vector λ is a non-negative intensity vector that forms the benchmark as a convex combination of observed farms, and the constraint $1'\lambda = 1$ imposes variable returns to scale (VRS). The terms $x_{p-m,j}$ and X_{p-m} exclude input m, whereas $x_{m,j}$ and X_m include only input m.

For a given farm j, let θ_m^* and λ^* be the optimal solution of model (Equation (1)). Then its projected water input and the corresponding reduction can be calculated by Equation (2), as follows:

$$\begin{aligned}
&\text{Projected water use}: && x_{m,j}^{\text{proj}} = \theta_m^* x_{m,j}, \\
&\text{Absolute reduction}: && \Delta x_{m,j} = x_{m,j} - x_{m,j}^{\text{proj}} = \left(1 - \theta_m^*\right) x_{m,j}, \\
&\text{Percentage reduction}: && \frac{\Delta x_{m,j}}{x_{m,j}} \times 100\% = \left(1 - \theta_m^*\right) \times 100\%.
\end{aligned} \tag{2}$$

Here:

$x_{m,j}$ is farm j 's observed water input (the m_{th} input).

$\theta_m^* \leq 1$ is the optimal water-use efficiency score from min $\theta, \lambda\theta_m$ (Equation (1)).

Thus, the model "Projects" each farm onto the frontier by shrinking its water use from $x_{m,j}$ down to $\theta_m^* x_{m,j}$, yielding a feasible water-saving $\Delta x_{m,j}$.

In our study, the estimated sub-vector technical efficiency θ_m also serves as the dependent variable in a Tobit regression model to identify the factors influencing WUE among irrigated farms in our sample, using farm-specific contextual variables as regressors. As detailed in Table 2, these variables capture key technical and socioeconomic dimensions: water cost, irrigation technique (seven-category system distinguishing precision methods, like micro-irrigation, from conventional approaches), water source (collective or non-collective resources reflecting infrastructure access), fertigation adoption, farm biophysical

Table 1
Summary of the most recent water-efficiency measurement studies implementing DEA approach.

References	Case studies	Input variables	Output variables	DEA approaches
Liu et al. (2020a)	30 Chinese provinces, 2012–2015	Surface water use; Groundwater use; Other water sources; Employment; FAI	Industrial value added; Wastewater discharged; Wastewater treated at WWTP	Conventional VRS approach; Non-oriented super-SBM
Liu et al. (2020b)	30 Chinese provinces, 2005–2015	Total water consumption; Employment; FAI	GDP; Wastewater directly discharged; Wastewater sent to WWTP	Conventional VRS approach; Non-oriented super-SBM
Fei et al. (2021)	China's agricultural sector: 30 provinces	Capital (fixed asset investment); Labour (agricultural employment); Water consumption	Agricultural GDP; Rebound effect (via water-demand elasticity)	Meta-frontier DEA; DIF-GMM; DID model;
Chen et al. (2021)	31 Chinese provinces, 2005–2015	Industrial water use; Industrial employment; FAI	Industrial value added	Conventional CRS (radial CCR) approach; Bootstrap DEA
Wei et al. (2021)	9 Yellow River Basin provinces, 2008-2017	Agriculture water use; Agricultural employment; FAI; Irrigated area; Chemical fertilizers	Agricultural value added; COD discharge; AN discharge	Conventional CRS approach; Super-efficiency Non-oriented SBM; Malmquist index
Yang (2021)	30 Chinese provinces, 2007-2019	Total water resources; Employment; Capital stock	GDP; Wastewater discharge	Conventional VRS approach; Non-oriented SBM
Ali et al. (2022)	36 districts (Punjab, Pakistan), 2015-2020	Water use; Coal consumption	GDP per capita; Waste gas emissions	Conventional VRS approach; Input-oriented BCC model
Deng and Zhang (2022)	30 Chinese provinces, 2002-2015	Water footprint in energy production; Employment; FAI; Energy consumption	Total industrial output	Conventional VRS approach; Input-oriented BCC model (Technical and scale efficiency measurement)
Wang and Wang (2022)	30 Chinese provinces, 2004-2019	Water use; Employment; Capital stock	GDP; Wastewater discharge	Conventional VRS approach; Super-efficiency Input-oriented BCC model
Zhao et al. (2022)	31 Chinese provinces, 2003-2018	Capital; Labour; Land; Energy; Water use	Regional GDP; Industrial wastewater; discharge; Industrial SO_2 emission; Industrial dust emission	VRS; Non-oriented Super SBM; Meta-frontier Malmquist Index
Zhuang et al. (2022)	30 Chinese provinces, 2011-2018	Industrial water use; Industrial employment; Energy use; WWTP investment & staff; WWTP count	- Intermediate: Industrial wastewater; Industrial FAI; Reused water; - Final: Industrial value added; CO_2 emissions; Solid waste	Two stages (WU, WWT); DNDEA; VRS; Non-radial DDF
Bronner et al. (2022)	13 federal states in Germany for the studied years 2013 and 2016	Labour (Water supply); Labour (WWT); Vegetation and water surface area; Freshwater released into nature	-Intermediate: Abstracted water; Supply connections; Network length; Wastewater reused; -Final: Gross Value Added (GVA); Sludge discharged	Four-stage DNDEA; CRS approach; Non-oriented SBM
Shi et al. (2022)	30 Chinese provinces, 2011-2018	Urban water use; Urban employment; WWTP capacity & Labour	- Intermediate: Urban wastewater produced; Urban FAI; - Final: GDP per capita; Grey water footprint	Two-stage DNDEA; CRS approach; Radial non-oriented SBM
Le et al. (2022)	29 Vietnamese sub-basins, 2010–2017	Water use (agriculture, industry, and services); Domestic and public water	-Intermediate: Sectoral GDP shares; Population metrics; - Final: Growth rates of GDP, sectoral GDP, population, urban population	Three-process (parallel-series) NDEA; CRS approach; Malmquist Index
Shan and Ying (2022)	30 Chinese cities, 2005-2015	Water use; Employment; Capital stock; Built-up area; WWTP ratio	Intermediate: Wastewater produced; - Final: GDP; Wastewater reused; Wastewater discharge	Conventional VRS approach; Non-oriented super-SBM; Modified RAM NDEA
Martinho et al. (2022)	EU Farm Accountancy Data Network (FADN) (2004–2018)	Labour input; Total utilized agricultural area; Livestock units; Total inputs (costs: seeds, fertilisers, feed, etc.); Total assets	Total output (crops, livestock, other products); Subsidies (CAP funds);	Basic DEA models; MPI index
Zhang et al. (2023)	7 sub-regions of Tumen River Basin, 2014–2019	Agricultural water; Industrial water; Domestic water	Grain output; Industrial value added; Population	Conventional CRS-CCR approach; Weighted-average efficiency
Czyżewski and Kryszak (2023)	Small farms in Poland, Romania, Serbia, and Moldova (Central and Eastern Europe)	Fertilisers, pesticides; labour; agricultural area; machinery; energy; livestock units; subsidies	Production value; biodiversity (crop diversity; grassland; orchards),	Hybrid DEA meta-frontier super-efficiency model with

(continued on next page)

Table 1 (*continued*)

References	Case studies	Input variables	Output variables	DEA approaches
			undesirable outputs (soil loss, GHG emissions)	environmental proxies and policy inputs.
André et al. (2024)	17 Spanish regions, 2001–2018	Labour; Capital; Household, firm, and municipal water use; Energy; Reused water; Treated wastewater; Losses	GDP; Treated wastewater	Conventional CRS-CCR approach; Two-stage NDEA vs. Dynamic SBM model
Lozano and Borrego-Marín (2024)	Global analysis: 126 countries (e.g., Australia, Western Europe, Central Asia)	Renewable groundwater; Renewable surface water; Cultivated area; Irrigated area; Rural pop.; Urban pop.	- Intermediate: Agricultural, industrial, municipal wastewater; - Final: Water productivity; Sectoral GVA; Population with safe water	Non-radial directional-distance network DEA; Two-stage meta-frontier (withdrawal and productivity)
Ait Sidhoum and Vrachioli (2025)	Greece (small-scale greenhouse farms), 2009-2013	Land; Labour; Seeds; Water use	Total revenue; Water loss	Basic DEA models; Eco-efficiency approach
García-Mollá et al. (2025)	Eastern Spain (region of Valencia)	Fertilisers; Phytosanitary products; Irrigation costs	Total income	Two-stage DEA model; met-frontier analysis
Wang and Xie (2025)	China (county-level data)	Labour; Land; Machine; Fertiliser; Water consumption	GDP of primary industry; GDP per capita	DEA and DID methods

Note: FAI: Fixed-asset investment; WWTP: Wastewater treatment plants; CRS: Constant returns to scale; VRS: Variable returns to scale; SBM: Slacks based measure; DIF-GMM: Difference-generalized method of moments; DID: Difference-in-difference estimation; COD: Chemical oxygen demand; AN: Ammonia nitrogen; SO_2: Sulphur dioxide; CO_2: Carbon dioxide; WU: Water use; NDEA: Network DEA; DNDEA: Dynamic NDEA; RAM: Range-adjusted measure of efficiency; Pop: Population. DDF: Directional distance function; CAP: Common agricultural policy; MPI: Malmquist productivity index; MLPI: Malmquist-Luenberger productivity index.

characteristics (altimetric areas, geographical locations, farm economic scales), farmer socio-demographics (farmers' age - under 40 years, farmers' education), and agronomic and production practices (production system, organic certification). Given that efficiency scores are bounded in [0,1], the Tobit specification is appropriate.

This two-step approach (DEA and Tobit regression) identifies both farm-level efficiency benchmarks and the broader contextual drivers shaping water productivity across heterogeneous farming systems, providing policy-relevant insights on the role of irrigation technologies, farm structure, and management practices.

3.2. Meta-frontier analysis

Conventional DEA models are relied on the assumption that all DMUs operate within a homogeneous environment and share identical technological conditions. In practice, however, farms diverge significantly across dimensions such as cropping patterns, irrigation regimes, water resource endowments, market supply-demand dynamics, technological adoption, regulatory frameworks. These variations give rise to distinct production frontiers that a single, uniform DEA approach cannot adequately capture. To address this limitation, Hayami and Ruttan (1970) proposed the meta-production function, thereby inaugurating the meta-frontier framework. Subsequent scholars integrated this concept with DEA - initially combining meta-frontier theory with stochastic frontier analysis (SFA) to estimate both group-specific and overarching technology frontiers, technical efficiencies, and technology gap ratios (Battese et al., 2004) - and later refined the methodology by replacing SFA with DEA's linear programming to construct multi-tiered frontiers (Du et al., 2014; O'Donnell et al., 2008).

Building on these advances, our study first measures water-use efficiency within each farm category to derive group frontier efficiency (GFE), then aggregates all farms to estimate meta-frontier efficiency (MFE) and finally computes the technology gap ratio (TGR) by comparing GFE and MFE, thus quantifying each farm's distance from the best-practice frontier. In details, if the N farms under study are divided into H groups, we denote the technology set available to group g by (Equation (3)):

$$\mathrm{T}_g \ (g = 1, \ldots, H) \tag{3}$$

and we define the meta-technology set as the union of all group-level technologies (Equation (4)):

$$\mathrm{T}_{\mathrm{meta}} = \bigcup_{g=1}^{H} \mathrm{T}_g \tag{4}$$

By construction, any input-output combination feasible in T_g is also feasible in $\mathrm{T}_{\mathrm{meta}}$.

For each farm i in group g, let

- θ_i be its observed performance (a composite score derived from the WUE model (Equation (1)),
- $\theta_i^{(g)*}$ be its projection onto the group- g frontier T_g,
- $\theta_i^{\mathrm{meta}\,*}$ be its projection onto the meta-frontier $\mathrm{T}_{\mathrm{meta}}$.

We then define two efficiency measures:

Group-frontier efficiency

$$\mathrm{GFE}_i^{(g)} = \frac{\theta_i}{\theta_i^{(g)*}}, 0 < \mathrm{GFE}_i^{(g)} \leq 1 \tag{5}$$

Meta-frontier efficiency

$$\mathrm{MFE}_i = \frac{\theta_i}{\theta_i^{\mathrm{meta}\,*}}, 0 < \mathrm{MFE}_i \leq 1 \tag{6}$$

Because $\mathrm{T}_g \subseteq \mathrm{T}_{\mathrm{meta}}$, it follows that $\varphi_i^{(g)*} \leq \varphi_i^{\mathrm{meta}\,*}$, and hence $\mathrm{MFE}_i \leq \mathrm{GFE}_i^{(g)}$.

The technology-gap ratio (TGR) for farm i in group g is then

Table 2
The description of the contextual variables.

Characters	Variables	Description	Unit
Water and irrigation management	Water cost	The cost of water for crop irrigation.	(€ m^3)
	Irrigation technique	Different irrigation techniques include: (1) Infiltration; (2) Surface irrigation (Flow irrigation); (3) Sprinkler irrigation (literally "Rain"); (4) Micro-irrigation; (5) Flood irrigation (or Submersion); (6) Micro-spray irrigation; (7) Other systems.	Categorical
	Source of the water	Two different water sources provers for farms: - Collective Irrigation System (Consortium) - Non-collective (self-supply) irrigation water sources (include: Natural River and Lake; Well; Artificial Pond (on-farm); Artificial Pond (third-party); Cistern and Water Tank; Other Sources).	Dummy (1 = Consortium system, 0 = otherwise)
	Fertigation	The process of delivering fertilisers, nutrients, and other water-soluble substances to crops via an irrigation system.	Dummy (1 = apply, 0 = do not apply)
	Irrigation intensity	The share of a farm's total area that is irrigated (irrigated area divided by total farm area), indicating the extent of irrigation use.	Fractional (percentage)
Farm specialization	Farm type	Farm production orientation classified into seven mutually exclusive types: field crops, horticulture, permanent crops, grazing livestock, granivores, mixed crops, and mixed crops & livestock.	Categorical
Farm biophysical characteristics	Altimetric area	Land classified by elevation and altitude, affecting farming practices and crop suitability: mountain (category 1), hill (category 2), and plain (category 3)	Categorical
	Geographical location	Farms are classified into three geographical locations: north (category 1), center (category 2), and south (category 3).	Categorical
	Farm Economic scale	Farms are classified into two economic scale categories based on general annual revenue.	Dummy (1 = small-medium, 0 = otherwise (large))
Farmer socio-demographics	Farmers' age	The range age of farm managers.	Dummy (1 = young; 0 = otherwise)
	Farmers' education	The education levels of the farmers.	Dummy (1 = university degree; 0 = otherwise)
Agronomic and production practices	Cultivation technique	The methods and practices used by farmers to plant, grow, and nurture crops or plants: open field crops (category 1), greenhouse crops (category 2), and industrial crops (category 3).	Categorical
	Organic	Organic farms implement ecologically sustainable practices that prohibit synthetic pesticides, fertilisers, and genetically modified organisms.	Dummy (1 = organic; 0 = otherwise)

Note: FADN classifies EU farms by Standard Output (SO): €25,000–€50,000 = small–medium; > €100,000 = large. Following Common Agricultural Policy, farmers' age under 40 years is considered as young managers.

$$\mathrm{TGR}_i^{(g)} = \frac{\mathrm{MFE}_i}{\mathrm{GFE}_i^{(g)}} = \frac{\theta_i^{(g)*}}{\theta_i^{\mathrm{meta}\,*}}, 0 < \mathrm{TGR}_i^{(g)} \leq 1 \tag{7}$$

A higher TGR (closer to 1) signifies a small technology gap between the group and meta-frontiers implying limited additional gains; whereas a lower TGR reveals a substantial gap and thus greater potential for improvement under the meta-frontier.

Finally, the total inefficiency of farm i under the meta-frontier, $\mathrm{MTI}_i^{(g)}$, decomposes into:

Technological-gap inefficiency

$$\mathrm{TGI}_i^{(g)} = \mathrm{GFE}_i^{(g)}\left(1 - \mathrm{TGR}_i^{(g)}\right) = \rho_i^{\mathrm{meta}} - \rho_i^{(g)}, 0 < \mathrm{TGI}_i^{(g)} \leq 1 \tag{8}$$

Managerial inefficiency

$$\mathrm{MI}_i^{(g)} = 1 - \mathrm{GFE}_i^{(g)} = \rho_i^{(g)}, 0 < \mathrm{MI}_i^{(g)} \leq 1 \tag{9}$$

Thus

$$\mathrm{MTI}_i^{(g)} = \mathrm{TGI}_i^{(g)} + \mathrm{MI}_i^{(g)} = \rho_i^{\mathrm{meta}} \tag{10}$$

Here, $\mathrm{TGI}_i^{(g)}$ captures losses due to the gap between group- and meta-technologies (e.g., limited spillovers or indigenous innovation), while $\mathrm{MI}_i^{(g)}$ reflects inefficiencies in resource allocation or managerial practices.

4. Data Source and Sample Design

This analysis utilizes farm-level microdata from the Italian Farm Accountancy Data Network (FADN),[1] the EU tool used to monitor the European agricultural economic situation and to support the programming and evaluation of the Common Agricultural Policy (CAP). In Italy, FADN is the main harmonized microeconomic source for analyzing farm incomes and structural dynamics in professional, market-oriented holdings (CREA, 2023). The survey provides detailed information on

[1] From 2025, the FADN is superseded by the Farm Sustainability Data Network (FSDN). This transition represents an evolution beyond FADN's original scope—which centered on agricultural income and business operations—to integrate systematic assessment of farms' environmental impact and social sustainability outcomes (https://agriculture.ec.europa.eu/data-and-analysis/farm-structures-and-economics/fsdn_en).

revenues, costs, margins and CAP support, and is designed to be representative by region, economic size and type of farming, while also enabling the construction of farm panels for specific analyses. According to the latest Italian FADN report (CREA, 2023), the survey covers a target population of about 566,338 farms (around 49% of Italian holdings) and more than 89% of the utilized agricultural area.

In this study, however, the empirical analysis relies on an analytical subset of FADN data constructed to enable cross-system benchmarking. We first retained only farms observed in all years 2018–2023 (balanced panel). We then computed, for each farm, multi-annual averages of all DEA inputs and outputs over 2018–2023, thereby smoothing year-to-year fluctuations and reducing the influence of year-specific shocks (e.g., climatic variability). Accordingly, the DEA is conducted on an averaged cross-section, where each farm enters the analysis once with its 2018–2023 mean input–output bundle. Monetary variables were deflated to 2020 constant prices, and variables were generally expressed per hectare to ensure comparability across production systems.

This approach aligns with a common stream in the DEA literature that collapses panel observations into multi-year averages to obtain stable performance measures; alternative treatments include estimating year-specific frontiers or adopting intertemporal frameworks (e.g., Malmquist or dynamic DEA). Given our objective of cross-system benchmarking rather than modelling productivity change over time, we follow the averaged cross-section approach.

To ensure data completeness for averaging and comparability across farms, we excluded observations with missing values in any of the required variables, obtaining a homogeneous dataset. Farm typology comprises seven types of farming aligned with FADN standards (field crops, horticulture, permanent crops, grazing livestock, granivores, mixed crops, mixed crops and livestock), which structure the comparative analysis (Table 3). In the DEA specification, all inputs and the output are expressed on a per-hectare basis, while irrigated area (ha) is retained as an absolute (scale) variable to enable farm-level computation of total water withdrawals and to capture scale effects relevant for resource management and policy assessment.

Given the frequent presence of outliers in farm microdata and their potential influence on frontier estimation, we detected and removed extreme values using the interquartile range (IQR) method, following established practice (Ait Sidhoum and Vrachioli, 2025; Chang et al., 2025; Pishini et al., 2025). After missing-data filtering and outlier removal, the eligible pool ranges from about 100 to 1200 farms per type of farming. For the efficiency analysis, we then drew an equal-allocation stratified simple random sample of 100 farms within each type of farming (without replacement)—corresponding to approximately 8–100% of the eligible farms within each group—yielding a final dataset of 700 farms. With six inputs and one output (seven variables), this sample size satisfies the usual DEA rule-of-thumb requiring at least three times the total number of inputs and outputs (Cooper et al., 2011). Importantly, sampling was stratified only by farming system: farms were randomly selected within each group without imposing additional constraints on the regional or economic-size distribution. Therefore, the final dataset should be regarded as an analytical subset for cross-system benchmarking rather than a design-weighted nationally representative FADN sample. This equal-n design avoids frontier construction being driven by the most populous systems and is consistent with comparable FADN-based DEA applications (e.g., Forleo et al., 2021).

The composition of the analytical sample across types of farming by macro-area (including North, Centre, and South), altimetric area, irrigation technique, and water-source governance is reported in Appendix Table A1.

5. Results

5.1. *The water-use efficiency at farming system level*

The water-use efficiency of each type of farming was first measured using DEA model, with the results presented in Table 4.

As can be seen, the aggregate analysis of all 700 farms (whole sample level) demonstrates relatively low water-use efficiency, with a mean WUE score of 0.204 and a median of 0.011, indicating substantial room for improvement across the agricultural sector. Only 98 farms (14%) achieved technical efficiency in water utilisation. Farm types performance analysis, however, showed that horticulture operations exhibit superior water-use efficiency performance, achieving the highest average (0.628) and median (0.974) WUE score, with 52% of farms operating at the efficiency frontier. This suggests that horticultural practices may incorporate more sophisticated irrigation technologies or crop management strategies. Permanent crops demonstrate the second-highest efficiency levels (mean WUE = 0.577, median = 0.835), with 48% of units achieving technical efficiency. The relatively low standard deviation (0.143) indicates more consistent performance within this farm type compared to others. On the other hand, mixed crops and livestock show the lowest water-use efficiency (mean WUE = 0.455, median = 0.285), with only 31% achieving efficiency. Grazing livestock also demonstrate suboptimal performance (mean WUE = 0.458, median

Table 4
Results of Water-use efficiency DEA model.

Farm Types	No. observation	Median	Std. Deviation	Average WUE score	Numbers of efficient farms
Field crops	100	0.430	0.228	0.568	48 (48%)
Horticulture	100	0.974	0.211	0.627	52 (52%)
Permanent crops	100	0.835	0.143	0.576	48 (48%)
Grazing livestock	100	0.241	0.215	0.457	34 (34%)
Granivores	100	0.648	0.311	0.587	44 (44%)
Mixed crops	100	0.411	0.250	0.526	45 (45%)
Mixed crops and livestock	100	0.285	0.214	0.455	31 (31%)
All farms	700	0.011	0.075	0.203	98 (14%)

Table 3
The mean values of the observed input and output dataset.

Farm Types	No. observation	Input						Output
		Irrigated area (ha)	Water amount (m^3 ha^{-1})	Fixed cost (€ ha^{-1})	Variable cost (€ ha^{-1})	Labour (h ha^{-1})	Machinery (h ha^{-1})	Production (€ ha^{-1})
Field crops	100	17.61	966.89	666.08	1786.75	103.35	39.27	5017.59
Horticulture	100	8.65	1203.24	5520.65	1,9576.37	1170.23	152.5	53,069.21
Permanent crops	100	8.11	1024.11	1419.47	2016.80	336.03	82.35	9988.12
Grazing livestock	100	21.00	1145.00	1187.00	573.00	36.00	24.00	1557.00
Granivores	100	37.69	891.85	1897.38	963.12	40.08	25.47	2056.02
Mixed crops	100	7.33	865.19	1168.09	1699.41	214.33	52.66	6666
Mixed crops and livestock	100	16.22	860.73	1193.90	1079.35	116.27	40.26	4371.34

= 0.241), with 34% efficiency rates, potentially reflecting extensive production systems with less precise water management. These values may reflect differences in required water volumes across diverse production systems and the relevance and attention the farm has to give to careful water management.

In addition, the percentage reduction in water use is also calculated by equation (2), with individual farm data presented in Table S1 of supplementary information, and aggregated averages by type of farming reported in Table 5.

All farm categories demonstrate considerable potential for water-use reduction, with mean reduction possibilities ranging from 37.24% to 54.46%. It is worthy pointing out that the maximum values represent theoretical upper bounds based on relative performance within the dataset rather than an implication that farms can operate with near-zero water. Specifically, this reduction potential indicates that an inefficient farm uses significantly more water than the most efficient peer for similar output, often due to disparities in irrigation technology (e.g., flood vs. drip) or management practices. For policy purposes, the mean values provide a more realistic estimate of achievable savings. This indicates widespread inefficient water utilisation practices across the analysed types of farming, suggesting substantial room for improvement in irrigation management and water conservation techniques. This analysis, for each type of farming, indicates that mixed crops and livestock operations exhibit the highest inefficiency, followed by grazing livestock and mixed crops. As stated before, horticulture demonstrates the lowest inefficiency among specialized farm types, while field crops, permanent crops, and granivores show similar moderate inefficiency levels. It is crucial to acknowledge that actual water reductions are constrained by crop-specific water requirements; therefore, the mean reduction potentials should be interpreted as an indicative benchmark under current technology, whereas the maximum values highlight severe outliers where management gaps are largest.

In general, the aggregate result for all farms combined (79.08% mean reduction) substantially exceeds the mean reductions observed within individual types of farming. This difference likely reflects an expanded efficiency frontier when the full sample is pooled: high-performing farms from some categories can act as benchmarks for others, raising the aggregate improvement estimate. To quantify the overlap of top performers across types of farming, we therefore employed the well-documented Jaccard similarity measure.[2] Using this approach, we identified how many farms in each category are classified as fully water-use efficient at the total scale (total fully efficient farms, n = 98).

Table 5
Results of the average water-use potential reduction (%) derived from the DEA model.

Farm Types	N	Minimum	Maximum	Mean (%)
Field crops	100	0.00	99.95	42.11
Horticulture	100	0.00	98.83	37.24
Permanent crops	100	0.00	99.97	42.34
Grazing livestock	100	0.00	99.76	52.20
Granivores	100	0.00	99.92	41.29
Mixed crops	100	0.00	99.88	46.33
Mixed crops and livestock	100	0.00	99.10	54.46
All farms	700	0.00	100.00	79.07

Note: Maximum values reflect relative inefficiency compared to the best-performing peers within the sample, rather than absolute biophysical minimums.

Fig. 1 presents the Jaccard similarity coefficients quantifying the relationship between water-use efficient farms within specific types of farming and the total pool of efficient farms. Because FADN types of farming are mutually exclusive, the analysis focuses on each type's individual contribution to the benchmark-efficient pool, presented here as a ranked comparison for clarity. The "All farms" comparison reveals the relative contribution of each type of farming to the total efficiency benchmark: horticulture exhibits the highest similarity coefficient, followed by mixed crops and livestock and field crops. Permanent crops and mixed crops show comparatively moderate similarity levels, while grazing livestock records a lower contribution. Granivores represent the lowest similarity among the production systems considered. These findings establish that water-use efficiency optimization is highly concentrated within specific systemic boundaries, suggesting that best practices are strongly aligned with distinct production typologies rather than being uniformly distributed across types of farming.

Moreover, as detailed in this figure, the absolute distribution of the 98 benchmarked water-use efficient farms is markedly uneven across types of farming. Horticulture emerges as the dominant contributor in both relative and absolute terms, while granivores consistently record the lowest values across both metrics. The intermediate types — mixed crops and livestock, field crops, permanent crops, and mixed crops — occupy a middle range, with grazing livestock positioned closer to the lower end of the distribution. In fact, this distribution pattern, when interpreted alongside the Jaccard coefficients, reveals that horticultural farming systems not only demonstrate the highest relative contribution to the efficient pool but also contribute the greatest absolute number of benchmark farms, while granivores consistently underperform in both metrics, highlighting significant sectoral disparities in water-use efficiency achievement at the regional level.

5.2. The water-use efficiency at meta-frontier level

Within the core phase of this research, several meta-frontier analyses are conducted to gain deeper insights into obtained WUE scores from the previous section. The results, both for individual farm and aggregated averages by farm type, are presented in Table S2 of supplementary information, as well as in Table 6 and Fig. 2. These visuals offer a clear comparison of performance across different farms.

In Table 6, group frontiers consistently demonstrate higher efficiencies compared to the pooled meta-frontier: horticulture achieves the highest meta-frontier and group-frontier efficiencies, along with the largest TGR, indicating relatively better performance within its group. Conversely, permanent crops show the lowest meta-frontier performance and experience significant technology losses. The table also highlights that mixed crops and livestock exhibit the greatest managerial shortfall, although their technology loss is comparatively moderate. Across clusters, the sample means across clusters suggest that most groups operate well below the meta-frontier, indicating room for efficiency improvements.

Fig. 2 complements these cluster statistics by depicting the empirical distribution of TGR: the distribution is strongly right-skewed, with the bulk of observations concentrated at low TGR values and a long right tail driven by a small set of relatively advanced farm types (horticulture being the distinguish principle). In particular, it visually emphasizes that grazing livestock and several crop-focused clusters lie far from the meta-frontier, while horticulture's relatively high TGR stands apart from the mass of lower-WUE observations.

These findings demonstrate varying levels of water-use inefficiency across farm types. To assess the significance of differences in TGR among

[2] The Jaccard similarity index is defined by $J(X,Y) = \frac{|X \cap Y|}{|X \cup Y|}$; it quantifies the proportion of elements common to X and Y relative to their union, with $J \in [0,1]$ (0 = no overlap; 1 = identical sets). In this study it indicates the share of farms classified as fully water-use efficient that are common to any pair of farm-type groups. Interested readers are referred to Vijayakumar et al. (2021) for a comprehensive methodological exposition of the calculation procedure.

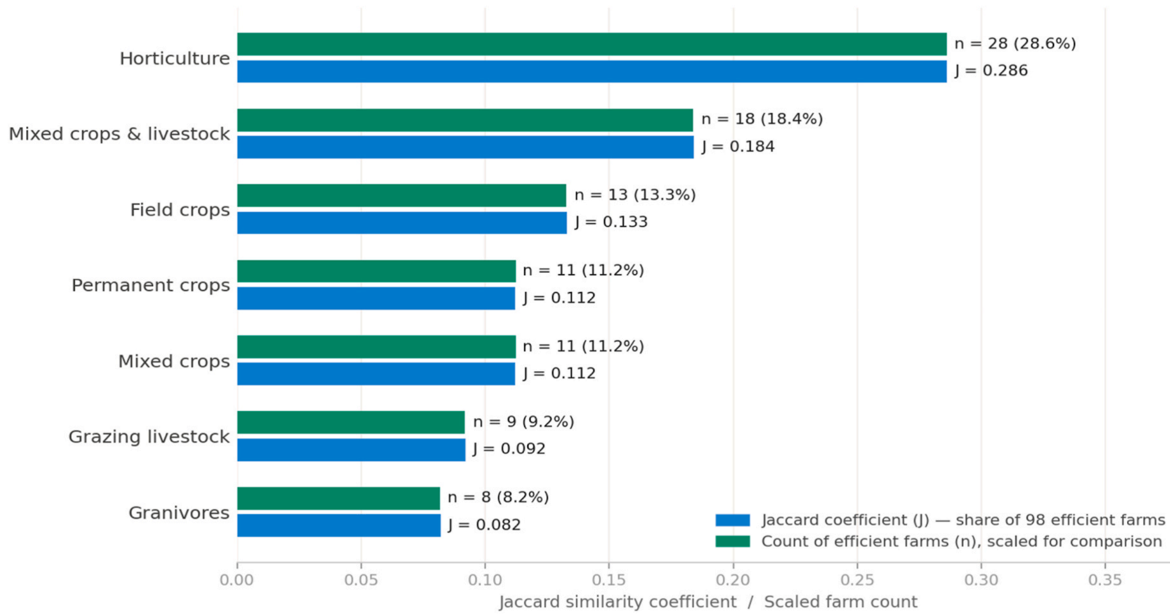

Fig. 1. Jaccard similarity of each farm type with the total pool of water-use efficient farms (n = 98). Note: Each coefficient reflects the proportional contribution of the respective farm type to the benchmark-efficient pool. J (blue) = relative proportion (0–1); n (green) = absolute count. Complementary metrics distinguish concentration from magnitude. Convergent rankings across both metrics confirm sectoral efficiency disparities are robust, not measurement artefacts. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 6
Summary of findings from meta-frontier analysis.

Farm Types	MFE	GFE	TGR	TGI	MI	MTI
Field crops	0.172	0.568	0.191	0.399	0.431	0.827
Horticulture	0.389	0.627	0.539	0.237	0.372	0.610
Permanent crops	0.141	0.576	0.223	0.435	0.423	0.858
Grazing livestock	0.143	0.457	0.165	0.321	0.542	0.856
Granivores	0.167	0.587	0.179	0.419	0.412	0.832
Mixed crops	0.151	0.526	0.201	0.378	0.473	0.848
Mixed crops and livestock	0.257	0.455	0.325	0.197	0.544	0.742
Average	0.203	0.542	0.260	0.341	0.457	0.796

farms, therefore, the Kruskal–Wallis (K-W)[3] rank sum test was applied. The results confirmed the presence of technological heterogeneity across the seven farm types, as the null hypothesis - stating no difference among the groups - was rejected (H-statistic: 108.26; P value: 4.7×10^{-21}) at the 1% significance level.

5.3. The factors affecting the water-use efficiency

In the final stage, the impact of explanatory variables on WEU at the sample-wide level is estimated using Tobit regression,[4] with the results depicted in Table 7.

The applied Tobit regression model analysing determinants of WUE in our sample of Italian irrigated farms demonstrates robust explanatory power and reveals several critical insights into factors driving efficient water management practices. Most notably, water cost exhibits a highly significant positive effect on efficiency, providing strong empirical support for market-based conservation policies that use pricing mechanisms to incentivise judicious water use. The choice of irrigation technology significantly affects WUE outcomes, with infiltration systems, surface irrigation, micro-irrigation, and other advanced methods all performing better than the commonly used sprinkler irrigation in Italy. Irrigation intensity exhibits a negative and highly significant coefficient, indicating that, conditional on type of farming and other covariates, farms with a larger share of irrigated area tend to display lower WUE scores. Among the studied farm types, horticulture exhibits a significantly higher WUE than the reference group, suggesting that this farming type benefits from structural advantages—such as technology intensity, production organization, or management practices. The farm economic scale (small-medium) is negatively associated with water-use efficiency. This marginally significant association may reflect scale-related constraints in smaller farms - for example limited access to capital, irrigation technologies, or managerial capacity. Industrial crops significantly outperform field crops in water use efficiency, likely due to repeated crops with higher economic returns that justify investments in advanced irrigation technologies and require careful resources management.

Geographic and topographic factors reveal notable spatial differences in water use efficiency across Italy. Central regions generally achieve higher efficiency compared to northern areas, while southern regions tend to perform less well. These variations can be linked to differences in water scarcity, climate, and institutional conditions. Topography also plays a significant role, with hill and mountain regions exhibiting much higher efficiency than plains, potentially due to water scarcity constraints that encourage more careful resource management, along with the prevalence of small-scale, intensive farming systems at higher elevations. In contrast, human capital factors such as age and education level do not show significant effects on WUE, indicating that technological adoption and economic incentives are more influential in shaping farmers' water conservation behaviors.

[3] The K-W test is a nonparametric, rank-based method for detecting differences among k independent groups (in our case, distinct farm types), and is robust to violations of parametric assumptions such as normality as well as to the presence of outliers (Ramachandran and Tsokos, 2015); the test statistic is $H = \frac{12}{N(N+1)} \sum_{i=1}^{k} \frac{R_i^2}{n_i} - 3(N+1)$, where the factor 12 is a scaling constant, n_i denotes the sample size of group $i, N = \sum_{i=1}^{k} n_i$, and R_i the sum of ranks in group i; under H_0, H is approximately χ^2_{k-1} (chisquare with $k-$ 1 degrees of freedom).

[4] The Tobit regression analysis was conducted using R version 4.5.1 with the AER package.

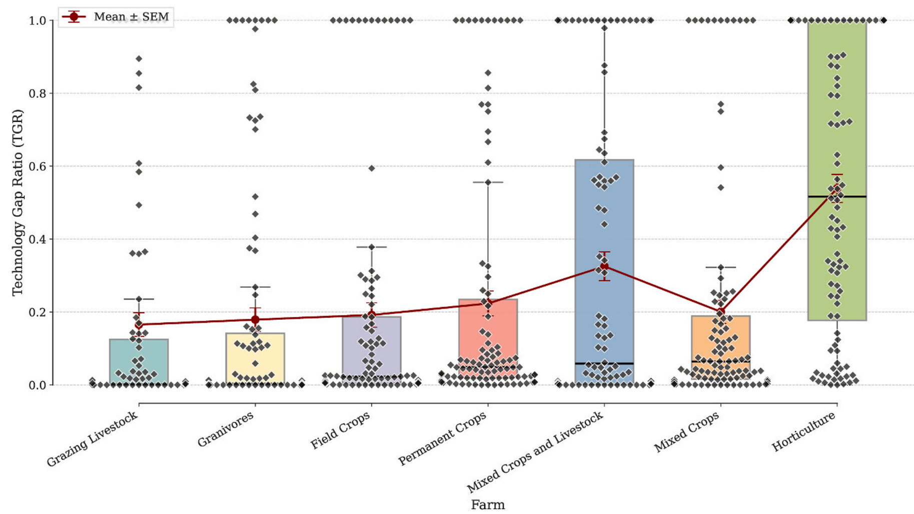

Fig. 2. Distribution of Technology Gap Ratio (TGR) Across Italian Agricultural Farms. Note: Mean ± SEM (brown solid line) indicates the mean across farms and its standard error, reflecting the precision of the population estimate. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 7
Tobit estimates of determinants of water use efficiency at meta-frontier level.

Variables	Coefficient (β)	Std. Error	Z score	p-value
Constant	0.199518	0.049974	3.992	0.0000654***
Water cost	0.009662	0.001568	6.163	7.13E-10***
Irrigation technique [a]				
Infiltration	0.219265	0.163713	1.339	0.018046*
Surface irrigation	0.111572	0.041248	2.705	0.00683**
Micro-irrigation	0.093442	0.03648	2.561	0.01042*
Flood irrigation	0.037945	0.186546	0.203	0.83882
Micro-spray irrigation	−0.016057	0.069689	−0.23	0.81777
Other systems	0.166185	0.052626	3.158	0.00159**
Source of the water	−0.002195	0.027816	−0.079	0.9371
Fertigation	−0.01682	0.028205	−0.596	0.550955
Irrigation intensity	−0.191404	0.042263	−4.529	5.93E-06***
Farm type [b]				
Horticulture	0.148795	0.053882	2.761	0.00575**
Permanent crops	−0.044707	0.048927	−0.914	0.36084
Grazing livestock	−0.037199	0.04759	−0.782	0.43441
Granivores	0.018265	0.047337	0.386	0.69961
Mixed crops	−0.056375	0.046463	−1.213	0.225
Mixed crops and livestock	0.018617	0.04699	0.396	0.69197
Farm Economic scale	−0.11398	0.060751	−1.876	0.06063†
Cultivation technique [c]				
Greenhouse crops	−0.210761	0.150379	−1.402	0.16105
Industrial crops	0.133715	0.065889	2.029	0.04242*
Organic	0.01211	0.036663	0.33	0.74118
Geographical location [d]				
Center	0.107894	0.049139	2.196	0.02811*
South	−0.074244	0.035034	−2.119	0.03407*
Altimetric area [e]				
Hills	0.092843	0.030414	3.053	0.00227**
Mountains	0.122195	0.037851	3.228	0.00125**
Farmers' age	−0.015653	0.03673	−0.426	0.66998
Farmers' education	0.02572	0.051498	0.499	0.61746
Log (scale)	−1.144374	0.026726	−42.819	<2e-16***

Notes: Log-likelihood: −192.2 (28 df) | Wald statistic: 167.7 (26 df), $p < 0.001$; Pseudo-R^2: McFadden = 0.281 | Cox & Snell = 0.193 | Nagelkerke = 0.361; Significance levels: †p < 0. 1, *p < 0.05; **p < 0.01; ***p < 0.001.
[a] Sprinkler irrigation was set as baseline.
[b] Field crops was set as baseline.
[c] Open field crop was set as baseline.
[d] North was set as baseline.
[e] plain area was set as baseline.

6. Discussion

This empirical research aims to measure water-use efficiency and identify technological gaps within Italian agricultural farms, with the overarching goal of addressing and understanding the water scarcity challenges faced by this sector. Towards this end, a DEA approach was firstly implemented to measure the WUE, identify inefficiencies, and project potential water reductions. The overall analysis of 700 farms indicates generally low water-use efficiency across the sample (Table 4). Horticulture performs best, with the highest average WUE, whereas mixed crops and livestock farms operate at the lowest sectoral efficiency level. An assessment of potential water savings reveals that mixed crops and livestock has the greatest inefficiency (Table 5), representing the largest scope for reduction, followed by grazing livestock and mixed cropping. Among specialized sectors, horticulture shows the smallest inefficiency, whereas field crops, permanent crops, and granivores exhibit moderate potential for water-use improvements. The relatively low elasticity of yield with respect to water volume is noteworthy: increasing water inputs produces less-than-proportional yield gains, so indiscriminate increases in water use can produce technical inefficiency (Benedetti et al., 2019). These results are in parallel with a recent study in southern Italy, which revealed that the average efficiency of agricultural farms is relatively low. Nonetheless, technical efficiency (TE) differs based on farm characteristics such as crop type, farm size, legal status, management practices, and the degree of farm specialization (Laureti et al., 2021). In addition, the very large inefficiency gaps observed in some farm groups may also reflect structural heterogeneity across farms, including differences in crop mix, soil quality, irrigation access, and local climatic conditions (Geffersa, 2023). Accordingly, part of the estimated water-saving potential may capture not only managerial inefficiency but also underlying agro-ecological constraints that are not fully observable in the present analysis. Considerable heterogeneity in WUE within farming systems suggests that best practices are unevenly adopted. Horticulture - because of its greater representation among efficient farms -could be an important source of transferable practices, while sectors with high similarity but low representation would benefit from focused knowledge-transfer programs to speed efficiency improvements (Ferreira et al., 2024).

Moreover, to illustrate the impact of farm-level disparities on WUE results at the sample-wide level, we applied a range of meta-frontier analysis in the next stage. The findings indicate the meta-frontier efficiency score is consistently lower than group-specific efficiencies for WUE across all farms, since group frontiers are subsets of the overarching meta-frontier technology (Table 6). In details, horticulture demonstrates the highest levels of efficiency, while permanent crops perform the worst relative to the meta-frontier, indicating significant technological inefficiency in that sector. Conversely, mixed crops and livestock exhibit the largest managerial gap, suggesting that management practices, rather than technology, are the primary constraint limiting their efficiency. Fig. 2 reinforces this finding; the right-skewed TGR distribution shows most sectors (e.g., grazing livestock) trail far below the meta-frontier, with only advanced sectors like horticulture nearing the efficiency frontier. This occurs by design because meta-frontier analysis incorporates greater heterogeneity in economic, social, and environmental conditions across the full sample compared to homogeneous individual farms (Lozano and Borrego-Marin, 2025; Lozano and Borrego-Marín, 2024). These findings align with recent research indicating that horticulture systems tend to use water more efficiently while achieving higher crop productivity per hectare. In contrast, other crop types like COP (cereals, oilseeds, and protein crops) and granivores mainly face managerial inefficiencies in utilising optimal land area and water use for maximum production, which results in reduced total factor productivity (Galluzzo, 2020; Masi et al., 2021).

The results of the Tobit model showed a significant positive correlation of water cost and WUE (Table 7). That indicates the need of reinforcing progressive volumetric-based irrigation charging in line with EU water framework directive (Bazzani et al., 2004). Due to significant performance differences in irrigation technology, Italy needs to promote high-efficiency irrigation practices, such as Micro-irrigation following findings that precision irrigation systems enhance efficiency in water utilisation (Casadei et al., 2018, 2021). Irrigated-area share, used as a proxy for reliance on irrigation, is negatively and statistically significantly associated with WUE, indicating that farms with a larger proportion of irrigated area tend to exhibit lower WUE. This finding is consistent with the first-stage analysis, which reported a low overall WUE score for the studied farms. Accordingly, targeted interventions—such as improved irrigation scheduling, enhanced monitoring, and the adoption of water-saving technologies—may increase efficiency (Hoover et al., 2023; Rawat and Kulshrestha, 2025); however, the observed relationship is correlational rather than causal and should be interpreted with caution. The lower efficiency of farms located in plain areas, with respect to hill and mountain, underlines the need to focus the intervention in those areas promoting the transfer of technologies and knowledge, moreover, the observed negative correlation between farm economic scale and WUE suggests that small-sized farms, often constrained by operational rigidity and limited resources, require not only targeted support—through technical guidance, incentive schemes, and collaborative management—but also integration to enhance resource (water) utilisation and overall efficiency (Galluzzo, 2013; Mizik, 2023). The higher performance of industrial crops indicates diversification strategies that save, reduce evapotranspiration, and increase sustainability (Yang et al., 2021). Lastly, internal differences—particularly low efficiency in Southern Italy— demand targeted measures and institution-building in response to climate-sensitive problems such as drought, flood, and pollution (Carboni and Russu, 2018; Netti et al., 2024). In the same direction can act an enhanced integration of national, regional, and territorial water authorities, which can support the adaptation to climate changes (Galeotti et al., 2025). Eventually, these results make clear that, in a context of growing water scarcity - especially acute in southern Italy - the capacity of the agricultural sector to adapt and optimise its water use remains insufficient. Taken together, these findings address the articulated research agendas of this work by documenting whether production expansion aligns with technical gains and water savings, mapping how WUE varies across crop groups and why some groups outperform the meta-frontier, identifying exogenous determinants of farm-level technical efficiency, and demonstrating regional policy-relevant divergence.

7. Policy Implication

The findings of this research must be interpreted within the evolving European framework for water resilience. The *European Water Resilience Strategy* and the *Green Deal's Farm to Fork Strategy* both emphasize the need to transform agriculture into a water-smart system, capable of maintaining productivity under growing water stress while reducing abstraction, enhancing reuse, and supporting ecological balance. The results of this study provide operational evidence to guide this transition in Italy, where irrigation remains the dominant pressure on freshwater resources. Italian agricultural and water-related policies should therefore take a leading role in implementing integrated water-resilience strategies. Demand-side reforms that internalise the scarcity value of water - notably volumetric pricing based on actual consumption - are essential to create reliable market signals that justify investments in automated, sensor-driven irrigation and real-time weather and soil-moisture decision support (Corbari et al., 2019; Koech and Langat, 2018). However, our empirical results —together with the lower performance observed among farms located in southern Italy—suggest that pricing reforms should be complemented by targeted public support to accelerate the adoption of efficient irrigation technologies and practices. Relevant instruments include Common Agricultural Policy (CAP) co-financing and rural development measures (through eco-schemes and agri-environmental-climate measures) as well as complementary grants or low-interest loans to reduce upfront capital constraints. These resources should prioritize modular and scalable precision-irrigation systems and ensure that investments produce measurable water-productivity gains. Crucially, volumetric charging should be implemented alongside farm-level technical diagnostics so that subsidies, extension and any penalty regimes are directed where they will have the most considerable marginal impact and do not penalise vulnerable producers (Beal et al., 2016; Maas et al., 2024).

At the national and regional level, policy design must recognise strong heterogeneity across various sectors, scales and territories and combine regulatory change with capacity building and geographically tailored support (Liu et al., 2021). River basin authorities, irrigation consortia and regional administrations should receive clearer mandates and stable financing to deploy volumetric metering, modernise conveyance infrastructure and implement performance-linked contracts with farmer organisations so outcomes are verifiable. Interventions should be tiered to farm-level constraints: permanent crops need capital support for precision technologies, while mixed crop-livestock operations require managerial training and extension services. Reforming irrigation consortia away from rigid rotational delivery toward responsive and knowledge-sharing networks will accelerate the diffusion of best practices from high-performing horticultural systems. Moreover, the economic scale of farms is a structural determinant of efficiency. The negative relationship between small farm size and WUE suggests that policy should promote voluntary land integration and cooperative arrangements. Such initiatives could strengthen competitiveness and sustainability, enhancing collective investment capacity and technological adoption (Vadez et al., 2023). Indeed, relying exclusively on mitigation is inadequate to avert the negative consequences of climate change; complementary adaptation and innovation measures are therefore essential. In Italy, fiscal incentives—such as tax credits for farmers—support private investments that enhance farm sustainability, including technologies and practices that reduce water consumption (Auci and Pronti, 2023).

To sum up, a coordinated Italian strategy— priced signals, CAP-backed incentives for smart irrigation, improved multi-level governance, farm diagnostics and outcome-based monitoring—can significantly raise aggregate water productivity while protecting vulnerable farms and ensuring public investments deliver measurable efficiency gains.

8. Concluding Remarks

The international community agrees that treating water as an economic good is imperative in achieving both efficient and equitable use. Treating water in this way encourages conservation as well as protection of water resources in the future. The European Union has encouraged innovative technologies as well as best practices that reduce water utilisation as well as increase WUE. In Italy, improving WUE is particularly important within the agricultural sector, as it plays a crucial role in supporting sustainable development and ensuring the long-term availability of water resources. To address this challenge, this study therefore implements a modified two-step DEA-meta-frontier approach to assess the WUE and identify the efficiency gaps and farm-level disparities in Italian agricultural sector. In doing so, using a sample-wide level of Italian farms and an ordered analytical strategy (DEA, meta-frontier decomposition, and Tobit regression), we find that overall WUE remains low, with noticeable sectoral heterogeneity, underscoring a pressing inefficiency in water resource management. Considerable variation exists between farm types and a sizable technology-management divide at the total scale, and sectoral contrasts are evident: horticulture is closest to the meta-technology, whereas permanent crops display the widest technology shortfall. This reveals that much of the sector lags significantly behind the overall technological benchmark, highlighting the limited diffusion of efficient practices and technologies. Econometric results corroborate systematic contextual effects: higher water prices and adoption of micro-irrigation are positively associated with WUE, while southern location is negatively associated with efficiency. Hence, amid escalating water scarcity in southern Italy, agricultural adaptation and water-use optimization remain inadequate. Production growth is not matched by water-efficiency gains, with marked crop-level heterogeneity, identifiable efficiency drivers, and regionally divergent, policy-relevant outcomes. Indeed, from a policy perspective, the evidence supports a coordinated strategy that combines demand-side instruments (well-designed volumetric pricing and tariff reform) with supply-side measures (targeted technology diffusion, extension and capacity building) to close both technology and management gaps -particularly by scaling successful horticultural practices and tailoring interventions to lagging regions. These steps will be essential for improving Italian agriculture's resilience to ongoing water scarcity while promoting efficient, equitable use of a critical natural resource.

A key advantage of this practical research lies in its integrated methodological approach, as it combines DEA, meta-frontier analysis, and econometric modelling to offer a multifaceted overall picture of WUE, thereby enabling focused interventions in situations of water scarcity. In addition to merely capturing inefficiency, this holistic approach captures transferable best practices being used by high-performing sectors, enhancing its usability by policymakers and practitioners. Indeed, by viewing what technologies and practices are already in use by the most efficient farms, decision-makers obtain a clear roadmap of how to transform underperforming farms into higher-WUE farms. In practice, precision irrigation, micro-irrigation, and other water-saving technologies become replicable solutions that could close the gap to inefficient farms.

Although the findings presented here are based on the specific case of Italian agriculture, the model draws on information from the EU FADN dataset. This foundation makes the approach applicable and adaptable to a wide range of agricultural systems across the EU, encompassing variations in crop types, geographic location, and agro-climatic conditions. Such comparability across case studies enables the development of policy recommendations tailored to specific contexts. Nonetheless, interpretation should be tempered by several limitations, most importantly those related to data availability. The studied contextual variables are limited in this application-oriented research: richer measurement of managerial and behavioural characteristics is required to disclose why some farms outperform their group frontier. Looking forward, future research should integrate richer data on farmer-level and socio-economic variables—such as years of farming experience, risk preferences, off-farm income, tenure and land fragmentation, access to credit and extension services, cooperative membership, irrigation scheduling and intensity of use—to better understand the drivers of efficiency disparities. In addition, because the analysis is based on multi-annual averages, it removes the time dimension and therefore does not capture temporal dynamics, interannual variability, or year-specific shocks affecting farm performance. As a result, short-run fluctuations due to weather anomalies, market volatility, policy changes, or other transitory events are not directly observed in the estimated efficiency scores. Furthermore, the effects of CAP measures on irrigation efficiency warrant evaluation because the Italian agricultural census provides comprehensive farm-level structural data—including land use, crop composition, land tenure, livestock, labor force and managerial characteristics, as well as indicators of digitalization—aggregated at the regional level. Linking these data to administrative CAP records would allow measurement of the incidence and intensity of relevant second-pillar investments (e.g., on-farm modernization, water-saving technologies) and enable testing of whether regional differences in Tobit-estimated WUE arise from heterogeneous program implementation, selection into programs, or underlying structural heterogeneity. We recommend including CAP indicators (participation dummies, support amounts, intervention types), regional fixed effects, and interaction terms. If administrative coverage is incomplete, use propensity-score matching, instrumental variables exploiting regional program variation, or multilevel models to account for farms nested within regions. A next step, therefore, is to extend the analysis at national scale by combining farm-level efficiency estimates with policy participation and territorial implementation information (e.g., RDP investment measures, eco-schemes), using appropriate panel or quasi-experimental approaches to quantify policy impacts on WUE.

This study contributes to the existing body of knowledge on water use efficiency in Italian agricultural sector and offers practical guidance for both policymakers and farmers. From a policy perspective, the urgent challenge is to address Italy's structural water scarcity by supporting the adoption of best practices from benchmark farms, while tailoring interventions to regional vulnerabilities. By doing so, policymakers can foster a transition where inefficient farms follow the technological pathways of the most efficient ones, ultimately improving resilience and sustainability of water use in Italian agriculture.

CRediT authorship contribution statement

Majid Zadmirzaei: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Severino Romano:** Writing – review & editing, Supervision, Conceptualization. **Mario Cozzi:** Writing – review & editing, Methodology, Conceptualization. **Adele Coppola:** Writing – review & editing, Methodology, Conceptualization. **Giulio Grassi:** Writing – original draft, Visualization, Software. **Alireza Amirteimoori:** Methodology, Formal analysis, Conceptualization. **Mauro Viccaro:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Funding acquisition, Data curation.

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.

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Appendix A

Table A1
Composition of the analytical sample by types of farming (percent within type; N = 100 per type of farming)

Characters	Variables	Field crops	Horticulture	Permanent crops	Grazing livestock	Granivores	Mixed crops	Mixed crops and livestock
Geographical location	North	60	45	42	70	90	51	66
	Center	17	25	5	6	4	10	20
	South	23	30	53	24	6	39	14
	Total	100	100	100	100	100	100	100
Altimetric area	Mountains	9	16	23	27	1	12	30
	Hills	32	42	32	26	15	38	32
	Plains	59	42	45	47	84	50	38
	Total	100	100	100	100	100	100	100
Irrigation technique	Infiltration	0	2	1	0	1	0	0
	Surface irrigation (Flow irrigation)	10	5	6	25	16	4	21
	Sprinkler irrigation (literally "Rain")	55	27	19	70	77	42	49
	Micro-irrigation	20	49	55	3	2	43	18
	Flood irrigation (or Submersion)	2	0	0	0	1	0	0
	Micro-spray irrigation	3	6	14	0	1	2	3
	Other systems	10	11	5	2	2	9	9
	Total	100	100	100	100	100	100	100
Source of the water	Consortium system,	64	35	59	75	72	53	48
	Others	36	65	41	25	28	47	52
	Total	100	100	100	100	100	100	100

Note: Values are percentages within each type of farming (equal-allocation analytical subset) and are provided for descriptive context; they are not design-weighted population shares.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2026.148203.

Data availability

The data that has been used is confidential.

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