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Sustainable agricultural performance in the European Union in the context of ecological transition, economic fairness, and support policies

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Abstract: This paper investigates the structural determinants of sustainable agricultural performance across the 27 European Union member states over the period 2012–2023, focusing on the interplay between economic efficiency, environmental sustainability, and social equity. Employing a panel quantile regression approach, the study captures the heterogeneous effects of organic farming practices, public support for agricultural research and development, income inequality, and environmental emissions on multiple dimensions of agricultural performance. The analysis underscores the importance of empirical evidence in designing integrated agricultural policies that enhance sustainability, competitiveness, and social cohesion, in alignment with key European strategies, including the Common Agricultural Policy 2023–2027, the European Green Deal, and the Farm to Fork strategy. The findings reveal that the influence of structural determinants varies significantly across the performance distribution, with stronger effects observed in lower-performing contexts. These results support increased public investment in agricultural research and innovation, the development of customised incentives for organic farming tailored to performance levels and farm structures, and the implementation of redistributive mechanisms to mitigate regional disparities in agricultural income. Higher agricultural income is consistently associated with greater value-added efficiency and lower ecological intensity, suggesting structural decoupling between economic growth and environmental pressure. Overall, the study highlights the need for targeted, data-driven policy interventions to foster innovation, resilience, and inclusive rural development across the European Union.

Keywords: ecological efficiency; economic development; European agriculture; income distribution; public policy; quantile panel analysis

In the context of the structural changes imposed by the ecological transition, digitalisation, and increasing climate pressures, sustainable agricultural performance is becoming an important benchmark for

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reconfiguring European public policies. Agriculture is no longer seen exclusively as a production sector but as a complex socio-ecological system at the intersection of food security, environmental protection, and social equity (European Environment Agency 2022; Angeon et al. 2024). The transition to a sustainable agricultural model requires a profound understanding of the relationships between the economic, institutional, and ecological determinants that shape agricultural performance in EU member states (European Commission 2024e).

Recent developments in international research highlight the limitations of unified or single-dimensional analyses of agricultural performance and emphasise the need to integrate composite indicators that simultaneously reflect economic efficiency, ecological impact, and redistributive equity (Taoumi and Lahrech 2023; OECD 2024a; Khan et al. 2025). Numerous studies emphasise the importance of using an analytical framework based on quantile distributions, capable of capturing structural variations at different levels of agricultural performance, thus overcoming the limitations of approaches based on aggregate averages, which tend to mask territorial disparities (Muduli and Chattopadhyay 2024; Shi and Wang 2024; Vishwakarma et al. 2025).

Unlike previous studies, which typically address a single dimension of performance (economic, environmental, or social), this research develops an integrated panel quantile model that simultaneously examines all three dimensions. By applying this multidimensional approach to 27 EU member states over the period 2012–2023, this study advances the existing literature by combining distributional analysis with policy-relevant considerations, linking quantile-based empirical findings directly to European strategies such as the Common Agricultural Policy (CAP) 2023–2027, the Green Deal, and the Farm to Fork strategy.

At the strategic level, documents such as the European Green Deal (European Commission 2023), the Farm to Fork strategy (European Commission 2024a), the CAP 2023–2027 (European Commission 2022), and the initiatives under Horizon Europe (European Commission 2024c) promote an agricultural model focused on innovation, resilience, climate neutrality, recognising agriculture as a cross-cutting driver of sustainability. The differentiated implementation of these policies across Europe creates an acute need for robust empirical analysis to assess the extent to which agricultural income, government support for research, organic farming, income equity, and greenhouse gas emissions influence sustainable agricultural performance, both economically and environmentally.

The research topic addressed in this study concerns the limited understanding of how economic, environmental, and redistributive dimensions jointly determine sustainable agricultural performance within the European Union. In the literature, numerous studies have examined these dimensions separately, and there remains a lack of an integrated analytical approach that simultaneously evidences interactions and heterogeneous effects across performance levels. This analysis highlights a distinct gap in the existing literature, as most prior research employs mean-based or aggregate models that overlook distributional complexity and cross-country disparities. By employing a panel quantile regression framework that integrates economic efficiency, ecological pressure, and equity dimensions, this study contributes to the literature by developing a multidimensional, evidence-based perspective on sustainable agricultural performance, thereby offering a methodological and empirical advancement over existing work.

This paper addresses the research topic by applying a quantile analysis to panel data for the 27 member states of the European Union over the period 2012–2023, using individual and composite indicators selected for their strategic and econometric relevance. The primary objective is to evaluate the quantile relationships between the explanatory variables and three complementary dimensions of agricultural performance: real agricultural income per unit of labour (log*AWU*), value-added efficiency in agriculture (*VAEI*), and environmental pressure intensity per unit of income (*EPIY*). The method employed provides a detailed analysis of the mechanisms by which agricultural policies can be adapted in order to promote sustainable, inclusive, and competitive rural development within the European Union.

The novelty of the paper lies in integrating a panel quantile approach at the European Union level, enabling analysis of agricultural performance from a tripartite economic, environmental, and redistributive perspective, using both conventional indicators and composite indices designed to capture synthetic dimensions of sustainability. In contrast to existing literature, which frequently favours average linear regression methods or aggregate models, this research makes a methodological contribution by exploring heterogeneous effects across the entire quantile spectrum of performance, thus highlighting structural mechanisms that central tendency estimates would otherwise mask. The research aligns both conceptually and empirically with key European strategies. It provides an analytical framework for assessing the impact of agricultural policies on the green transition and the balance of rural territories based

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on the CAP for the 2023–2027 framework, the Green Deal, the Farm to Fork strategy, and Horizon Europe.

The objectives of this paper are:

i) Investigating the effects of organic farming and public support for research and development on real agricultural income per unit of labour.

ii) Assessing the relationship between agricultural income and value-added efficiency in agriculture, based on the distribution of performance across member states.

iii) Analysing the impact of agricultural income on ecological pressure per unit of income, with a view to exploring the potential for decoupling economic efficiency and environmental pressure intensity.

iv) Formulating evidence-based European public policy recommendations that support the transition towards resilient agriculture.

This research makes a valuable contribution to the literature by highlighting the complex interactions between structural factors and sustainable agricultural performance, and by supporting the need for differentiated European agricultural policies grounded in empirical evidence and aligned with the objectives of the green transition, social equity, and systemic resilience. The analytical framework developed in this paper incorporates three interrelated and complementary dimensions: ecological transition, economic equity, and supportive policies, each represented by distinct empirical indicators. Ecological transition is captured through variables reflecting environmental performance, organic farming, and emission intensity; economic fairness is represented by redistributive indicators such as agricultural income and the Gini coefficient; and supportive policies are measured through government expenditure on agricultural research and development, reflecting institutional capacity to foster innovation and competitiveness. A comprehensive understanding of achieving sustainability in European agriculture emerges from the alignment of ecological objectives with social inclusion and economic efficiency.

The key strength of this study is its ability to provide empirical evidence to guide agricultural policymakers, researchers, and rural stakeholders by quantifying the heterogeneous effects of economic, environmental, and redistributive factors. The findings contribute to the design of differentiated agricultural strategies that enhance competitiveness while supporting environmental sustainability and social cohesion. The results strengthen the empirical basis for European initiatives such as the CAP 2023–2027, the European Green Deal, and the Farm to Fork strategy, helping to operationalise sustainability objectives in an equitable and context-sensitive manner across member states.

Literature review. The conceptual framework of sustainable agricultural performance has been developing towards an in-depth understanding of the interactions among economic, environmental, and social processes within agricultural systems. This approach, reflected in the sustainable transition paradigm, perceives agriculture as a complex adaptive system influenced by technical innovation, ecological limitations, market dynamics, and institutional support (Gamage et al. 2024; OECD 2024b; Behera et al. 2025; Popescu et al. 2025). Within this framework, agricultural performance is no longer measured solely by productivity indicators but by the capacity of farming systems to maintain efficiency, resilience, and equity under changing climatic and socioeconomic conditions (Zawalińska et al. 2022; Selbonne et al. 2023; Martín-García et al. 2025). Concepts such as agroecological transition, multifunctional agriculture, and extended agricultural efficiency reflect this paradigm shift, emphasising systemic linkages between production, ecosystem services, and social inclusion (Nowack et al. 2022; Zeng et al. 2023; Stempfle et al. 2025). These theoretical evolutions converge with the European Union's sustainability agenda, particularly the European Green Deal and the CAP 2023–2027, which prioritise green innovation, climate neutrality, and territorial cohesion as interdependent pillars of sustainable rural development (European Commission 2023, 2024b).

This theoretical reconfiguration is reinforced by the transformations outlined by the European Green Deal (European Commission 2023), the Farm to Fork strategy (European Commission 2024b) and the reform of the CAP for the period 2023–2027 (European Commission 2022). The institutional initiatives promote agriculture with a focus on innovation, climate neutrality, responsible resource use, and rural equity. In this context, the literature increasingly emphasises the need for integrated assessment tools that capture both the economic added value and the environmental costs, as well as the role of agriculture in maintaining the vitality of rural communities. New analytical approaches support the adoption of composite indicators and advanced statistical methods, such as panel quantile regression, capable of capturing the systemic heterogeneity in agricultural performance across member states and among different segments of farmers (Bocean 2024; Ha et al. 2024; Georgescu et al. 2025). These methodological developments provide a more nuanced understanding of the agroecological transition and offer empirical support for the formulation of differentiated and equitable public policies at the European Union level.

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At the same time, there has been a clear trend towards refining the indicators used in sustainable performance analysis by integrating environmental and social components into traditional economic assessment. For example, some studies (Asghar and Faridi 2022; Diop et al. 2024) propose eco-efficiency indicators, which incorporate negative externalities into the analysis of economic returns. The use of composite indicators is identified as particularly important for understanding the complexity of the ecological transition in agriculture and for supporting advanced empirical modelling grounded in dynamic, multidimensional structural relationships. One of the most significant and complex topics in contemporary literature on sustainable agriculture is the impact of organic farming on economic performance and value-added efficiency. Organic farming, defined by the prohibition of synthetic pesticides, the promotion of biodiversity, and respect for natural soil cycles, was initially perceived as a marginal alternative, reserved for niche consumers oriented towards organic products. In the last decade, organic farming has become a strategic priority for the European Union, being enshrined as a key objective in the Farm to Fork strategy and the European Green Deal, which aims to achieve a threshold of 25% of the total agricultural area of the EU by 2030 (European Commission 2025f).

Beyond the already established role of organic farming in the agroecological transition, recent literature highlights the growing importance of regenerative agriculture as a complementary paradigm aimed at restoring long-term ecosystem functions. Regenerative agriculture involves the adoption of practices such as diversified crop rotations, cover crops, minimal tillage, and integrated soil-based management to improve fertility, increase biodiversity, and optimise water and nutrient cycles (Sher et al. 2024; Hajji-Hedfi et al. 2025; Kumar et al. 2025; Moisés et al. 2025). Unlike organic farming, which focuses primarily on restricting the use of synthetic inputs, regenerative agriculture emphasises restoring soil health and increasing its capacity to sequester carbon. Numerous studies suggest that these systems contribute to increasing soil carbon stocks, strengthening drought resilience, and sustaining productivity under adverse climatic conditions (EASAC 2022; Khangura et al. 2023; Shukla et al. 2025; Udumann et al. 2025).

Some studies have drawn attention to the close relationship between regenerative practices and the emergence of carbon credit mechanisms, which provide financial incentives to farmers who can demonstrate reductions in agricultural emissions or additional carbon sequestration in soils (Barbato and Strong 2023; Baumber et al. 2024; Villat and Nicholas 2024; Cammarata et al. 2025). Carbon markets, whether voluntary or regulated, allow positive climate outcomes to be converted into additional income, thereby supporting the adoption of low-emission technologies and sustainable land management. The effectiveness of these markets depends on the standardisation of measurement methodologies, transaction costs, market transparency, and the avoidance of non-additional risks (Li and Martino 2024; OECD 2024c; Awazi et al. 2025; Kochar et al. 2025).

At the European level, these developments are reflected in the EU Carbon Farming Initiative (European Commission 2025b) and the 2024 proposal on carbon capture certification (EU Regulation 2024/3012), which promote results-based assessment and support carbon credit trading in agriculture (European Commission 2024e). The integration of regenerative agriculture and carbon-based mechanisms into sustainability trajectories thus extends the analytical framework beyond organic farming, anchoring sustainability in measurable ecosystem benefits and opening new channels for resilient and inclusive agricultural development. In addition, the new eco-schemes under the CAP (European Commission 2025e) include specific carbon farming measures, such as soil conservation, expansion of perennial vegetation cover, and crop diversification, designed to reward farms that generate measurable climate benefits. Through these instruments, the EU aims to integrate carbon value into rural economic models and accelerate the transition to climate neutrality in agriculture.

The adoption of regenerative practices and carbon farming schemes can influence key indicators of agricultural performance, both by reducing environmental pressure and by increasing income, generating different effects depending on the structure and performance of farms. The integration of regenerative agriculture and carbon markets into European agricultural policies outlines a transition towards production models geared towards quantifiable results, strengthening the interdependence between economic and environmental performance.

On this basis, the first hypothesis is formulated:

H_1: The increase in organically farmed land has a differentiated effect on agricultural income and economic efficiency, with significant benefits in the lower quantiles and negative effects in the extremes of the distribution.

This hypothesis posits that organic farming serves as a corrective and recovery tool for low-productivity farms but can become a constraint for large or high-performing farms in the absence of adaptive strategies that enable higher product value and compensation

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for compliance costs. The hypothesis also implies testing the effect in different deciles of the distribution, in a quantile framework, to capture the heterogeneity and possible inflexion points of the relationship.

Another major and well-represented direction in the literature on agricultural sustainability is the analysis of the role of public research and development in increasing economic efficiency, competitiveness, and net income from agriculture. This topic is often approached from the perspective of an 'augmented production function', in which investments in R&D are treated as indirect productive inputs with knock-on effects on total factor productivity. Reference studies and meta-analyses (Czubak et al. 2021; Markow et al. 2023; Urbancová et al. 2025) show that the social return on public investment in agricultural research is among the highest of all economic sectors, due to spillover effects and the diffusion of knowledge to farmers, which amplify the economic and social impact of these investments.

Within the European Union, this theoretical framework has been translated into concrete public policies through the Horizon 2020 (European Commission 2021) and Horizon Europe (European Commission 2024c) research programmes, which have allocated substantial funds to modernise and digitise agriculture.

At the same time, studies warn that the benefits of research are not distributed evenly across member states, rural regions, and farm categories. Existing research (Wolfert et al. 2023; Rajkhowa and Baumüller 2024; Sargani et al. 2025; Vărzaru 2025) highlights the importance of the degree of innovation uptake, which depends on factors such as digital infrastructure, human capital, the structure of the agricultural extension system, and farmers' openness to change. In member states with robust extension systems and continuous farmer training policies, investment in research generates much more consistent economic effects than in countries where technology transfer is weak or discontinuous (European Commission 2024d; Ottone and Barbieri 2025).

In this context, the second hypothesis is formulated:

H_2: Government support for agricultural research and development has a significant positive impact on real agricultural income per unit of labour in all performance deciles.

This hypothesis is theoretically supported by the augmented production function model and empirical literature on the direct (through process innovation) and indirect (through dissemination and spillovers) impact of research on agricultural performance. Within the quantile model, the robustness of the effect across the entire performance spectrum is tested, assuming that the benefits of research are generalisable and not limited to elite farms. This test allows for the formulation of relevant conclusions on the universality and equity of the impact of agricultural innovation in European agricultural policy.

The literature on the interaction between real agricultural income and value-added efficiency in agriculture has developed significantly in recent decades, particularly given the recognition of agricultural income as an indicator of performance and a functional determinant of the agri-food sector's performance. This relationship is conceptualised in economic literature through a double causality: on the one hand, agricultural income reflects the productivity and competitiveness of farmers; on the other hand, it conditions their ability to make strategic investments, adopt advanced technologies, and access high value-added markets (Doukas et al. 2023; Martini et al. 2023; Eurostat 2025i; Miaris et al. 2025).

Empirical research (Metta et al. 2022; Abiri et al. 2023; European Commission 2025c; Liang and Qiao 2025) suggests that higher levels of net agricultural income per unit of labour facilitate farm modernisation through equipment purchases, technological conversion, digitisation, access to agricultural advisory services and improved management practices. Recent analyses at the OECD country level (Bernini and Galli 2024; OECD 2024b; Lankoski et al. 2025) show that higher-income farms are more efficient in their use of productive inputs and natural resources, which is particularly relevant given the current pressures for sustainability. These findings are also confirmed by European studies highlighting the role of agricultural income in facilitating access to knowledge, vocational training, and innovation networks (Jankelová and Joniaková 2021; Ragazou et al. 2022; European Council of Young Farmers 2023; Gutiérrez Cano et al. 2023; Kountios et al. 2024).

More recent studies (Cahyadi et al. 2024; Fiore et al. 2024; Castillo-Díaz et al. 2025; Hermans et al. 2025) support the importance of integrating the income dimension into agricultural efficiency analysis models, highlighting that income determines not only the technological level of the farm, but also its ability to integrate circularity principles, adopt agroecological practices, and capitalise on opportunities for economic diversification. Income becomes an essential channel through which public policies can stimulate sustainable performance.

Based on these considerations, the third hypothesis is formulated:

H_3: Real agricultural income significantly increases the efficiency of value added in agriculture across the entire quantitative spectrum.

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The hypothesis reflects the central role of agricultural income in facilitating access to innovation and resources. However, it assumes that the effect's magnitude varies with farm performance, with theoretical expectations of a stronger impact in the lower and middle segments of the distribution, which justifies the empirical approach based on panel quantile regressions.

Empirical research results support this dynamic, particularly in developed agricultural economies, where investments in precision agriculture, emission-reducing technologies, smart crop rotation, bio-fertilisers, and the digitisation of supply chains contribute to reducing the environmental impact per unit of income generated (Costa et al. 2023; Getahun et al. 2024; Behera et al. 2025; Petrovic et al. 2025). Furthermore, analyses (Guth et al. 2022; Weltin and Hüttel 2023; Bernini and Galli 2024; Szafraniec-Siluta et al. 2024) on European farms show that medium- and high-income farms have significantly lower ecological intensity, as they have the financial and human capital necessary to adopt eco-efficient solutions. Similarly, other analyses (Ameur and Leauthaud 2024; Vishwakarma and Ranjan 2024; von Cossel et al. 2025) argue that the integration of advanced agroecological practices, such as cover crop systems, reduced chemical inputs, and integrated soil management, is significantly more common in profitable and well-capitalised farms, suggesting an inverse relationship between income level and ecological pressure.

Some literature warns of the existence of threshold effects and a possible nonlinear relationship, in which investment in environmentally friendly technologies becomes possible only after reaching a critical income level. Various studies (Savin and van den Bergh 2024; Taylor and Bhasme 2024; Williams et al. 2024; Frascarelli et al. 2025) have shown that, on farms in the lower performance deciles, agricultural income is often used to ensure subsistence and working capital, with little room for ecological innovation, while on farms in the upper deciles, ecological pressure decreases proportionally with income growth, confirming the relative decoupling hypothesis.

Within this conceptual and empirical framework, the fourth hypothesis is formulated:

H_4: Higher agricultural income is associated with lower ecological pressure per unit of income, highlighting a significant inverse relationship between economic performance and ecological intensity.

This hypothesis builds on the theoretical premises of relative decoupling and aligns with current trends in the sustainability literature, but it requires testing the relationship across multiple deciles of performance to identify structural regularities, scale effects, or inflexion points. Methodologically, this approach allows for the capture of nonlinear and conditional relationships relevant to the formulation of differentiated agricultural policies by farm type and level.

Despite significant progress in the literature on agricultural sustainability, a critical review of existing studies reveals several methodological and conceptual limitations that warrant further research. Most econometric analyses of agricultural performance use traditional linear approaches, which assume homogeneity in the relationships between variables and fail to capture the distributional complexity of performance. This assumption is problematic in a sector characterised by significant structural variability across farms, regions, and member states, driven by institutional, geographical, and socioeconomic differences. Quantile regression on panel data offers a superior alternative, capable of capturing the heterogeneous and nonlinear effects of predictors at different levels of performance.

Second, the current literature lacks integration of economic, ecological, and redistributive dimensions into a common analytical framework. Most studies treat agricultural income (*AWU*), value-added efficiency (*VAEI*), and ecological pressure (*EPIY*) separately, without systematically linking them in a coherent model that captures their interactions and trade-offs. Furthermore, although there is an emerging literature on ecological decoupling and the impact of organic farming or public research on performance, few studies adopt a pan-European structural perspective based on comparative panel data across the 27 EU member states. This limits the ability to formulate differentiated public policy recommendations according to agricultural performance profiles.

Consequently, this research fills a well-defined gap, both empirically and methodologically, identified in the literature, by applying a quantile panel model for the period 2012–2023, which simultaneously integrates economic dimensions (real agricultural income per *AWU*), efficiency (*VAEI*), and environmental sustainability (*EPIY*). The proposed approach allows the identification of differentiated structural relationships across quantiles, highlighting how agricultural policies and investments in research or greening influence performance at different initial levels of the farm or member state.

This contribution is significant from a theoretical point of view, by employing a robust methodology adapted to the complexity of the data, and from a practical perspective, by providing relevant empirical evidence for European policymakers. In the context of the

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new CAP 2023–2027, the European Green Deal, and the Farm to Fork strategy, the results of this research can guide budgetary calibrations, funding priorities, and environmental and social conditionality mechanisms to achieve a fair and effective agroecological transition in the European Union.

The proposed study enhances the scientific framework for agricultural sustainability in the EU through its methodological approach and the integration of synthetic indicators that simultaneously capture economic efficiency, redistributive equity, and environmental pressure. The main findings of this study could serve as a framework for developing evidence-based public policy proposals specifically designed to address the diverse structural characteristics of European agriculture.

MATERIAL AND METHODS

This study employs an econometric approach to evaluate sustainable agricultural performance across the 27 member states of the European Union, utilising a panel data set from 2012 to 2023. The selected timeframe for the study represents a significant phase in the development of European policy on sustainable agriculture, ecological transition, and social fairness. Beginning in 2012, the European Union commenced an extensive evaluation of the strategic framework for agriculture and rural development, culminating in successive reforms of the CAP for the 2014–2020 period, succeeded by the 2021–2022 transition framework and the formal introduction, in 2023, of the new CAP 2023–2027, which for the first time incorporates national strategic plans aligned with the objectives of the European Green Deal.

This period also encompasses the convergence of several major strategic initiatives of the EU: the Farm to Fork strategy and the Biodiversity strategy for 2030, launched in 2020 as central pillars of the European Green Deal, as well as the implementation of the 2030 Agenda for Sustainable Development, emphasising Goal 2 (zero hunger), Goal 7 (affordable and clean energy) and Goal 10 (reduced inequalities). At the same time, the period analysed captures the cumulative effects of exogenous crises that have put additional pressure on the balance between economic performance, environmental sustainability, and distributive equity. The dataset includes various agricultural, economic, and environmental metrics to understand the complexities of sustainable agricultural performance. Explanatory variables include: government support for agricultural research (log*GOVRD*), share of organic farmland (log*ORGUAA*), ammonia emissions (log*AMMEMIS*), gross value added in agriculture (log*GVAAGR*), greenhouse gas emissions from agriculture (log*GHGAG*), real GDP *per capita* (log*RGDP*), Gini coefficient (log*GINI*), pesticide sales (log*PEST*), and final energy consumption in agriculture (log*ENCONAG*) according to Table 1. All variables were logarithmically transformed to reduce asymmetry, improve the interpretation of elasticities, and alleviate concerns about heteroscedasticity, in line with methodological guidelines in the literature. (Bergougui et al. 2024; Georgescu and Kinnunen 2025; Wen et al. 2025).

In addition to the primary variables, the study introduces three composite indicators, constructed based on theoretically grounded ratios: *EPIY* (ecological pressure index per unit of income), which reflects the ecological pressure associated with the generation of a unit of agricultural income [Equation (1)]; *AEEI* (agricultural energy efficiency index), which expresses energy efficiency in relation to agricultural productivity [Equation (2)]; and *VAEI* (value added efficiency index), an efficiency index that captures the economic return of agriculture in relation to the resources used [Equation (3)]. The integration of these composite indicators addresses the need to quantify more subtle dimensions of sustainability that cannot be adequately captured by direct indicators and provides a synthetic view of the interdependencies among economic efficiency, environmental pressures, and structural equity.

Ecological pressure index per unit of income (*EPIY*):

$$EPIY_{it} = \frac{\log GHGAG_{it} + \log AMMEMIS_{it} + \log PEST_{it}}{\log AWU_{it}} \quad (1)$$

Agricultural energy efficiency index (*AEEI*):

$$AEEI_{it} = \frac{\log AWU_{it}}{\log ENCONAG_{it}} \quad (2)$$

Value added efficiency index (*VAEI*):

$$VAEI_{it} = \frac{\log GVAAGR_{it}}{\log RGDP_{it} \times \log GINI_{it}} \quad (3)$$

In terms of the econometric strategy adopted, this research uses quantile regressions in a panel data context, a robust methodological approach that is increasingly used in economic studies investigating uneven distributions and heterogeneous structural behaviours (Koenker and Bassett 1978; Portnoy 2019). Quantile regression allows the examination of the effects of explanatory variables on different points of the conditional distribution

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Table 1. Presentation of indicators

Indicators	Symbol	Unit of measurement	Source
Agricultural real factor income per annual work unit	log*AWU*	chain-linked volumes, index 2015 = 100	Eurostat (2025a)
Government support for agricultural research and development	log*GOVRD*	EUR million	Eurostat (2025f)
Area under organic farming	log*ORGUAA*	percentage of total utilised agricultural area	Eurostat (2025c)
Ammonia emissions from agriculture	log*AMMEMIS*	tonne	Eurostat (2025b)
Gross value added of the agricultural industry - basic and producer prices	log*GVAAGR*	EUR million	Eurostat (2025h)
Greenhouse gas emissions from agriculture	log*GHGAG*	percentage	Eurostat (2025g)
Real GDP *per capita*	log*RGDP*	EUR *per capita*	Eurostat (2025k)
Gini coefficient of equivalised disposable income	log*GINI*	percentage	Eurostat (2025e)
Pesticide sales	log*PEST*	kilogram	Eurostat (2025j)
Final energy consumption by the agriculture and forestry sector	log*ENCONAG*	tonnes of oil equivalent per hectare of utilised agricultural area	Eurostat (2025d)

Source: Prepared by the authors based on Eurostat data

(Q10, Q20, Q30, Q40, Q50, Q60, Q70, Q80, Q90), capturing asymmetries, extremes, and non-uniform effects that cannot be detected by estimating the mean. Differences in the determinants of agricultural performance between countries with low, medium, or high levels of efficiency can thus be investigated. The application of quantile regression in a panel data framework allows control for unobserved individual effects and reduces specification problems, as recommended in the literature (Canay 2011; Lamarche 2021; Chen 2024; Galvao and Montes-Rojas 2024).

The methodology used aligns with recent developments in applied econometrics and is acknowledged for its capacity to yield robust findings (Canay 2011; Chen, 2024). The use of quantile regressions to explore sustainable agricultural performance provides an in-depth understanding of the varying impacts of public policies, ecological transition, and socioeconomic factors on agricultural performance across different structural segments of the European Union. The estimates were generated using Stata 18 (StataCorp LLC., USA) econometric software, which facilitates the estimation of panel quantile regression models.

The general equations of econometric models are:

Model 1 – determinants of real agricultural income (*AWU*) in Equation (4).

Model 2 – determinants of economic efficiency (*VAEI*) in Equation (5).

Model 3 – determinants of ecological pressure relative to income (*EPIY*) in Equation (6).

$$\begin{aligned} Quant_{\tau}\left(\log AWU_{it}\right) &= \alpha_{\tau} + \beta_{1\tau}\log GOVRD_{it} + \beta_{2\tau}\log ORGUAA_{it} + \beta_{3\tau}\log GHGAG_{it} + \beta_{4\tau}\log RGDP_{it} + \\ &+ \beta_{5\tau}\log GINI_{it} + \beta_{6\tau}EPIY_{it} + \beta_{7\tau}AEEI_{it} + \beta_{8\tau}VAEI_{it} + \varepsilon_{it}^{(\tau)} \end{aligned} \tag{4}$$

$$\begin{aligned} Quant_{\tau}\left(VAEI_{it}\right) &= \alpha_{\tau} + \beta_{1\tau}\log AWU_{it} + \beta_{2\tau}\log GOVRD_{it} + \beta_{3\tau}\log ORGUAA_{it} + \beta_{4\tau}\log GHGAG_{it} + \\ &+ \beta_{5\tau}\log RGDP_{it} + \beta_{6\tau}\log GINI_{it} + \beta_{7\tau}EPIY_{it} + \beta_{8\tau}AEEI_{it} + \varepsilon_{it}^{(\tau)} \end{aligned} \tag{5}$$

$$\begin{aligned} Quant_{\tau}\left(EPIY_{it}\right) &= \alpha_{\tau} + \beta_{1\tau}\log AWU_{it} + \beta_{2\tau}\log GOVRD_{it} + \beta_{3\tau}\log ORGUAA_{it} + \beta_{4\tau}\log GHGAG_{it} + \\ &+ \beta_{5\tau}\log RGDP_{it} + \beta_{6\tau}\log GINI_{it} + \beta_{7\tau}AEEI_{it} + \beta_{8\tau}VAEI_{it} + \varepsilon_{it}^{(\tau)} \end{aligned} \tag{6}$$

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where: $Quant_\tau(Y_{it})$ – the quantile of order $\tau \in \{0.1, 0.2, ..., 0.9\}$ of the conditional distribution of the dependent variable Y, for country i at time t; α_τ – the intercept specific to each quantile; β_τ – the vector of quantile-specific regression coefficients measuring the effect of the explanatory variables; $\varepsilon_{it}^{(\tau)}$ – the error term specific to the quantile, it denotes the observations for country i and year t.

The use of panel quantile regressions provides an in-depth perspective on the heterogeneous effects of agricultural sustainability determinants across the performance distribution, contributing to a more rigorous assessment of European policies in this area.

RESULTS AND DISCUSSION

In the context of the structural reforms promoted by the European Union to enhance ecological transition and territorial equity, the results indicate that various economic and ecological factors significantly influence sustainable agricultural performance across the 27 member states. The quantile analysis allows for a nuanced investigation of these relationships beyond general averages, highlighting significant structural variations across countries with low, medium, or high performance in terms of agricultural income, value-added efficiency, and related ecological pressures. The quantile analysis enables a detailed examination of these relationships, extending general averages and emphasising significant structural differences among countries with low, medium, or high performance regarding agricultural income, value-added efficiency, and associated ecological pressure.

Descriptive statistics. The analysis of the descriptive statistics presented in Table 2 highlights substantial variation across EU member states in agricultural performance and related structural indicators.

According to the results presented in Table 2, real agricultural income per annual work unit (*AWU*) averages 114.46 units (index 2015 = 100), with a standard deviation of 26.41, reflecting significant disparities between countries with a high-performing agricultural sector and those where agricultural productivity is below the EU average. The variable ranges from 57.66 to 225.66, indicating systemic gaps in agricultural infrastructure, human capital, and institutional support. The average government funding for agricultural research and development (*GOVRD*) is EUR 108.42 million, but this is unevenly distributed, as shown by a median of EUR 35.60 million and a high standard deviation of EUR 196.50 million. This marked dispersion reveals the polarisation of public investment in agricultural research, suggesting that only a few countries allocate significant resources in this direction, while others show little financial commitment. The organic agricultural area (*ORGA*), expressed as a percentage of the total agricultural area, averages 8.77%, but varies considerably (from 0.06% to 25.69%), reflecting the uneven penetration of organic farming across the EU. The median value (7.49%) and the 75th percentile (11.97%) indicate that more than half of the member states are below the critical level for the agro-ecological transition. Greenhouse gas emissions from agriculture (*GHGAG*), expressed as a percentage of the national total, fall within a wide range (2.40–36.60%), with an average of 11.53% and a median of 9.85%, signalling the existence of agricultural structures with very high levels of ecological intensity, which are likely to require priority reforms.

Real gross domestic product *per capita* (*RGDP*) ranges from EUR 7 530 to EUR 107 570, with an average of EUR 31 006, confirming the persistence of a significant East–West economic gap. The high standard

Table 2. Descriptive statistics

Variable	Mean	SE of mean	Median	SD	Minimum	Maximum	Percentiles		
							25	50	75
AWU	114.457	1.467	107.660	26.414	57.66	225.66	97.665	107.660	127.337
GOVRD	108.424	10.916	35.596	196.500	0.14	1 121.62	9.965	35.596	92.583
ORGUAA	8.769	0.332	7.485	5.986	0.06	25.69	4.030	7.485	11.970
GHGAG	11.535	0.364	9.850	6.554	2.40	36.60	7.400	9.850	13.050
RGDP	31 006.327	1 156.561	23 530.000	20 818.104	7 530.00	107 570.00	16 067.500	23 530.000	42 982.500
GINI	29.855	0.220	29.250	3.966	20.90	40.80	26.925	29.250	32.875

AWU – agricultural real factor income per annual work unit; *GINI* – Gini coefficient of equivalised disposable income; *GHGAG* – greenhouse gas emissions from agriculture; *GOVRD* – government support for agricultural research and development; *ORGUAA* – area under organic farming; *RGDP* – real GDP *per capita*

Source: Elaborated by authors

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Table 3. Variance inflation factor (VIF)

Variable	*VIF*	1/*VIF*
VAEI	8.699	0.115
log*GOVRD*	5.562	0.180
EPIY	5.529	0.181
log*RGDP*	2.332	0.429
AEEI	2.220	0.450
log*GINI*	1.751	0.571
log*GHGAG*	1.732	0.577
log*ORGUAA*	1.128	0.886
Mean *VIF*	3.619	–

AEEI – agricultural energy efficiency index; *EPIY* – environmental pressure intensity per unit of income; *GINI* – Gini coefficient of equivalised disposable income; *GHGAG* – greenhouse gas emissions from agriculture; *GOVRD* – government support for agricultural research and development; *ORGUAA* – area under organic farming; *RGDP* – real GDP *per capita*; *VAEI* – value added efficiency index

Source: Elaborated by authors

deviation (EUR 20 818) highlights the structural nature of this disparity and justifies including this variable in the model as a control for economic convergence. The Gini coefficient, used as a proxy for income inequality, varies within a relatively moderate range (20.90–40.80), with an average of 29.85 and a standard deviation of 3.97. The close values of the median and mean suggest a relatively balanced distribution, but the extremes indicate significant differences in redistribution across states, with potential impacts on territorial cohesion and the absorption capacity of sustainable agricultural policies.

The analysis of variance inflation factor (*VIF*) values in Table 3 allows assessment of multivariate collinearity among the explanatory variables used in the quantile models.

VIF values are essential for assessing the robustness of econometric estimates, as high multicollinearity can lead to unstable coefficients and a loss of statistical significance, even in the presence of real economic relationships. According to the results in Table 3, the average *VIF* calculated for the entire model is 3.619, a value which, according to methodological standards (Kalnins and Praitis Hill 2023; Kwilinski et al. 2023), does not signal a problem of multicollinearity, as the critical alarm threshold is generally considered to be 10.

The correlation matrix analysis presented in Table 4 provides a preliminary insight into the linear relationships between the explanatory variables and the panel quantile model variables, highlighting economically

Table 4. Matrix of correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) log*AWU*	1.000	–	–	–	–	–	–	–	–
(2) log*GOVRD*	0.174	1.000	–	–	–	–	–	–	–
(3) log*ORGUAA*	0.116	0.192	1.000	–	–	–	–	–	–
(4) log*GHGAG*	0.185	0.279	−0.012	1.000	–	–	–	–	–
(5) log*RGDP*	0.041	0.216	0.108	0.049	1.000	–	–	–	–
(6) log*GINI*	−0.033	−0.078	−0.211	0.222	−0.389	1.000	–	–	–
(7) *EPIY*	−0.215	0.772	0.007	0.364	−0.066	0.139	1.000	–	–
(8) *AEEI*	0.374	−0.042	−0.122	0.435	−0.467	0.487	0.051	1.000	–
(9) *VAEI*	0.194	0.871	0.064	0.338	0.187	0.155	0.844	0.065	1.000

AEEI – agricultural energy efficiency index; *AWU* – agricultural real factor income per annual work unit; *EPIY* – environmental pressure intensity per unit of income; *GINI* – Gini coefficient of equivalised disposable income; *GHGAG* – greenhouse gas emissions from agriculture; *GOVRD* – government support for agricultural research and development; *ORGUAA* – area under organic farming; *RGDP* – real GDP *per capita*; *VAEI* – value added efficiency index

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and statistically relevant links, as well as potential risks of theoretical collinearity.

There is a moderate positive correlation between real agricultural income per unit of labour (log*AWU*) and agricultural resource efficiency (*AEEI*), with a coefficient of 0.374, suggesting that Member States with higher agricultural productivity tend also to show greater efficiency in the use of energy and inputs. Weak but positive correlations between log*AWU* and variables such as log*GOVRD* (0.174) and log*GHGAG* (0.185) suggest an indirect relationship, in which both government investment in research and the intensity of agricultural emissions may contribute marginally to the formation of agricultural income, depending on the structure of production systems. The relationship between log*GINI* and *AEEI* is significantly negative (–0.467), suggesting that states with higher inequality tend to exhibit lower agricultural efficiency due to fragmented resource access and regional disparities.

RESULTS AND DISCUSSION

The results presented in Table 5 highlight significant quantitative variations in the impact of ecological, economic, and institutional determinants on real agricultural income per unit of labour (log*AWU*), providing a granular, distributed picture of the factors shaping agricultural performance within the EU.

The coefficient of determination (R^2) gradually increases from 0.539 (Q10) to 0.713 (Q90), indicating an increasing level of explanatory power of the model as it moves towards the upper quantiles of the agricultural income distribution. This suggests that the selected determinants explain variation in agricultural performance more effectively in states with higher

Table 5. Results of panel quantile regression estimates for real agricultural income per AWU (dependent variable: log*AWU*)

log*AWU*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
log*GOVRD*	0.047***	0.054***	0.066***	0.063***	0.049***	0.041***	0.028***	0.020**	0.018***
	(0.015)	(0.010)	(0.010)	(0.010)	(0.008)	(0.007)	(0.007)	(0.009)	(0.006)
log*ORGUAA*	0.005	0.006	0.007	0.011	0.000	–0.015**	–0.009	–0.012	–0.031***
	(0.014)	(0.010)	(0.010)	(0.010)	(0.008)	(0.007)	(0.007)	(0.009)	(0.006)
log*GHGAG*	0.156***	0.142***	0.113***	0.094***	0.074***	0.076***	0.079***	0.081***	0.095***
	(0.028)	(0.019)	(0.019)	(0.019)	(0.016)	(0.013)	(0.013)	(0.017)	(0.012)
log*RGDP*	–0.163***	–0.184***	–0.180***	–0.157***	–0.141***	–0.144***	–0.157***	–0.177***	–0.224***
	(0.027)	(0.018)	(0.018)	(0.018)	(0.016)	(0.013)	(0.012)	(0.017)	(0.011)
log*GINI*	–0.481***	–0.528***	–0.462***	–0.401***	–0.424***	–0.473***	–0.515***	–0.532***	–0.625***
	(0.107)	(0.072)	(0.073)	(0.072)	(0.063)	(0.052)	(0.050)	(0.066)	(0.046)
EPIY	–0.220***	–0.236***	–0.247***	–0.249***	–0.243***	–0.244***	–0.244***	–0.253***	–0.271***
	(0.0160)	(0.0108)	(0.0110)	(0.0108)	(0.00955)	(0.00783)	(0.00754)	(0.00997)	(0.00698)
AEEI	0.110***	0.112***	0.125***	0.133***	0.119***	0.106***	0.093***	0.063***	0.006
	(0.037)	(0.025)	(0.025)	(0.025)	(0.022)	(0.018)	(0.017)	(0.023)	(0.016)
VAEI	0.024***	0.026***	0.025***	0.024***	0.025***	0.026***	0.028***	0.030***	0.032***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
_cons	3.887***	4.126***	4.097***	3.960***	3.956***	4.067***	4.170***	4.352***	4.825***
	(0.244)	(0.166)	(0.169)	(0.166)	(0.146)	(0.120)	(0.115)	(0.152)	(0.107)
R^2	0.539	0.540	0.544	0.572	0.603	0.632	0.657	0.675	0.713
Observations	324	324	324	324	324	324	324	324	324

** and ***significance levels at 0.05 and 0.01, respectively; standard errors are in parentheses; *AEEI* – agricultural energy efficiency index; *AWU* – agricultural real factor income per annual work unit; *EPIY* – environmental pressure intensity per unit of income; *GINI* – Gini coefficient of equivalised disposable income; *GHGAG* – greenhouse gas emissions from agriculture; *GOVRD* – government support for agricultural research and development; *ORGUAA* – area under organic farming; *RGDP* – real GDP *per capita*; *VAEI* – value added efficiency index

Source: Elaborated by authors

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productivity levels. The quantile results indicate a differentiated effect of the area under organic farming on agricultural income. In the lower quantiles (Q10–Q40), the coefficients associated with log*ORGUAA* are positive (0.005–0.007) but insignificant, suggesting a marginal positive effect in low-productivity agricultural economies. Starting with Q60, the effects become negative and statistically significant: −0.015 (Q60), −0.031 (Q90), indicating a negative association between the expansion of organic farming and agricultural income in regions with high agricultural performance. This finding validates H_1 and is consistent with the literature (Makinde 2024; Mgendi 2024; Boros et al. 2025; Willer 2025), indicating that the transition to organic farming involves compliance costs, initial yield losses, and market infrastructure deficiencies, especially in advanced regions operating on volume and efficiency. At the same time, European strategies, such as the Farm to Fork strategy and the European Green Deal, promote the green transition but recognise the need for differentiated financial support tailored to each Member State's economic structure, which supports a heterogeneous interpretation of these effects. The coefficients for log*GOVRD* are positive and statistically significant ($P < 0.01$ or $P < 0.05$) in all quantiles, from Q10 (0.047) to Q90 (0.018) and demonstrate that public investment in agricultural research contributes significantly to agricultural income growth, validating H_2. This result is supported by empirical literature (Sonderegger et al. 2022; Wang et al. 2022; Ranran and Jingsuo 2024; Liang and Qiao 2025), which highlights that public agricultural research has high social returns and produces spillover effects on productivity and sustainability. In addition, the European strategic framework, through the Horizon Europe programme and the CAP 2023–2027, emphasises the role of applied research and innovation in agriculture as central pillars of modernising the European agri-food system.

Figure 1 presents the heterogeneous dynamic of causal relationships between structural determinants and

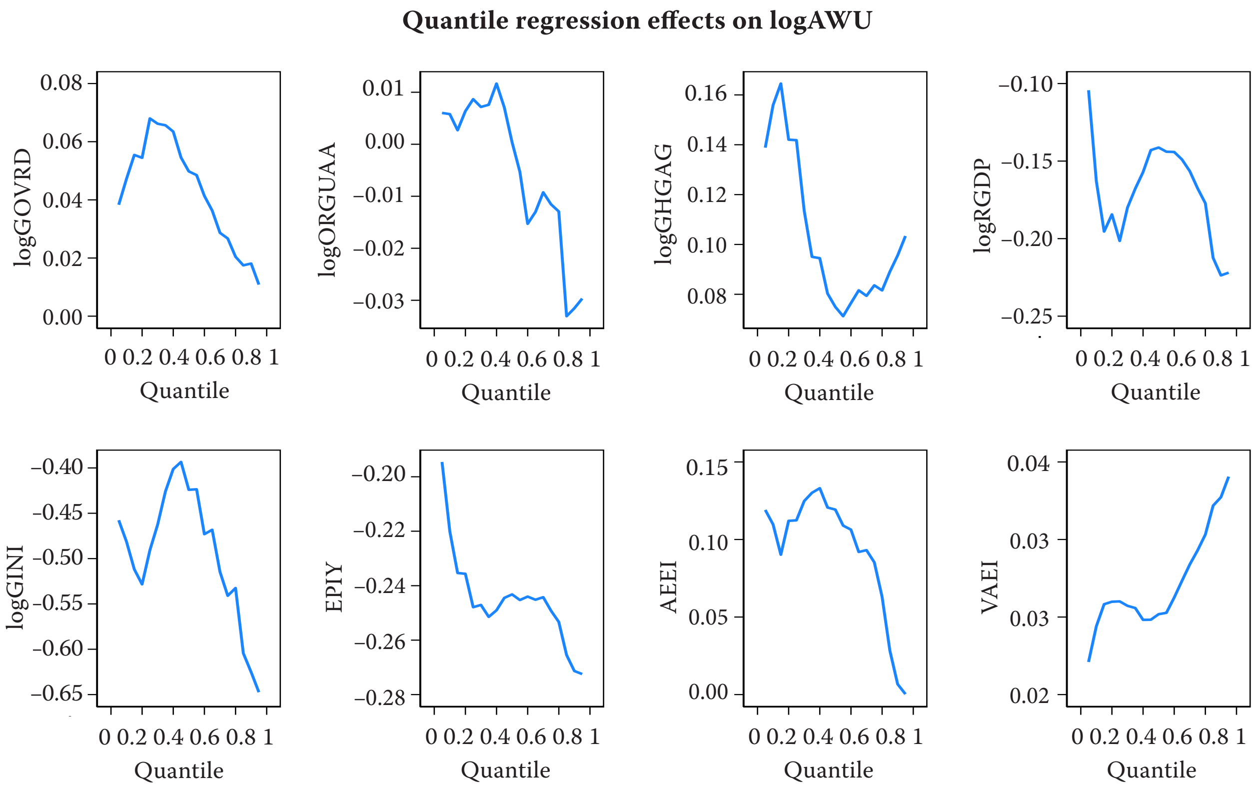

Figure 1. Evolution of quantile coefficients for log*AWU* according to agricultural performance quantiles

AEEI – agricultural energy efficiency index; *AWU* – agricultural real factor income per annual work unit; *EPIY* – environmental pressure intensity per unit of income; *GINI* – Gini coefficient of equivalised disposable income; *GHGAG* – greenhouse gas emissions from agriculture; *GOVRD* – government support for agricultural research and development; *ORGUAA* – area under organic farming; *RGDP* – real GDP *per capita*; *VAEI* – value added efficiency index

Source: Elaborated by authors

agricultural performance, outlining an analytical picture in which the intensity and direction of the impact vary significantly across conditional distribution segments. This configuration epistemologically validates the methodological choice of quantile panel regressions, as it allows the identification of latent economic regularities and dissociated marginal effects, and is determinant in developing differentiated, well-calibrated agricultural policies for the structural diversity of the European agricultural landscape.

In order to investigate the relationship between real agricultural income per unit of labour and value added efficiency in agriculture, as well as the influence exerted by other structural, economic, and ecological determinants, Table 6 presents the results of the panel quantile regression estimates for the dependent variable *VAEI*, providing a nuanced perspective on the heterogeneity of effects across the conditional distribution of agricultural performance in the member states of the European Union.

According to Table 6, the high and robust values of the coefficient of determination R^2, ranging between 0.782 (Q90) and 0.814 (Q10), indicate an exceptional explanatory power of the quantile models in capturing the variation in the efficiency of value added in agriculture (*VAEI*) according to the selected explanatory variables.

The quantile coefficients estimated for the log*AWU* variable remain consistently positive and statistically significant (P < 0.01) throughout the quantile interval, with a slight downward trend from 24.876 (Q10) to 20.164 (Q90), reflecting a persistent structural relationship between the level of real agricultural income per unit of labour and the efficiency of value added in agriculture (*VAEI*), validating H_3. This quantile configuration indicates a positive, decreasing marginal elasticity, suggesting that, at lower levels of performance,

Table 6. Results of panel quantile regression estimates for the value added efficiency index (dependent variable: *VAEI*)

VAEI	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
log*AWU*	24.876***	23.971***	22.331***	22.453***	21.184***	21.470***	21.641***	21.500***	20.164***
	(1.069)	(1.197)	(1.160)	(0.999)	(1.120)	(1.486)	(1.539)	(1.564)	(1.818)
log*GOVRD*	0.234	0.258	0.459**	0.446**	0.510**	0.506*	0.782**	1.275***	1.695***
	(0.214)	(0.240)	(0.233)	(0.200)	(0.225)	(0.298)	(0.309)	(0.314)	(0.365)
log*ORGUAA*	0.442**	0.249	0.293	0.434**	0.574**	0.079	−0.117	−0.507	−0.865**
	(0.214)	(0.240)	(0.232)	(0.200)	(0.224)	(0.298)	(0.308)	(0.313)	(0.364)
log*GHGAG*	−2.775***	−2.954***	−2.587***	−2.494***	−2.417***	−2.708***	−3.048***	−3.186***	−4.292***
	(0.402)	(0.451)	(0.437)	(0.376)	(0.422)	(0.560)	(0.580)	(0.589)	(0.685)
log*RGDP*	5.990***	5.839***	5.395***	5.169***	5.157***	5.170***	4.776***	4.411***	4.335***
	(0.348)	(0.390)	(0.378)	(0.325)	(0.364)	(0.484)	(0.501)	(0.509)	(0.592)
log*GINI*	18.436***	17.628***	16.718***	15.811***	15.483***	18.102***	19.038***	20.389***	21.568***
	(1.423)	(1.594)	(1.545)	(1.330)	(1.491)	(1.978)	(2.049)	(2.082)	(2.420)
EPIY	7.115***	6.994***	6.686***	6.710***	6.601***	6.505***	6.322***	5.948***	5.949***
	(0.237)	(0.266)	(0.257)	(0.222)	(0.248)	(0.330)	(0.342)	(0.347)	(0.404)
AEEI	−0.097	−0.391	−0.843	−.0956*	−0.653	−2.514***	−2.430***	−2.021**	−0.437
	(0.573)	(0.642)	(0.622)	(0.536)	(0.600)	(0.796)	(0.825)	(0.838)	(0.975)
_cons	−124.83***	−119.52***	−110.88***	−108.82***	−105.43***	−106.46***	−105.02***	−103.08***	−101.98***
	(4.171)	(4.672)	(4.529)	(3.900)	(4.369)	(5.797)	(6.005)	(6.102)	(7.094)
R^2	0.814	0.810	0.811	0.805	0.797	0.788	0.785	0.796	0.782
Observations	324	324	324	324	324	324	324	324	324

*, ** and ***significance levels at 0.1, 0.05 and 0.01, respectively; standard errors are in parentheses; *AEEI* – agricultural energy efficiency index; *AWU* – agricultural real factor income per annual work unit; *EPIY* – environmental pressure intensity per unit of income; *GINI* – Gini coefficient of equivalised disposable income; *GHGAG* – greenhouse gas emissions from agriculture; *GOVRD* – government support for agricultural research and development; *ORGUAA* – area under organic farming; *RGDP* – real GDP *per capita*; *VAEI* – value added efficiency index

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increasing labour remuneration has a more pronounced leverage effect on economic efficiency, while in the upper quantile returns are relatively saturated, possibly associated with the efficiency already achieved by human capital. The findings are in line with the literature highlighting the positive relationship between labour productivity and multifactor efficiency in agriculture (Kryszak et al. 2021; Đokić et al. 2022; Laddha et al. 2022; Aydin et al. 2023), but also extend to the institutional and technological dimensions, given that the digital transformation of agriculture, supported by initiatives such as 'Smart Villages' (European Commission 2019; European Network for Rural Development 2021; Bokun and Nazarko 2023; Emerllahu and Bogataj 2024) and 'Agriculture 4.0' (Mihret et al. 2025), contribute to optimising decision-making processes, automating repetitive tasks, and allocating resources more efficiently, thereby amplifying the impact of labour income on the added value generated. In this regard, the CAP 2023–2027 (European Commission 2024f), Through its pillars focused on innovation, digitisation, and human capital, it consolidates the conditions for agricultural income to become not just a result, but a major tool for sustainable economic performance, in which the interaction between skills, technology, and intellectual capital redefines the paradigm of added value in the European agricultural sector.

The positive and significant coefficients for log*GOVRD*, increasing towards the upper quantiles, indicate an amplification of the effect of public research in high-performing agricultural economies, confirming H_2. The effects of log*ORGUAA* are heterogeneous: beneficial at low performance levels and negative at high quantiles, suggesting possible yield constraints in advanced organic farms. Log*GHGAG* has a negative systemic impact on *VAEI*, reflecting the environmental costs of intensification, while log*RGDP* is positive across the entire distribution, signalling territorial complementarities.

Figure 2 highlights significant variations in regression coefficients on the conditional distribution

Quantile regression effects on VAEI

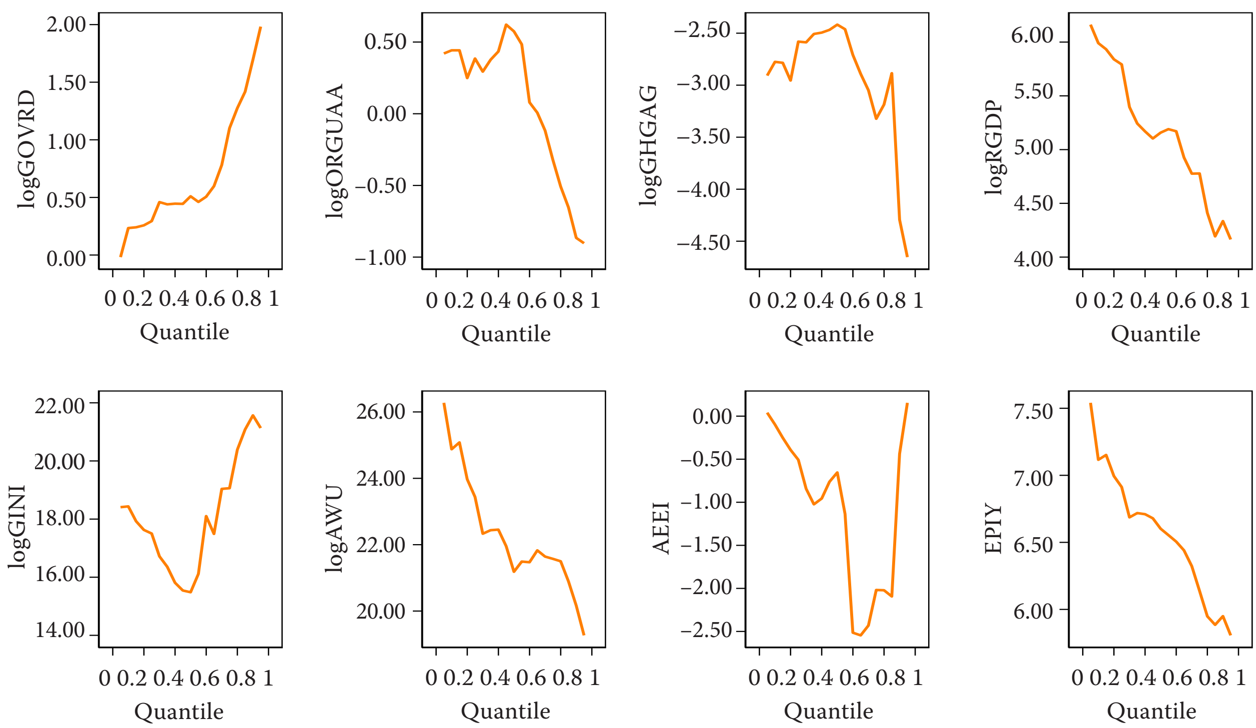

Figure 2. The quantile effects of predictors on value-added efficiency in agriculture (*VAEI*)

AEEI – agricultural energy efficiency index; *AWU* – agricultural real factor income per annual work unit; *EPIY* – environmental pressure intensity per unit of income; *GINI* – Gini coefficient of equivalised disposable income; *GHGAG* – greenhouse gas emissions from agriculture; *GOVRD* – government support for agricultural research and development; *ORGUAA* – area under organic farming; *RGDP* – real GDP *per capita*

Source: Elaborated by authors

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of *VAEI*, indicating heterogeneous structural relationships between determinants and agricultural efficiency. The impact of log*GOVRD* increases progressively, suggesting that public investment in research becomes increasingly efficient in high-performing agricultural economies, while the effect of log*AWU* gradually declines, reflecting labour productivity convergence. The negative trajectory of log*GHGAG* confirms the environmental costs of intensification, and the nonlinear shapes of the coefficients for log*ORGUAA*, log*GINI*, and *EPIY* suggest trade-offs among environmental sustainability, economic equity, and productive efficiency in the European green transition.

Table 7 provides a detailed quantile overview of the factors influencing ecological intensity per unit of income (*EPIY*), using a robust panel quantile model with a constant number of observations (n = 324) and high R^2 coefficients (0.801–0.845), which denotes consistent explanatory power across all deciles of agricultural performance.

The coefficients for log*AWU* are negative, significant, and relatively constant in magnitude across the entire quantile spectrum (from –3.019 to –3.489), validating H_4. This result indicates that an increase in real agricultural income per unit of labour is associated with a systematic reduction in environmental pressure per unit of economic value generated, suggesting a structural efficiency of agricultural practices as economic productivity increases. This relationship is entirely in line with the literature supporting the hypothesis of relative decoupling between economic growth and environmental pressure (Eurostat 2025i; Herman 2025; Mance et al. 2025), but also with the strategic guidelines of the European Green Deal (European Commission 2023)

Table 7. Results of panel quantile regression estimates for determinants of ecological intensity per unit of agricultural income (dependent variable: *EPIY*)

EPIY	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)
	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
log*AWU*	–3.019***	–3.342***	–3.281***	–3.335***	–3.282***	–3.395***	–3.412***	–3.388***	–3.489***
	(0.222)	(0.154)	(0.128)	(0.128)	(0.129)	(0.118)	(0.110)	(0.111)	(0.095)
log*GOVRD*	0.235***	0.266***	0.237***	0.196***	0.160***	0.131***	0.098***	0.068**	0.067***
	(0.056)	(0.039)	(0.032)	(0.032)	(0.033)	(0.030)	(0.028)	(0.028)	(0.002)
log*ORGUAA*	–0.027	–0.001	0.015	–0.025	–0.032	–0.057*	–0.071**	–0.119***	–0.110***
	(0.056)	(0.039)	(0.032)	(0.032)	(0.032)	(0.030)	(0.028)	(0.028)	(0.024)
log*GHGAG*	0.815***	0.573***	0.530***	0.416***	0.412***	0.426***	0.379***	0.380***	0.356***
	(0.100)	(0.069)	(0.057)	(0.057)	(0.058)	(0.053)	(0.049)	(0.050)	(0.043)
log*RGDP*	–0.947***	–0.842***	–0.823***	–0.691***	–0.720***	–0.729***	–0.694***	–0.795***	–0.828***
	(0.087)	(0.060)	(0.050)	(0.050)	(0.050)	(0.046)	(0.042)	(0.043)	(0.037)
log*GINI*	–1.029**	–1.720***	–1.698***	–1.480***	–1.769***	–1.964***	–1.911***	–2.078***	–2.215***
	(0.418)	(0.290)	(0.241)	(0.240)	(0.243)	(0.221)	(0.206)	(0.209)	(0.179)
AEEI	–0.154	0.281***	0.260***	0.246***	0.187**	0.170**	0.098	–0.036	–0.085
	(0.152)	(0.105)	(0.087)	(0.087)	(0.088)	(0.080)	(0.075)	(0.076)	(0.065)
VAEI	0.100***	0.102***	0.103***	0.104***	0.109***	0.114***	0.117***	0.121***	0.121***
	(0.008)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
_cons	14.55***	15.56***	15.42***	14.86***	15.36***	15.92***	15.87***	16.67***	17.35***
	0.869	0.603	0.501	0.500	0.505	0.460	0.429	0.435	0.373
R^2	0.801	0.803	0.799	0.797	0.797	0.802	0.809	0.823	0.845
Observations	324	324	324	324	324	324	324	324	324

*, ** and ***significance levels at 0.1, 0.05 and 0.01, respectively; standard errors are in parentheses; *AEEI* – agricultural energy efficiency index; *AWU* – agricultural real factor income per annual work unit; *EPIY* – environmental pressure intensity per unit of income; *GINI* – Gini coefficient of equivalised disposable income; *GHGAG* – greenhouse gas emissions from agriculture; *GOVRD* – government support for agricultural research and development; *ORGUAA* – area under organic farming; *RGDP* – real GDP *per capita*; *VAEI* – value added efficiency index

Source: Elaborated by authors

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and the Farm to Fork strategy (European Commission 2024b), which promote an agricultural transition towards a model in which the intensity of emissions and environmental impact per unit of income decreases with the adoption of smart, digital, and sustainable practices. The results obtained validate H_4 and reinforce the argument that increasing agricultural income is a necessary condition for the successful implementation of green transformations in agriculture (Boix-Fayos and de Vente 2023; European Environmental Agency 2024).

The coefficients for log*GOVRD* are positive and significant across all deciles, but declining (from 0.266 to 0.067), suggesting that public investment in agricultural research may initially generate an intensification of inputs, but become more environmentally efficient in high-performing farms, in line with the literature on the Kuznets environmental curve and the efficient use of innovation (Bernini and Galli 2024). Log*ORGUAA* becomes negative and significant at the upper quantiles, indicating that organic farming reduces environmental pressure only in advanced structures capable of internalising transition costs (Lewandowski et al. 2024). Log*GHGAG* has a robust positive impact, confirming the contribution of agricultural emissions to ecological intensity (European Environment Agency 2024; FAO 2024; Zhao et al. 2025). Log*GINI* has a negative and increasing effect, suggesting that equity in agricultural income distribution contributes to sustainability, in line with the principles of the CAP 2023–2027. While *AEEI* is only significant in the lower quantiles, *VAEI* is positive across the entire distribution, suggesting a possible tension between maximising economic value and ecological impact – a key challenge in the transition to resilient and green agriculture (European Commission 2024a; Ikram and Sadki 2024; Ruml et al. 2025).

Figure 3 presents the quantile trajectories of the regression coefficients for EPIY, highlighting significant

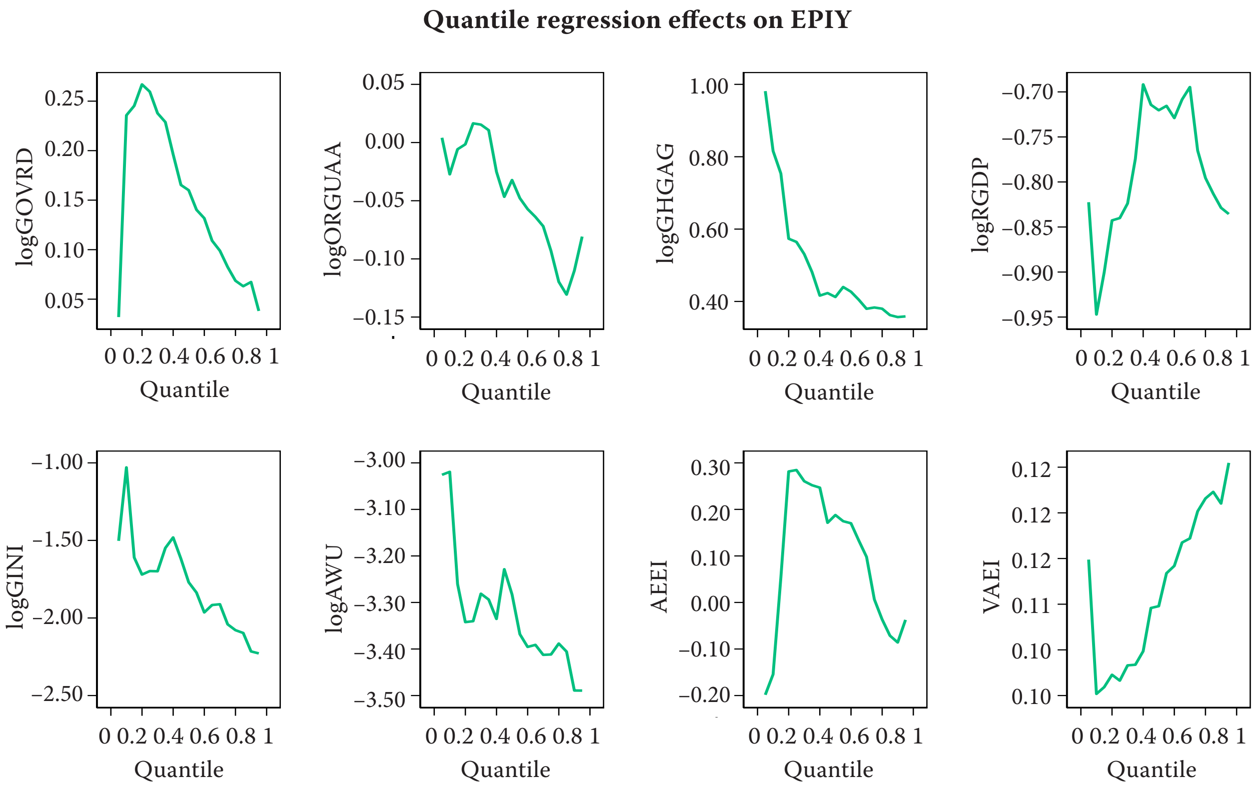

Figure 3. The quantile effects of predictors on ecological intensity per unit of agricultural income (*EPIY*)

AEEI – agricultural energy efficiency index; *AWU* – agricultural real factor income per annual work unit; *GINI* – Gini coefficient of equivalised disposable income; *GHGAG* – greenhouse gas emissions from agriculture; *GOVRD* – government support for agricultural research and development; *ORGUAA* – area under organic farming; *RGDP* – real GDP *per capita*; *VAEI* – value added efficiency index

Source: Elaborated by authors

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variations in the structural relationships between determinants and ecological intensity in agriculture.

A decreasing relationship is observed for log-*GOVRD*, suggesting that public support for research has a marginal positive environmental impact on poorly performing farms, but fades in the upper deciles, confirming the selective technological efficiency hypothesis (Ait Sidhoum et al. 2023; Zielinski et al. 2023; Savickienė et al. 2025). Similarly, the log*AWU* effect is negative and stable, indicating that increasing agricultural income per unit of labour systematically contributes to reducing environmental pressure per unit of value, validating the premises of ecological decoupling in the context of the green transition (Corsi et al. 2024; Czyżewski et al. 2025; Istudor et al. 2025). Log*GINI* exhibits a pronounced negative impact, especially at lower quantiles, suggesting that income equity supports ecological sustainability. In contrast, *VAEI* shows a growing positive effect, suggesting that maximising added value remains associated with a relative intensification of environmental pressure, a tension relevant to the objectives of the European Green Deal.

To understand how these results manifest differently across countries, the analysis was extended to a comparative analysis, highlighting the causal mechanisms between national policies, agricultural structures, and environmental performance. The research suggests that the sustainable performance of European agriculture is not a homogeneous process, indicating complex causal interactions among governmental policies, agricultural structures, levels of technical innovation, and country-specific environmental constraints. (Streimikis et al. 2022; Mergoni et al. 2024; Georgescu et al. 2025).

In Western and Northern European countries such as France, Germany, the Netherlands, Denmark, and Sweden, sustainable agricultural performance results from consistent investment in agricultural research and development, tax incentives for innovation, and the integration of low-emission practices. Public policies focused on the green transition have led to a decoupling between productivity growth and environmental pressure through the adoption of precision technologies, digital agriculture, and eco-certification schemes (Fusco et al. 2023; Prigoreanu et al. 2024; Romaldi et al. 2024; European Commission 2025d; OECD 2025).

In Southern Europe, countries such as Italy, Spain, Greece, and Portugal have made notable progress in increasing added value and expanding organic farming, but results remain sensitive to climatic factors and the availability of natural resources (Calabro and Vieri 2023; Ondrasek et al. 2023; van Leeuwen et al. 2024; European Commission 2025g). Environmental pressure is amplified by dependence on irrigation and vulnerability to drought, which creates a trade-off between economic and environmental efficiency. However, recent policies to integrate renewable energy into agriculture and to adapt water management practices offer favourable prospects for reducing emissions and strengthening rural resilience (Mondal et al. 2025; Said et al. 2025; Singh 2025).

In Central Europe, countries such as Austria, the Czech Republic, Slovenia, and Hungary are demonstrating a positive convergence between economic and environmental performance, thanks to structural reforms, the efficient use of European funds, and the expansion of agricultural research infrastructure (Streimikis et al. 2022; Nowak and Zakrzewska 2024; Radlinska 2024; Herman 2025). In these countries, institutional cooperation and agricultural advisory systems accelerate the adoption of sustainable practices, strengthening the transition to smart, competitive agriculture.

In contrast, Eastern Europe, represented by Poland, Romania, Bulgaria, and the Baltic states, continues to lag significantly behind the European average in terms of both economic efficiency and environmental performance (Prokop et al. 2022; Bartosiewicz et al. 2025; Jambor and Gorton 2025). These economies face structural challenges, including land fragmentation, insufficient investment in innovation, and poor agricultural infrastructure. However, government support policies and CAP-funded rural development programmes are helping to gradually reduce these differences and increase environmental resilience (Manta et al. 2024; European Commission 2025a; Ronzhin et al. 2025).

A country-level comparative analysis highlights that sustainable agricultural performance in the European Union is determined by a complex balance among economic, institutional, and ecological factors, and that the cause-and-effect relationships between national policies and environmental outcomes differ considerably across countries. Countries with a tradition of innovation and solid institutional infrastructure can achieve both economic growth and emissions reductions, while countries in transition still face challenges in integrating green technologies and strengthening rural governance. The findings underscore the importance of tailoring European agricultural policies to national specificities in order to support sustainable convergence and the achievement of the European Green Deal objectives.

The empirical results of this study highlight structural relationships between agricultural income, efficiency, and environmental sustainability, and these

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findings resonate with broader international evidence while also revealing specific European particularities. The positive impact of real agricultural income per unit of labour on value-added efficiency, coupled with its negative effect on environmental pressure, confirms the hypothesis of a relative decoupling between economic growth and ecological intensity. Similar patterns were reported in Eastern Europe, where agricultural growth was accompanied by improvements in eco-efficiency indicators and in studies on CO_2 decoupling in emerging economies (Akdoğan et al. 2023). These results reinforce the argument that higher incomes not only enhance competitiveness but also create the financial space needed to adopt green technologies, a conclusion consistent with evidence from Bavarian dairy farms where agri-environmental measures improved both economic and ecological efficiency.

The consistently positive role of government support for agricultural research (*GOVRD*) underscores the importance of innovation in shaping sustainable performance. This aligns with the literature highlighting that public agricultural R&D generates some of the highest social returns of any economic sector (Markow et al. 2023; Urbancová et al. 2025), while international studies confirm that the efficiency of innovation policies is amplified in high-performing economies with strong institutional and digital infrastructures (Al frijat and Elamer 2025). The heterogeneity identified across quantiles in our analysis resonates with evidence from Asian and North American contexts, where disparities in the uptake of agricultural technologies lead to uneven productivity and sustainability gains.

The differentiated impact of organic farming is also noteworthy. While our results show marginally positive effects in lower-performing economies and significant negative effects in higher-performing contexts, international evidence similarly points to yield constraints and higher compliance costs for advanced farms (Lewandowski et al. 2024). At the same time, studies conducted in developing regions indicate that organic practices can act as a recovery mechanism for small-scale farmers, supporting resilience and resource efficiency (Ameur and Leauthaud 2024). These findings highlight the need for differentiated policy interventions tailored to farm type and performance level.

The negative effects of greenhouse gas (GHG) emissions on value-added efficiency confirm that intensive agricultural practices entail high environmental costs, echoing international analyses linking intensification to sustainability trade-offs (Bernini and Galli 2024). Moreover, the negative association between income inequality (*GINI*) and sustainable performance indicators reinforces the role of distributive equity in agricultural systems. This finding is consistent with comparative studies in emerging economies, which show that income disparities reduce farmers' absorptive capacity and undermine ecological sustainability (Al frijat and Elamer 2025).

Taken together, these results strengthen the argument that sustainable agricultural policies must integrate economic, ecological, and redistributive dimensions simultaneously. They also demonstrate that the European case is not isolated but embedded in broader international dynamics where innovation, inclusiveness, and resilience emerge as cross-cutting conditions for successful agroecological transitions.

The results of the study highlight the need to reconfigure European agricultural policies in an integrative direction that simultaneously delivers economic performance, social cohesion, and environmental sustainability. The robust inverse relationship between real agricultural income and environmental pressure per unit of value-added reveals that improving labour efficiency in agriculture is not only a prerequisite for competitiveness, but also a means of reducing the intensity of environmental impacts. In this regard, public policies should prioritise investments in digitisation, smart infrastructure, vocational training, and technology transfer, anchored in the logic of low-carbon precision agriculture.

Strengthening innovation capacity at the farm and territorial agricultural structure levels, as evidenced by the significant impact of public support for research and development, requires operational convergence between the CAP 2023–2027 pillars and the funding instruments of Horizon Europe. This convergence must be operationalised through rural innovation ecosystems, applied knowledge networks, and interoperable digital infrastructures that facilitate the circulation of green technologies and agroecological practices throughout the European rural area. At the same time, integrating the principles of open science and farm data sovereignty can stimulate farmers' participation in knowledge generation and use, fostering the resilience of farming communities to systemic crises.

The redistributive dimension of agricultural policies requires conceptual and operational recalibration, as inequalities in agricultural income distribution undermine the system's sustainability. Policies should include mechanisms for the progressive correction of territorial and social imbalances, through targeted support for small and family farms, inclusive financing instruments, and active policies to support the establishment of young farmers and economic diversification in marginalised

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areas. This could achieve a structural balance between the objectives of efficiency, equity, and sustainability, in line with the EU Rural Strategy and the principles of the European Green Deal.

In a paradigm characterised by geopolitical instability, climatic unpredictability, and health and energy crises, the future framework of agricultural policy must be contemplative, based on multilevel governance, institutional flexibility, and intersectoral alignment. A polycentric strategy is necessary for the European Union to convert agriculture into a strategic instrument for the green and digital transformation, therefore enhancing its role as a worldwide leader in establishing a sustainable, equitable, and resilient agri-food system.

CONCLUSION

The study analyses various factors influencing sustainable agricultural performance across European Union member states using a quantile and multidimensional approach. It incorporates composite measures related to economic efficiency, social equity, and environmental sustainability. By applying quantile regression to panel data from 2012 to 2023, the research demonstrates varying connections between structural elements and composite indices of agricultural efficiency and environmental impact across different performance levels. A key contribution of the study is its emphasis on the heterogeneous nature of the relationships between agricultural economic performance and environmental pressures, which differ significantly across the performance spectrum. This study focuses its analysis on relevant European Union strategies, especially the CAP 2023–2027, the European Green Deal, the Farm to Fork strategy, and Horizon Europe, which provide an empirical basis for re-evaluating agricultural policies within an integrative framework that harmonises competitiveness, equity, and sustainability goals. The inclusion of composite indicators into the econometric model methodologically enhances the evaluation of agricultural performance, serving as a resource for academics and policymakers.

The study expands the literature on sustainable agricultural governance by highlighting the complexity of structural relationships and the need for an analytical framework that is sensitive to heterogeneity, territoriality, and systemic transition. The results obtained support the need for smart, differentiated agricultural policies that are empirically grounded and forward-looking, with a view to strengthening the resilience of the European agri-food system in the face of multiple crises and climate pressures.

In terms of future research directions, it is necessary to extend the analysis to the regional level (NUTS 2) to capture territorial disparities more accurately and to evaluate agricultural policies in the local context. A spatial approach, integrating spatial autocorrelation models or spatial quantile regressions, could enhance understanding of diffusion effects and interdependencies between regions. At the same time, integrating qualitative data through mixed-methods or comparative case studies would enable analysis of institutional procedures, stakeholders' perspectives, and systemic obstacles in the green transformation process.

REFERENCES

Abiri R., Rizan N., Balasundram S.K., Shahbazi A.B., Abdul-Hamid H. (2023): Application of digital technologies for ensuring agricultural productivity. Heliyon, 9: e22601.

Ait Sidhoum A., Mennig P., Sauer J. (2023): Do agri-environment measures help improve environmental and economic efficiency? Evidence from Bavarian dairy farmers. European Review of Agricultural Economics, 50: 918–953.

Akdoğan T., Erkara E., Mert B., Hiçyılmaz B., Alataş S., Karakaya E. (2023): Understanding material and energy use in the processes of decoupling CO_2 emissions from economic growth. Environmental Science and Pollution Research, 30: 80863–80883.

Al frijat Y.S., Elamer A.A. (2025): Human capital efficiency, corporate sustainability, and performance: Evidence from emerging economies. Corporate Social Responsibility and Environmental Management, 32: 1457–1472.

Ameur F., Leauthaud C. (2024): Assessing the integration of agroecological principles in smallholder farming systems in North African irrigated plains. Agroecology and Sustainable Food Systems, 49: 1463–1488.

Angeon V., Casagrande M., Navarrete M., Sabatier R. (2024): A conceptual framework linking ecosystem services, socio-ecological systems and socio-technical systems to understand the relational and spatial dynamics of the reduction of pesticide use in agrifood systems. Agricultural Systems, 213: 103810.

Asghar M., Faridi M.Z. (2022): An assessment of eco-efficiency and its determinants: Evidence from macroeconomic data. Journal of Environmental Assessment Policy and Management, 24: 2250035.

Awazi N.P., Alemagi D., Ambebe T.F. (2025): Promoting the carbon market in agroforestry systems: the role of global, national and sectoral initiatives. Discover Forests, 1: 9.

Aydin M., Degirmenci T., Yavuz H. (2023): The influence of multifactor productivity, research and development expenditure,

https://doi.org/10.17221/329/2025-AGRICECON

renewable energy consumption on ecological footprint in G7 countries: Testing the environmental Kuznets Curve hypothesis. Environmental Modeling & Assessment, 28: 693–708.

Barbato C.T., Strong A.L. (2023): Farmer perspectives on carbon markets incentivizing agricultural soil carbon sequestration. npj Climate Action, 2: 26.

Bartosiewicz A., Gniadkowska Szymańska A., Kucharski A. (2025): Sustainable development in the European union countries: panel data evidence from the transport and storage sector. Environmental Sciences Europe, 37: 174.

Baumber A., Cross R., Ampt P., Waters C., Ringbauer J., Bowdler I., Scott A., Gordon L., Sutton A., Metternicht G. (2024): Soil-based carbon farming: Opportunities for collaboration. Journal of Rural Studies, 108: 103268.

Behera D., Fathima J., Saady N.M.C., Zendehboudi S., Albayati T.M., Al-nayili A., Chatterjee P., Ponnusami V., Peach B., Espinoza J.E.R. (2025): Sustainable agriculture through environmental adaptation engineering for waste management. Green Technologies and Sustainability, 4: 100242.

Bergougui B., Mehibel S., Boudjana R.H. (2024): Asymmetric nexus between green technologies, economic policy uncertainty, and environmental sustainability: Evidence from Algeria. Journal of Environmental Management, 360: 121172.

Bernini C., Galli F. (2024): Economic and environmental efficiency, subsidies and spatio-temporal effects in agriculture. Ecological Economics, 218: 108120.

Bocean C.G. (2024): A cross-sectional analysis of the relationship between digital technology use and agricultural productivity in EU countries. Agriculture, 14: 519.

Boix-Fayos C., de Vente J. (2023): Challenges and potential pathways towards sustainable agriculture within the European Green Deal. Agricultural Systems, 207: 103634.

Bokun K., Nazarko J. (2023): Smart villages concept – A bibliometric analysis and state-of-the-art literature review. Progress in Planning, 175: 100765.

Boros A., Szólik E., Desalegn G., Tőzsér D. (2025): A systematic review of opportunities and limitations of innovative practices in sustainable agriculture. Agronomy, 15: 76.

Cahyadi E.R., Hidayati N., Zahra N., Arif C. (2024): Integrating circular economy principles into agri-food supply chain management: A systematic literature review. Sustainability, 16: 7165.

Calabro G., Vieri S. (2023): Limits and potential of organic farming towards a more sustainable European agri-food system. British Food Journal, 126: 223–236.

Cammarata M., Timpanaro G., Scuderi A. (2025): Regenerative agriculture meets the Carbon Market: exploring economic potential in Mediterranean orange groves. Environmental Challenges, 20: 101257.

Canay I.A. (2011): A simple approach to quantile regression for panel data. The Econometrics Journal, 14: 368–386.

Castillo-Díaz F.J., Belmonte-Ureña L.J., Gálvez-Sánchez F.J., Camacho-Ferre F. (2025): Sustainable technological innovations in agriculture: Financial challenges and investment priorities under the European Green Deal. Journal of Environmental Management, 389: 126150.

Chen L. (2024): Two-step estimation of quantile panel data models with interactive fixed effects. Econometric Theory, 40: 419–446.

Corsi G., Guarino R., Muñoz-Ulecia E., Sapio A., Franzese P.P. (2024): Uneven development and core-periphery dynamics: A journey into the perspective of ecologically unequal exchange. Environmental Science & Policy, 157: 103778.

Costa F., Frecassetti S., Rossini M., Portioli-Staudacher A. (2023): Industry 4.0 digital technologies enhancing sustainability: Applications and barriers from the agricultural industry in an emerging economy. Journal of Cleaner Production, 408: 137208.

Czubak W., Pawłowski K.P., Sadowski A. (2021): Outcomes of farm investment in Central and Eastern Europe: The role of financial public support and investment scale. Land Use Policy, 108: 105655.

Czyżewski B., Staniszewski J., Staniszewska J., Guth M. (2025): Does increasing agricultural efficiency contribute to food security – Trade-offs of value addition in crop production? Sustainable Development, 33: 939–970.

Diop T., Blancard S., Legras S., Marchand S., Védrine L. (2024): Exploring the linkages between farm efficiency, farm environmental performance, and agri-environmental scheme adoption: Lessons from France. Journal of Environmental Management, 366: 121519.

Đokić D., Novaković T., Tekić D., Matkovski B., Zekić S., Milić D. (2022): Technical efficiency of agriculture in the European Union and Western Balkans: SFA method. Agriculture, 12: 1992.

Doukas Y.E., Salvati L., Vardopoulos I. (2023): Unraveling the European agricultural policy sustainable development trajectory. Land, 12: 1749.

EASAC (2022): Regenerative Agriculture in Europe. Vienna, EASAC. Available at https://easac.eu/publications/details/regenerative-agriculture-in-europe

Emerllahu V., Bogataj D. (2024): Smart Villages as infrastructure of rural areas: Literature review and research agenda. IFAC-PapersOnLine, 58: 268–273.

European Commission (2019): Supporting Smart Village Strategies. Brussels, European Commision. Available at https://agriculture.ec.europa.eu/common-agricultural-policy/rural-development/supporting-smart-village-strategies_en

European Commission (2021): Horizon 2020. Brussels, European Commision. Available at https://research-and-innovation.ec.europa.eu/funding/funding-opportunities/funding-programmes-and-open-calls/horizon-2020_en

https://doi.org/10.17221/329/2025-AGRICECON

European Commission (2022): The Common Agricultural Policy at a Glance. Brussels, European Commision. Available at https://agriculture.ec.europa.eu/common-agricultural-policy/cap-overview/cap-glance_en#cap-2023-27 (accessed July 15, 2025)

European Commission (2023): A European Green Deal. Brussels, European Commision. Available at https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal_en

European Commission (2024a): EU agricultural outlook 2024–35: A resilient sector adapts to climate change, sustainability concerns, and shifting consumer demand. Brussels, European Commision. Available at https://agriculture.ec.europa.eu/media/news/eu-agricultural-outlook-2024-35-resilient-sector-adapts-climate-change-sustainability-concerns-and-2024-12-11_en

European Commission (2024b): Farm to Fork strategy. Brussels, European Commision. Available at https://food.ec.europa.eu/horizontal-topics/farm-fork-strategy_en

European Commission (2024c): Horizon Europe. Brussels, European Commision. Available at https://research-and-innovation.ec.europa.eu/funding/funding-opportunities/funding-programmes-and-open-calls/horizon-europe_en

European Commission (2024d): Strategic Dialogue on the Future of EU Agriculture. Brussels, European Commision. Available at https://agriculture.ec.europa.eu/common-agricultural-policy/cap-overview/committees-and-expert-groups/strategic-dialogue-future-eu-agriculture_en

European Commission (2024e): Sustainable Agricultural Practices and Methods. Brussels, European Commision. Available at https://agriculture.ec.europa.eu/cap-my-country/sustainability/environmental-sustainability/sustainable-agricultural-practices-and-methods_en (accessed July 15, 2025)

European Commission (2024f): The Common Agricultural Policy at a Glance. Brussels, European Commision. Available at https://agriculture.ec.europa.eu/common-agricultural-policy/cap-overview/cap-glance_en

European Commission (2025a): An Environmentally Sustainable CAP. Brussels, European Commision. Available at https://agriculture.ec.europa.eu/cap-my-country/sustainability/environmental-sustainability/cap-and-environment_en

European Commission (2025b): Carbon Removals and Carbon Farming. Brussels, European Commision. Available at https://climate.ec.europa.eu/eu-action/carbon-removals-and-carbon-farming_en

European Commission (2025c): Digitalisation of Agriculture and Rural Areas in the EU. Brussels, European Commision. Available at https://agriculture.ec.europa.eu/overview-vision-agriculture-food/digitalisation_en

European Commission (2025d): Digitalising the EU Agricultural Sector. Brussels, European Commision. Available at https://digital-strategy.ec.europa.eu/en/policies/digitalisation-agriculture

European Commission (2025e): Eco-Schemes. Brussels, European Commision. Available at https://agriculture.ec.europa.eu/common-agricultural-policy/income-support/eco-schemes_en

European Commission (2025f): Organic Action Plan. Brussels, European Commision. Available at https://agriculture.ec.europa.eu/farming/organic-farming/organic-action-plan_en

European Commission (2025g): EU Agricultural Outlook 2024–2035. Brussels, European Commision. Available at https://agriculture.ec.europa.eu/data-and-analysis/markets/outlook/medium-term_en

European Council of Young Farmers (2023): Smart farmers for smart farming.Brussels, CEJA. Available at https://wordpress.ceja.eu/wp-content/uploads/2023/05/CEJA-policy-paper-Smart-farmers-for-smart-farming-May-2023.pdf

European Environment Agency (2022): Rethinking Agriculture. Copenhage, European Environment Agency. Available at https://www.eea.europa.eu/publications/rethinking-agriculture

European Enviromental Agency (2024): Solutions for restoring Europe's agricultural ecosystems. Copenhagen, European Evironmental Agency. Available at https://www.eea.europa.eu/en/analysis/publications/solutions-for-restoring-europes-agricultural-ecosystems

European Environment Agency (2024): Greenhouse Gas Emissions from Agriculture in Europe. Copenhagen, European Environment Agency. Available at https://www.eea.europa.eu/en/analysis/indicators/greenhouse-gas-emissions-from-agriculture

European Network for Rural Development (2021): Smart Villages. Available at https://eu-cap-network.ec.europa.eu/index_en

Eurostat (2025a): Agricultural real factor income per annual work unit (AWU). [Dataset]. Available at https://ec.europa.eu/eurostat/databrowser/view/sdg_02_20/default/table?lang=en (accessed July 15, 2025)

Eurostat (2025b): Ammonia emissions from agriculture. [Dataset]. Available at https://ec.europa.eu/eurostat/databrowser/view/sdg_02_60/default/table?lang=en (accessed July 15, 2025)

Eurostat (2025c): Area under organic farming. [Dataset]. Available at https://ec.europa.eu/eurostat/databrowser/view/sdg_02_40/default/table?lang=en (accessed July 15, 2025)

Eurostat (2025d): Final energy consumption by agriculture and forestry sector – Tonne of oil equivalent per hectare of UAA. [Dataset]. Available at https://ec.europa.eu/eurostat/databrowser/view/tai04/default/table?lang=en (accessed July 15, 2025)

https://doi.org/10.17221/329/2025-AGRICECON

Eurostat (2025e): Gini coefficient of equivalised disposable income. [Dataset]. Available at https://ec.europa.eu/eurostat/databrowser/view/tessi190/default/table?lang=en (accessed July 15, 2025)

Eurostat (2025f): Government support to agricultural research and development. [Dataset]. Available at https://ec.europa.eu/eurostat/databrowser/view/sdg_02_30/default/table?lang=en (accessed July 15, 2025)

Eurostat (2025g): Greenhouse gas emissions from agriculture. [Dataset]. Available at https://ec.europa.eu/eurostat/databrowser/view/tai08/default/table?lang=en (accessed July 15, 2025)

Eurostat (2025h): Gross value added of the agricultural industry - basic and producer prices. [Dataset]. Available at https://ec.europa.eu/eurostat/databrowser/view/tag00056/default/table?lang=en (accessed July 15, 2025)

Eurostat (2025i): Performance of the agricultural sector. [Dataset]. Available at https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Performance_of_the_agricultural_sector (accessed July 15, 2025)

Eurostat (2025j): Pesticide sales. [Dataset]. Available at https://ec.europa.eu/eurostat/databrowser/view/aei_fm_salpest09/default/table?lang=en (accessed July 15, 2025)

Eurostat (2025k): Real GDP *per capita*. [Dataset]. Available at https://ec.europa.eu/eurostat/databrowser/view/sdg_08_10/default/table?lang=en (accessed July 15, 2025)

FAO (2024): Greenhouse gas emissions from agrifood systems. Global, regional and country trends, 2000–2022. Rome, FAO. Available at https://www.fao.org/statistics/highlights-archive/highlights-detail/greenhouse-gas-emissions-from-agrifood-systems.-global--regional-and-country-trends--2000-2022/en

Fiore V., Borrello M., Carlucci D., Giannoccaro G., Russo S., Stempfle S., Roselli L. (2024): The socio-economic issues of agroecology: A scoping review. Agricultural and Food Economics, 12: 16.

Frascarelli A., Ciliberti S., Bartolucci P.E., Mastandrea G. (2025): The CAP coherence between redistributive and environmental goals: Do the allocation criteria for direct payments play a role? Agricultural and Food Economics, 13: 15.

Fusco G., Campobasso F., Laureti L., Frittelli M., Valente D., Petrosillo I. (2023): The environmental impact of agriculture: An instrument to support public policy. Ecological Indicators, 147: 109961.

Galvao A.F., Montes-Rojas G.V. (2024): Multi-dimensional panels in quantile regression models. In: Matyas L. (ed): The Econometrics of Multi-dimensional Panels: Theory and Applications. Cham, Springer: 325–351.

Gamage A., Gangahagedara R., Subasinghe S., Gamage J., Guruge C., Senaratne S., Randika T., Rathnayake C., Hameed Z., Madhujith T., Merah O. (2024): Advancing sustainability: The impact of emerging technologies in agriculture. Current Plant Biology, 40: 1–16. https://doi.org/10.1016/j.cpb.2024.100420

Georgescu I., Kinnunen J. (2025): Assessing the impact of nuclear energy on load capacity, economic growth, and innovation: A quantile-on-quantile analysis for Finland. Journal of Cleaner Production, 512: 145693.

Georgescu P.-L., Barbuta-Misu N., Zlati M.L., Fortea C., Antohi V.M. (2025): Quantifying the performance of European agriculture through the new european sustainability model. Agriculture, 15: 210.

Getahun S., Kefale H., Gelaye Y. (2024): Application of precision agriculture technologies for sustainable crop production and environmental sustainability: A systematic review. The Scientific World Journal, 2024: 2126734.

Guth M., Stępień S., Smędzik-Ambroży K., Matuszczak A. (2022): Is small beautiful? Techinical efficiency and environmental sustainability of small-scale family farms under the conditions of agricultural policy support. Journal of Rural Studies, 89: 235–247.

Gutiérrez Cano L.F., Zartha Sossa J.W., Orozco Mendoza G.L., Suárez Guzmán L.M., Agudelo Tapasco D.A., Quintero Saavedra J.I. (2023): Agricultural innovation system: Analysis from the subsystems of R&D, training, extension, and sustainability. Frontiers in Sustainable Food Systems, 7: 1176366.

Ha T.M., Manevska-Tasevska G., Weih M., Hansson H. (2024): Heterogeneity in farmers' stage of behavioural change in intercropping adoption: An application of the Transtheoretical Model. Agricultural and Food Economics, 12: 12.

Hajji-Hedfi L., Bargougui O., Rhouma A., Wannassi T., Khlif A., Dali S., Gamaoun W. (2025): Regenerative agriculture: A sustainable path for boosting plant and soil health. Phyton-International Journal of Experimental Botany, 94: 2255–2284.

Herman E. (2025): Changes and challenges in EU agricultural holdings and their impact on rural development. Land, 14: 1080.

Hermans T., Beintema N., Alho C.F., van der Poel M. (2025): Experiences in assessing the impact of circular economy interventions in agrifood systems – A review. Sustainability, 17: 1406.

Ikram M., Sadki J.E. (2024): Resilient and sustainable green technology strategies: A study of Morocco's path toward sustainable development. Sustainable Futures, 8: 100327.

Istudor N., Constantin M., Privitera D., Ignat R., Petrescu I.-E., Teodor C. (2025): Systemic competitiveness in the EU cereal value chain: A network perspective for policy alignment. Land, 14: 731.

Jambor A., Gorton M. (2025): Twenty years of EU accession: Learning lessons from Central and Eastern European agriculture and rural areas. Agricultural and Food Economics, 13: 1.

https://doi.org/10.17221/329/2025-AGRICECON

Jankelová N., Joniaková Z. (2021): The role of innovative work behaviour and knowledge-based dynamic capabilities in increasing the innovative performance of agricultural enterprises. Agricultural Economics, 67: 363–372.

Kalnins A., Praitis Hill K. (2023): The VIF score. What is it good for? Absolutely nothing. Organizational Research Methods, 28: 58–75.

Khan R.Z., Razak L.A., Premaratne G. (2025): Green growth and sustainability: A systematic literature review on theories, measures and future directions. Cleaner and Responsible Consumption, 17: 100274.

Khangura R., Ferris D., Wagg C., Bowyer J. (2023): Regenerative agriculture – A literature review on the practices and mechanisms used to improve soil health. Sustainability, 15: 2338.

Kochar R., Kalsie A., Deka N. (2025): Voluntary Carbon Markets (VCMs) in a nutshell: A systematic review based on the empirical evidence from across the globe. Journal of Cleaner Production, 522: 146261.

Koenker R., Bassett G. (1978): Regression quantiles. Econometrica, 46: 33–50.

Kountios G., Kanakaris S., Moulogianni C., Bournaris T. (2024): Strengthening AKIS for sustainable agricultural features: Insights and innovations from the European Union: A literature review. Sustainability, 16: 7068.

Kryszak Ł., Świerczyńska K., Staniszewski J. (2021): Measuring total factor productivity in agriculture: A bibliometric review. International Journal of Emerging Markets, 18: 148–172.

Kumar A., Antoniella G., Blasi E., Chiti T. (2025): Recent advances in regenerative sustainable agricultural strategies for managing soil carbon and mitigating climate change consequences. CATENA, 258: 109208.

Kwilinski A., Lyulyov O., Pimonenko T. (2023): The coupling and coordination degree of digital business and digital governance in the context of sustainable development. Information, 14: 651.

Laddha Y., Tiwari A., Kasperowicz R., Bilan Y., Streimikiene D. (2022): Impact of information communication technology on labor productivity: A panel and cross-sectional analysis. Technology in Society, 68: 101878.

Lamarche C. (2021): Quantile regression for panel data and factor models. In: Banerjee A. (ed): Oxford Research Encyclopedia of Economics and Finance. Online Ed. New York, Oxford Academic.

Lankoski J., Nales E., Valin H. (2025): Assessing the Impacts of Agricultural Support Policies on the Environment. OECD Food, Agriculture and Fisheries Papers, No. 223. Paris, OECD. Available at https://www.oecd.org/en/publications/assessing-the-impacts-of-agricultural-support-policies-on-the-environment_808f110c-en.html

Lewandowski I., von Cossel M., Winkler B., Bauerle A., Gaudet N., Kiesel A., Lewin E., Magenau E., Marting Vidaurre N.A., Müller B., Schlecht V., Thumm U., Trenkner M., Vargas-Carpintero R., Weickert S., Weik J., Reinmuth E. (2024): An adapted indicator framework for evaluating the potential contribution of bioeconomy approaches to agricultural systems resilience. Advanced Sustainable Systems, 8: 2300518.

Li X., Martino S. (2024): Assessing the economic feasibility of voluntary carbon markets in land use management scenarios for Scottish saltmarshes. Ocean & Coastal Management, 251: 107099.

Liang J., Qiao C. (2025): Digital economy and high-quality agricultural development: Mechanisms of technological innovation and spatial spillover effects. Sustainability, 17: 3639.

Makinde P. (2024): A comprehensive review on transitioning into organic farming. Asian Journal of Research in Agriculture and Forestry, 10: 45–59.

Mance D., Pedić A., Mance D. (2025): Economic development and pesticide use in EU agriculture. Chemosphere, 380: 144461.

Manta A.G., Doran N.M., Bădîrcea R.M., Badareu G., Gherțescu C., Lăpădat C.V. (2024): Does Common Agricultural Policy influence regional disparities and environmental sustainability in European Union countries? Agriculture, 14: 2242.

Markow J., Fieldsend A.F., von Münchhausen S., Häring A.M. (2023): Building agricultural innovation capacity from the bottom up: Using spillover effects from projects to strengthen agricultural innovation systems. Agricultural Systems, 209: 103670.

Martín-García J., Gómez-Limón J.A., Menor-Campos A. (2025): Farms' economic resilience: assessment, drivers and policy-making. Environmental and Sustainability Indicators, 27: 100740.

Martini E., Pagella T., Mollee E., van Noordwijk M. (2023): Relational values in locally adaptive farmer-to-farmer extension: How important? Current Opinion in Environmental Sustainability, 65: 101363.

Mergoni A., Dipierro A.R., Colamartino C. (2024): European agricultural sector: The tortuous path across efficiency, sustainability and environmental risk. Socio-Economic Planning Sciences, 92: 101848.

Metta M., Ciliberti S., Obi C., Bartolini F., Klerkx L., Brunori G. (2022): An integrated socio-cyber-physical system framework to assess responsible digitalisation in agriculture: A first application with Living Labs in Europe. Agricultural Systems, 203: 103533.

Mgendi G. (2024): Unlocking the potential of precision agriculture for sustainable farming. Discover Agriculture, 2: 87.

Miaris G., Hansson H., Sok J. (2025): The relationship between entrepreneurial orientation and farmers' satisfaction with business performance: Insights from Swedish agriculture. The International Journal of Entrepreneurship and Innovation.

https://doi.org/10.17221/329/2025-AGRICECON

Mihret Y.C., Takele M.M., Mintesinot S.M. (2025): Advancements in Agriculture 4.0 and the needs for introduction and adoption in Ethiopia: A review. Advances in Agriculture, 2025: 8828400.

Moisés C., Arrobas M., Tsitos D., Pinho D., Rezende R.F., Rodrigues M.Â. (2025): Regenerative agriculture: Insights and challenges in farmer adoption. Sustainability, 17: 7235.

Mondal K., Chowdhury M., Dutta S., Satpute A.N., Jha A., Khose S., Gupta V., Das S. (2025): Synergising agricultural systems: A critical review of the interdependencies within the water-energy-food nexus for sustainable futures. Water-Energy Nexus, 8: 167–188.

Muduli A., Chattopadhyay P.B. (2024): Assessing hydrogeochemical facies and Groundwater Quality Index in rapidly urbanizing coastal region: A GIS-based approach with machine learning for enhanced management. Environmental Science and Pollution Research, 32: 31306–31330.

Nowack W., Schmid J.C., Grethe H. (2022): Social dimensions of multifunctional agriculture in Europe – Towards an interdisciplinary framework. International Journal of Agricultural Sustainability, 20: 758–773.

Nowak A., Zakrzewska A. (2024): How competitive is the agriculture in European Union member states? An assessment of changes over the past decade. Agriculture, 14: 612.

OECD (2024a): Agricultural Policy Monitoring and Evaluation 2024: Innovation for Sustainable Productivity Growth. Paris, OECD. Available at https://doi.org/https://doi.org/10.1787/74da57ed-en

OECD (2024b): Sustainable Agricultural Productivity to Address Food Systems Challenges Measurement, Data, Drivers and Policies. Paris, OECD. Available at https://www.oecd.org/en/events/2024/10/sustainable-agricultural-productivity-to-address-food-systems-challenges-measurement-data-drivers-and-policies.html

OECD (2024c): The Interplay between Voluntary and Compliance Carbon Markets: Implications for Environmental Integrity. Paris, OECD. Available at https://www.oecd.org/en/publications/the-interplay-between-voluntary-and-compliance-carbon-markets_500198e1-en.html

OECD (2025): Agricultural Policy Monitoring and Evaluation 2025: Making the Most of the Trade and Environment Nexus in Agriculture. Paris, OECD. Available at https://doi.org/https://doi.org/10.1787/a80ac398-en

Ondrasek G., Horvatinec J., Kovačić M.B., Reljić M., Vinceković M., Rathod S., Bandumula N., Dharavath R., Rashid M.I., Panfilova O., Kodikara K.A.S., Defterdarović J., Krevh V., Filipović V., Filipović L., Čop T., Njavro M. (2023): Land resources in organic agriculture: trends and challenges in the twenty-first century from global to Croatian contexts. Agronomy, 13: 1544.

Ottone V., Barbieri M. (2025): Implementation arrangements for research and innovation policies in the Italian, Spanish, French, and German national recovery plan: A comparative analysis of emerging challenges for multi-level governance. Review of Policy Research, 42: 234–251.

Petrovic B., Kononets Y., Csambalik L. (2025): Adoption of drone, sensor, and robotic technologies in organic farming systems of Visegrad countries. Heliyon, 11: e41408.

Popescu D.M., Duica M.C., Duta (Ghita) N.M., Duica A., Voinea C.M., Stanescu, G. (2025): Transforming Agriculture for a Sustainable Future: Economic, Ethical, and Environmental Perspectives. Sustainability, 17: 1–18. https://doi.org/10.3390/su17125518

Portnoy S. (2019): Edgeworth's time series model: Not AR(1) but same covariance structure. Journal of Econometrics, 213: 281–288.

Prigoreanu I., Ungureanu B.A., Ungureanu G., Ignat G. (2024): Analysis of sustainable energy and environmental policies in agriculture in the EU regarding the European Green Deal. Energies, 17: 6428.

Prokop V., Gerstlberger W., Zapletal D., Kotkova Striteska M. (2022): The double-edged role of firm environmental behaviour in the creation of product innovation in Central and Eastern European countries. Journal of Cleaner Production, 331: 129989.

Radlinska K. (2024): Changes in the structure of agriculture in Central and Eastern Europe in the light of the European Green Deal. Sustainability, 17: 104.

Ragazou K., Garefalakis A., Zafeiriou E., Passas I. (2022): Agriculture 5.0: A new strategic management mode for a cut cost and an energy efficient agriculture sector. Energies, 15: 3113.

Rajkhowa P., Baumüller H. (2024): Assessing the potential of ICT to increase land and labour productivity in agriculture: Global and regional perspectives. Journal of Agricultural Economics, 75: 477–503.

Ranran C., Jingsuo L. (2024): The impact of agricultural production agglomeration on agricultural economic resilience: Based on spatial spillover and threshold effect test. Frontiers in Sustainable Food Systems, 8: 1464732.

Romaldi G., Zoboli R., Speck S., Tagliapietra S., Paleari S., Pronti A., D'Amato A. (2024): Investment needs and gaps for the sustainability transition in Europe: Rethinking the European Green Deal as an EU industrial strategy. ETC CE Report 2024/8. Available at https://www.eionet.europa.eu/etcs/etc-ce/products/etc-ce-report-2024-8-investment-needs-and-gaps-for-the-sustainability-transition-in-europe-rethinking-the-european-green-deal-as-an-eu-industrial-strategy

Ronzhin A., Figurek A., Surovtsev V., Dibirova K. (2025): Digital transformation and precision farming as catalysts of rural development. Land, 14: 1464.

Ruml A., Chen C., Kubitza C., Kernecker M., Grossart H.-P., Hoffmann M., Holz M., Wessjohann L.A., Lotze-Campen H., Dubbert M. (2025): Minimizing trade-offs

https://doi.org/10.17221/329/2025-AGRICECON

and maximizing synergies for a just bioeconomy transition. Energy Research & Social Science, 125: 104089.

Said Z., Vigneshwaran P., Shaik S., Rauf A., Ahmad Z. (2025): Climate and carbon policy pathways for sustainable food systems. Environmental and Sustainability Indicators, 27: 100730.

Sargani G.R., Wang B., Leghari S.J., Ruan J. (2025): Is digital transformation the key to agricultural strength? A novel approach to productivity and supply chain resilience. Smart Agricultural Technology, 10: 100838.

Savickienė R., Namiotko V., Galnaitytė A. (2025): Evaluating the technical efficiency of dairy farms under technological heterogeneity: Evidence from Lithuania. Agriculture, 15: 1469.

Savin I., van den Bergh J. (2024): Reviewing studies of degrowth: Are claims matched by data, methods and policy analysis? Ecological Economics, 226: 108324.

Selbonne S., Guindé L., Causeret F., Chopin P., Sierra J., Tournebize R., Blazy J.-M. (2023): How to measure the performance of farms with regard to climate-smart agriculture goals? A set of indicators and its application in Guadeloupe. Agriculture, 13: 297.

Sher A., Li H., ullah A., Hamid Y., Nasir B., Zhang J. (2024): Importance of regenerative agriculture: climate, soil health, biodiversity and its socioecological impact. Discover Sustainability, 5: 462.

Shi S., Wang X. (2024): Analysis of human capital effects introducing Bayesian quantile regression in the process of industrial structural upgrading. PLOS One, 19: e0304730.

Shi S., Wang X. (2025) Correction: Analysis of human capital effects introducing Bayesian quantile regression in the process of industrial structural upgrading. PLoS ONE 20(4): e0322560. https://doi.org/10.1371/journal.pone.0322560

Shukla A., Rai N., Mohapatra R., Thriveni V., Yadav K.K., Upadhyay L., Ghosh S. (2025): Assessing the role of regenerative practices in enhancing soil carbon sequestration in farmlands: A Review. Journal of Scientific Research and Reports, 31: 231–246.

Singh V.K. (2025): Adapting agriculture: The case of European policy frameworks for climate resilience. Environmental Management, 75: 1615–1627.

Sonderegger G., Heinimann A., Diogo V., Oberlack C. (2022): Governing spillovers of agricultural land use through voluntary sustainability standards: A coverage analysis of sustainability requirements. Earth System Governance, 14: 100158.

Stempfle S., Russo S., Fiore V., Sardaro R., La Sala P., Roselli L. (2025): Characterizing the agroecological transition of Italian farming systems using FADN database. Environmental and Sustainability Indicators, 26: 100616.

Streimikis J., Yu Z., Zhu N., Baležentis T. (2022): Achievements of the European Union member states toward the development of sustainable agriculture: A contribution to the structural efficiency approach. Technological Forecasting and Social Change, 178: 121590.

Szafraniec-Siluta E., Strzelecka A., Ardan R., Zawadzka D. (2024): Determinants of financial security of European Union farms – A factor analysis model approach. Agriculture, 14: 119.

Taoumi H., Lahrech K. (2023): Economic, environmental and social efficiency and effectiveness development in the sustainable crop agricultural sector: A systematic in-depth analysis review. Science of The Total Environment, 901: 165761.

Taylor M., Bhasme S. (2024): Why do farmers disadopt successful innovations? Socio-ecological niches and rice intensification. Agronomy, 14: 2238.

Udumann S.S., Dissanayaka N., Nuwarapaksha T., Atapattu A.J. (2025): Regenerative agricultural practices for sustainable soil health and food production. In: Babu S., Das A., Rathore S.S., Singh R., Singh R. (eds): Ecological Solutions to Agricultural Land Degradation. Singapore, Springer: 117–143.

Urbancová H., Vrabcová P., Madzík P., Kocourek A. (2025): Synergic strategies in reinforcing the pluralistic paradigm, inclusion and diversity as a catalyst for social sustainability focusing on agribusinesses. Agricultural Economics – Czech, 71: 273–284.

van Leeuwen C., Sgubin G., Bois B., Ollat N., Swingedouw D., Zito S., Gambetta G.A. (2024): Climate change impacts and adaptations of wine production. Nature Reviews Earth & Environment, 5: 258–275.

Vărzaru A.A. (2025): Digital revolution in agriculture: Using Predictive models to enhance agricultural performance through digital technology. Agriculture, 15: 258.

Villat J., Nicholas K.A. (2024): Quantifying soil carbon sequestration from regenerative agricultural practices in crops and vineyards. Frontiers in Sustainable Food Systems, 7: 1234108.

Vishwakarma S., Zhang X., Lyubchich V. (2025): Unveiling the drivers contributing to global wheat yield shocks through quantile regression. Artificial Intelligence in Agriculture, 15: 564–572.

Vishwakarma V., Ranjan R. (2024): Agroecological approaches to sustainable development. Frontiers in Sustainable Food Systems, 8: 1405409.

von Cossel M., Scordia D., Altieri M., Gresta F. (2025): Spotlight on agroecological cropping practices to improve the resilience of farming systems: A qualitative review of meta-analytic studies. Frontiers in Agronomy, 7: 1495846.

Wang S., Zhu J., Wang L., Zhong S. (2022): The inhibitory effect of agricultural fiscal expenditure on agricultural green total factor productivity. Scientific Reports, 12: 20933.

Weltin M., Hüttel S. (2023): Sustainable intensification farming as an enabler for farm eco-efficiency? Environmental and Resource Economics, 84: 315–342.

Wen Z., Bukhari W.A.A., Troise C., Bukhari A.A.A., Bresciani S. (2025): Does renewable energy facilitate the

https://doi.org/10.17221/329/2025-AGRICECON

achievement of COP-28 goals? Evidence from the world's top climate laggard economies. Sustainable Development, 33: 5779–5798.

Willer H., Trávníček J., Schlatter B. (eds) (2025): The World of Organic Agriculture: Statitstics and Emerging Trends 2025. Frick, FiBL and Bonn, IFOAM. Available at https://www.fibl.org/en/shop-en/1797-organic-world-2025

Williams T.G., Bürgi M., Debonne N., Diogo V., Helfenstein J., Levers C., Mohr F., Stratton A.E., Verburg P.H. (2024): Mapping lock-ins and enabling environments for agri-food sustainability transitions in Europe. Sustainability Science, 19: 1221–1242.

Wolfert S., Verdouw C., van Wassenaer L., Dolfsma W., Klerkx L. (2023): Digital innovation ecosystems in agri-food: Design principles and organizational framework. Agricultural Systems, 204: 103558.

Zawalińska K., Wąs A., Kobus P., Bańkowska K. (2022): A framework linking farming resilience with productivity: Empirical validation from Poland in times of crises. Sustainability Science, 17: 81–103.

Zeng S., Li J., Wanger T.C. (2023): Agroecology, technology, and stakeholder awareness: Implementing the UN Food Systems Summit call for action. iScience, 26: 107510.

Zhao G., Werku B.C., Bulto T.W. (2025): Impact of agricultural emissions on goal 13 of the sustainable development agenda: In East African strategy for climate action. Environmental Sciences Europe, 37: 35.

Zielinski M., Jadczyszyn J., Sobierajewska J. (2023): Predispositions and challenges of agriculture from areas particularly facing natural or other specific constraints in Poland in the context of providing environmental public goods under EU policy. Agricultural Economics – Czech, 69: 309–320.

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