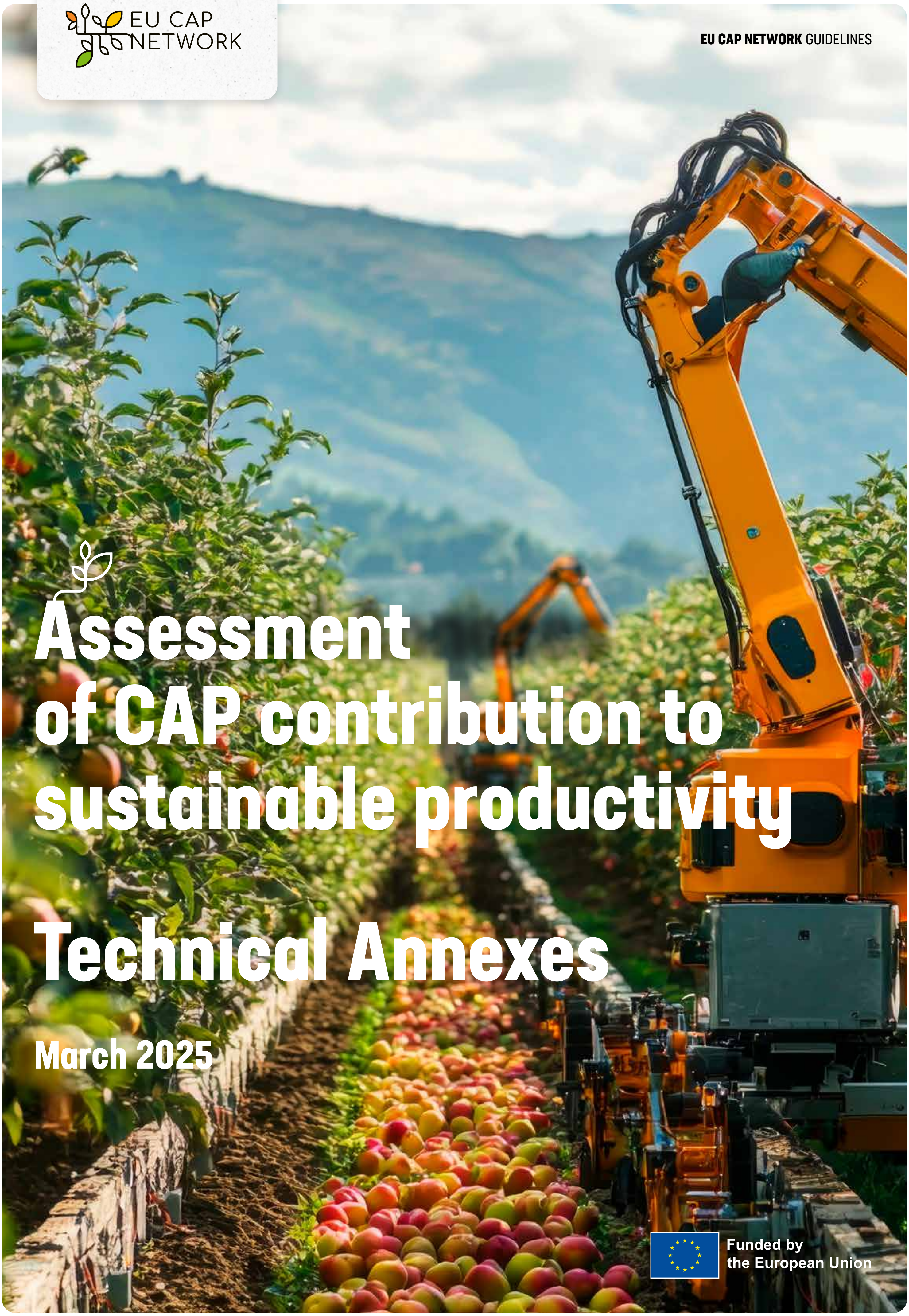
EU CAP NETWORK



Assessment of CAP contribution to sustainable productivity

Technical Annexes

March 2025

Funded by the European Union

Recommended citation:

EUROPEAN COMMISSION – Directorate-General for Agriculture and Rural Development – Unit A.3 (2025): Assessment of CAP contribution to sustainable productivity.

EU CAP NETWORK

The European Evaluation Helpdesk for the CAP is responsible for providing support for monitoring and evaluation activities at the EU and Member State level. It works under the guidance of DG AGRI's Unit A.3 (Policy Performance Unit) of the European Commission. The European Evaluation Helpdesk for the CAP supports all evaluation stakeholders, in particular DG AGRI, national authorities, Managing Authorities and evaluators, through the development and dissemination of appropriate methodologies and tools; the collection and exchange of good practices; capacity building and communicating with network members on evaluation-related topics.

Additional information about the activities of European Evaluation Helpdesk for the CAP is available on the Internet through the Europa server https://eu-cap-network.ec.europa.eu/support/evaluation.

Table of Contents

List of figures

List of tables

List of boxes

List of acronyms

AES	agri-environmental scheme payments
AKIS	Agricultural Knowledge Innovation System
ANC	areas facing natural or other specific constraints
ASD	areas with specific disadvantages
ATE	average treatment effect
ATT	average treatment effect on the treated
AWU	annual working units
BISS	basic income support for sustainability
BLUE	best linear unbiased estimator
CAP	Common Agricultural Policy
CATS	clearence audit trail system
CDP	coupled direct payments
CEM	coarsened exact matching
CES	constant elasticities of scale
CFE	control function estimator
CGE	computable general equilibrium
CIE	counterfactual impact evaluation
CIS	coupled income support
CIS-YF	complementary income support for young farmers
CRE	correlated random effects
CRISS	complementary redistributive income support for sustainability
CSR	corporate social responsibility
CULTAN	controlled uptake long term ammonium nutrition
DDP	decoupled direct payments
DEA	data envelopment analysis
DMU	decision-making unit
EAP	environmentally-adjusted productivity
EIP	European Innovation Partnership
ENVCLIM	environmental, climate-related and other management commitments CAP interventions
ES	ecosystem services
ESG	environmental, social and corporate governance
FADN	Farm Accountancy Data Network
FAO	Food and Agriculture Organisation
FD	free distribution
FE	fixed effect
FSDN	Farm Sustainability Data Network
GDP	gross domestic product
GHG	greenhouse gas
GMM	generalised method of moments
IAM	integrated assessment model
INVEST	support to farm investments
JRC	Joint Research Centre
LCM	latent class model
LEADER/ CLLD	Liaison entre actions de développement de l'économie rurale / Community-led local development
LFA	less-favoured areas
LMM	minerals policy monitoring programme
LPIS	land parcel identification system
LSDV	least squares dummy variable
MBP	materials balance principle
MPI	malmquist productivity index
MTFP	multilateral total factor productivity
NCA	natural capital accounting
NUTS	nomenclature of territorial units for statistics
OECD	Organization for Economic Cooperation and Development
OLS	ordinary least square
PL	pesticide load
PMEF	Performance and Monitoring Evaluation Framework
PP	partial productivity
PPP	purchasing power parity
PSM	propensity score matching
QA	quantity of active ingredients
RDP	Rural Development Programme
RE	random effects
SCI-GROW	screening concentration in ground water (index)
SE	scale efficiency
SEEA	system for integrated environmental and economic accounting
SFA	stochastic frontier analysis
SI	sustainability index
SO	Specific Objective(s)
SYS-GMM	system generalised method of moments
TE	technical efficiency
TFI	treatment frequency index
TFP	total factor productivity
TREIA	Texas Renewable Energy Industries Alliance
UAA	utilised agricultural area
VA	value added
WDA	weak disposability assumption

Annex 1 Possible FADN variables to assess the CAP's contribution to sustainable productivity

Annex 1 lists, for each possible FADN (Farm Accountancy Data Network) variable, its definition and the code or formula with which it is associated.

[A] Information on agricultural outputs and inputs

Variable	Definition	Formula/Details
Y Output	Total output (euro)	SE131
	Farm net value dded (euro)	SE415
	Crop Output (euro)	SE135
	Livestock output (euro)	SE206
	Other output (euro)	SE256
K Capital	Fixed capital without land value (euro)	SE441 – ALNDAGR_CV_X
	Total assets (euro)	SE436
Livestock	Total number of livestock units	SE080
L Land	Land value (euro)	Value of the rented land (see below) + ALNDAGR_CV_X
	UAA (ha)	SE025
N Labour	Total full-time equivalent labour input (hours worked annually)	SE011
M Intermediate inputs	Materials variable costs (euro)	SE281 + SE336
	Total specific costs (euro)	SE281
	Total farming overheads (euro)	SE336

[B] Information needed to estimate the value of the rented land

Variable	Definition	Formula/Details
Fixed capital on UAA owned	Value of fixed assets per ha of UAA owned (euro)	Value of fixed assets / UAA owned (SE025-SE030)
Land rent	Rent per ha of rented UAA (euro)	Rent paid SE375 / Rented UAA (SE030)
Rate of return of rent – Farm level = RoRR – Farm level	Rate of return of rent at farm level	Rent_UAA / Fixed capital on UAA owned
Rate of return of rent – Aggregated	Aggregated rate of return of rent for NUTS2	Median of RoRR – Farm level
UAA rented	Rented UAA (ha)	SE030
Value of the rented land	Value of the rented land (euro)	Rent paid SE375 / Rate of return of rent – Aggregated

[C] Information on environmental aspects

Variable	Definition	Formula/Details
N_2	Fertiliser. Quantity of N in mineral fertilisers used	SE296
P_2O_5	Fertiliser. Quantity of P_2O_5 in mineral fertilisers used	SE297
K_2O	Fertiliser. Quantity of K_2O in mineral fertilisers used	SE298
Crop_prot	Crop protection products costs (euro)	SE300
Energy	Energy costs (euro)	SE345
Fert	Fertiliser costs (euro)	SE295
Water_Value	Water value (euro)	H_FO_5040_V
Ren_energy_Sales	Production of renewable energy – Sales value (euro)	L_SA_2030_V
IRR_UAA	UAA under irrigation (ha)	IRRAA
	Farming practices	FSDN [1]
	Landscape features	FSDN
	Soil management	FSDN
	Nutrient use and management	FSDN
	Carbon farming	FSDN
	Water use and management	FSDN
	Antimicrobial use	FSDN
	Plant protection use	FSDN
	Animal welfare	FSDN
	Biodiversity	FSDN
	Certification schemes	FSDN
	Energy consumption and energy production	FSDN
	Food loss on primary production level	FSDN
	Waste management	FSDN

1 All details for the FSDN variables can be found in Annex VIII of Commission Implementing Regulation (EU) 2024/2746 of 25 October 2024 laying down rules for the application of Council Regulation (EC) N° 1217/2009 setting up the Farm Sustainability Data Network and repealing Commission Implementing Regulation (EU) 2015/220. https://eur-lex.europa.eu/eli/reg_impl/2024/2746/oj#anx_VIII.

[D] Information on social aspects

Variable	Definition	Formula/Details
N_AWU	Total labour input in AWU	SE010
N	Total labour input in hours	SE011
N_Unp_AWU	Unpaid labour input in AWU	SE015
N_Unp	Unpaid labour input in hours	SE016
N_Pay_AWU	Paid labour input in AWU	SE020
N_Pay	Paid labour input in hours	SE021
	Gender balance	FSDN
	Share of off-farm income	FSDN
	Education	FSDN
	Training	FSDN
	Safety	FSDN
	Social inclusion	FSDN
	Infrastructure and essential services	FSDN
	Generation renewal	FSDN

[E] Information on CAP interventions

Variable	Definition	Formula/Details
CDP	Coupled direct payments (euro)	SE610 + SE615
DDP	Direct decoupled payments (euro)	SE630
RDPa	Rural Development Payments excluding investment (euro)	SE624 - SE406
AES	Rural development payments for agri-environmental schemes (euro)	SE621
LFA	Rural development payments for less favourable areas (euro)	SE622
RDPOther	Other annual rural development payments (euro)	RDPa - AES - LFA
INVEST	Rural development subsidies on investments (euro)	SE406

[F] Other information that can be used as control variables

Variable	Definition	Formula/Details
Economic size	Total economic size in EUR	SIZEUR
Year of birth	Year of birth of holder-manager	C_UR_10_B
UAA_OWN	UAA owned (ha)	SE025 - SE030
Type of ownership	1 = family farm; 2 = partnership; 3 = company with profit objective; 4 = company with non-profit objective	A_CL_110_C
Type of farming	Type of farming from FADN classification	TF14
Region	NUTS3 region where the farm is located	A_LO_40_N
	Innovation and digitalisation	FSDN
NUTS 2	NUTS NUTS2	A_LO_40_N2
NUTS 3	NUTS NUTS3	A_LO_40_N
ORGANIC	Organic farming code	A_CL_140_C
IRR: TYP	Irrigation system type	A_OT_210_C
LFA_Code	Less-favoured area code	A_CL_160_C
NAT_2'K_ Coce	Natura 2000 area share	A_CL_190_C
Altitude Code	Altitude code	A_CL_170_C
EC_SIZE_ Code	Economic size class (6 classes)	SIZ6
ToF_14	Type of farming (14 groups)	TF14
ToF_8	Type of farming (8 groups)	TF8
PDO	Protected designation of origin (PDO)/Protected geographical indication (PGI) Code	A_CL_150_C
Prec	Precipitation	From Copernicus or JRC AGRI4CAST
Temp	Temperature	From Copernicus or JRC AGRI4CAST
Humidity	Humidity	From Copernicus or JRC AGRI4CAST
GDD	Growing degree day	From Copernicus or JRC AGRI4CAST

Annex 2 Further details on partial productivity

Annex 2 complements Chapter 4.2 of the guidelines on partial indicators. It offers a list of the most common indexes of partial productivity and the rationale for using them. It also lists the different levels of analysis and explains the results of these indexes. Finally, it lists the advantages and disadvantages of using partial productivity indicators.

Description

Partial productivity (PP) measures are specific indicators that relate the output of an economic system to one of the inputs used in producing that output.

Compared with total factor productivity, which consider multiple inputs simultaneously, partial productivity describes farm's productivity along a specific dimension [2].

In the formula below, the specific input is generally land, labour or non-land capital (but other more disaggregated inputs can be used, e.g. fertilisers). The general formula for partial productivity is given by:

$$\text{Partial productivity} = \frac{\text{Total Output}}{\text{Specific input}}$$

The following indexes are commonly used in the literature:

$$\text{Labour Productivity} = \frac{\text{Total Output}}{\text{Total Labour}}$$

$$\text{Labour Productivity (yield)} = \frac{\text{Total Output}}{\text{Total land}}$$

$$\text{Capital Productivity} = \frac{\text{Total Output}}{\text{Total Capital}}$$

$$\text{Material Productivity} = \frac{\text{Total Output}}{\text{Total Material used}}$$

By concentrating on individual inputs, partial productivity measures allow for a detailed assessment of the efficiency of resource utilisation in agriculture. This approach is useful for identifying specific areas of improvement, implementing targeted policies and evaluating the impact of agricultural practices on productivity referring to specific inputs.

For instance, by measuring the productivity of land or labour in agricultural production, policymakers can identify inefficiencies, promote sustainable practices and enhance productivity in the sector. Moreover, partial productivity measures enable policymakers to tailor interventions to address specific challenges or opportunities within the agricultural sector e.g. by assessing the productivity of fertiliser use, policymakers can develop strategies to promote efficient nutrient management, reduce negative environmental externalities and improve agricultural sustainability in the EU with respect to fertiliser use. Additionally, these measures facilitate the comparison of different inputs and their contributions to output as they convert inputs and outputs into comparable ratios, allowing for evidence-based decision-making and optimising resource allocation in agriculture [3].

Evaluating the impact of CAP interventions on partial productivity can also be useful. For example, there may be interventions to stimulate investments in more efficient irrigation systems and their impact on water partial productivity can be evaluated.

Data sources and requirements

In the context of agricultural policy, PP can be assessed at the levels of individual farms, regions or nations.

Individual farm level: at the individual farm level, FADN or other bookkeeping datasets provide detailed data that enables the estimation of PP for various farm types (it is possible to evaluate the commonly utilised inputs such as labour, land, capital, materials and other inputs). The FADN allows policymakers to analyse productivity differences across different types of farming, altimetric regions, geographical regions and countries. FADN data can also allow for the comparison of PP between farms operated by younger and older farmers, men or women, or other specific farm characteristic groups. It also facilitates comparisons over years offering insights into trends and the effectiveness of agricultural policies at the micro level.

Regional/national level: on a larger scale, PP can be evaluated using aggregated data from sources such as Eurostat, national statistical agencies and international organisations like the Food and Agriculture Organization (FAO) and the Organisation for Economic Co-operation and Development (OECD).

How to interpret the results

- Efficiency assessment: a higher PP value indicates a more efficient use of the input in generating output. For example, higher labour productivity (output per hour worked) suggests that labour is used more efficiently.
- Comparative analysis: PP can be used to compare the productivity of the same input across different periods, types of farms or geographical locations.

2 Murray, A., *Partial versus Total Factor Productivity Measures: An Assessment of their Strengths and Weaknesses*, International Productivity Monitor, Centre for the Study of Living Standards, vol. 31, 2016, pp. 113-126. https://ideas.repec.org/a/sls/ipmsls/v31y20168.html; and Murray, A., Sharpe, A., *Partial versus Total Factor Productivity: Assessing Resource Use in Natural Resource Industries in Canada*, CSLS Research Reports 2016-20, Centre for the Study of Living Standards, 2016. https://ideas.repec.org/p/sls/resrep/1620.html.
3 Ball, V.E., *Output, Input, and Productivity Measurement in U.S. Agriculture 1948-79*, American Journal of Agricultural Economics, Vol. 67, N° 3, August 1985, pp. 475-486. https://doi.org/10.2307/1241066.

Advantages and disadvantages

Table 1. Pros and cons of partial productivity indicators in comparison with other methods

Pros	Cons
Simplicity and specificity Partial productivity measures are straightforward as they relate output to a single input. This simplicity makes them easy to calculate and understand. It is particularly useful for quick assessments and for analyses specifically focused on one type of input.	**Partiality** Partial productivity measures productivity by considering only one input at a time, which can misrepresent farm or sector performance. It does not account for interactions (e.g. substitutions) between different inputs.
Direct measurement Partial productivity can be directly calculated from single data sources such as farm surveys. It does not require complex information about prices, other inputs or advanced statistical methods.	**Unit differences** Different inputs are often measured in different units, making direct comparisons challenging. For example, comparing milk per hectare (land productivity) with milk per cow (animal productivity) involves different units and contexts, complicating the assessment of which input contributes more to overall productivity.
	Fox's paradox Partial productivity is prone to Fox's paradox. The overall performance of a farm may depend on the share of its most or least efficient enterprise; a multi-product farm may produce each product more efficiently than another farm, but when all products are considered **together**, it may no longer be the most efficient [4].
	Case of constant returns to scale The use of partial productivity is limited to cases where constant returns to scale are feasible. Constant returns to scale imply proportional changes in inputs and outputs. This assumption can represent a strong limitation in the use of this indicator.

Source: EU CAP Network supported by the European Evaluation Helpdesk for the CAP (2025)

4 Fox, K.J., *Efficiency at Different Levels of Aggregation: Public vs. Private Sector Firms*, Economics Letters, Vol. 65, N° 2, November 1999, pp. 173-176. https://doi.org/10.1016/S0165-1765(99)00147-0; Karagiannis, G., *More on the Fox Paradox*, Economics Letters, Vol. 116, N° 3, September 2012, pp. 333-334. https://doi.org/10.1016/j.econlet.2012.04.002; and Mosnier, C., Benoit, M., Minviel, J.J., and Veysset, P., *Does Mixing Livestock Farming Enterprises Improve Farm and Product Sustainability?*, International Journal of Agricultural Sustainability, Vol. 20, N° 3, May 4, 2022, pp. 312-326. https://doi.org/10.1080/14735903.2021.1932150.

Annex 3 Further details on environmental and social indicators

Annex 3 complements Chapter 4.2 of the guidelines on partial indicators by describing the possible environmental and social indicators that can be used to measure sustainable productivity. Specific focus is given to the resilience capacity indicators, including their definition and where they can be applied as well as their shortcomings. Real examples of environmental and social variables in the national databases of the Netherlands and Ireland illustrate how they can be used in practice to address gaps in the FADN database.

3.1. Environmental indicators of agriculture

Defining environmental indicators that measure the environmental impacts of agriculture-related to an input can be done by classifying the environmental impacts of agricultural activities into a wide range of interrelated categories.

- **Nutrient flows**, namely phosphorus (P), nitrogen (N) and potassium (K). While these nutrients are essential to promote food production, their excessive use has caused several environmental and health problems in relation to water quality. For instance, nitrogen surpluses have created eutrophication problems, and potassium surpluses contribute to soil erosion. The three indicators of this first category are the surpluses of nitrogen, phosphorus and potassium.
- **GHG emissions**, namely carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O). The primary source of CO_2 emissions is the use of fossil fuel energy, CH_4 emissions are mainly associated with enteric fermentation in ruminant animals and manure management, and N_2O emissions are produced by soil denitrification. The three indicators in this category are simply the amount of CO_2, CH_4 and N_2O emissions. More detailed indicators can be defined by distinguishing direct and indirect emissions [5], especially CO_2 emissions.
- **Plant protection products,** including pesticides. Pesticide use indicators have mainly focused on the volume or intensity of applications (i.e. quantity of active ingredients (QA) and the treatment frequency index (TFI), neglecting all the risks associated with their use. Following the example of the Danish case, three risk-adjusted indicators are suggested – pesticide load (PL), which corresponds to human health, ecotoxicology and environmental fate. The PL for human health is the sum of all health risk score points. The PL for ecotoxicology captures the acute toxicity to mammals, birds, fish, daphnia, algae, aquatic plants, earthworms and bees, and chronic toxicity to fish, daphnia and earthworms. Finally, the PL for environmental fate covers the half-life [6] in soil, the bio-concentration factors and the SCI-GROW (screening concentration in groundwater) index. These three indicators summarise well the impacts of pesticides on the environment and humans, as decreasing the amount of pesticides can still be related to increased toxicity with the use of more efficient but more hazardous active ingredients.
- **Carbon sequestration's** potential beneficial environmental impact. Carbon sinks offer one of the most significant opportunities for mitigating the agricultural sector's GHG emissions. According to the OECD, about 4% of the annual total anthropogenic GHG emissions could be offset by carbon sequestration in agricultural soils [7]. Several practices can improve soil carbon sequestration potential, including no-tillage or reduced tillage, regenerative agricultural practices (e.g. agroforestry and cover crops) and the application of biochar. Biochar, produced from organic waste through pyrolysis, not only sequesters carbon for long periods of time, but also enhances soil health by improving nutrient and water retention, as well as increasing soil pH and microbial activity. These enhancements facilitate greater nutrient availability and uptake by plants, potentially leading to improved crop yields. In parallel, a new strategy around negative emission technologies (NETs) has been developed to sequester atmospheric CO_2 in agricultural lands. A potential implication here relates to the fact that soil organic carbon is an indicator of soil health and, therefore, vital for sustainable food production [8]. In the case of the EU, among the five missions governing the Horizon Europe research and innovation programme for 2021-2027, the transition towards healthy soils is stressed to achieve a 75% increase in healthy soils by 2030 [9]. In addition, agricultural policies, e.g. through eco-schemes interventions, have an important role to play in the uptake of recommended management practices. The indicator for this category is the annual carbon flow in agricultural lands.

5 Direct emissions are those happening within the farm boundary e.g. fossil fuels used on the farm, enteric fermentation and soil denitrification. Indirect emissions are associated with the manufacturing of agricultural inputs or some processing and marketing occurring outside the boundary of the farm, e.g. GHG emissions from producing mineral fertilisers.

6 The half-life, indicates the time required to reduce the concentration by 50% from any concentration point in time, see: https://www.epa.gov/pesticide-science-and-assessing-pesticide-risks/guidance-calculate-representative-half-life-values. Accessed 28 August 2024.

7 Henderson, B., Lankoski, J., Flynn, E., Sykes, A., Payen, F., MacLeod, M., *Soil Carbon Sequestration by Agriculture: Policy Options*, OECD Publishing, number 174, 2022. https://doi.org/10.1787/63ef3841-en.

8 FAO and ITPS, *Global soil organic carbon map (gsocmap) technical report*, Food and Agriculture Organization of the United Nations, Rome, 2018.

9 European Commission, Directorate-General for Research and Innovation, Veerman, C., Pinto Correia, T., Bastioli, C. et al., *Caring for soil is caring for life – Ensure 75% of soils are healthy by 2030 for food, people, nature and climate – Report of the Mission board for Soil health and food*, Publications Office, 2020. https://data.europa.eu/doi/10.2777/821504.

- **Renewable energy production at the farm level**. According to the Texas Renewable Energy Industries Alliance (TREIA), renewable energy is "any energy resource that is naturally regenerated over a short time scale and derived directly from the sun (such as thermal, photochemical and photoelectric), indirectly from the sun (such as wind, hydropower and photosynthetic energy stored in biomass) or from other natural movements and mechanisms of the environment (such as geothermal and tidal energy). Renewal energy does not include energy resources derived from fossil fuels, waste products from fossil sources or waste products from inorganic sources" [10]. These technologies offer great opportunities to reduce GHG emissions and strategically alleviate the agricultural system's dependency on non-renewable energy. One indicator here could be the megajoules (MJ) of renewable energy produced.
- **Biodiversity**. Biodiversity is one of the most complex and debated agricultural production indicators because it functions both as an input and an output. Its measurement is further complicated by its diffuse nature and the intricate interactions within ecosystems. Despite these challenges, biodiversity is commonly defined by properties such as richness, evenness and heterogeneity [11]. These properties can also encompass considerations for endemic or undesirable species. In their review of scientific literature, Elmiger et al. [12] categorise biodiversity indicators into two groups: biotic indicators, which include all living organisms such as plants, birds, insects and mammals, and non-biotic indicators, which refer to environmental and management conditions. Examples of biodiversity indicators include the 'farmland birds index', or the percentage of species and habitats of community interest related to agriculture with stable or increasing trends [13].

The case of natural capital

Apart from the standard inputs used when evaluating agricultural production performance (labour, buildings, machinery, fertilisers, pesticides, seeds, etc.), agriculture relies on natural resources such as soil nutrients, water for irrigation, and the biodiversity of pollinators (defined as 'non-man-made inputs' in the guidelines). They are part of the ecosystem services (ES). Given the importance of ES, including them in decision-making is widely accepted. Within the framework of productivity assessment, we define ecosystems as assets/stocks, hence natural capital, that, combined with the traditional inputs, provide a flow of benefits to society. The main challenge here is how to assess natural capital. Natural capital accounting (NCA) is a systematic approach to valuing natural resources, i.e. the natural stocks and the flows of benefits they provide. The System for Integrated Environmental and Economic Accounting (SEEA) is a widely acknowledged NCA approach for incorporating natural capital into macroeconomic analyses and informing policy decisions at both national and subnational levels [14]. NCA can also be conducted at the farm level, including indicators, such as soil health (soil organic matter, minerals and PH), biodiversity (flora and fauna), and water resources. All these indicators are very difficult to obtain so proxies can be used instead. For instance, in the case of soil natural capital, the soil biodiversity can be proxied by the soil organic carbon.

Along with the natural capital, other 'exogenous'/local environmental conditions play a crucial role in agricultural production. These environmental conditions include weather indicators (rain, temperature, humidity, growing degree days, etc.), altitude and slope. We do not label these variables as natural capital but instead as environmental variables essential for assessing agricultural productivity [15].

10 Roy, N.,K., and Das, A., *Prospects of Renewable Energy Sources*, in Islam, M., R., Roy, N., K., and Rahman, S., (eds.), *Renewable Energy and the Environment*, Singapore, Springer Singapore, 2018, pp. 1-39. http://dx.doi.org/10.1007/978-981-10-7287-1_1.

11 Yang, H., and Pollitt, M., *The Necessity of Distinguishing Weak and Strong Disposability among Undesirable Outputs in DEA: Environmental Performance of Chinese Coal-Fired Power Plants*, Energy Policy, Vol. 38, Nº 8, August 2010. https://doi.org/10.1016/j.enpol.2010.03.075.

12 Elmiger, B.N., Finger, R., Ghazoul, J., and Schaub, S., *Biodiversity indicators for result-based agri-environmental schemes – Current state and future prospects*, Agricultural Systems, 204:103538, 2023. https://doi.org/10.1016/j.agsy.2022.103538.

13 See more: https://agriculture.ec.europa.eu/common-agricultural-policy/cap-overview/cmef_en. Accessed 10 September 2024.

14 Fleming, A., O'Grady, A.P., Stitzlein, C., Ogilvy, S., Mendham, D., and Harrison, M.T., *Improving Acceptance of Natural Capital Accounting in Land Use Decision Making: Barriers and Opportunities*, Ecological Economics, Vol. 200, October 2022. https://doi.org/10.1016/j.ecolecon.2022.107510.

15 Njuki, E., Bravo-Ureta, B.E., and Cabrera, V.E., *Climatic Effects and Total Factor Productivity: Econometric Evidence for Wisconsin Dairy Farms*, European Review of Agricultural Economics, Vol. 47, Nº 3, June 15, 2020, pp. 1276-1301. https://doi.org/10.1093/erae/jbz046.

3.2. Social indicators of agriculture

In productivity studies, the social dimension is another salient, but generally overlooked pillar of sustainability, undoubtedly due to its subjective and ambiguous characteristics. Social sustainability indicators can be classified into two groups: indicators accounting for internal social objectives (i.e. those that relate to the farm-level community), and indicators accounting for external social objectives (i.e. those that relate to society as a whole) [16]. The next table summarises potential social indicators.

Table 2. Social indicators associated with agricultural activities

General category	Sub-category	Indicators
Internal social sustainability	Human capital and education	Education; Agricultural training of farm managers and employees; Age structure (e.g. age of farm manager, age of the youngest associate); Succession potential.
	Working conditions	Working time; Workload (work intensity and painfulness, physical load, stress); Workforce: with salaries; family farms/businesses; Work safety and accidents (number of accidents, working days lost because of occupational accidents); Farm safety plans (e.g. workplace risk assessment); Gender balance; Presence of workers with disabilities; Wages for hired workers in comparison to a reference wage; Administrative burden (e.g. number of forms to fill, time spent on administrative duties).
	Quality of life	Work-life balance; Isolation (e.g. farmer lives alone, internet connection, spatial accessibility to services – railway/bus station, post office, general practitioner, pharmacy, childcare, primary school and grocery retailer); On-farm and off-farm incomes; Proximity to natural amenities.

16 Lebacq, T., Baret, P.V., and Stilmant, D., *Sustainability Indicators for Livestock Farming. A Review*, Agronomy for Sustainable Development, Vol. 33, Nº 2, April 2013, pp. 311-327. https://doi.org/10.1007/s13593-012-0121-x; and Robling, H., Abu Hatab, A., Säll, S., and Hansson, H., *Measuring Sustainability at Farm Level – A Critical View on Data and Indicators*, Environmental and Sustainability Indicators, Vol. 18, June 2023. https://doi.org/10.1016/j.indic.2023.100258.

General category	Sub-category	Indicators
External social sustainability	Multifunctionality	Ecosystem services; Employment; Agricultural landscape (e.g. richness – pastures, meadows, crop areas, fallow lands); Number of farmers; Regional value-added.
	Acceptable agricultural practice	GHG emissions; Nutrient balances; Animal welfare (e.g. grazing practices, animal appearance, risk of mastitis incidence, antibiotic treatments, culling rate, veterinary costs, flexible feeding and stall systems, scraper and cow mattresses, space adequacy, birth management, freedom of movement and stocking density).
	Quality of product	Milk fat, protein content, and somatic cells in milk production; Organic farming; Protected designation of origins; Other certification schemes; On-farm food loss; Pesticides and antibiotics residues in agricultural products.

Source: EU CAP Network supported by the European Evaluation Helpdesk for the CAP (2025)

Although widespread in large businesses or manufacturing firms, corporate social responsibility (CSR) is another way of weighing agricultural impacts on society. The Commission defines CSR as "the responsibility of enterprises for their impacts on society" [17]. This implies that companies 'should have in place a process to integrate social, environmental, ethical, human rights and consumer concerns into their business operations and core strategy in close collaboration with their stakeholders to maximise the creation of shared value for their owners/shareholders and civil society at large and to identify, prevent and mitigate possible adverse impacts [18].

CSR thereby encompasses not only the environmental dimension of agricultural production, but also its social dimension. CSR can be evaluated using actual volumes of corresponding outputs (e.g. volume of GHG emissions) or a scoring system. For instance, the rating agency Sustainalytics [19] provides environmental, social and corporate governance (ESG) sophisticated scores for companies using data from multiple sources such as annual reports, CSR reports, CSR websites, press releases, local newspapers or relevant websites.

17 European Commission, Directorate-General for Internal Market, Industry, Entrepreneurship and SMEs, *Corporate Social Responsibility, Responsible Business Conduct, and Business & Human Rights: Overview of Progress*, Publications Office, 2019. https://ec.europa.eu/docsroom/documents/34482.
18 See previous footnote.
19 For more information, see: https://www.sustainalytics.com/. Accessed 10 September 2024.

The case of social capital

Social capital should not be neglected among the immaterial inputs that participate directly or indirectly in agricultural production. There is no clear-cut definition of social capital. For instance, Woolcock and Narayan [20] defined social capital as "the norms and networks that enable people to act collectively", while Lin [21] defined it as "resources embedded in a social structure, which are accessed/ mobilised in purposive actions". Social capital positively impacts performance through three channels: transmission of valuable information (dense networks allow rapid and reliable transmission of relevant information), opportunism problems (social proximity might induce loyalty and trust), and collective actions like risk pooling or scale economies [22]. Social capital can also generate negative impacts, for instance, a lack of incentives to seek out new economic and commercial opportunities, engage in innovative, risky and best performing behaviours and a collusion effect through exclusion. An optimal level of social capital will require balancing levels of strong (bonding) and weak (bridging) ties. Callois and Aubert [23] suggested some classes of indicators to evaluate social capital in rural areas.

Table 3. Indicators of social capital

Class of phenomenon	Indicators
Social homogeneity	Gini index on income
Trust, loyalty, reciprocity	Rate of telephone users not in the directory, charity gifts
Cooperation	Average farm size, fiscal integration coefficient
Conservatism	Vote for conservative parties
Density of local links	Participation in associations, average household size, density of bars and sports facilities, share of commuters
Bridging social capital	Emigration/immigration indicators, business links, electoral turnout, number of subsidies granted

Source: adapted from Callois and Aubert (2007)

Many of the indicators presented in the above table are not measured at the farm level, but at a territory level, where local differences in production areas are captured.

In conclusion, it is worth discussing the overarching indicator of resilience. The concept of resilience highlights the importance of effectively managing uncertainty and adapting to dynamic environments. Less resilient farms cannot deal with the multitude of risks spreading from droughts, climate change and environmental degradation, pests and disease outbreaks, changing regulations, market volatility, socioeconomic pressures, COVID-19 and the war in Ukraine. At the policy level, strengthening the resilience of the EU food system has been embedded in the 2020 CAP reform, which aims to enhance the resilience of European agriculture through various strategies and measures: climate adaptation and mitigation, risk management tools, rural development programs (including support for young farmers), biodiversity and environmental conservation, and community-led local development (CLLD), including the LEADER Initiative [24]. In addition, the 2023-2027 CAP reform introduced a new delivery model, granting more flexibility to Member States to tailor interventions to their specific needs while aligning with EU-wide objectives, such as eco-schemes, enhanced conditionality and social conditionality. Apart from the obvious policy considerations in enhancing resilience, the main challenge resides in measuring it. Resilience can be defined in three dimensions namely robustness, adaptation and transformation [25]. A recent study of nine European countries [26] suggested some indicators to assess the three dimensions of resilience. They suggested the following classification.

20 Woolcock, M., and Narayan, D., *Social Capital: Implications for Development Theory, Research, and Policy*, The World Bank Research Observer, Vol. 15, Nº 2, August 1, 2000, pp. 225-249. https://doi.org/10.1093/wbro/15.2.225.

21 Lin, N., *Social Capital: A Theory of Social Structure and Action*, 1st ed., Cambridge University Press, 2001. https://doi.org/10.1017/CBO9780511815447.

22 Callois, J.-M., and Aubert, F., *Towards Indicators of Social Capital for Regional Development Issues: The Case of French Rural Areas*, Regional Studies, Vol. 41, Nº 6, August 2007, pp. 809-821. https://doi.org/10.1080/00343400601142720.

23 Ibid.

24 For more information, see: https://eu-cap-network.ec.europa.eu/networking/leader_en.

25 Meuwissen, M.P.M., Feindt, P.H., Spiegel, A., Termeer, C.J.A.M., Mathijs, E., Mey, Y.D., Finger, R., et al., *A Framework to Assess the Resilience of Farming Systems*, Agricultural Systems, Vol. 176, November 2019, p. 102656. https://doi.org/10.1016/j.agsy.2019.102656.

26 Slijper, T., De Mey, Y., Poortvliet, P.M., and Meuwissen, M.P.M., *Quantifying the Resilience of European Farms Using FADN*, European Review of Agricultural Economics, Vol. 49, Nº 1, January 10, 2022, pp. 121-150. https://doi.org/10.1093/erae/jbab042.

Table 4. Overview of the resilience capacity indicators

In the table, positive (negative) directions indicate that higher values of an indicator imply higher (lower) levels of resilience capacity. Application indicates to what farm types a specific indicator applies. ACP=arable, crop and perennial farms.

Resilience capacity	Resilience capacity indicator (indicator name)	Definition	Direction	Application
Robustness	Resistance (*resistance*)	Percentage decrease in profitability	+	ACP, livestock, mixed
	Shock (*shock*)	Occurs if profitability decreases by at least 30%	-	ACP, livestock, mixed
	Recovery rate after year 1 (*recovery rate*)	Degree of recovery after one year, expressed as a percentage of the decrease in profitability	+	ACP, livestock, mixed
Adaptation	Crop diversity (*crop diversity*)	Change in crop diversity	+/-	ACP, mixed
	Fertiliser, crop protection and energy costs (*FCE*)	Percentage change in fertiliser, crop protection and energy costs per hectare	+/-	ACP, mixed
	Irrigation (*irrigation*)	Percentage change in irrigated area	+/-	ACP, mixed
	Labour (*labour*)	Percentage change in annual working units (AWU) per hectare	+/-	ACP, livestock, mixed
	Livestock units per hectare (*LU*)	Percentage change in livestock units per hectare	+/-	Livestock, mixed
	Feed ratio (*feed ratio*)	Percentage change in the ratio of on-farm produced food to total feed costs	+/-	Livestock, mixed
Transformation	Organic (*organic*)	Conversion from conventional to organic farming or vice versa	+	ACP, livestock, mixed
	Farm type (*farm type*)	Change in farm type (TF8 classification)	+	ACP, livestock, mixed
	Farm tourism (*tourism*)	Revenue from farm tourism represents at least 30% of total revenue	+	ACP, livestock, mixed

Source: adapted from Slijper et al. (2022)

Note: TF8 classifies farm types according to the following types: 1 = fieldcrops, 2 = horticulture, 3 = wine, 4 = other permanent crops, 5 = milk, 6 = other grazing livestock, 7 = granivores, and 8 = mixed

Although not explicitly mentioned, resilience implies independence from off-farm resources, especially non-renewable energy and mineral fertilisers. The Ukrainian war has revealed the vulnerability of the EU agricultural system to energy price shocks and geopolitical threats. This dependency could be analysed by understanding farmers' demand for non-renewable energy-intensive inputs or by measuring the efficiency of these inputs. Currently, the FADN can provide elements to address this issue. Another related indicator is autonomy, which is a multifaceted concept that encompasses various dimensions of independence and self-sufficiency within the agricultural context. It can be defined in terms of economic (e.g. financial independence), operational (e.g. technological self-sufficiency) and decision-making (e.g. strategic planning) aspects.

3.3. Note on the data available for computing environmental and social indicators

Annex 1 provides a list of environmental and social indicators [27] that can be found in the FADN database. However, the available indicators represent a poor representation of the environmental and social dimensions. For instance, regarding natural capital, there is no information about the land management practices, not even on the existence of hedgerows or buffer strips (such information is available in the LPIS (Land Parcel Identification System), but this database does not include the economic data necessary for a productivity assessment). A poor proxy of soil management can be machinery costs, including maintenance, amortisation and machinery cooperative or external service expenses. In addition, in the FADN, the localisation of farms at the municipality level is missing (only NUTS2 location is available), so weather and soil information cannot be precisely considered.

In the social dimension, the labour variable is poorly measured and expressed in annual working units (AWU). For instance, one annual work unit is equivalent to one person working full-time on the holding. One person cannot exceed one work unit equivalent, even if their actual working time exceeds the norm for the region and type of holding. Other indicators include some rural development subsidies (e.g. subsidies for young and new farmers and animal welfare payments). Succession potential can be proxied by the farm asset size and the level of investments. Some previously mentioned variables, like concentrate feed and veterinary costs per livestock unit and building size (expressed in monetary terms in FADN data) per livestock unit, can be used to assess animal welfare.

In the FADN, information on environmental and social indicators is poor. Nevertheless, some countries have included in their national FADN database some variables associated with the environmental and social impacts of agriculture. The table below shows some environmental and social variables present in the national databases of the Netherlands and Ireland [28].

27 Note that the indicators provided in FADN are not related to the input yet.

28 This is a partial list of the studies that have described some of these indicators:

- Dolman, M.A., Sonneveld, M.P.W., Mollenhorst, H., and De Boer, I.J.M., *Benchmarking the Economic, Environmental and Societal Performance of Dutch Dairy Farms Aiming at Internal Recycling of Nutrients*, Journal of Cleaner Production, Vol. 73, June 2014, pp. 245-252. https://doi.org/10.1016/j.jclepro.2014.02.043;
- Skevas, T., and Lansink, A.O., *Reducing Pesticide Use and Pesticide Impact by Productivity Growth: The Case of Dutch Arable Farming*, Journal of Agricultural Economics, Vol. 65, N° 1, January 2014, pp. 191-211. https://doi.org/10.1111/1477-9552.12037;
- Buckley, C., Wall, D.P., Moran, B., and Murphy, P.N.C., *Developing the EU Farm Accountancy Data Network to Derive Indicators around the Sustainable Use of Nitrogen and Phosphorus at Farm Level*, Nutrient Cycling in Agroecosystems, Vol. 102, N° 3, July 2015, pp. 319-333. https://doi.org/10.1007/s10705-015-9702-9;
- Buckley, C., Wall, D.P., Moran, B., O'Neill, S., and Murphy, P.N.C., *Farm Gate Level Nitrogen Balance and Use Efficiency Changes Post Implementation of the EU Nitrates Directive*, Nutrient Cycling in Agroecosystems, Vol. 104, N° 1, January 2016, pp. 1-13. https://doi.org/10.1007/s10705-015-9753-y; Ryan, M., Hennessy, T., Buckley, C., Dillon, E.J., Donnellan, T., Hanrahan, K., and Moran, B., *Developing Farm-Level Sustainability Indicators for Ireland Using the Teagasc National Farm Survey*, Irish Journal of Agricultural and Food Research, Vol. 55, N° 2, December 1, 2016, pp. 112-125. https://doi.org/10.1515/ijafr-2016-0011;
- Dillon, E.J., Hennessy, T., Buckley, C., Donnellan, T., Hanrahan, K., Moran, B., and Ryan, M., *Measuring Progress in Agricultural Sustainability to Support Policy-Making*, International Journal of Agricultural Sustainability, Vol. 14, N° 1, January 2, 2016, pp. 31-44. https://doi.org/10.1080/14735903.2015.1012413;
- Lamkowsky, M., Oenema, O., Meuwissen, M.P.M., and Ang, F., *Closing Productivity Gaps among Dutch Dairy Farms Can Boost Profit and Reduce Nitrogen Pollution*, Environmental Research Letters, Vol. 16, N° 12, December 1, 2021. DOI 10.1088/1748-9326/ac3286;
- Wang, S., Ang, F., and Lansink, A.O., *Mitigating Greenhouse Gas Emissions on Dutch Dairy Farms. An Efficiency Analysis Incorporating the Circularity Principle*, Agricultural Economics, Vol. 54, N° 6, November 2023, pp. 819-837. https://doi.org/10.1111/agec.12804.

Table 5. Environmental and social variables collected in the Netherlands and Ireland

Country	Dimensions	Variables
The Netherlands	Environmental related variables	Nutrient surpluses (N and P)
		Pesticides kilograms of active matter
		Pesticides environmental impact points – EIP, for groundwater, surface water and soil
		Megajoules (MJ) of energy used on the farm (electricity and several fuels)
		Megajoules (MJ) of energy produced on the farm (solar panels, wind, biogas from digestion)
		GHG emissions (with Tier-3 computation)
		N-emissions (ammonia and other N: N_2, NO_x)
		Water volume (m^3) used for irrigation
	Animal welfare	Daily dose of antibiotics per animal
		Hours of grazing
		Age of culling/longevity
Ireland	Environmental indicators	GHG emissions
		Nutrient balances
	Social sustainability indicators	Farmer Physical & Psychological Well-Being (Loneliness and mental health, financial pressures, Rural Crime, Access to farm labour)
		Social Isolation (Access to essential services to avoid isolation and lack of relationship between people, e.g. banks, supermarkets, libraries, etc.)
		Succession (Challenges around farm transfer, Attractiveness of farming as a career)
		Animal Welfare (Poor Animal Welfare as an indicator of poor farmer well-being, Animal Comfort, e.g. housing and health, Consumer queries)
		Rural policy & development (Resilience and change, Effect of emigration on rural regions, Availability of services)
		Broadband (Challenging for business and communication)

Source: EU CAP Network supported by the European Evaluation Helpdesk for the CAP (2025)

These are only two examples. There are certainly other national FADN data with environmental and social variables.

As a general note, it should be stressed that the above indicators mainly represent farming practices (or proxies of these) or pedoclimatic conditions and not environmental impacts per se. This may be problematic as there is a huge heterogeneity in agricultural practices that is not reflected in the proxy indicators, which can also be reflected in the environmental impacts.

Annex 4 Further details on TFP

Annex 4 complements Chapter 4.3 of the guidelines on total indicators in relation to TFP. It consists of several parts.

First, Annex 4.1 provides a summary of all possible approaches for estimating TFP according to various characteristics and potential applications.

Second, Annexes 4.2-4.6 offer details on each of these approaches, including a detailed description and why it is useful, technical formulas for calculations, data sources and requirements, methodological steps and insights on how to read the results. Each section concludes with a summary of the advantages and disadvantages of the method. Examples from the literature are also provided where possible.

Finally, Annex 4.7 covers possible issues and caveats in estimating productivity by listing the advantages and disadvantages of production functions, considering possible biases and examining the case of own labour, land and capital.

Annex 4 is useful for better understanding each approach for estimating TFP and identifying what is required to apply it in practice (e.g. technical aspects/calculations, data needs and expertise required) while taking all possible issues into account.

4.1. Summary of the possible approaches to estimate TFP

4.1.1. Possible approaches

Total factor productivity (TFP) is the ratio of all outputs divided by all inputs. Both outputs and inputs are aggregated. TFP can be measured by observing farms or firms or by analysing data from sectors, regions or countries [29].

Assessing changes in TFP helps explain which inputs (or factors) contribute to the growth of production and whether there are gains in production that cannot be explained by the growth of inputs. Sometimes, the term 'multifactor-productivity' is used instead of 'total factor productivity' because, in an empirical analysis, it is not possible to account for all factors that may come in different qualities for which data does not exist or are only available at prohibitive costs.

TFP grows when production grows at a faster rate than the quantity of inputs.

The growth rate of production is, therefore, the sum of two growth rates: TFP and inputs used [30]. TFP is, therefore, also referred to as a 'residual' - something that contributes to production growth but cannot be identified as a specific input or its quality and rate of change. TFP grows when farms become more technically efficient e.g. by spreading fertiliser carefully on the field (i.e. the technical efficiency change is positive) and/or when there is technological progress, for example when new methods are employed that contribute to lower costs (e.g. variable rate fertilisation, which saves fertiliser) or higher yields (e.g. genetically superior crop varieties). TFP is a CAP Strategic Plan (CSP) context indicator [31].

TFP, according to the classification of del Gatto et al. [32] and Ackerberg et al. [33], can be assessed using approaches that vary according to two main characteristics.

1. Deterministic vs stochastic methodologies
2. Methodologies that rely on technological frontiers or not

The table below, adapted from del Gatto et al., and integrated by Ackerberg et al., provides a framework for classifying productivity measurement approaches used in microeconomic analyses.

29 OECD, *Measuring Productivity - OECD Manual: Measurement of Aggregate and Industry-level Productivity Growth*, Organisation for Economic Co-operation and Development, 2021. https://www.oecd-ilibrary.org/industry-and-services/measuring-productivity-oecd-manual_9789264194519-en.

30 Bureau, J. C., & Antón, J., *Agricultural Total Factor Productivity and the environment: A guide to emerging best practices in measurement*, Organisation for Economic Co-operation and Development, 2022. https://doi.org/10.1787/6fe2f9e0-en.

31 The European Commission has set up the common monitoring and evaluation framework (CMEF) to assess the performance of the 2014-20 common agricultural policy (CAP) and improve its efficiency. The definition of the context indicators is provided in: https://agriculture.ec.europa.eu/common-agricultural-policy/cap-overview/cmef_en. Accessed 21-06-2024.

32 Del Gatto, M., Di Liberto, A., and Petraglia, C., *MEASURING PRODUCTIVITY*, Journal of Economic Surveys, Vol. 25, N° 5, December 2011, pp. 952-1008. https://doi.org/10.1111/j.1467-6419.2009.00620.x.

33 Ackerberg, D.A., *Timing Assumptions and Efficiency: Empirical Evidence in a Production Function Context*, The Journal of Industrial Economics, Vol. 71, N° 3, September 2023, pp. 644-674. https://doi.org/10.1111/joie.12340; and Ackerberg, D.A., Caves, K., and Frazer, G., *Identification Properties of Recent Production Function Estimators*, Econometrica, Vol. 83, N° 6, 2015, pp. 2411-2451. https://doi.org/10.3982/ECTA13408.

Table 6. Available methodologies for TFP estimation

	Deterministic methodologies	Stochastic methodologies	
		Parametric	Semi-parametric
Non-frontier	Index numbers	Dynamic panel data (DPD)	Control function estimator (CFE)
Frontier	Data envelopment analysis (DEA) with and without index numbers	Stochastic frontier analysis (SFA)	

Source: EU CAP Network supported by the European Evaluation Helpdesk for the CAP (2025)

4.1.2. Deterministic vs. stochastic methodologies

Deterministic methodologies

Deterministic methodologies assume that state variables are uniquely determined by the coefficients in the model and by the sets of previous states of these variables. They perform consistently for a given set of parameters and initial conditions, resulting in a unique solution.

- Advantages: simple and easy to implement, often used when the focus does not consider exogenous factors.
- Disadvantages: do not account for random shocks or measurement errors.

Stochastic methodologies

Stochastic methodologies incorporate random errors to account for variability in output that is not explained by input levels alone.

- Advantages: suitable for settings with unpredictable drivers, providing a more realistic assessment of performance.
- Disadvantages: require specific hypotheses about the underlying functions to model and predict outcomes accurately.

Within stochastic methodologies, it is possible to differentiate further between **parametric and semi-parametric methods.**

- Parametric methods rely on a predefined mathematical relationship between inputs and outputs.
- Semi-parametric methods blend predefined approaches with flexible, non-parametric elements to better capture the complexities of production processes.

4.1.3. Non-Frontier vs frontier methods

Non-frontier methods

Non-frontier methods do not explicitly identify the efficiency gap between actual and potential output/input.

Index numbers

- Type: deterministic [34]
- Description: index numbers quantify the ratio of aggregate output to aggregate inputs over time. These indices, such as the Laspeyres, Paasche, Fisher and Törnqvist, are grounded in economic index theory and used to measure productivity changes, assuming competitive markets and efficient producer behaviour.
- Applications: these indices are useful for investigating aggregate productivity trends over time and decomposing changes into price and volume effects.

Dynamic panel data (DPD)

- Type: stochastic, parametric
- Description: the dynamic panel approach, developed by Blundell & Bond [35], is utilised to analyse panel data by calculating productivity as the Solow residual. This method incorporates both time dynamics and individual effects, addressing unobserved individual heterogeneity and endogeneity issues by employing lagged variables as instruments.
- Applications: DPD models are particularly suitable for real-world agricultural settings where unpredictable factors can significantly impact productivity.

34 According to the classification of del Gatto et al. (2011), Ackerberg et al. (2015) and Ackerberg (2023). This applies to the case of indexes such as the Laspeyres, Paasche, Fisher, and Törnqvist.
35 Blundell, R., and Bond, S., *GMM Estimation with Persistent Panel Data: An Application to Production Functions*, Econometric Reviews, Vol. 19, Nº 3, January 2000, pp. 321-340. https://doi.org/10.1080/07474930008800475.

Control function estimator (CFE)

- Type: stochastic, semi-parametric
- Description: CFE (or proxy variables method) is a two-step econometric approach that uses a proxy variable to represent unobserved productivity. Methods introduced by Olley & Pakes [36], Levinsohn & Petrin [37], Ackerberg et al. [38] and Wooldridge [39] construct such proxies using investment and intermediate inputs to control for unobserved productivity.
- Applications: CFE is used to obtain consistent input elasticity estimates and address endogeneity issues, providing a more accurate and reliable measure of TFP.

Frontier methods

Frontier methods estimate the maximum possible output for given inputs (or the minimum possible input for a given output), identifying the gap between actual and potential output/input (defined by the production frontier) as inefficiency.

Data envelopment analysis (DEA)

- Type: deterministic, non-parametric
- Description: DEA is a non-parametric method for estimating production frontiers, which empirically measures the productive efficiency of DMUs responsible for converting inputs into outputs. DEA constructs a piecewise linear surface (or frontier) to envelop the data points representing the most efficient units. This frontier serves as a benchmark against which the efficiency of all units is assessed.
- Applications: DEA has been used to estimate productivity indices like Malmquist or Hicks-Moorsteen, effectively measuring TFP through distance functions.

Stochastic frontier analysis (SFA)

- Type: stochastic, parametric
- Description: SFA is an econometric methodology employed for the measurement of technical efficiency and productivity. Unlike DEA, which attributes all deviations from the frontier to inefficiencies, SFA distinguishes between random errors (statistical noise) and inefficiency. This distinction allows SFA to provide more nuanced insights into the sources of inefficiency.
- Applications: SFA enables the simultaneous estimation of efficiency scores and the identification of factors contributing to inefficiencies, such as farm-specific characteristics or adherence to policy measures like CAP.

4.2. Details on the index number approach

Description

An index number is a real number that measures changes in a set of related variables. Conceptually, index numbers may be used for comparisons over time, space, or both.

Productivity indexes estimating TFP are based on the concept that TFP represents the efficiency gains or technological progress in production, which allows for increased output without a proportional increase in inputs like labour and capital. These indexes aim to quantify the 'extra' output not explained by the accumulation of input factors, thus capturing the effects of improvements in how inputs are used. Such improvements could be due to technological advancements (i.e. technological progress), better management practices (that increase technical efficiency) or other factors that enhance productivity.

According to Coelli et al. [40], index numbers are crucial for measuring productivity. The primary application of index numbers is in quantifying changes in TFP, which necessitates the derivation of distinct input and output quantity index numbers, collectively referred to as TFP index numbers.

Index numbers are used as a methodological framework for comparing output and input levels across different farms to measure productivity changes. TFP indices may be utilised in binary comparisons, aimed at contrasting two specific periods or cross-sectional units, or in multilateral scenarios, where the TFP index is calculated for several cross-sectional units concurrently.

The following are the most used approaches:

- Laspeyres index: this index calculates productivity by using base year prices to value output and input quantities. It provides a view of productivity changes relative to a fixed point in time.
- Paasche index: unlike the Laspeyres, the Paasche index uses current-year prices for its calculations. This makes it responsive to recent changes in price and quantity, reflecting more up-to-date economic conditions.
- Fisher index: the Fisher index, considered ideal, is the geometric mean of the Laspeyres and Paasche indices, combining their strengths.
- Törnqvist index: this index is a flexible form that uses the weighted geometric mean of price or quantity ratios, with weights reflecting average shares of total expenditure or revenue. It is deemed a 'superlative' index due to its adaptability to changes in price and quantity data over time.

Two additional indexes, the Malmquist productivity index and Färe-Primont productivity index are computed with the DEA approach and are explained below when describing DEA (Section 4.5).

36 Olley, G.S., and Pakes, A., *The Dynamics of Productivity in the Telecommunications Equipment Industry*, Econometrica, Vol. 64, N° 6, November 1996. https://doi.org/10.2307/2171831.
37 Levinsohn, J., and Petrin, A., *Estimating Production Functions Using Inputs to Control for Unobservables*, Review of Economic Studies, Vol. 70, N° 2, April 2003, pp. 317-341. https://doi.org/10.1111/1467-937X.00246.
38 See the full reference for Ackerberg et al. (2007) in footnote 33.
39 Wooldridge, J.M., *On Estimating Firm-Level Production Functions Using Proxy Variables to Control for Unobservables*, Economics Letters, Vol. 104, N° 3, September 2009, pp. 112-114. https://doi.org/10.1016/j.econlet.2009.04.026.
40 Coelli, T., Lauwers, L., and Van Huylenbroeck, G., *Environmental Efficiency Measurement and the Materials Balance Condition*, Journal of Productivity Analysis, Vol. 28, N° 1, October 1, 2007, pp. 3-12. https://doi.org/10.1007/s11123-007-0052-8.

Box 1. Example from literature

Baldoni and Esposti [41] use index numbers to calculate TFP by means of a multilateral (transitive) TFP (MTFP) index, following the Hick-Moorsteen approach. This approach constructs the index as the ratio of a Fisher output quantity index to a Fisher input quantity index. The analysis was conducted in Italy at the farm level, focusing on individual farms, with data covering the period from 2008 to 2015. This method allows for a detailed examination of how various farm-specific drivers, such as management practices and access to resources, influence productivity.

The study found significant variations in agricultural TFP across Italian regions. It highlights that productivity spillovers are significant but occur over a limited spatial range, typically within a radius of 100 kilometres. For example, a productivity shock in one region, such as Parma, primarily affects neighbouring regions like Reggio Emilia and Modena, with the impact diminishing beyond this range. This finding underscores the importance of selecting an appropriate spatial scale for analysis to accurately capture the dynamics of agricultural productivity.

The results suggest that spatial and dynamic drivers, such as geographical proximity and technological contiguity, play crucial roles in influencing farm productivity. The study's comprehensive assessment underscores the complexity of measuring agricultural productivity and the necessity of considering these drivers in the analysis. This approach provides a robust framework for understanding the regional dynamics of agricultural productivity, which can inform more effective agricultural and regional development policies.

Conceptually, all index numbers measure changes in the levels of a set of variables from a reference period. The reference period is denoted as the 'base period' (s). The period for which the index is calculated is called the 'current period' (t).

Let p_{mj} and q_{mj} represent the price and quantity, respectively, of the $m-th$ netput (a term that refers to all outputs and inputs) in the M netputs being considered $(m = 1,2, \dots, m)$ in the $j-th$ period $(\mathcal{J} = s, t)$.

Let I_{st} represent a general index number for the current period, t, with s as the base period. Similarly, let V_{st}, P_{st}, and Q_{st} represent value, price and quantity index numbers, respectively [42].

The value changes from period s to t is given by the ratio of the value of products in t and s, valued at their respective prices:

$$V_{st} = \frac{\sum_{m=1}^{M} p_{mt} q_{mt}}{\sum_{m=1}^{M} p_{ms} q_{ms}}$$

The index, V_{st}, measures the change in the value of the basket of quantities of M netputs from period s to period t. This formulation can be translated as:

$$V_{st} = \frac{p_t q_t}{p_s q_s} = \frac{p_t}{p_s} \times \frac{q_t}{q_s}$$

NOTE: Member States must exercise caution when using index numbers, as these measures must satisfy several fundamental properties to be reliable. One critical property is transitivity, which ensures that the index allows for consistent comparisons across multiple points in time and space. This property has posed challenges for many decades; for instance, standard index numbers like the Fisher index do not satisfy the transitivity requirement. Although newer indices like EKS or Färe-Primont meet this criterion, they come with trade-offs, such as increased complexity, violation of other properties or other restrictive assumptions to guarantee transitivity. Therefore, it is essential to recognise that no single index can be deemed the best for all contexts; instead, the choice of index should align with the specific objectives and data availability of the analysis.

Data sources and requirements

Data requirements

- Choose the appropriate panel data set. Some models are usually adopted at the individual farm level as it enables the use of samples with sufficient observations [43]. In agriculture, this often involves data from sources like the FADN for price indexes, complemented with Eurostat data, also used to deflate monetary values.
- Ensure the data includes relevant variables such as output, labour, capital and other inputs.

Data preparation

- Check for errors and outliers: clean the data by identifying and correcting errors, outliers, and missing values.
- Transformation: normalise the data if inputs and outputs are measured on different scales.

41 Baldoni, E., and Esposti, R., *Agricultural Productivity in Space: An Econometric Assessment Based on Farm-Level Data*, American Journal of Agricultural Economics, Vol. 103, N° 4, August 2021, pp. 1525-1544. https://doi.org/10.1111/ajae.12155.
42 Without a loss of generality, s and t may refer to two farms instead of periods, and quantities may refer to input or output quantities.
43 The use of DPD at regional or national level is discouraged even if it is possible, given the low number of observations that may compromise the robustness of the results.

Methodological steps

The primary objective of using index numbers is to measure changes in a set of related variables over time or across different regions. In the context of productivity analysis, index numbers are used to estimate TFP, which represents the efficiency gains or technological progress in production.

Various index number formulas can be used, including the Laspeyres, Paasche, Fisher and Törnqvist indices. Each of these indices has its method of weighting and aggregating input and output quantities. For instance, the Laspeyres index uses base period weights, while the Paasche index uses current period weights. The Fisher index, being the geometric mean of the Laspeyres and Paasche indices, balances the strengths of both. The Törnqvist index, on the other hand, uses a weighted geometric mean of quantity ratios, with weights reflecting average shares of total expenditure or revenue. These indices help in quantifying the changes in productivity by comparing the aggregated outputs to the aggregated inputs over different periods.

Laspeyres Index

$$TFP_L = \frac{\sum_{j=1}^{J} q_{jt} p_{j0}}{\sum_{k=1}^{K} q_{kt} p_{k0}}$$

Where

- q_{jt} is the quantity of output j in period t ;
  p_{j0} is the price of output j in the base period 0
- q_{kt} is the quantity of input k in period j ;
  p_{k0} is the price of input k in the base period 0

Paasche Index

$$TFP_P = \frac{\sum_{j=1}^{J} q_{jt} p_{jt}}{\sum_{k=1}^{K} q_{kt} p_{kt}}$$

Where the prices p_{jt} and p_{kt} are from the current period t rather than the base period.

Fisher Index

$$TFP_F = \sqrt{TFP_L \times TFP_p}$$

The Fisher index is the geometric mean of the Laspeyres and Paasche indices. It corrects the upward bias of Laspeyres and the downward bias of Paasche.

Törnqvist Index

$$\ln TFP_T = \sum_{i=1}^{N} 0.5(S_{it} + S_{it-1}) \ln(\frac{q_{it}}{q_{it-1}})$$

Where s_{it} is the share of output i quantity relatives, using the average revenue shares in the two periods as weights.

Laspeyres, Paasche, Fisher and Törnqvist indices use price and quantity data to directly measure productivity changes over time. Index numbers are valuable for estimating productivity when prices and quantities are available.

The Laspeyres and Paasche indices are straightforward to calculate, making them suitable for general assessments of agricultural productivity where a detailed analysis is not required. However, these indices assume simplistic linear production structures that may not hold for the complex nature of agricultural production. They can also have upward (Laspeyres) and downward (Paasche) biases. In contrast, the Fisher and Törnqvist indices are 'superlative index numbers' that provide a good approximation for more intricate agricultural production functions [44].

Given the unique characteristics of agricultural production, the Fisher and Törnqvist indices can better account for the variability in agricultural production.

Laspeyres and Paasche indices are straightforward to calculate at farm-level. Fisher and Törnqvist indices are more suitable for detailed analyses of farm-level productivity drivers, as they can account for the different types of farm production.

From a theoretical point of view, at regional/country level Fisher and Törnqvist indices are often preferred because they can better account for aggregation across the diverse outputs and inputs of farms in a region or country than Laspeyres and Paasche indices (see aggregation bias in Section 4.7 Issues in productivity estimation). However, in reality, if regional/national farm-level price and quantity data are limited, the Laspeyres and Paasche indices can be used to provide an assessment of overall agricultural productivity change.

How to read the results

If Laspeyres, Paasche and Fisher indices, have a base at 100 (in other cases they can be at base 1, but the meaning is the same), a value greater than 100 for a given period (t) indicates productivity growth compared to the base period (s), while a value less than 100 indicates a decline in productivity.

The Törnqvist index is calculated as the weighted geometric mean of output and input growth rates using average revenue/cost shares as weights. Values greater than 1 indicate productivity growth, while values lower than 1 show a decrease in productivity.

Note that the annual values may vary a lot. As underlined by the Commission in the description of its TFP indicator [45], this may be due to the climatic conditions that affect crop yields and have a strong impact on the crop output and, as a consequence, on the indicator. Therefore, a moving average over three years may be advised to be calculated to smooth the weather effect.

44 Suppose a farm produces two outputs (wheat and corn) using two inputs (labour and fertiliser). The Laspeyres index uses the base period input and output quantities as weights. It may overstate productivity growth if the farm shifts towards goods that are becoming relatively cheaper over time. The Paasche index uses the current period quantities as weights. It may understate productivity growth if the farm shifts towards inputs that are becoming relatively more expensive. The Fisher index is the geometric mean of the Laspeyres and Paasche indices. It treats both periods symmetrically and does not suffer from the same upward or downward biases. The Törnqvist index uses the log change in inputs and outputs, weighted by the average share of each input/output across the two periods. Like the Fisher index, it is free from substitution bias.

45 For the full list of indicators, see DG AGRI: https://agriculture.ec.europa.eu/common-agricultural-policy/cap-overview/cmef_en. Accessed 10 September 2024.

Box 2. Understanding aggregate productivity trends over time

Consider a country that produces two main agricultural products: wheat and corn. Over a period of ten years, the government wants to analyse productivity trends in the agricultural sector.

- Data collection: quantities produced; gather data on the quantities of wheat and corn produced each year.
  Prices: collect data on the prices of wheat and corn for the same period.
- Using the Fisher index calculation: calculate the Fisher index, which balances the weights of both periods, providing a more accurate reflection of productivity changes.
- Analysis price effect: determine how much of the productivity change is due to changes in the prices of wheat and corn.
- Volume effect: determine how much of the productivity change is due to changes in the quantities produced.

By using the Fisher index, the government can accurately track productivity trends over the 10-year period and understand the contributions of price and volume changes to overall productivity. This helps in making informed policy decisions to enhance agricultural productivity.

Source: EU CAP Network supported by the European Evaluation Helpdesk for the CAP (2025)

Advantages and disadvantages

Table 7. Pros and cons of index numbers

Pros	Cons
Simplicity Straightforward to calculate using price, quantity and value data without requiring assumptions about the production function or farmer behaviour.	**Aggregation bias** When using aggregated data, there is a risk of spatial aggregation bias, which can distort the true picture of productivity changes due to the loss of detailed information in comparison with farm data level.
Flexibility in the use The Fisher and Törnqvist indices are superlative index numbers that can better approximate flexible production functions, capturing input substitution and non-constant returns to scale.	**Bias** May have biases – Laspeyres has an upward bias, Paasche has a downward bias – If not using a superlative index.
Useful for time trend It is useful to investigate the aggregate productivity trends over time and decompose changes into price and volume effects.	**Data requirement** Requires data on prices and quantities of all inputs and outputs, which may be challenging for some agricultural products. Not particularly suitable for a farm-level analysis.
Data requirement This approach is very useful for aggregated data, for example at a country or regional level.	

Source: EU CAP Network supported by the European Evaluation Helpdesk for the CAP (2025)

4.3. Details on the dynamic panel data models

4.3.1. Description

Dynamic panel data (DPD) models belong to the group of correlation dynamic models. DPD models are highly effective for estimating productivity, primarily because they capture the dynamic nature of production processes by incorporating lagged dependent variables [46], and because they tackle endogeneity concerns (see Section 4.7 Issues in productivity estimation).

Here are the key contexts and reasons why DPD models are appropriate.

- Time-varying productivity: agricultural productivity is influenced by various drivers that change over time, such as technological progress, changes in farming practices, and changes in environmental conditions. DPD models can effectively handle such time-varying unobserved effects, allowing for a more accurate estimation of productivity.
- Lagged effects: agricultural production often involves lagged effects, where inputs used in one period affect outputs in subsequent periods. For example, investments in irrigation infrastructure or orchards may not yield immediate benefits but improve productivity over time. Dynamic models can incorporate these lagged relationships to understand better how current actions affect future productivity.
- Control for endogeneity: input levels (like labour, land and capital) are often endogenously determined e.g. by expected output and productivity shocks. DPD models incorporate instruments and techniques like the generalised method of moments (GMM) to address the endogeneity of these inputs, providing more reliable estimates of the production function coefficients.
- Unobserved Heterogeneity: farms and agricultural enterprises differ in many unobservable aspects, such as managerial skills, land quality, and microclimate conditions. DPD models can control for these unobserved individual effects, allowing for a more accurate estimation of TFP.

In summary, the suitability of DPD models for estimating TFP in agricultural economics stems from their ability to handle the dynamic nature of agricultural production, account for unobserved heterogeneity and address endogeneity issues by utilising the rich temporal information available in panel datasets.

The process of estimating TFP through dynamic panel data models encompasses two principal steps.

- Estimation of the production function: this step uses an econometric model, specifically the GMM estimator, to estimate the production function's coefficients. This estimator addresses multiple endogeneity issues and includes the lagged value of output. It is essential for accurately modelling the relationship between inputs (like labour and capital) and output, considering the dynamic nature of production processes.
- Calculation of TFP as the Solow residual: the Solow residual is calculated as the difference between actual production and the portion of production attributed to measured inputs. It represents the portion of output growth that the growth in inputs such as capital and labour cannot explain [47].

Box 3. TFP and Solow residual concept

The Solow residual, a concept introduced by Solow [48], is one measure of TFP. It represents the portion of output growth that the growth in inputs such as capital and labour cannot explain. In other words, the Solow residual captures the impact of technological progress or efficiency improvements that allow a farm to increase its output without increasing its capital and labour inputs.

The DPD model and the CFE are econometric techniques that estimate TFP based on the Solow residual approach. These methods aim to isolate the contribution of technological progress and efficiency gains to output growth after accounting for the contributions of capital and labour inputs.

The Solow residual can be obtained using, as an example, the Cobb Douglas production $Y = \Omega \cdot N^{\alpha} \cdot K^{\beta}$ (but this concept remains the same for the other production functions), or the log formulation as $ln\Omega =\cdot lnY - (\hat{\alpha}\ lnN - \hat{\beta}\ lnK)$.

The Solow residual can be estimated at the individual farm level or at the regional/national level. In the case of the farm level, the Solow residual measures how much output a farm produces compared to what would be predicted based on the input quantities. This relies on the assumptions of constant returns to scale.

The comparison is made against a theoretical benchmark where output should increase proportionately with inputs, assuming no changes in technology or efficiency. A TFP value higher than one indicates the farm is achieving higher output than expected for the given inputs, suggesting technological advancements or improved efficiency. Conversely, a TFP value lower than one implies the farm is generating less output than expected for the given inputs, pointing to inefficiencies or technological setbacks.

Source: EU CAP Network supported by the European Evaluation Helpdesk for the CAP (2025)

46 In econometrics, a 'lagged dependent variable' refers to a previous period's value of the dependent variable, included as an explanatory variable in a model. This approach helps capture the dynamic effects and temporal dependencies in the data. For example, if a study examines the impact of various factors on farmers' incomes, the model could include the previous year's income (lagged dependent variable) to take into account the persistence of income over time.

47 The estimation of TFP using Solow residual with DPD and CFE is expected TFP for this expected motivation of that error term is iid and $error \sim N(0,\sigma^2)$.

48 Solow, R.M., *Technical Change and the Aggregate Production Function*, The Review of Economics and Statistics, Vol. 39, N° 3, August 1957, p. 312. https://doi.org/10.2307/1926047.

Data requirements and preparation

Data requirements

- Choose the appropriate panel data set. DPD is usually adopted at the individual farm level as this level enables the use of samples with sufficient observations [49]. In agriculture, this often involves data from sources like the FADN, complemented with Eurostat data for price indexes also used to deflate monetary values.
- Ensure the data includes relevant variables such as output, labour, capital, and other inputs.
- This method should be applied to a group of farms that have the same production technology. Moreover, these farms should belong to the same Member State to take into account country-specific drivers such as local agricultural policies, environmental conditions, and economic contexts.
- The minimum time span that is necessary is generally three time periods. This requirement stems from the need to construct valid instruments for the lagged dependent variable and other endogenous regressors. Specifically:
  - Time period 1 – provides the initial conditions
  - Time period 2 – allows for the first differencing
  - Time period 3 – provides the second lag, which serves as an instrument for the first-differenced equation

Data preparation:

- Check for errors and outliers: clean the data by identifying and correcting errors, outliers and missing values.
- Transformation: normalise the data if inputs and outputs are measured on different scales. The log transformation of inputs and outputs is needed for the Cobb-Douglas production function.
- Panel structure: ensure the data is structured as a panel, with observations for each farm across multiple time periods. It is not mandatory to have a balanced panel dataset, meaning that it is acceptable if observations for each farm are not available for the entire period.

Methodological steps

This approach is based on a two-step procedure [50] that is described here for a generic farm-level analysis.

STEP 1 - Production function estimation

In the first step, the production function for the $I_{t,h}$ farm at time t is estimated using the Cobb-Douglas production function.

In this simple case [51], only two factors are used: capital stock - $K_{i,t}$ - and labour - $N_{i,t}$. The Cobb-Douglas production function is written as follows:

$$Y_{i,t} = \Omega_{i,t} K_{it}^{\beta K} N_{it}^{\beta N} e^{\epsilon i,t} \quad i = 1, \dots, N; \quad t = 1, \dots, T \qquad (1)$$

where $Y_{i,t}$ is output, $\Omega_{i,t}$ is the level of TFP, and $X := \{K,N\}$ represents the set of inputs used for the production function estimation (in this case, capital and labour).

To estimate the Cobb-Douglas function as reported in formula (1), the logarithmic transformation is adopted (small letters) [52]:

$$y_{i,t} = \alpha_{i,t} + \beta_X x_{i,t} + \omega_{i,t} + \epsilon_{i,t} \qquad (2)$$

The production function, to reduce the autocorrelation bias, is adopted using the Cochrane-Orcutt formulation to consider that the current level of productivity derives from the past level. This transformation removes the transmission and simultaneity bias and removes first-order autocorrelation. With this formulation, it also introduced the autoregressive component of production, transforming the Cobb-Douglas into a dynamic formulation [53]:

$$y_{i,t} = \rho y_{i,t-1} + \beta_{x,t} x_{i,t} - \rho \beta_{x,t} x_{i,t-1} + (1-\rho)\eta_i + (\gamma_t - \rho\gamma_{t-1}) + \xi_{i,t} \qquad (3)$$

49 The use of the DPD at regional or national level is discouraged even if it is possible, given the low number of observations that may compromise the robustness of the results.
50 Biagini, L., Antonioli, F., and Severini, S., *The Impact of CAP Subsidies on the Productivity of Cereal Farms in Six European Countries: A Historical Perspective (2008-2018)*, Food Policy, Vol. 119, August 2023. https://doi.org/10.1016/j.foodpol.2023.102473; and Mary, S., *Assessing the Impacts of Pillar 1 and 2 Subsidies on TFP in French Crop Farms*, Journal of Agricultural Economics, Vol. 64, N° 1, February 2013, pp. 133-144. https://doi.org/10.1111/j.1477-9552.2012.00365.x.
51 In the more complex case it is necessary to adopt an Augmented Cobb-Douglas production function that, over than $K_{i,t}$ (excluding the land value) and $N_{i,t}$, include also represents the amount of land - $L_{i,t}$ - and materials - $M_{i,t}$.
52 $X := \{K,N\}$ and $\alpha_{i,t}$ is the constant term and $\omega_{i,t}$ is the logarithm of $\Omega_{i,t}$.
53 All required stapes are reported in Biagini et al. (2023).

With ρ the autoregressive term, and $\varepsilon_{i,t}$ the residual error.

The SYS-GMM [54] developed by Blundell & Bond [55] ingeniously solves multiple endogeneity issues.

The SYS-GMM estimator can address potential endogeneity issues (See Section 4.7.2 Possible biases) and provides a suitable solution for these endogeneity issues using instrumental variables, fixed effects and robust error terms.

Farms for which non-observable time invariant variables (such as farm size, geographic location, product specialisation, managerial abilities, different natural characteristics of the soil, etc.) may affect the production function, using first-difference transformation (subtracting past values from current values) can reduce the endogeneity deriving from omitted variables.

As explained earlier, inputs (like labour, land and capital) are often endogenously determined by expected output and productivity shocks. In addition, unobserved heterogeneity may be present; farms and agricultural enterprises differ in many aspects that are not easily observable, such as managerial skills, land quality and microclimate conditions. DPD models can control for these unobserved individual effects, allowing for a more accurate estimation of TFP. These endogeneity issues can be reduced using lagged values of the dependent variable and other instruments to address endogeneity. For example, the Arellano-Bond estimator uses lagged levels of the dependent variable as instruments for the differenced equation.

$$E[y_{i,t-2}(\Delta y_{it} - \rho \Delta y_{i,t-1})] = 0 \qquad (4)$$

In the SYS-GMM estimator, equations in levels and first differences are combined to improve the efficiencies of instrumental variables.

The SYS-GMM model should be validated through a series of specification tests. These include tests for autocorrelation, the Sargan test for the suitability of the instruments, Wald tests for the specification of the model and R2 values for the goodness of fit. The results of these tests indicate the overall econometric validity of the SYS-GMM model in the empirical context.

STEP 2 – TFP estimation

SYS-GMM allows us to estimate the Cobb-Douglas production function generating a set of Solow residuals. This is the starting point to assess the farm-level TFP in the following way

$$\ln TFP_{i,t} = [y_{i,t} - (\hat{\beta}_k k_{i,t} + \hat{\beta}_n n_{i,t})] \qquad (4)$$

In other words, this is the difference between the current level of output $y_{i,t}$ minus the level of production $\hat{y}_{i,t} - (\hat{\beta}_k k_{i,t} + \hat{\beta}_n n_{i,t})$ explained by the input $K_{i,t}$, $n_{i,t}$, β_k, β_n retrieved with step 1.

Considering that the values of π_1 and π_2 are coefficients directly estimated from Equation (3). However, given the constraints $\pi_1 = \beta_{x,t}$ and $\pi_1 = \rho\beta_{x,t}$, the true value of $\beta_{x,t}$ must be recalculated. This is achieved by minimising the distance between π_1 and $\frac{\pi_2}{\rho}$ where ρ represents the autoregressive coefficient.

For this motivation, to find the right values of $\hat{\beta}_k$ and $\hat{\beta}_n$ we need to find the minimum distance between $\beta_{x,t}$ obtained from π_1 and one which obtains as $\beta_{x,t} = \frac{\pi_2}{\rho}$ considering that ρ is the autoregressive coefficient (common factor restriction) using a minimum distance estimator (MDE).

The MDE [56] is a statistical method necessary to adjust for unobserved heterogeneity across individuals or time. MDE is adopted to estimate β_k using the value $\pi_{1,k}$ and $\pi_{2,k}$ and β_n relied on $\pi_{1,n}$ and $\pi_{2,n}$.

To obtain the correct value of TFP, it is necessary, according to Skevas et al. [57] (equation 8 in the cited paper) and Ding et al. [58] (equation 2a in the cited paper), in order to restore the Färe & Primont [59] proportionality condition, to use this formula:

$$\ln TFP_{i,t} = y_{i,t} - [\frac{1}{\hat{\beta}_k + \hat{\beta}_n}(\hat{\beta}_k k_{i,t} + \hat{\beta}_n n_{i,t})] \qquad (5)$$

Software implementation: implement the model using statistical software such as R, Stata, or MATLAB. These platforms offer packages and functions specifically designed for dynamic panel data models (e.g. 'plm' in R, 'xtabond' in Stata).

54 Using Ordinary Least Squares (OLS) to identify coefficients β_X would deliver biased results (Ackerberg et al., 2007; Marschak & Andrews, 1944). Mundlak, (1963) solved the issue by using individual fixed effects (η_i) and time intercepts (γ_t), $y_{i,t} = \alpha_{i,t} + \beta_X x_{i,t} + \gamma_t + (\eta_i + \omega_i) + \varepsilon_{i,t}$ .Despite this effort, this estimator does not solve the autoregressive bias derived from productivity (the actual value of productivity deriving from the past value) and simultaneity bias (the input variable is adopted at the same time of production).

55 Blundell, R., and Bond, S., *Initial Conditions and Moment Restrictions in Dynamic Panel Data Models, Journal of Econometrics*, Vol. 87, N° 1, November 1998, pp. 115-143. https://doi.org/10.1016/S0304-4076(98)00009-8; and Blundell, R., and Bond, S., *GMM Estimation with Persistent Panel Data: An Application to Production Functions*, Econometric Reviews, Vol. 19, N° 3, January 2000, pp. 321-340. https://doi.org/10.1080/07474930008800475.

56 Blundell, R., Bond, S., and Meghir, C., *Econometric Models of Company Investment*, in L. Mátyás and P. Sevestre (eds.), The Econometrics of Panel Data, Vol. 28, Springer Netherlands, Dordrecht, 1992, pp. 388-413. https://doi.org/10.1080/07474930008800475; and Chamberlain, G., *Multivariate Regression Models for Panel Data*, Journal of Econometrics, Vol. 18, N° 1, January 1982, pp. 5-46. https://doi.org/10.1016/0304-4076(82)90094-X.

57 Skevas, I., Lansink, A.O., and Skevas, T., *Analysing Inefficiency in a Non-parametric Spatial-dynamic By-production Framework: A k -nearest Neighbour Proposal*, Journal of Agricultural Economics, Vol. 74, N° 2, June 2023, pp. 591-607. https://doi.org/10.1111/1477-9552.12522.

58 Ding, S., Guariglia, A., and Harris, R., *The Determinants of Productivity in Chinese Large and Medium-Sized Industrial Firms, 1998-2007*, Journal of Productivity Analysis, Vol. 45, N° 2, April 2016, pp. 131-155. https://doi.org/10.1007/s11123-015-0460-0.

59 Färe, R., and Primont, D., *Multi-Output Production and Duality: Theory and Applications*, Springer Netherlands, Dordrecht, 1995. https://doi.org/10.1007/978-94-011-0651-1.

Figure 1. Graphical representation of the methodological steps of the DPD model

Step 1: Estimation Cobb-Douglas production function via SYS-GMM

$$y_{i,t}=\rho y_{i,t-1} + \pi_1 x_{i,t} + \pi_2 x_{i,t-1} + (\eta_i^* + \gamma_t^* + \omega\{i,t\})$$

↓

Minimum distance estimator (MDE) to retrieve β_x

↓

Step 2: TFP estimation as Solow residual (using the coefficients $\hat{\beta}_x$ from MDE)

$$\ln TFP_{i,t} = [y_{i,t} - (\hat{\beta}_k x_{i,t})]$$

Source: adapted from Biagini et al. (2023)

How to read the results

The estimated coefficients provide insights into how changes in input levels affect output. The TFP is calculated as the Solow residual, capturing the effects of technological progress and efficiency improvements.

The estimated values are expressed in a logarithm form. To obtain the value of TFP it is necessary to use this formula: $TFP = e^{ln(TFP)}$

High TFP values indicate high productivity and vice versa. Hence, increases over time in the level of TFP indicate increases over time in the productivity of the considered farms.

It is important to note that the TFP calculated using this method only reflects the variable components, excluding any fixed factors. This means that the analysis does not consider time-invariant elements, such as soil fertility or the designation of less favourable areas.

Box 4. Literature example of TFP calculated using the Solow residual and SYS-GMM

Biagini et al [60] investigated the effects of CAP subsidies on the TFP of cereal farms across six European countries using individual farm data (FADN). TFP was calculated using the Solow residual and SYS-GMM. This method involves estimating a production function and deriving TFP as the part of output growth that is not explained by the input growth. The production function used in this study was a Cobb-Douglas function, which includes inputs such as land, labour, capital and materials. Land is measured in value rather than in hectares, allowing for a more accurate assessment of its contribution to production given varying land values across regions. The analysis was conducted at the farm level, focusing specifically on cereal farms. This included farms primarily engaged in the production of field crops within the specified countries. The study covered six European countries: France, Germany, Italy, Poland, Spain and the United Kingdom. The analysis period spanned from 2008 to 2018, providing a comprehensive overview of the productivity impacts over a decade.

Source: EU CAP Network supported by the European Evaluation Helpdesk for the CAP (2025)

60 See the full reference for Biagini et al (2023) in footnote 50.

Advantages and disadvantages

Table 8. Pros and cons of DPD models in comparison with other methods

Pros	Cons
Efficiency The system GMM estimator, by incorporating a system of instrumental variables in both first differences and levels, effectively addresses the problem of the use of weak instruments. This approach results in more efficient and consistent estimates, as it leverages additional moment conditions to enhance the robustness of the estimation process.	**Complexity** DPD models, including system GMM, require advanced econometric skills. This is because they involve complex estimation techniques and handle potential issues like endogeneity, autocorrelation, and heteroskedasticity.
Exploits panel data advantages It leverages the panel data structure of panel data (including non-balanced panels). This allows studying dynamics over time, providing insights into how past values of the dependent variable influence current values, which is useful for understanding productivity changes over time.	**Data requirement** SYS-GMM relies on a panel dataset of individual farms (e.g. FADN). The dataset must include only farms represented for at least three years. This is to have lagged values of dependent variables (two lagged values, in t and t-1) and lagged for explanatory variables. These are adopted as instrumental variables.
Controls for endogeneity DPD estimation addresses most endogeneity issues, including the correlation between explanatory variables and error terms, omitted variable bias, and unobserved panel heterogeneity.	**Sample size limitation** Farms with negative values of input or output, when adopted to the logarithm transformation, are not taken into consideration. This (very limited but existing) number of cases has to be excluded from the analysis.
Flexibility in modelling DPD allows for the inclusion of lagged dependent variables and a distributed lag structure for explanatory variables. This allows for accommodating dynamic relationships that other methods do not.	**Production function** Despite some attempts [61], DPD adopted only the Cobb-Douglas Production function. This imposes some restrictions on the assumed technology that may not be verified.

Source: EU CAP Network supported by the European Evaluation Helpdesk for the CAP (2025)

61 Ibid.

4.4. Details on the control function estimator approach

Description

CFE is a robust econometric method used to estimate TFP while addressing the issue of endogeneity in production function estimation. This approach requires two steps. The first step is divided into two stages.

- First-stage regression: the process begins with estimating a regression where a proxy variable for productivity is used, considering that TFP influences the level of inputs but is not directly observable by researchers. Typically, the proxy used can be investment or intermediate inputs. This proxy variable is then regressed on capital and other inputs. This step helps to capture the unobserved productivity shocks that significantly influence the output but are not directly observable.
- Second-stage estimation: the estimated proxy or control function obtained from the first stage is then included in the second-stage estimation of the main production function. This inclusion acts as a control for the endogeneity of the inputs (see Section 4.7 Issues in productivity estimation), ensuring that the estimates of the production function coefficients (like labour and capital elasticities) are consistent and not biased by omitted variables or reverse causality.

Finally, TFP is calculated as the residual from the production function that is estimated in the second step (Solow residual) (see Box 3: TFP and Solow residual concept, in Section 4.3 Description of the DPD approach).

The use of CFE is based on two fundamental assumptions.

- Strict monotonicity: a proxy variable, such as investment or materials, consistently rises in response to increases/decreases in unobserved productivity. This consistent relationship enables the use of the proxy variable to account for changes in productivity that are not directly observable.
- Timing: firms observe their productivity shock before making non-fixed input choices like labour, but only after choosing capital and other fixed inputs. This timing assumption is crucial for identification.

In practice, the method uses the Cobb-Douglas production function with log-linearisation of input and output:

$$y_{i,t} = \alpha_{i,t} + \beta_X x_{i,t} + \omega_{i,t} + \varepsilon_{i,t} \qquad (6)$$

Then, defining the proxy variable as a strictly monotonic function of unobserved productivity change is necessary. The proxy variables adopted in the CFE can be intermediate inputs or investments. This proxy helps to isolate the effect of these changes from the observed inputs, thereby correcting for potential biases (particularly simultaneity and transmission bias) in the estimation of production functions.

The development and refinement of the control function estimator method have been significantly influenced by the contributions of several authors[62]. Additionally, Wooldridge [63] introduced a one-stage variant of this method that relies on GMM.

Box 5. Literature example of TFP calculated using a control function estimator

The study of Rizov et al. [64] investigated the impact of CAP subsidies on farm TFP in the EU, employing a CFE that directly incorporated the effect of subsidies. The study focused on both decoupled and coupled CAP subsidies, examining their impacts before and after the decoupling reform implemented in 2003. The analysis covered the period from 1990 to 2008, providing a comprehensive view over nearly two decades. The study conducted an analysis using data from individual farms across EU-15 countries, sourced from the FADN measures at the farm level, within six farm-type samples for each country. The study found that CAP subsidies had a negative impact on farm productivity before the decoupling reform. After the reform, the effect of subsidies on productivity became more nuanced, turning positive in several EU-15 countries.

Source: EU CAP Network supported by the European Evaluation Helpdesk for the CAP (2025)

62 Olley, G.S., & Pakes, A., (1996); Levinsohn, J., & Petrin, A., (2003); Ackerberg et al. (2007;2015).

63 Wooldridge, J.M., *On Estimating Firm-Level Production Functions Using Proxy Variables to Control for Unobservables*, Economics Letters, Vol. 104, Nº 3, September 2009, pp. 112-114. https://doi.org/10.1016/j.econlet.2009.04.026.

64 Rizov, M., Pokrivcak, J., and Ciaian, P., *CAP subsidies and productivity of the EU farms*, International Association of Agricultural Economists 2012 Conference, Foz do Iguacu, Brazil, August 18-24, 2012. https://ideas.repec.org/p/ags/iaae12/124970.html.

Data requirements and preparation

Data requirements

- Choose the appropriate panel data set. CFE is usually adopted at the individual farm level as this level enables the use of samples with sufficient observations [65]. In agriculture, this often involves data from sources like the FADN, complemented with Eurostat data for price indexes also used to deflate monetary values.
- Ensure the data includes relevant variables such as output, labour, capital and other inputs.
- This method should be applied to a group of farms that adopt the same production function. Moreover, these farms should belong to the same Member State to take into account country-specific drivers such as local agricultural policies, environmental conditions and economic contexts.
- The minimum time span that is necessary is generally three time periods. This requirement stems from the need to construct valid instruments for the lagged dependent variable and other endogenous regressors.
- In case of using materials as proxy: (i) the first period is used to compute the expected value of the productivity shock conditional on capital and the proxy; (ii) the second period is used to estimate the conditional expectation of the productivity shock; and (iii) the third period is needed to identify the labour coefficient.
- In case of using investment as proxy: as investment needs to be non-zero, at least three periods are needed to allow for non-zero investment to be observed for a reasonable number of farms.

Data preparation

- Check for errors and outliers: clean the data by identifying and correcting errors, outliers and missing values.
- Transformation: normalise the data if inputs and outputs are measured on different scales. In particular, for production functions take into account that it adopted the log transformation. This is not mandatory for all types of production but specifically for Cobb-Douglas or similar.
- Panel structure: the CFE is in general used at the farm level with a panel dataset. Ensure the data is structured as a panel, with observations for each farm across multiple time periods. It is not mandatory to have a balanced panel dataset, meaning that it is acceptable if observations for each farm are not available for the entire period.

Methodological steps

STEP 1 – production function estimation

- Model specification

The production function is typically specified as a Cobb-Douglas form, but other forms like Translog or CES can also be used. The general form of the production function is:

$$Y_{it} = \Omega_{it} \cdot K_{it}^{\beta k} \cdot L_{it}^{\beta l} \, N_{it}^{\beta n}$$

where Y_{it} is the output, K_{it} is capital, N_{it} is labour, L_{it} is land, and Ω_{it} represents total factor productivity (TFP).

- Classification of the variables: fixed, quasi-fixed and free variables
  - Fixed variables: inputs that can change very slowly and can be assumed in the short time fixed, such as land L_{it}
  - Quasi-fixed variables: inputs that can change but with some adjustment costs, such as capital K_{it}
  - Free variables: inputs that can be adjusted freely in the short term, such as labour N_{it}
- Proxy variable selection
  - Choose proxy variables that can control for unobserved productivity shocks. Common proxies include investment or intermediate inputs like materials [66]. The proxy variable should be correlated with the unobserved productivity shocks, but not with the error term.
- Estimation of productivity

With the Cobb-Douglas production function, the logarithm transformation of all the variables (indicated in lowercase letters) is used.

$$y_{it} = \beta_0 + \beta_k k_{i,t} + \beta_n n_{i,t} + \beta_l l_{i,t} + \omega_{i,t} + \eta_{i,t}$$

With ω_{it} is the log of productivity and η_{it} is the measurement error that can be serially correlated. Both ω_{it} and η_{it} are unobservable.

It is necessary to assume that ω_{it} follows an exogenous first-order Markov process:

$$p\left(\omega_{i,t} | \{\omega_{i,\tau}\}_{\tau=0}^{t}, I_{i,t-1}\right) = p\left(\omega_{i,t} | \omega_{i,t-1}\right)$$

OR that the actual level of productivity depends on the past level, which is considered an accumulation of the past information available by the farmer.

Specifically for the capital, it is necessary to write the law of motion of the capital [67]:

$$k_{i,t} = (1-\delta) k_{i,t-1} + i_{i,t-1})$$

The level of the proxy, in this case, investments, is chosen at time $t-1$, knowing that it depends on capital (in this case, composed of fixed L_{it} and quasi fixed factors K_{it}) and on the level of productivity (ω).

$$i_{i,t-1} = f(k_{i,t-1}, l_{i,t-1}, \omega_{i,t-1})$$

65 The use of the DPD at regional or national level is discouraged even if it is possible, given the low number of observations that may compromise the robustness of the results.
66 See footnotes 36 and 37 for the full references for Olley & Pakes (1996) and Levinsohn & Petrin (2003).
67 In this case use as proxy the investments, but the same process is conducted using materials.

We can invert this formula as:

$$\omega_{i.t-1} = f^{-1}(k_{i,t-1},\, l_{i,t-1},\, i_{i,t-1}) = g(k_{i,t-1},\, l_{i,t-1},\, i_{i,t-1})$$

Considering that $p\,(\omega_{i,t}|\omega_{i.t-1})$ or $\omega_{i,t}{=}p\omega_{i.t-1}$ we can write:

$$\omega_{i.t} = \rho\omega_{i.t-1} = \rho g(k_{i,t-1},\, l_{i,t-1},\, i_{i,t-1}) = h(k_{i,t-1},\, l_{i,t-1},\, i_{i,t-1})$$

Where h is a non-parametric function (polynomial or kernel function), we insert this non-parametric function into the production function.

$$y_{it} = \beta_0 + \beta_k k_{i,t} + \beta_n n_{i,t} + \beta_l l_{i,t} + h(k_{i,t-1},\, l_{i,t-1},\, i_{i,t-1}) + \eta_{i,t}$$

Where we can obtain the estimation function parameters $\hat{\beta}_k$ and $\hat{\beta}_n$.

Example of implementation

1. Data collection: gather data on output, inputs (capital, labour, materials) and a suitable proxy variable (e.g. investment or intermediate inputs)
2. First stage regression: obtain the non-parametric function
3. Second stage estimation: incorporate the non-parametric function into the production function as a control function

The CFE is a robust method for estimating production functions in the presence of endogeneity. By using proxy variables to control for unobserved productivity shocks, it provides consistent and unbiased estimates, making it a valuable tool for evaluating the impact of agricultural policies and interventions on farm productivity.

STEP 2 – TFP estimation

Similar to SYS-GMM, it is possible to estimate productivity based on the Cobb-Douglas production function generating a set of Solow residuals. These are the starting points to assess the farm-level TFP in the following way:

$$lnTFP_{i,t} = [y_{i,t} - (\hat{\beta}_k k_{i,t} + \hat{\beta}_n\, n_{i,t} + \hat{\beta}_l\, l_{i,t})]$$

This is the difference between the current level of output $y_{i,t}$ minus the level of production $\hat{y}_{i,t}{=}(\hat{\beta}_k k_{i,t} + \hat{\beta}_n\, n_{i,t} + \hat{\beta}_l\, l_{i,t})$ explained by the input $k_{i,t}$, $n_{i,t}$ and $l_{i,t}$ considering the value of $\hat{\beta}_k$ and $\hat{\beta}_n$ retrieved by step 1.

To obtain the correct value of TFP, it is necessary, similarly to DPD, to restore the Färe & Primont [68] proportionality condition by using this formula:

$$lnTFP_{i,t} = y_{i,t} - [\frac{1}{\hat{\beta}_k + \hat{\beta}_n + \hat{\beta}_l}(\hat{\beta}_k k_{i,t} + \hat{\beta}_n n_{i,t} + \hat{\beta}_l l_{i,t})]$$

How to read the results

Interpreting the results of the CFE requires a deep understanding of the drivers that influence agriculture productivity, particularly the differences between fixed factors. This process involves examining how efficiently resources like labour and capital are used to produce outputs, considering the impact of investments, improvements in worker productivity and the strategic use of resources.

The CFE method is particularly valuable because it helps address issues of endogeneity, where explanatory variables are correlated with the error term in a model, thus providing more accurate and reliable estimates of TFP. Using the CFE, researchers can derive TFP values as Solow residuals specific to each farm and that vary over time.

Similar to DPD, high TFP values indicate highly productive farms and vice versa. Therefore, increases in TFP over time suggest an increase in the productivity of the considered farms. Unlike DPD, TFP calculated using CFE includes fixed components. This means that the analysis considers both time-invariant elements, such as soil fertility or the designation of less favourable areas, and that TFP can be changed by the farm in the short term.

Analyse the drivers of productivity

Drivers of productivity can be assessed with a regression analysis. In other words, the correlation models explained in Chapter 5 of the guidelines can be used to determine the impact of various explanatory variables (the drivers) on productivity. The dependent variable is the TFP, and the explanatory variables may include CAP measures, farm size, access to credit, farmer experience or age, production specialisation and product mix.

68 See footnote 59 for the full reference of Fare & Primont (1995).

Advantages and disadvantages

Table 9. Pros and cons of CFE for productivity estimation

Pros	Cons
Dynamic modelling The inclusion of dynamics in the production function estimation captures the effect of past productivity shocks on current output.	**Sensitivity to proxy variable choice** The results are highly sensitive to the choice of proxy variable, and the strict monotonicity assumption required for the proxy may not always hold, potentially biasing the estimates.
Flexibility in proxy variable selection Allows for the use of various proxy variables to control for unobserved productivity, providing flexibility in application across different contexts and datasets.	**Reliance on timing assumptions** Depends on specific timing assumptions regarding when farms observe productivity shocks relative to their input choices. Violations of these assumptions can lead to biased estimates.
Controls for endogeneity Effectively addresses the endogeneity of input choices by controlling for unobserved productivity shocks, leading to more consistent estimates of production function coefficients and TFP.	**Sample size limitation** In some variants, such as the Olley-Pakes approach, only firms with positive investments can be included, which may significantly reduce the sample size and affect the representativeness of the results. After adopting the logarithm transformation, farms with non-positive input or output values are excluded.
No need for external instruments Unlike DPD, the CFE does not rely on external instrument variables, which can be difficult to justify or obtain.	**Production function** Currently, CFE adopts only the Cobb-Douglas production function to estimate TFP.
Exploits panel data advantages It leverages the panel data structure to study dynamics over time, providing insights into how past values of the dependent variable influence current values, which is essential for understanding productivity changes.	**Potential for other biases** While it controls for endogeneity, the approach may not fully account for other potential biases, such as measurement errors or omitted price variables, which could also affect TFP estimates.

Source: EU CAP Network supported by the European Evaluation Helpdesk for the CAP (2025)

4.5. Details on the data envelopment analysis

Description

The data envelopment analysis (DEA) is a linear programming technique used to measure the relative[69] efficiency of a homogeneous set[70] of decision-making units (DMUs; farms in the case of agricultural policy assessment) that use multiple inputs to produce output. DEA constructs an empirical production frontier with the DMUs in the sample to measure efficiency and aims to identify the sources and amounts of inefficiency for every DMU included in the analysed sample.

Data requirements and preparation

In the case of agricultural policy analysis, data for DEA mostly originates from Member State-specific FADN individual farm data sets for a given year and usually for the most recent one. Nevertheless, FADN data should be checked for errors, outliers and missing values which can all significantly affect the validity of the analysis. Also, it is necessary to normalise the data if inputs and outputs are measured in different scales. Furthermore, the number of DMUs to be analysed should be large enough to allow for a meaningful analysis.

Methodological steps

The standard practice is to estimate a single frontier for the whole sample of farms considered. However, in the case of significant technology heterogeneity, more than one farm-type specification can be utilised, reflecting (indicatively) different output-specialisation and production sustainability orientations, to capture differences in available resource endowments, economic infrastructure and other characteristics of the physical, social, institutional and economic environment, which altogether entails technological heterogeneity. For example, different frontiers can be estimated for different farm types (e.g. livestock farms vs crop farms), or for farms with different technologies (e.g. organic farms vs conventional farms).

This step also involves choosing the DEA model, which can be input-oriented or output-oriented and involves a decision whether the focus is on minimising inputs for a given level of outputs (input-oriented) or maximising outputs for a given level of inputs (output-oriented). Also, it involves a choice between assuming constant returns to scale (all firms operate at an optimal scale) or variable returns to scale (firms operate at different scales).

This is followed by the construction of the DEA model, namely the formulation of the linear programming problem for each DMU, which defines the efficiency frontier and calculates the efficiency score. This is done through the use of DEA-specific software or linear programming solvers such as R or MATLAB.

The following step involves retrieving the solution of the linear programming problem for each DMU to obtain efficiency scores and the identification of the efficient frontier which consists of the sample's DMUs with an efficiency score of 1.

The extension of efficiency analysis in time dimension results in productivity analysis. TFP, as a measure of productivity, considers not only the contribution of each production factor but also the role of the interaction of inputs within the production process. In this line, the time evolution of productive efficiency is captured by the Malmquist TFP index (MPI) which is defined as time t as:

$$MPI_t = (\Delta TE)_t \times (TC)_t$$

Where TC is technical change (or technological change) and ΔTE denotes a change in technical efficiency between periods t and $t-1$.

Technical change captures the ability of the farms to introduce new technologies – innovation which becomes available and pushes the frontier 'outwards' (technological progress) or 'inwards' (technological deterioration). In this line, although disruptive innovations are of primary importance for the movement of the frontier, the exploitation of the technological progress by each farm may be realised based on incremental innovation. The ΔTE term is defined as the ratio of the farm's technical efficiency in time t to the farm's technical efficiency in a period $t-1$.

The Färe-Primont productivity index is based on fixed weights, making it a transitive index that allows for multilateral and multi-temporal comparisons, unlike the Malmquist index, which is better suited for bilateral comparisons. The Färe-Primont index uses implicit or shadow prices to aggregate inputs and outputs, with these prices often obtained using methods such as DEA. The transitivity property is achieved by selecting a representative observation (e.g. the sample mean), for which shadow prices are computed and applied in the aggregation process. Like the Malmquist index, the Färe-Primont productivity index can also be decomposed into meaningful components, such as technical change, efficiency and scale changes.

How to read the results

DEA estimates efficiency scores for each DMU and indicates how close it is to the efficient frontier. A score of 1 indicates that the DMU is on the efficiency frontier, and hence, is considered efficient. Scores less than 1 indicate efficiency losses. By identifying the sources and extent of inefficiency, it facilitates the improvement of productive performance by targeting specific areas of inefficiency.

Values of the Malmquist TFP index greater than one indicate improvement in productivity, while values less than one indicate deterioration. The same applies to each one of the two components of the Malmquist index (TC and ΔTE).

69 The efficiency score is calculated by comparing the DMU's performance to the best-performing DMU in the set analysed.
70 Homogeneous in terms of operating under similar technology conditions and using the same types of inputs to produce the same types of output; in that sense, any differences in their efficiencies can be attributed to their management and operational practices.

Analyse the drivers of productivity

Drivers of productivity can be assessed with truncated regression analyses to determine the impact of various explanatory variables (the drivers) on productivity [71]. The dependent variable is the TFP, and the explanatory variables may include CAP measures, farm size, access to credit, farmer experience or age, production specialisation, product mix, etc.

Advantages and disadvantages

Advantages and disadvantages of DEA can be summarised as follows.

Table 10. Pros and cons of the DEA

Pros	Cons
Multiple inputs and outputs DEA simultaneously considers multiple inputs and outputs and hence, is appropriate for the analysis of productive performance of complex systems.	**Data sensitivity** DEA results can be sensitive to the selection of inputs and outputs. Also, results can be sensitive to data quality and accuracy. Furthermore, DEA cannot handle zero values in the dataset.
Non-parametric method DEA is a non-parametric method suitable for evaluating the relative efficiency of DMUs without imposing specific functional forms or assumptions on the production process.	**Handling of noise** DEA does not consider the noise in data which may result in an underestimation of the efficiency of the analysed firms. To address this limitation of DEA, a two-stage bootstrapped DEA is used and results present bias corrected technical efficiency (bcTE) scores.
Relative efficiency measurement DEA measures the relative efficiency of DMUs of a sample by comparing them to the best performers in the sample used, and not against a single best practice. This can provide insights into the practices of the most efficient firms in the sample considered.	**Number of DMUs** The reliability of DEA estimates diminishes when the number of firms analysed is relatively small.
	Outlier sensitivity DEA is sensitive to outliers and extreme values can disproportionately affect the efficiency frontier.
	Lack of causal inference If not combined with causal analysis, DEA scores do not possess causal properties.
	Interpretability When combined with causal analysis, DEA results can be difficult to interpret. Interpretation requires careful explanation and understanding of the relevant (for each analysis) context.

Source: EU CAP Network supported by the European Evaluation Helpdesk for the CAP (2025)

71 Simar, L. and Wilson, P.W., *Estimation and Inference in Two-Stage Semi-parametric Models of Production Processes*, Journal of Econometrics, Vol. 136, N° 1, January 2007, pp. 31-64. https://www.sciencedirect.com/science/article/abs/pii/S0304407605001594.

4.6. Details on stochastic frontier analysis

Description

The stochastic frontier analysis (SFA) is an econometric method used to estimate the efficiency of DMUs by separating random noise from inefficiency in the production process. This technique is widely employed in various fields, including economics, finance and operations research, to analyse the production function or cost function. In summary, the key components of the SFA approach are first a production function that describes the relationship between inputs and the output. For this first part, a functional form must be assumed e.g. Cobb-Douglas or Translog are generally used. The second component is the inefficiency term that measures the degree to which a DMU, that was given to a set of inputs, maximises output. The standard SFA approach relies on assuming specific distributions for the inefficiency term, for example, half-normal, truncated normal or exponential distributions. The final component is the random noise, which captures output variability due to drivers outside the DMU's control (e.g. weather, luck). For this last component, a standard normal distribution is assumed.

Once all three key components are defined, parameters of the production technology are generally obtained through maximum likelihood, which involves non-linear programming. Many software like Limdep, R and Stata allow the estimation of the standard SFA models.

Data requirements and preparation

The inputs and the output variables must be clearly defined. In the case of multiple outputs, the standard SFA model must be extended using some complex representations of the production technology. In the cases where the production function is assumed to be either a Cobb-Douglas or a Translog functional form, a specific requirement for the data (inputs and output) is that they must be strictly positive since these functional forms involve a logarithm. Fortunately, there are some transformations or specific functional forms that can be used to accommodate zero and negative data.

Methodological steps

As with any benchmarking study, the first step in running a SFA model is to clearly define the objective of the analysis, such as measuring technical efficiency, cost efficiency or allocative efficiency. Next, you must select the DMUs whose efficiency will be analysed. After gathering data on relevant inputs and outputs – such as labour, capital, materials, and output quantities or values – the next critical step in the SFA framework is to define the functional form of the production or cost function. More advanced representations of production technology, like the distance function, may also be considered. Common choices for the functional form include the Cobb-Douglas function for its simplicity or the Translog function for its flexibility. For example, in the case of the production function, we have:

$$Y_i = f(X_i;\beta) \times e^{(V_i - U_i)}$$

Where:

- Y_i = output
- X_i = inputs
- Y_i = parameters to be estimated

Another critical step in the process is specifying the error terms. Typically, the random error term v_i is assumed to follow a normal distribution, $N(0,\sigma_v^2)$, while the inefficiency term u_i follows a distribution defined on positive values, such as the half-normal, exponential, truncated normal, Rayleigh or gamma distributions. Once these steps are completed, the model can be estimated using maximum likelihood to obtain the production and variance parameters. Estimation can be performed using econometric software like Stata, R or specialised packages such as Limdep. Post-estimation steps include model diagnostics and checks (e.g. model fit, statistical tests), calculating efficiency scores, and analysing and interpreting the results. Additionally, cross-validation and robustness checks can be conducted to ensure the reliability of the findings.

How to read the results

Once the SFA model is estimated (using Cobb Douglas or Translog), the production frontier parameters can be interpreted as elasticities. For instance, in the case of milk production, if the elasticity of intermediate consumption is 0.45, this implies that if this input increases by 1% milk production will also increase by 0.45%. The model also provides distribution parameters for the inefficiency and the random noise term.

Using these parameters, the efficiency of each observation can be measured. An efficiency score of 0.94, or 94%, in the case of milk production, means that given the current level of the inputs, milk production is 6% lower than its potential maximum level.

Much like in DEA, TFP changes can be estimated using an SFA and decomposed into its constituent parts, such as technical change and efficiency change. Assuming that TFP change is calculated as the difference between changes in output and input, given by:

$$\frac{dTFP}{dt} = \frac{dY}{dt} - \sum_j S_j \frac{dX}{dt}$$

A value of 0.021 indicates an annual increase in TFP of 2.1%.

Analyse the drivers of productivity

Drivers of productivity can be assessed with a regression analysis. In other words, the correlation models explained in Chapter 5 of the guidelines can be used to determine the impact of various explanatory variables (the drivers) on productivity. However, in SFA, the correlation analysis is not performed in a separate stage but simultaneously with the stage of estimating the production function. The dependent variable is the TFP, and the explanatory variables may include CAP measures, farm size, access to credit, farmer experience or age, production specialisation and product mix.

4.6.1. Advantages and disadvantages

The advantages and disadvantages of the SFA approach are summarised in the next table.

Table 11. Pros and cons of the SFA

Pros	Cons
Handling of noise This is the core advantage of the SFA approach. By accounting for random errors and statistical noise in the data, SFA provides a more accurate and realistic measure of efficiency compared to deterministic approaches. SFA therefore provides some flexibility, which is particularly useful in real-world data where such noise is unavoidable.	**Multiple inputs and outputs** SFA can handle multiple output variables, but this requires using a complex representation of the production technology.
Statistical Inference SFA models facilitate statistical testing for various hypotheses, including the presence of inefficiency and the significance of different inputs.	**Specification of the production function** The choice of the functional form for the production function (e.g. Cobb-Douglas, Translog) significantly impacts the results. Incorrect specifications can lead to biased efficiency estimates. In the case of the use of a flexible functional form like the Translog, standard economic assumptions can be violated (e.g. non-positive marginal productivity). Moreover, the assumptions regarding the distribution of the inefficiency term (e.g. half-normal, truncated normal) affect the results. However, the inefficiency distribution assumption does not affect the ranking (in terms of efficiency) of the DMUs.
Technology parameters SFA provides detailed information about the production function parameters (elasticities, marginal productivities), which can be useful for policy analysis and decision-making.	**Data requirements** SFA requires a large sample size and good quality data. In addition, while SFA can be applied to cross-sectional data, panel data (multiple observations over time for each DMU) generally provides more robust estimates but also requires more extensive data collection.
Flexible distributional assumptions SFA allows for various statistical distributions of the inefficiency term (e.g. half-normal, truncated normal, exponential, gamma and Rayleigh), making it adaptable to different contexts and types of data.	**Collinearity among the inputs** As an econometric approach, SFA is subject to a high correlation between the input variables, which can affect the quality of the estimation.
Outlier sensitivity SFA is less sensitive to outliers and extreme values.	**Complexity of estimation and results** SFA estimations are based on nonlinear programming for the estimation of corresponding maximum likelihoods. The results of SFA models, including efficiency scores and parameter estimates, can be complex and challenging to interpret for non-experts.
Environmental control variables/efficiency determinants Several environmental variables, like temperature and precipitation, directly affect agricultural production. These environmental variables can be easily handled in SFA. Moreover, SFA can easily handle drivers of efficiency in a single step.	

Source: EU CAP Network supported by the European Evaluation Helpdesk for the CAP (2025)

4.7. Further issues in productivity estimation

4.7.1. The choice of the production functions

Cobb-Douglas production function

The Cobb-Douglas production function is one of the most widely used forms due to its simplicity and empirical applicability. It is expressed as:

$$Y = \Omega \cdot N^{\alpha} \cdot K^{\beta}$$

Where Y represents the total output, N and K are the inputs of labour and capital, respectively, Ω is a constant term representing total factor productivity, and α and β are the output elasticities of labour and capital, respectively. These elasticities measure the percentage change in output resulting from a one per cent change in labour or capital, holding other factors constant. The Cobb-Douglas function assumes that there are constant returns to scale if $\alpha + \beta = 1$ increasing returns to scale if $\alpha + \beta > 1$, and decreasing returns to scale if $\alpha + \beta < 1$.

Advantages

- Simplicity: easy to estimate and interpret
- Empirical applicability: widely used in empirical studies

Disadvantages

- Assumption of constant elasticities: may not capture varying relationships between inputs and outputs

Translog (transcendental logarithmic) production function

The Translog production function is a flexible extension of the Cobb-Douglas function. Unlike the Cobb-Douglas function, which assumes constant elasticities of substitution between inputs, the Translog function allows these elasticities to vary. This flexibility enables it to more accurately capture the changing relationships between inputs like labour and capital as their proportions change in the production process. The Translog function is expressed as:

$$ln(Y) = a_0 + a_L ln(N) + a_k ln(K) + \frac{1}{2} b_{NN}(ln(N))^2 + \frac{1}{2} b_{KK}(ln(K))^2 + b_{NK}\, ln(N)\, ln(K)$$

Where a_0, a_N, a_K, b_{NN}, b_{KK}, and b_{NK} are the coefficients to be estimated. This function allows for interactions between inputs, meaning the effect of changing one input on output can depend on the level of other inputs. The Translog function is particularly useful for analysing cases where the substitution between inputs is not constant.

Advantages

- Flexibility: can capture varying elasticities of substitution
- Detailed interaction: allows for interaction terms between inputs

Disadvantages

- Complexity: more complex to estimate and interpret compared to Cobb-Douglas
- Data requirements: requires more data for accurate estimation

Constant elasticity of substitution (CES) production function

The CES production function is another flexible form that allows for a constant but not necessarily unitary elasticity of substitution between inputs. It is given by:

$$Y = A[\delta N^{-\rho} + (1-\delta)K^{-\rho}]^{-\frac{\sigma}{\rho}}$$

Where A is a scale parameter, δ represents the distribution parameter between inputs, ρ is a parameter related to the elasticity of substitution (σ), and $\sigma = \frac{1}{1+\rho}$ is the elasticity of substitution between labour and capital. The CES function can represent a range of substitution possibilities, from perfect substitutes ($\sigma = \infty$) to perfect complements ($\sigma = 0$). This flexibility makes the CES function suitable for analysing production processes where the ease of substituting between labour and capital is an important factor.

- **Advantages**
  - Flexibility: can model a wide range of substitution possibilities
  - Applicability: suitable for various production processes
- **Disadvantages**
  - Complexity: more complex than Cobb-Douglas
  - Estimation challenges: requires careful estimation of parameters

4.7.2. Possible biases

In productivity estimation, understanding the distinction between endogeneity and bias is crucial. Endogeneity occurs when explanatory variables are correlated with the error term, often due to omitted variables, measurement errors or simultaneity. This can lead to bias, which refers to systematic errors in parameter estimates, resulting in inaccurate results. Addressing these issues is essential for accurate productivity analysis.

1) Simultaneity problem

The estimation of production functions often encounters the simultaneity problem, where farm productivity is both contemporaneously and serially correlated with input choices. This correlation arises because more productive farms may increase their inputs in response to higher current and anticipated future profitability.

- Contemporaneous correlation: occurs when farms adjust their inputs, such as labour, to match current productivity levels.
- Serial correlation: input decisions are influenced by productivity expectations based on past performance.

In a single input scenario, the bias is generally upward. However, in a multivariate context where multiple inputs like labour and capital are considered, the direction of bias becomes indeterminate. For instance, if labour and capital are positively correlated, but labour has a stronger correlation with the productivity term, the estimated coefficient for labour is likely to be overstated, while that for capital is understated [72].

2) Omitted prices problem

When estimating productivity using revenue data instead of actual physical output, unobserved price variations can introduce significant errors. Revenue data may not accurately reflect the actual volume of production due to price fluctuations that are not controlled for in the model. Consequently, these unaccounted price effects can systematically bias the estimated coefficients, leading to distorted productivity estimates. Essentially, the model may attribute changes in revenue to changes in productivity when, in fact, they are due to price variations, thus misleading the analysis [73].

3) Transmission problem

The transmission problem refers to the issue that arises when unobservable productivity drivers influence the level of inputs a farm uses and the output it produces. This correlation between the unobserved productivity and the observed inputs leads to biased production function estimates if standard estimation techniques are used without addressing this endogeneity issue. Essentially, farms may adjust their input levels based on their productivity, which is not directly observable to researchers, thus complicating the accurate estimation of TFP [74].

4) Selection bias

This bias arises when only surviving farms are included in the estimation, ignoring those that have exited the market. It generally leads to a downward bias in the capital coefficient, as farms with lower productivity are more likely to exit [75].

5) Aggregation biases

Aggregation bias refers to the discrepancy between macro-level parameters and the average of micro-level parameters or considering a function like a generalisation of the whole sample without considering differences between the groups of farms (e.g. type of farmers). Aggregating from micro-level production functions to an aggregate production function often requires assumptions that may not hold, such as identical production functions across units, leading to potential biases.

Another case of aggregation bias can arise when the data analysis is conducted at a macro level using micro level data (aggregation of individual FADN data into national data). For this reason, we must be very careful when carrying out these operations, trying to maintain the representativeness of the sample [76].

72 Breunig, R., & Wong, M., *Estimation of total factor productivity. Quantitative Tools for Microeconomic Policy Analysis*, December 2005, pp. 195-214. https://researchportalplus.anu.edu.au/en/publications/estimation-of-total-factor-productivity.

73 Van Beveren, I., *Total Factor Productivity Estimation: A Practical Review*, Journal of Economic Surveys, Vol. 26, N° 1, February 2012, pp. 98-128. https://doi.org/10.1111/j.1467-6419.2010.00631.x.

74 See footnote 36 for Olley & Pakes (1996).

75 See footnote 64 for Rizov et al. (2013).

76 Baldoni, E., Coderoni, S., and Esposti, R., *The Complex Farm-Level Relationship between Environmental Performance and Productivity: The Case of Carbon Footprint of Lombardy Farms*, Environmental Science & Policy, Vol. 89, November 2018, pp. 73-82. https://doi.org/10.1016/j.envsci.2018.07.010; and Severini, S., Tantari, A., and Di Tommaso, G., *The Instability of Farm Income. Empirical Evidences on Aggregation Bias and Heterogeneity among Farm Groups*, Bio-Based and Applied Economics, April 13, 2016, pp. 63-81. https://doi.org/10.13128/BAE-16367.

Annex 5 Further details on sustainable productivity

Annex 5 complements Chapter 4.3 of the guidelines on total indicators in relation to sustainable productivity. It explains the approaches to account for environmental and social impacts into a productivity assessment, using a modelling framework. It consists of three parts.

Annex 5.1 offers a definition of the production technology that takes into account both the environmental and the social dimensions.

Annex 5.2 presents an overview of the approaches incorporating environmental impacts into traditional production theory (description of single-equation and multi-equation frameworks).

Annex 5.3 goes further to present possible methods for measuring sustainable productivity based on the technology modelling of Annex 5.2, including descriptions, data needs, methodological steps, how to read the results and a list of advantages and disadvantages of each method.

Annex 5 is useful for experienced evaluators with technical knowledge, who can obtain more details on formulas that can be used and their differences, as well as data required to better prepare for evaluations of sustainable productivity.

5.1. Definition of the production technology accounting for economic, environmental and social dimensions

A proper measurement of sustainable productivity must account for standard marketed inputs and outputs, as well as non-priced inputs and outputs. Therefore, a new definition of production technology to account for both the environmental and the social dimensions is required.

Moreover, the technology representation can also be expanded to account for flows in all types of capital. For instance, in the case of natural capital, resource depletion can be explicitly included.

A certain number of standard properties are assumed for the production technology [77]. Nevertheless, additional properties will be provided depending on how some outputs, especially bad/undesirable outputs, are considered. To this aim, we define the concepts of rival and joint outputs [78].

Rival outputs are such that a given amount of input is allocated to produce them. Therefore, given that the inputs are divided among the outputs, the relation between rival outputs is negative. Consider, for instance, a crop farm that produces wheat and barley. If, for example, some of the inputs (land, fertilisers, labour, etc.) are diverted towards producing more wheat, then fewer inputs are available for producing barley, so its production level will therefore decrease.

Joint outputs imply that the same amount of inputs is available for all the outputs. This means that inputs are not allocated to producing one output to the detriment of the other. Therefore, there is a positive correlation between outputs in this category. This assumption is usually assumed when modelling by-products or pollution in the technology. This assumption is at the core of several **models of pollution-generating technologies** and is believed to be in line with the **materials balance principle** [79] – thermodynamics law [80]. Consider the case of methane emission from enteric fermentation. Animals are used to produce milk, but they also generate methane from their biological processes. Therefore, animals (herd size) simultaneously generate milk and CH_4. In this case, milk production and CH_4 are positively correlated.

Based on the previous definitions, for any farm, the undesirable outputs are joint with the economic outputs. Moreover, all the good outputs are rivals (economic, social and good environmental outputs). However, diversion from the latter assumption can be observed in practice e.g. animal welfare [81]. In the case of animal welfare, at extremely low levels, animals endure significant suffering (e.g. due to inadequate space, care, feed and veterinary services), leading to poor economic performance (e.g. due to sickness and high mortality). As animal welfare improves, the benefits of increased output (e.g. higher growth rates, better reproduction and lower mortality) outweigh the costs of increased inputs (e.g. more space, better care, improved veterinary services), resulting in enhanced economic performance up to a maximum point. This example shows a positive relationship between animal welfare and economic outputs. It does not assume any relation between the social and the good environmental outputs with the desirable outputs. Many of these relations can be tested empirically.

The most notable difference between the different output types comes from the jointness of the undesirable outputs with the economic outputs. Therefore, in the following sub-section, an overview is presented of the approaches incorporating environmental impacts into traditional production theory [82].

77 Färe, R., and Grosskopf, S., *Intertemporal Production Frontiers: With Dynamic DEA*, Springer Netherlands, Dordrecht, 1996. https://doi.org/10.1007/978-94-009-1816-0.
78 Murty, S., and Russell, R.R., *Bad Outputs*, in S.C. Ray, R. Chambers, and S. Kumbhakar (eds.), Handbook of Production Economics, Springer Singapore, Singapore, 2020, pp. 1-53. https://doi.org/10.1007/978-981-10-3450-3_3-1.
79 The materials balance principle is a fundamental concept in environmental economics and industrial ecology. It states that for any production process, the mass of inputs must equal the mass of outputs, considering both products and waste. This principle is rooted in the law of conservation of mass, which asserts that matter cannot be created or destroyed in an isolated system.
80 Dakpo, K.H., Jeanneaux, P., and Latruffe, L., *Modelling Pollution-Generating Technologies in Performance Benchmarking: Recent Developments, Limits and Future Prospects in the Nonparametric Framework*, European Journal of Operational Research, Vol. 250, N° 2, 2016, pp. 347-359. https://doi.org/10.1016/j.ejor.2015.07.024.
81 Henningsen, A., Czekaj, T.G., Forkman, B., Lund, M., and Nielsen, A.S., *The Relationship between Animal Welfare and Economic Performance at Farm Level: A Quantitative Study of Danish Pig Producers*, Journal of Agricultural Economics, Vol. 69, N° 1, February 2018, pp. 142-162. https://doi.org/10.1111/1477-9552.12228.
82 Zhou, P., Ang, B.W., and Poh, K.L., *A Survey of Data Envelopment Analysis in Energy and Environmental Studies*, European Journal of Operational Research, Vol. 189, N° 1, August 2008, pp. 1-18. https://doi.org/10.1016/j.ejor.2007.04.042.

5.2. Review of approaches for modelling pollution-generating technologies

There are two prominent families of pollution-generating technologies modelling. The first family is the **single-equation framework** and the second is the **multi-equation framework**. The single equation representation contains the most popular approaches for including undesirable outputs in the production technology, namely treating by-products as an additional input or undesirable output variable under the famous **weak disposability assumption (WDA)** (see definition below). Because of the assumption of undesirable outputs being joint outputs to the economic ones, models that treat these by-products as standard output (then rival) are excluded from this review. As underlined by Førsund [83], under this rivalry property, in addition to the counterintuitive trade-off between bad outputs and economic outputs – which can only be increased (decreased) by decreasing (increasing) bads for a constant level of inputs – all inputs can be allocated to the production of all the other outputs, and the level of bad outputs will simply be zero, without any additional costs.

5.2.1. Single-equation framework

› **Treating by-products as input**

Under this approach, the positive correlation between by-products and economic outputs is maintained. Moreover, for the advocates of this approach, reducing by-products "requires the diversion of inputs from the production of desirable outputs, for abatement purposes; i.e. it requires the use of additional inputs or sacrifice of desirable outputs. Therefore, pollutants can essentially be treated as inputs into the production process" [84]. There exists a plethora of studies that treat by-products as input [85].

› **Treating by-products as output under the WDA**

The WDA implies that any reduction in the level of the by-products must also be accompanied by a decrease in the level of the economic outputs; therefore, reducing by-products is costly [86]. Like in the case where by-products are treated as input, the WDA approach has met considerable success in the literature [87].

Despite their appealing nature, both above approaches have severe limitations regarding relations between the different variables involved in the production process, violating basic properties of the materials balance principle. For instance, in the model where by-products are treated as input, there is a counterintuitive negative relation between by-products and inputs that generate them. The WDA also generates inconsistent trade-offs between by-products and inputs/economic outputs [88].

Within the single-equation family, a branch of approaches redefined the production technology to measure **eco-efficiency** (frontier eco-efficiency models as classified by Lauwers) [89]. The idea of these new models is to relate indicators of environmental pressures to economic values (e.g. value-added) [90]. Eco-efficiency is examined through the ratio of the economic value of goods and services produced to environmental pressures. An example of such a ratio at the macro level is GDP per CO_2 emissions. As such, the eco-efficiency is related to the decoupling index [91]. An advantage of this approach is that it does not require data on inputs. This could also be considered a limit of the approach as it does not show how by-products are generated nor how inputs like natural capital contribute to the economic outputs [92].

83 Førsund, F.R., *Multi-Equation Modelling of Desirable and Undesirable Outputs Satisfying the Materials Balance*, Empirical Economics, Vol. 54, N° 1, February 2018, pp. 67-99. https://doi.org/10.1007/s00181-016-1219-9.

84 Hailu, A., and Veeman, T.S., *Non-Parametric Productivity Analysis with Undesirable Outputs: An Application to the Canadian Pulp and Paper Industry*, American Journal of Agricultural Economics, Vol. 83, N° 3, 2001, pp. 605-616. https://doi.org/10.1111/0002-9092.00181.

85 Cropper, M.L., and Oates, W.E., *Environmental Economics: A Survey*, Journal of Economic Literature, Vol. 30, N° 2, 1992, pp. 675-740. https://www.jstor.org/stable/2727701; Pittman, R.W., *Issue in Pollution Control: Interplant Cost Differences and Economies of Scale*, Land Economics, Vol. 57, N° 1, February 1981. https://doi.org/10.2307/3145748; Reinhard, S., Lovell, C.A.K., and Thijssen, G., *Econometric Estimation of Technical and Environmental Efficiency: An Application to Dutch Dairy Farms*, American Journal of Agricultural Economics, Vol. 81, N° 1, February 1999, pp. 44-60. https://doi.org/10.2307/1244449.

86 Färe, R., and S. Grosskopf, *A Comment on Weak Disposability in Nonparametric Production Analysis*, *American Journal of Agricultural Economics*, Vol. 91, N° 2, 2009, pp. 535-538; and Kuosmanen, T., *Weak Disposability in Nonparametric Production Analysis with Undesirable Outputs*, American Journal of Agricultural Economics, Vol. 87, N° 4, 2005, pp. 1077-1082. https://doi.org/10.1111/j.1467-8276.2005.00788.x.

87 Pham, M.D., and Zelenyuk, V., *Weak Disposability in Nonparametric Production Analysis: A New Taxonomy of Reference Technology Sets*, European Journal of Operational Research, Vol. 274, N° 1, April 2019, pp. 186-198. https://doi.org/10.1016/j.ejor.2018.09.019; Piot-Lepetit, I., Vermersch, D., *Pricing Organic Nitrogen Under The Weak Disposability Assumption: An Application to the French Pig Sector*, Journal of Agricultural Economics, Vol. 49, N° 1, March 1998, pp. 85-99. https://doi.org/10.1111/j.1477-9552.1998.tb01253.x; Roshdi, I., Hasannasab, M., Margaritis, D., and Rouse, P., *Generalised Weak Disposability and Efficiency Measurement in Environmental Technologies*, European Journal of Operational Research, Vol. 266, N° 3, May 2018, pp. 1000-1012. https://doi.org/10.1016/j.ejor.2017.10.033; and Yang et al. (2010).

88 See footnote 80 for Dakpo et al. (2016) for an extensive discussion of the limits of the WDA in the case of DEA.

89 Lauwers, L., *Justifying the Incorporation of the Materials Balance Principle into Frontier-Based Eco-Efficiency Models*, Ecological Economics, Vol. 68, N° 6, April 2009, pp. 1605-1614. https://doi.org/10.1016/j.ecolecon.2008.08.022.

90 Kuosmanen, T., and Kortelainen, M., *Measuring Eco-efficiency of Production with Data Envelopment Analysis*, Journal of Industrial Ecology, Vol. 9, N° 4, October 2005, pp. 59-72. https://doi.org/10.1162/108819805775247846; Kuosmanen, T., *Measurement and Analysis of Eco-efficiency: An Economist's Perspective*, Journal of Industrial Ecology, Vol. 9, N° 4, February 2008, pp. 15-18. https://doi.org/10.1162/108819805775248025.

91 Generally speaking, the decoupling index quantifies the extent to which economic growth is separated from environmental pressure. It indicates how effectively an economy can increase its output or income while reducing the negative environmental impacts associated with that growth.

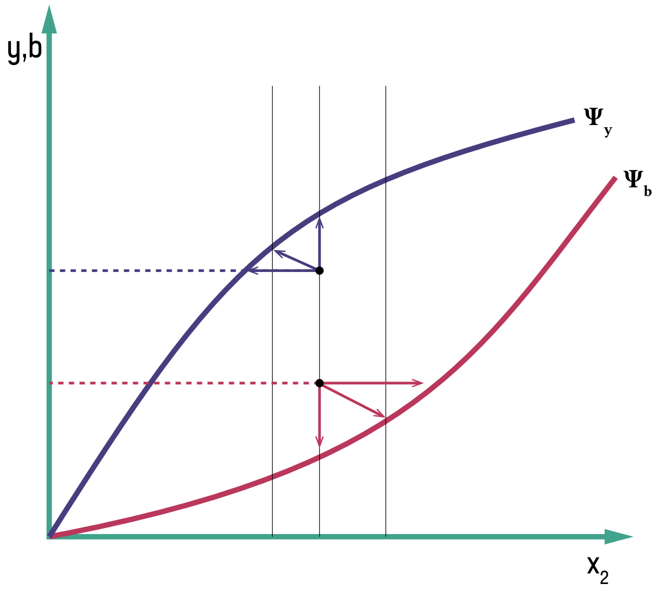
92 Applications of the eco-efficiency models can be found in: Baráth, L., Bakucs, Z., Benedek, Z., Fertő, I., Nagy, Z., Vígh, E., Debrenti, E., and Fogarasi, J., *Does Participation in Agri-Environmental Schemes Increase Eco-Efficiency?*, Science of The Total Environment, Vol. 906, January 2024. https://doi.org/10.1016/j.scitotenv.2023.167518; Eder, A., Salhofer, K., and Scheichel, E., *Land Tenure, Soil Conservation, and Farm Performance: An Eco-Efficiency Analysis of Austrian Crop Farms*, Ecological Economics, Vol. 180, February 2021. https://doi.org/10.1016/j.ecolecon.2020.106861; Kortelainen, M., *Dynamic Environmental Performance Analysis: A Malmquist Index Approach*, Ecological Economics, Vol. 64, N° 4, February 2008, pp. 701-715. https://doi.org/10.1016/j.ecolecon.2007.08.001; Picazo-Tadeo, A.J., Gómez-Limón, J.A., and Reig-Martínez, E., *Assessing Farming Eco-Efficiency: A Data Envelopment Analysis Approach*, Journal of Environmental Management, Vol. 92, N° 4, April 2011, pp. 1154-1164. https://doi.org/10.1016/j.jenvman.2010.11.025; Picazo-Tadeo, A.J., Beltrán-Esteve, M., and Gómez-Limón, J.A., *Assessing Eco-Efficiency with Directional Distance Functions*, European Journal of Operational Research, Vol. 220, N° 3, August 2012, pp. 798-809. https://doi.org/10.1016/j.ejor.2012.02.025; and Picazo-Tadeo, A.J., Castillo-Giménez, J., and Beltrán-Esteve, M., *An Intertemporal Approach to Measuring Environmental Performance with Directional Distance Functions: Greenhouse Gas Emissions in the European Union*, Ecological Economics, Vol. 100, April 2014, pp. 173-182. https://doi.org/10.1016/j.ecolecon.2014.02.004.

5.2.2. Multi-equation framework

Recently, an alternative approach that overcomes the limits of the single-equation framework has been suggested by Førsund and Murty et al. [93], where the 'by-production' is a multi-equation framework. The philosophy of this approach goes beyond the standard single relation to represent technologies by assuming multiple relations. In the simple case, one relation describes the production of the economic outputs, and a second relation describes the mechanisms of pollution generation. For the operationalisation of this approach, inputs are split into two categories: those that do not generate by-products (service inputs) and those that do (materials inputs).

Here, the **by-production representation** of the technology implies that the overall technology lies at the intersection of two sub-technologies: one for the good outputs and the other for the bad outputs.

Figure 2. The by-production representation



Source: adapted from Dakpo et al. (2017) 94

In this representation, we assume that natural and social capital do not generate any by-products (other assumptions can be imposed). Moreover, the model can be generalised to more than two sub-technologies. Nevertheless, this requires a good knowledge of the systems being represented/evaluated.

Several studies considered the by-production approach auspicious for modelling pollution-generating technologies by providing proper trade-offs between variables and being compatible with the materials balance principle [95]. In addition, by-production is getting widely used in many empirical applications [96]. A practical challenge with the by-production approach is rigorously separating inputs into polluting and non-polluting categories, which requires a thorough understanding of the production technology and the methods used to obtain environmental variables.

A somewhat transversal family of approaches directly uses the materials balance principle (MBP). The MBP is based on the first law of thermodynamics related to the mass conservation. In other words, the total mass in inputs must equal the mass of the desirable outputs plus the residuals (by-products) mass. Based on this definition, the MBP overlooks non-material inputs/outputs.

It is worth noting that for non-material outputs (social outputs), their mass contents equal zero. The MBP fits the nutrient balance examination [97]. The first advantage of the MBP is that it is neither an input nor an output, and its implementation does not require the introduction of extra variables (by-products *z*) in the modelling of the technology. Therefore, the positive correlation (jointness property) between by-products and economic outputs, which is at the core of all the previous approaches, is avoided here. By-products are reduced by minimising the balance equation. It operates similarly as **a cost minimisation objective (iso-cost lines), estimating iso-environmental lines** as in the next figure.

93 Førsund, F.R., *Good Modelling of Bad Outputs: Pollution and Multiple-Output Production*, International Review of Environmental and Resource Economics, Vol. 3, N° 1, August 13, 2009, pp. 1-38. http://dx.doi.org/10.1561/101.00000021; and Murty, S., Russell, R.R., and Levkoff, S.B., *On Modeling Pollution-Generating Technologies*, Journal of Environmental Economics and Management, Vol. 64, N° 1, July 2012, pp. 117-135. https://doi.org/10.1016/j.jeem.2012.02.005.

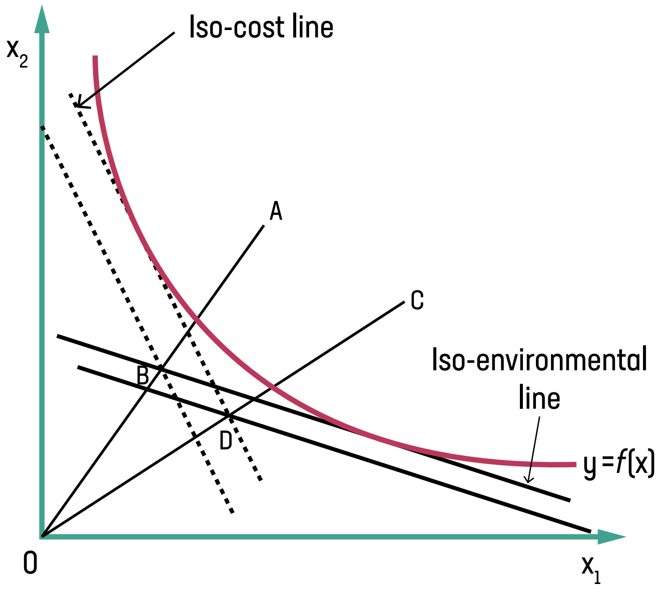
94 Dakpo, K.H., Jeanneaux, P., and Latruffe, L., *Greenhouse Gas Emissions and Efficiency in French Sheep Meat Farming: A Non-Parametric Framework of Pollution-Adjusted Technologies*, European Review of Agricultural Economics, Vol. 44, N° 1, February 2017, pp. 33-65. https://doi.org/10.1093/erae/jbw013.

95 Dakpo, (2016) ; Dakpo, K.H., and Ang, F., *Modelling Environmental Adjustments of Production Technologies: A Literature Review: Externalities and Environmental Studies*, in T. Ten Raa and W.H. Greene (eds.), The Palgrave Handbook of Economic Performance Analysis, Springer International Publishing, Cham, 2019, pp. 601-657. https://doi.org/10.1007/978-3-030-23727-1_16; and Førsund, F.R., *Performance Measurement and Joint Production of Intended and Unintended Outputs*, Journal of Productivity Analysis, Vol. 55, N° 3, June 2021, pp. 157-175. https://doi.org/10.1007/s11123-021-00599-9.

96 Dakpo et al., (2017) and Ait Sidhoum, A., Mennig, P., and Sauer, J., *Do Agri-Environment Measures Help Improve Environmental and Economic Efficiency? Evidence from Bavarian Dairy Farmers*, European Review of Agricultural Economics, Vol. 50, N° 3, June 13, 2023, pp. 918-953. https://doi.org/10.1093/erae/jbad007; Ang, F., Kerstens, K., and Sadeghi, J., *Energy Productivity and Greenhouse Gas Emission Intensity in Dutch Dairy Farms: A Hicks-Moorsteen By-production Approach under Non-convexity and Convexity with Equivalence Results*, Journal of Agricultural Economics, Vol. 74, N° 2, June 2023, pp. 492-509. https://doi.org/10.1111/1477-9552.12511; Baležentis, T., Blancard, S., Shen, Z., and Štreimikienė, D., *Analysis of Environmental Total Factor Productivity Evolution in European Agricultural Sector*, Decision Sciences, Vol. 52, N° 2, April 2021, pp. 483-511. https://doi.org/10.1111/deci.12421; Chambers, R.G., Serra, T., and Lansink, A.O., *On the Pricing of Undesirable State-Contingent Outputs*, European Review of Agricultural Economics, Vol. 41, N° 3, July 1, 2014, pp. 485-509. https://doi.org/10.1093/erae/jbu018; Dakpo, K.H., and Lansink, A.O., *Dynamic Pollution-Adjusted Inefficiency under the by-Production of Bad Outputs*, European Journal of Operational Research, Vol. 276, N° 1, 2019, pp. 202-211. https://doi.org/10.1016/j.ejor.2018.12.040; and Meng, Y., Shen, Z., Štreimikienė, D., Baležentis, T., Wang, S., and Zhang, Y., *Investigating the Impact of Agricultural Informatization on the Carbon Shadow Price*, Journal of Cleaner Production, Vol. 445, March 2024. https://doi.org/10.1016/j.jclepro.2024.141330.

97 Coelli et al. (2007); and Hoang, V.-N., and Alauddin, M., *Input-Orientated Data Envelopment Analysis Framework for Measuring and Decomposing Economic, Environmental and Ecological Efficiency: An Application to OECD Agriculture*, Environmental and Resource Economics, Vol. 51, N° 3, March 2012, pp. 431-452. https://doi.org/10.1007/s10640-011-9506-6.

Figure 3. Iso-cost and iso-environmental lines



Source: adapted from Coelli et al. (2007)

A second advantage of the MBP is that it does not exclude situations where minimising by-products might also be cost-reducing, reflecting a win-win strategy [98]. The MBP approach has its limitations. It primarily concentrates on material inputs, neglecting any potential interactions between material and non-material inputs. Consequently, this method may classify DMUs that use minimal material inputs as environmentally efficient (minimum level of undesirable outputs), even if they heavily depend on non-material inputs [99]. In addition, one can add the lack of universally accepted weights for different material inputs and multiple by-products [100]. Since the mass balance equation is an accounting identity, it does not explicitly show how by-products are generated. Finally, a recent extension of the MBP approach to the dynamic framework has been proposed by Kuosmanen and Kuosmanen [101], who suggested considering stocks rather than flows, the same way capital stocks fluctuate with (dis)investment flows.

Several empirical studies have also applied and extended the materials balance approach for environmental analysis in the agricultural sector [102].

98 Porter, M.E., Linde, C.V.D., *Toward a New Conception of the Environment-Competitiveness Relationship*, Journal of Economic Perspectives, Vol. 9, N° 4, November 1, 1995, pp. 97-118. https://www.jstor.org/stable/2138392.

99 Dakpo et al., (2016); and Ebert, U., and Welsch, H., *Environmental Emissions and Production Economics: Implications of the Materials Balance*, American Journal of Agricultural Economics, Vol. 89, N° 2, May 2007, pp. 287-293. https://doi.org/10.1111/j.1467-8276.2007.00997.x.

100 Hoang, V.-N., and Rao, D.S.P., *Measuring and Decomposing Sustainable Efficiency in Agricultural Production: A Cumulative Exergy Balance Approach*, Ecological Economics, Vol. 69, N° 9, July 2010, pp. 1765-1776. https://doi.org/10.1016/j.ecolecon.2010.04.014.

101 Kuosmanen, N., and Kuosmanen, T., *Modeling Cumulative Effects of Nutrient Surpluses in Agriculture: A Dynamic Approach to Material Balance Accounting*, Ecological Economics, Vol. 90, June 2013, pp. 159-167. https://doi.org/10.1016/j.ecolecon.2013.03.016.

102 These include: Aldanondo-Ochoa, A.M., Casasnovas-Oliva, V.L., and Almansa-Sáez, M.C., *Cross-Constrained Measuring the Cost-Environment Efficiency in Material Balance Based Frontier Models*, Ecological Economics, Vol. 142, December 2017, pp. 46-55. https://doi.org/10.1016/j.ecolecon.2017.06.006; Guesmi, B., and Serra, T., *Can We Improve Farm Performance? The Determinants of Farm Technical and Environmental Efficiency*, Applied Economic Perspectives and Policy, Vol. 37, N° 4, December 2015, pp. 692-717. https://doi.org/10.1093/aepp/ppv004; Hoang, V.-N., and Alauddin, M., *Assessing the Eco-Environmental Performance of Agricultural Production in OECD Countries: The Use of Nitrogen Flows and Balance*, Nutrient Cycling in Agroecosystems, Vol. 87, N° 3, July 2010, pp. 353-368. https://doi.org/10.1007/s10705-010-9343-y; Hoang, V.-N., A *Frontier Functions Approach to Optimal Scales of Sustainable Production*, Environment and Development Economics, Vol. 19, N° 5, 2014, pp. 566-584. https://doi.org/10.1017/S1355770X14000023; Hoang, V.-N., and Coelli, T., *Measurement of Agricultural Total Factor Productivity Growth Incorporating Environmental Factors: A Nutrients Balance Approach*, Journal of Environmental Economics and Management, Vol. 62, N° 3, November 2011, pp. 462-474. https://doi.org/10.1016/j.jeem.2011.05.009; Hoang, V.-N., and Nguyen, T.T., *Analysis of Environmental Efficiency Variations: A Nutrient Balance Approach*, Ecological Economics, Vol. 86, February 2013, pp. 37-46. https://doi.org/10.1016/j.ecolecon.2012.10.014; and Trang, N.T., Tu, V.H., Son, L.T., and Son, N.P., *Is Super-Intensive Shrimp Farming More Environmentally Friendly? An Application of Material Balance Principle in the Mekong Delta*, Environment, Development and Sustainability, Vol. 25, N° 3, March 2023, pp. 2670-2687. https://doi.org/10.1007/s10668-022-02156-2.

5.3. Approaches for measuring sustainable TFP

We present here some possible methods for measuring sustainable productivity, based on technology modelling explained in the previous section.

5.3.1. Eco-productivity indices

Description

The eco-productivity index, which, by extension, is also called the decoupling index, is defined as the ratio of aggregated economic, environmental and social outputs (desirable outputs) to the aggregated value of by-products. It allows comparisons between farms and between different periods.

This ratio is defined similarly to the traditional TFP, which is the ratio of an output index to an input index. Therefore, several methods can be used to estimate the eco-productivity index, similar to the estimation of TFP.

- If price information is available for all the outputs, price-based indices like Laspeyres, Paasche, Fisher, Lowe, and Geometric Young can be used.
- If price information is not available for non-marketed outputs, estimation techniques can be used to compute the index, such as:
  - The Malmquist index suggested by Kortelainen [103] to measure eco-productivity. It also allows for some economically meaningful productivity decompositions, most notably into separate measures of efficiency change and technical change.
  - The Hicks-Moorsteen index using DEA models suggested by O'Donnell [104]. It is an improvement of the Malmquist index which lacks multiplicative completeness (ratio of an output to an input).
  - A range of indices suggested by O'Donnell [105], that allow comparison in time and space and satisfy the transitivity property, which implies that comparisons between two observations do not change when they are compared indirectly via a third one [106]. They are an improvement of the Malmquist and the Hicks-Moorsteen indices, which do not satisfy the transitivity property.

Data sources and requirements

The estimation of the eco-productivity index requires information on outputs for all the three dimensions of sustainability: economic, environmental and social. No input information is necessary for computing this index. In addition to this, the requirements are similar to the case of the traditional TFP indices measure.

Methodological steps

We define the eco-productivity index that compares, for instance, farm i in period t to farm k in period s as:

$$ECO\,(y_{it},\, b_{it},\, y_{ks},\, b_{ks}) = \frac{GI(y_{it},\, y_{ks})}{BI(b_{it},\, b_{ks})}$$

This ratio is similar to traditional TFP, which is the ratio of an output index to an input index. However, in this case, the output index represents good outputs (GI), while the input index represents bad outputs (BI). Therefore, several methods can be used to estimate the eco-productivity index, similar to the estimation of TFP. If price information is available for all the outputs, price-based indices like Laspeyres, Paasche, Fischer, Lowe, and Geometric Young can be used. Unfortunately, these prices are generally unavailable for social outputs and by-products. In the literature, only the economic output is considered in the numerator of the eco-productivity index but the index can take on the philosophy of the standard eco-productivity index by linking three output types: economic, environmental and social. One might even call it the eco-socio-productivity index. It is worth noting that, rigorously speaking, the eco-socio-productivity index is not a TFP index, as inputs are not considered in its estimation. Nevertheless, it provides crucial insights into how the three output types are related.

As price information is unavailable for non-marketed outputs, estimation techniques can be used to compute the index. Regarding eco-productivity, Kortelainen [107] suggested using the Malmquist index. The Malmquist index is based on Shephard's distance functions. These distance functions can be estimated using the non-parametric DEA or the parametric SFA. The Malmquist index also allows for some economically meaningful productivity decompositions, most notably into separate measures of efficiency change and technical change. However, O'Donnell [108] criticised the Malmquist index for its lack of multiplicative completeness (ratio of an output to an input) and suggested the Hicks-Moorsteen index estimated using DEA models. Nor does the Malmquist nor the Hicks-Moorsteen index satisfy the transitivity property, which implies that comparisons between two observations do not change when they are compared indirectly via a third one. Therefore, O'Donnell [109] discussed a new range of indices that allow comparison in time and space without violating the transitivity property. These indices can be additive or multiplicative using fixed weights (shadow prices, shadow value shares) or based on the benefit-of-the-doubt, which uses variable weights while still satisfying the transitivity property.

103 See footnote 92 for Kortelainen (2008).
104 O'Donnell, C.J., *Measuring and Decomposing Agricultural Productivity and Profitability Change**, Australian Journal of Agricultural and Resource Economics, Vol. 54, N° 4, October 2010, pp. 527-560. https://doi.org/10.1111/j.1467-8489.2010.00512.x.
105 O'Donnell, C.J., *Productivity and Efficiency Analysis: An Economic Approach to Measuring and Explaining Managerial Performance*, Springer Singapore, Singapore, 2018. https://doi.org/10.1007/978-981-13-2984-5.
106 O'Donnell, C.J., *Nonparametric Estimates of the Components of Productivity and Profitability Change in U.S. Agriculture*, American Journal of Agricultural Economics, Vol. 94, N° 4, July 2012, pp. 873-890. https://doi.org/10.1093/ajae/aas023.
107 See footnote 92, for Kortelainen (2008).
108 See footnote 104 for O'Donnell (2010).
109 See footnote 105 for O'Donnell (2018).

How to read the results

A value greater than 1 indicates that eco-productivity of farm i in period t has increased compared to farm k in period s, while a value less than 1 indicates a decline in eco-productivity.

Table 12. Advantages and disadvantages

Pros	Cons
Easy to understand In the case where economic and environmental 'bads' are considered, the index can be related to a decoupling index.	**Data requirement** Requires data on prices and quantities of all outputs, which may be challenging for some agricultural products.
Easy to calculate In single-output cases, the eco-productivity is very easy to compute as it does not require any price or weight information.	**Shadow price or weight computation** As market prices are generally not available for environmental outputs, these need to be estimated (shadow prices or weights) using an appropriate representation of the production technology.
Beyond economics This index can be related to a decoupling index, a notion used in climate science.	**Partiality** The eco-productivity index does not involve information on inputs. Therefore, it provides a partial view of the production processes.

Source: EU CAP Network supported by the European Evaluation Helpdesk for the CAP (2025)

5.3.2. Environmentally-adjusted productivity indices

Description

There has been an evolution in the development of productivity indices that take into account environmental performance. This annex offers the technical details for these indices, as well as their limitations that have led to their improvements. Here, the indices are presented in an order which shows their evolution from the simplest to the most advanced/improved.

- The environmentally-adjusted productivity (EAP) index of Färe et al. and Zaim [110]. It is the ratio of a quantity index of desirable outputs and a quantity index of undesirable outputs (by-products).
- A new class of EAP, as suggested by Abad [111], defined as the ratio of a quantity index of desirable outputs and a quantity index of both inputs and undesirable outputs (by-products).
- An alternative version of the Abad productivity index based on the by-production approach, suggested by Dakpo et al. [112]. It is defined as the ratio of a quantity index of desirable outputs and a quantity index of both service inputs and undesirable outputs (by-products), and in this way it overcomes the double accounting of material inputs.
- The sustainable productivity index, or sustainability index (SI) for all inputs and outputs, as recently suggested by O'Donnell and Cobourn et al. [113]. It measures the changes in the volume of rival outputs, the changes in the volume of the by-products, and the changes in the volume of inputs. A novelty of this sustainable TFP index is that it takes into account the preferences of the decision-maker.

110 Färe, R., Grosskopf, S., and Hernandez-Sancho, F., *Environmental Performance: An Index Number Approach*, Resource and Energy Economics, Vol. 26, N° 4, December 2004, pp. 343-352. https://doi.org/10.1016/j.reseneeco.2003.10.003; and Zaim, O., *Measuring Environmental Performance of State Manufacturing through Changes in Pollution Intensities: A DEA Framework*, Ecological Economics, Vol. 48, N° 1, January 2004, pp. 37-47. https://doi.org/10.1016/j.ecolecon.2003.08.003.
111 Abad, A., *An Environmental Generalised Luenberger-Hicks-Moorsteen Productivity Indicator and an Environmental Generalised Hicks-Moorsteen Productivity Index*, Journal of Environmental Management, Vol. 161, September 2015, pp. 325-334. https://doi.org/10.1016/j.jenvman.2015.06.055.
112 Dakpo, K.H., Jeanneaux, P., and Latruffe, L., *Pollution-Adjusted Productivity Changes: Extending the Färe Primont Index with an Illustration with French Suckler Cow Farms*, Environmental Modeling & Assessment, Vol. 24, N° 6, December 1, 2019, pp. 625-639. https://doi.org/10.1007/s10666-019-09656-y.
113 O'Donnell, C., *How to Build Sustainable Productivity Indexes*, CEPA Working Papers Series WP102022, School of Economics, University of Queensland, Australia, 2022. https://ideas.repec.org/p/qld/uqcepa/182.html; and Cobourn, K., O'Donnell, C., Antón, J., Henderson, B., *An Index Theory Based Approach to Measuring the Environmentally Sustainable Productivity of Agriculture*, OECD Food, Agriculture and Fisheries Papers Working Papers, No.213, Paris, 2024. https://doi.org/10.1787/bf68fb78-en.

Data sources and requirements

Computing an environmentally-adjusted TFP requires the most complete set of data. In addition to the requirements of the standard TFP indices, information on non-marketed outputs like 'bads' and social outcomes is necessary.

Methodological steps

Like the eco-productivity index, Färe et al. and Zaim [114] suggested an environmental performance index, which is the ratio of a quantity index of desirable outputs and a quantity index of undesirable outputs (by-products). The main difference between this environmentally-adjusted productivity (EAP) index and the eco-productivity index is that all variables, including inputs, are considered when calculating the EAP indices. Färe et al., in their modelling of the production technology, assumed the WDA for the by-products. The limits of this approach have been extensively discussed in the literature. Nevertheless, the index can be calculated by representing the technology as in the by-production approach. The productivity index EAP can be obtained as:

$$EAP\left(y_{it}, b_{it}, y_{ks}, b_{ks}, y_0, b_0, x_0\right) = \frac{GI\left(y_{it}, y_{ks}, b_0, x_0\right)}{BI\left(b_{it}, b_{ks}, y_0, x_0\right)}$$

where

$$GI(y_{it}, y_{ks}, b_0, x_0) = \frac{D_y(y_{it}, b_0, x_0)}{D_y(y_{ks}, b_0, x_0)}$$

and

$$BI(b_{it}, b_{ks}, y_0, x_0) = \frac{D_b(b_{it}, y_0, x_0)}{D_b(b_{ks}, y_0, x_0)}$$

D_y and D_b are distance functions that can be obtained using the DEA representation of the by-production approach. y_0, b_0, x_0 are given vectors of desirable and undesirable outputs and inputs, respectively. The EAP index satisfies a bunch of index number axioms, including transitivity. As pragmatic as this new index can be, one may still wonder if it is a TFP index, as no index related to the inputs appears in the formulation.

As a solution, Abad [115] suggested a new class of EAP defined as the ratio of a quantity index of desirable outputs and a quantity index of both inputs and undesirable outputs (by-products). The new index can be written as:

$$EAP(y_{it}, b_{it}, x_{it}, y_{ks}, b_{ks}, x_{ks}) = \frac{GI(y_{it}, y_{ks})}{XBI(b_{it}, b_{ks}, x_{it}, x_{ks})}$$

Unfortunately, in that study, the WDA is maintained for the by-products. Dakpo et al. [116] recently suggested an alternative version of this productivity index based on the by-production approach. Moreover, to overcome the double accounting of material inputs, they define the productivity index as the ratio of a quantity index of desirable outputs and a quantity index of both service inputs and undesirable outputs (by-products):

$$\mathrm{EAP}(y_{it}, b_{it}, x_{1,it}, y_{ks}, b_{ks}, x_{1,ks}) = \frac{GI(y_{it}, y_{ks})}{XBI(b_{it}, b_{ks}, x_{1,it}, x_{1,ks})}$$

O'Donnell [117] suggested a sustainability index for all inputs and outputs. The sustainable productivity index, or sustainability index (SI), is defined as:

$$SI(y_{it}, b_{it}, x_{it}, y_{ks}, b_{ks}, x_{ks}) = \frac{[GI(y_{it}, y_{ks})]^{1-\eta}[BI(b_{it}, b_{ks})]^{-\eta}}{XI(x_{it}, x_{ks})}$$

114 See footnote 110 for the full reference on Fare et al. (2004) and Zaim (2004).
115 See footnote 111 for Abad (2015).
116 See footnote 112 for Dakpo et al. (2019).
117 See footnote 113 for O'Donnell (2022).

Where GI is an index that measures the changes in the volume of rival outputs, BI is an index that measures the changes in the volume of the by-products and XI is a volume input index. A novelty of this sustainable TFP index is the inclusion of the (decision-maker's) preference parameter $\eta \in [0,1]$ which gives weight to the by-products index. When $\eta = 0$ the decision-maker ignores the by-products, and the SI collapses to the traditional TFP index. Conversely, when $\eta = 1$ the economic and social outputs are ignored. The weights used to estimate GI, BI and XI can be obtained either as the shadow normalised prices obtained using proper modelling of the technology or by using the benefit-of-doubt approach. The preference parameter η can be econometrically estimated using the equation:

$$\ln GI(y_{it}, y_{ks}) - \ln XI(x_{it}, x_{ks}) = \eta[\ln GI(y_{it}, y_{ks}) + \ln BI(b_{it}, b_{ks})] + e_{itks}$$

How to read the results

A value greater than 1 indicates that the environmentally-adjusted-productivity of farm i in period t has increased compared to farm k in period s, while a value less than 1 indicates a decline in eco-productivity.

Table 13. Advantages and disadvantages

Pros	Cons
Complete picture By considering all variables involved in the production process, the environmentally (and socially) adjusted TFP provides a more complete picture of sustainable productivity.	**Complexity** Requires an adequate modelling of pollution-generating technology. The by-production approach advocated here is based on the estimation of multiple sub-technologies rather than one in the standard approaches.
Policy-maker preferences The sustainable productivity index suggested by O'Donnell [118] allows the inclusion of the policymaker's preferences by choosing the weight given to the 'bad' and the good output indices. This might provide insightful information, especially when comparing different countries.	**Shadow price or weight computation** As market prices are generally unavailable for environmental outputs, these need to be estimated (shadow prices), which adds more complexity to the estimation.

Source: EU CAP Network supported by the European Evaluation Helpdesk for the CAP (2025)

118 Ibid.

Annex 6 Methods for assessing the CAP impact on productivity scores observed

Annex 6 complements Chapter 5 of the guidelines on methods for assessing the CAP impact on sustainable productivity. The different methods recommended are described in detail in this Annex. The description includes a technical explanation (with relevant formulas), methodological steps for implementing each method and examples of application, suggestions for software implementation in carrying out the estimation, as well as the advantages and disadvantages of each method.

Annex 6 is useful for evaluators familiar with advanced methods for assessing CAP impacts.

6.1. Details on propensity score matching

Propensity score matching (PSM) is a counterfactual impact evaluation (CIE) method. PSM is a statistical technique used to estimate the causal effect of a treatment (e.g. a specific CAP intervention) on an outcome (e.g. productivity) by accounting for the non-random assignment of treatments. This method is particularly useful in observational studies where a random assignment is not feasible. PSM aims to create a balanced comparison group that mimics the characteristics of the treatment group, thereby reducing selection bias.

6.1.1. Technical explanation

The propensity score is calculated using a logistic regression model or similar statistical models, where the probability of receiving the treatment is modelled as a function of observed variables. These covariates are characteristics of the DMUs (e.g. regions, individuals) that are believed to influence both the likelihood of receiving the treatment and the outcome of interest. The general form of the logistic regression model for calculating the propensity score is:

$$\text{logit}[P(D=1|X)] = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k$$

Where

- $D(T=1|X)$ is the probability of receiving the treatment given covariates X
- D is the treatment assignment (1 if treated, 0 if not treated)
- $X_1, X_2, \ldots, X_k$ are the covariates
- $\beta_0, \beta_1, \beta_2, \beta_3, \ldots, \beta_k$ are the coefficients

The logit function is the natural log of the odds ratio of receiving the treatment and the model estimates the coefficients β that best predict the probability of treatment assignment based on the covariates. Once the model is estimated, the propensity score for each DMU is the predicted probability of receiving the treatment, calculated by plugging the observed covariates into the model.

When evaluating the CAP's impact, the treatment generally refers to a specific CAP measure and the covariates could include characteristics that influence both the selection into a particular policy mix and the outcomes of interest (e.g. UAA, type of crop produced and fixed capital). Using covariates in propensity score calculations can help account for the non-random assignment of the CAP treatment across farms, allowing the estimation of the causal impact of the CAP measure on the outcomes, while reducing selection bias. The calculated propensity scores are then used in subsequent analyses to adjust for the non-random assignment of the treatment and estimate its causal impact on the outcomes.

Methodological steps for implementing propensity score matching

Define the objective and select units

Clearly define the objective of the study and select the farms (all farms of the sample or specific samples based on the farm's type of farming, altimetric zone, etc.) to be analysed.

Select covariates and collect data

Identify and collect data on covariates that influence both the likelihood of receiving the treatment and the outcome of interest. Common data sources include FADN individual farm data sets, national statistical agencies, and other relevant databases.

Estimate propensity scores

A logistic regression model will be used to estimate the propensity scores. The model should include all relevant covariates. The general form of the logistic regression model is:

$$\text{logit}[P(D=1|X)] = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k$$

Choose a matching algorithm

Select an appropriate matching algorithm to match treated units with control units based on their propensity scores. Common matching methods include the following.

- Nearest neighbour matching (NNM) matches each treated unit to one or more untreated units with the closest propensity score.
- Calliper matching adds a restriction on the maximum allowed distance between the propensity scores of the matched units.
- Radius matching matches all untreated units within a specified radius of the propensity score of a treated unit.
- Kernel matching uses a weighted average of all untreated units to construct the counterfactual outcome for each treated unit.
- Stratification matching divides the range of propensity scores into intervals or strata and estimates the treatment effect within each stratum.
- Optimal full matching forms matched sets that may include multiple treated and untreated units, minimising the total distance across all matches.
- Coarsened exact matching (CEM) temporarily coarsens each observed variable into substantively meaningful groups and then performs exact matching on these coarsened data.

Assess matching quality

Evaluate the quality of the matching by checking the balance of covariates between the treated and control groups. This can be done using standardised bias, balancing property tests, and pseudo R^2 tests.

Estimate treatment effects

To estimate the treatment effects using PSM, calculate the average treatment effect (ATE) and average treatment effect on the treated (ATT) using the following formulas.

- Average treatment effect (ATE)

$$\text{ATE} = \frac{1}{N}\sum_{i=1}^{N}\left(Y_i^{D=1} - Y_i^{D=0}\right)$$

where

1. N is the total number of units (both treated and control)
2. $Y_i^{D=1}$ is the outcome for the treated unit i
3. $Y_i^{D=0}$ is the outcome for the matched control unit i

- Average treatment effect on the treated (ATT)

$$\text{ATT} = \frac{1}{N_D}\sum_{i\in D}\left(Y_i^{D=1} - Y_i^{D=0}\right)$$

where

1. N_D is the number of treated units
2. $Y_i^{D=1}$ is the outcome for the treated units i
3. $Y_i^{D=0}$ is the outcome for the matched control units i

Perform sensitivity analysis

Conduct a sensitivity analysis to assess how robust the estimated treatment effects are to potential hidden biases.

Example of application

In the context of evaluating the impact of CAP measures on TFP, the following steps could be taken.

1. **Objective**: assess the impact of a specific CAP measure on TFP.
2. **Units**: select farms from the FADN database.
3. **Covariates:** include variables such as farm size, type of production, amount of UAA, level of mechanisation and livestock numbers.
4. **Propensity scores**: estimate propensity scores using a logistic regression.
5. **Matching algorithm**: use NMM with a calliper to ensure suitable matches.
6. **Matching quality**: check the balance of covariates between treated and control groups.
7. **Estimate ATE:** calculate the mean TFP for treated farms and the mean TFP for untreated farms. The difference between these means gives the ATE.
8. **Sensitivity analysis**: perform a sensitivity analysis to check the robustness of the results.

6.1.2. Estimation

Software Implementation: Implement the model using statistical software, such as R, Stata or MATLAB. These platforms offer packages and functions specifically designed for PSM (e.g. 'MatchIt' in R, 'psmatch2' in Stata).

6.1.3. Advantages and disadvantages

Table 14. Pros and cons of PSM

Pros	Cons
Reduces selection bias PSM helps reduce selection bias by matching treated units with control units with similar characteristics. This is particularly useful in observational studies where a random assignment is not possible, such as evaluating the impact of CAP interventions on productivity.	**Reliance on observed covariates** PSM can only control for observed covariates. If unobserved or unmeasured variables influence both the treatment assignment and the outcome, then PSM cannot account for these, potentially leading to biased results. This is a significant limitation in studies where not all relevant variables can be observed or measured.
Simplifies analysis PSM simplifies the analysis by creating a matched sample that is balanced on observed covariates. It allows researchers to approximate a randomised controlled trial, making the comparison of treated and control groups more straightforward and focused on the treatment effect.	**Matching quality depends on covariate choice** The success of PSM heavily depends on the choice and quality of covariates used to calculate the propensity score.
Improves causal inference PSM enhances the credibility of causal inference by ensuring that the comparison between treatment and control groups is made on a like-for-like basis. This is crucial when assessing the impact of policy interventions like CAP interventions, where other confounding factors could affect productivity.	**Does not guarantee balance** Achieving balance on all relevant covariates between treated and control groups can be challenging. Inadequate balance can still exist after matching, which might necessitate additional adjustments or more sophisticated matching algorithms, complicating the analysis.
Flexibility in matching PSM offers various matching techniques (e.g. nearest neighbour, calliper matching), allowing researchers to choose the best method for their data structure and research objectives. This flexibility can help achieve a better balance and more precise estimates of treatment effects.	**Loss of data** PSM often leads to a reduction in sample size because it only includes matched units in the analysis. This can result in a loss of valuable data, especially if many units do not find a suitable match, potentially affecting the study's statistical power.
	Complexity in implementation Implementing PSM correctly requires careful consideration of various technical details, such as choosing an appropriate matching algorithm, deciding on the calliper width, and assessing the post-matching balance. These complexities might pose challenges, especially for researchers less familiar with the method.
	Restriction on the applicability It is necessary to have both treated and untreated farms. For example, if the treatment is decoupled payments, then this method cannot be used because the untreated subsample is empty.

Source: EU CAP Network supported by the European Evaluation Helpdesk for the CAP (2025)

6.2. Details on difference-in-difference

Difference-in-difference (DiD) is a quasi-experimental design used to estimate causal relationships in observational studies. It compares the changes in outcomes over time between a treatment group (e.g. farms receiving a specific CAP measure) and a control group (e.g. farms not receiving the measure). The key assumption is that, in the absence of treatment, the average change in the outcome would have been the same for both groups.

6.2.1. Technical Explanation

The DiD estimator can be formally expressed as:

$$\text{DiD} = (\bar{Y}_{D=1,post} - \bar{Y}_{D=1,pre}) - (\bar{Y}_{D=0,post} - \bar{Y}_{D=0,pre})$$

Where

- $\bar{Y}_{D=1,post}$ is the average outcome for the treatment group after the intervention
- $\bar{Y}_{D=1,pre}$ is the average outcome for the treatment group before the intervention
- $\bar{Y}_{D=0,post}$ is the average outcome for the control group after the intervention
- $\bar{Y}_{D=0,pre}$ is the average outcome for the control group before the intervention

In regression form, the DiD model can be specified as

$$Y_{it} = \alpha + \beta_1 \text{Post}_d + \beta_2 \text{Treat}_i + \beta_3 (\text{Post}_d \times \text{Treat}_i) + \epsilon_{it}$$

Where

- Y_{it} is the outcome variable for unit i at time t
- Post_d is a binary indicator equal to 1 if the observation is in the post-treatment period, and 0 otherwise
- Treat_i is a binary indicator equal to 1 if the unit is in the treatment group, and 0 otherwise
- $\text{Post}_d \times \text{Treat}_i$ is the interaction term between the post-treatment period and the treatment group
- β_3 is the DiD estimator, capturing the treatment effect
- ϵ_{it} is the error term

Methodological steps for Implementing DiD

Define the objective and select units

- Objective: clearly define the objective of the study, such as assessing the impact of a specific CAP measure on farm productivity.
- Select units: identify the farms to be analysed, ensuring a clear distinction between the treatment group (farms receiving the CAP measure) and the control group (farms not receiving the measure).

Select covariates and collect data

- Identify covariates: identify and collect data on covariates that influence both the likelihood of receiving the treatment and the outcome of interest. Common data sources include FADN individual farm data sets, national statistical agencies, and other relevant databases.
- Data collection: gather data on the outcome variable (e.g. TFP) and covariates for both pre-treatment and post-treatment periods.

Estimate the DiD model

- Specify the model: formulate the DiD model described above, including the interaction term to capture the treatment effect.
- Estimate the model: use statistical software (e.g. R, Stata) to estimate the DiD model. Ensure that the model includes fixed effects to control for time-invariant characteristics of the units.

Estimate treatment effects

- Calculate DiD estimator: calculate the DiD estimator (β_3) to determine the causal impact of the CAP measure on the outcome variable.
- Interpret results: interpret the estimated treatment effect in the context of the study objective.

Perform sensitivity analysis

- Robustness checks: conduct sensitivity analysis to assess the robustness of the estimated treatment effects to potential hidden biases. This may include placebo tests, varying the time periods, or using alternative matching algorithms.

Example of application

- **Objective**: assess the impact of a specific CAP measure on TFP.
- **Units**: select farms from the FADN database.
- **Covariates**: include variables such as farm size, type of production, amount of UAA, level of mechanisation, and livestock numbers.
- **DiD model**: estimate the DiD model using the specified covariates and interaction term.
- **Estimate treatment effect**: calculate the mean TFP for treated farms and the mean TFP for untreated farms. The difference between these means gives the DiD estimator.
- **Sensitivity analysis**: perform a sensitivity analysis to check the robustness of the results.

A specific example of the application of DiD is provided in the main text of the guidelines in Chapter 5 when discussing the method.

6.2.2. Estimation

Software implementation: implement the model using statistical software such as R or Stata. These platforms offer packages and functions specifically designed for DiD (e.g. 'did' and 'fixest' in R, 'diff', 'didregress' and 'xtreg' in Stata).

6.2.3. Advantages and disadvantages

Table 15. Pros and cons of DiD

Pros	Cons
Ability to control for unobserved Confounders DiD is particularly effective in controlling for unobserved confounders that are constant over time. By comparing changes over time between treated and control groups, DiD can isolate the effect of the treatment from other factors that do not vary in the short term.	**Parallel trend assumption** A critical assumption of the DiD method is that, in the absence of treatment, the treated and control groups would have followed parallel paths over time. Violation of this assumption can lead to biased estimates, making it crucial to test for parallel trends before applying DiD.
Utilisation of quasi-experiments DiD is well-suited for exploiting quasi-experiments, where the treatment is not randomly assigned but occurs due to policy changes or other external factors. This makes it a powerful tool for evaluating the impact of policy measures like the Common Agricultural Policy (CAP) on productivity.	**Sensitivity to external shocks** While DiD controls for time-invariant unobserved heterogeneity, it can still be biased by external shocks that differentially affect the treated and control groups during the study period. Identifying and accounting for such shocks can be challenging.
Simplicity and flexibility The DiD approach is relatively straightforward to implement and can be adapted to various data structures and settings. It can handle different types of data and is compatible with both linear and non-linear models.	**Limited to short-term effects** DiD is most effective for evaluating short-term effects, as it assumes that the treatment's impact is captured within the study period. Long-term effects that evolve after the study period may not be accurately estimated.
Robustness to model specification Since DiD focuses on changes over time rather than levels, it is less sensitive to model misspecification. This robustness enhances the reliability of the causal estimates derived from DiD analyses.	**Requirement for data over time** DiD requires data from before and after the treatment for both treated and control groups. In many cases, especially for policy evaluations like those involving CAP interventions, obtaining suitable and comparable longitudinal data can be difficult.
	Difficulty in identifying appropriate control groups For policies like CAP, finding a control group that is unaffected by the policy yet similar in all other respects to the treated group can be challenging. This difficulty can compromise the validity of the DiD estimates.

Source: EU CAP Network supported by the European Evaluation Helpdesk for the CAP (2025)

6.3. Details on ordinary least squares

Ordinary least squares (OLS) belong to the group of correlation static models. The goal of OLS is to assess the level of correlation between a dependent variable and one or more explanatory variables that, in our context, are productivity and level of the considered CAP interventions respectively. OLS is a method for estimating the parameters in a linear regression model by minimising the sum of the squared differences between the observed dependent variable and those predicted by the linear function of the explanatory variables. The OLS estimator is derived under the assumption that the error terms are normally distributed, homoscedastic (constant variance), and uncorrelated.

6.3.1. Technical Explanation

The general form of the OLS regression model is:

$$Y = X\beta + \epsilon$$

Where

- Y is the dependent variable (e.g. productivity)
- X is the matrix of explanatory variables (e.g. CAP measures, farm characteristics)
- β is the vector of coefficients to be estimated
- ϵ is the error term

The OLS estimator for β is given by

$$\hat{\beta} = (X'X)^{-1}X'Y$$

This estimator is obtained by solving the normal equations

$$X'X\hat{\beta} = X'Y$$

Methodological steps for implementing OLS

Define the objective and select units

- Objective: clearly define the objective of the study, such as estimating the impact of specific CAP measures on farm productivity.
- Select units: choose the farms or regions to be analysed. This could involve selecting all farms or specific types of farming only, or particular altimetric zones.

Select covariates and collect data

- Identify covariates: determine the covariates that influence both the likelihood of receiving the CAP treatment and the outcome of interest (e.g. farm size, type of production, amount of UAA, level of mechanisation and livestock numbers).
- Data collection: collect data from sources such as the FADN, national statistical agencies, and other relevant databases.

Estimate the OLS model

- Specify the model: formulate the linear regression model to include the dependent variable (e.g. productivity) and the explanatory variables (e.g. CAP measures, farm characteristics). The model can be specified as:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \dots + \beta_k X_{ki} + \epsilon_i$$

  where Y_i is the productivity of farm i, $X_{1i}, X_{2i}, \dots, X_{ki}$, are the explanatory variables, and ϵ_i is the error term.

- Estimate parameters: use statistical software (e.g. R, Stata, MATLAB) to estimate the parameters β using the OLS method.

Assess model

- Check assumptions: verify the assumptions of the OLS model, including linearity, independence, homoscedasticity and normality of residuals.
- Diagnostic tests: perform diagnostic tests such as the Breusch-Pagan test for heteroscedasticity, the Durbin-Watson test for autocorrelation, and the variance inflation factor (VIF) for multicollinearity.

Estimate treatment effects

- Calculate effects: estimate the treatment effects of CAP measures on productivity by interpreting the coefficients of the CAP-related variables in the regression model.
- Interpret results: analyse the estimated coefficients to understand the magnitude and direction of the impact of CAP measures on farm productivity.

Perform sensitivity analysis

- Robustness checks: conduct sensitivity analyses to assess the robustness of the estimated treatment effects. This may involve using alternative model specifications, different sets of covariates, or different subsamples of the data.

Example of application

- **Objective**: assess the impact of a specific CAP measure on TFP.
- **Units**: select farms from the FADN database.
- **Covariates**: include variables such as farm size, type of production, amount of UAA, level of mechanisation, and livestock numbers.
- **OLS model**: estimate the OLS model using the specified covariates.
- **Estimation**: calculate the correlation between TFP and the CAP measure.
- **Sensitivity analysis:** perform sensitivity analysis to check the robustness of the results.

6.3.2. Estimation

Software Implementation: Implement the model using statistical software such as R or Stata. These platforms offer packages and functions specifically designed for OLS (e.g. 'lm' in R, 'regress' in Stata).

6.3.3. Advantages and disadvantages

Table 16. Pros and cons of OLS

Pros	Cons
Simplicity and ease of use OLS is straightforward to implement and interpret, making it accessible for researchers and policymakers.	**Based on strong assumptions that may not hold** OLS relies heavily on its assumptions. The estimates can be biased and inefficient if these are violated (e.g. non-linearity, heteroscedasticity).
Efficiency under certain conditions When the assumptions of OLS are met (linearity, no multicollinearity, homoscedasticity, and normality of errors), it provides the Best Linear Unbiased Estimator (BLUE), ensuring efficiency.	**Susceptibility to outliers** OLS is sensitive to outliers, which can disproportionately influence the model estimates, leading to misleading results.
Widely available tools OLS can be performed using a wide range of statistical software, making it widely accessible for analysis.	**Limited to linear relationships** OLS is designed for linear relationships. If the true relationship between CAP interventions and productivity is non-linear, OLS may not capture the complexity of the relationship. However, the variables can, under some conditions, be transformed to accommodate non-linear relationships, for example, using squared or polynomial transformation.
Facilitates understanding of relationships By estimating the coefficients of independent variables, OLS helps in understanding the direction and magnitude of the relationship between CAP interventions and productivity.	**Potential for multicollinearity** In cases where independent variables are highly correlated, multicollinearity issues arise. This implies that OLS estimates can become unstable and lead to wrong interpretations of the results.
Good for predictive modelling When the primary interest is in prediction, and the OLS assumptions are reasonably met, it can be a powerful tool for forecasting productivity based on CAP interventions.	**Does not account for endogeneity** OLS cannot inherently address endogeneity issues. This latter arises when independent variables are correlated with the error term. Under this condition, estimates are biased and do not provide useful indications.

Source: EU CAP Network supported by the European Evaluation Helpdesk for the CAP (2025)

6.4. Details on fixed effect

The fixed effect (FE) model is a statistical technique that also belongs to the group of correlation models. It shares some characteristics with the OLS but is more advanced.

FE is used to estimate the impact of variables that vary over time within a DMU (e.g. farm, region) while controlling for time-invariant characteristics of those DMUs. In contrast to OLS, this method can be applied if panel data are available because the same DMUs are observed over multiple time periods.

6.4.1. Technical explanation

The general form of the FE model can be expressed as:

$$Y_{it} = \alpha_i + \beta X_{it} + \gamma_t + \epsilon_{it}$$

Where

- Y_{it} is the dependent variable (e.g. productivity) for DMU i at time t
- α_i represents the DMU-specific fixed effects, capturing time-invariant characteristics of the DMUs
- X_{it} is a vector of explanatory variables (e.g. CAP measures, input usage) that vary over time
- β is the vector of coefficients for the explanatory variables
- γ_t represents time fixed effects, capturing time-specific effects that are common across DMUs
- ϵ_{it} is the error term

The FE model assumes that the DMU-specific effects (α_i) are correlated with the explanatory variables X_{it} , which allows for controlling unobserved heterogeneity that could bias the estimates.

Methodological steps for implementing the FE model

Define the objective and select units

- Clearly define the objective of the study, such as assessing the impact of specific CAP measures on farm productivity.
- Select the units of analysis, which could be individual farms, regions or countries.

Select covariates and collect data

- Identify and collect data on covariates that influence both the likelihood of receiving the CAP treatment and the outcome of interest (e.g. farm size, type of production, input usage).
- Common data sources include FADN individual farm data sets, national statistical agencies, and other relevant databases.

Estimate the FE model

- Specify the FE model, including the dependent variable (e.g. productivity) and explanatory variables (e.g. CAP measures, input usage).
- Use statistical software (e.g. R, Stata) to estimate the model. The general form of the Fixed Effect model is:

$$Y_{it} = \alpha_i + \beta X_{it} + \gamma_t + \epsilon_{it}$$

- Ensure that the model includes DMU-specific fixed effects (α_i) and time fixed effects γ_t to control for unobserved heterogeneity and time-specific effects.

Assess model

- Use diagnostic tests (e.g. Hausman test) to ensure the appropriateness of the fixed effect model over alternative models (e.g. random effect model).

Perform sensitivity analysis:

- Use alternative model specifications and robustness checks to validate the findings.

Example of application

In the context of evaluating the impact of CAP measures on TFP, the following steps could be taken.

- **Objective:** assess the impact of a specific CAP measure on TFP.
- **Units:** select farms from the FADN database.
- **Covariates:** include variables such as farm size, type of production, amount of UAA, level of mechanisation, and livestock numbers.
- **FE model:** estimate the model using the specified covariates and include farm-specific and time fixed effects.
- **Model quality:** check the R2, F-test.
- **Estimation**: calculate the correlation between CAP measure and TFP.
- **Sensitivity analysis**: perform a sensitivity analysis to check the robustness of the results.

6.4.2. Estimation

Software Implementation: Implement the model using statistical software such as R or Stata. These platforms offer packages and functions specifically designed for the fixed effect (e.g. 'plm' in R, 'xtreg' in Stata).

6.4.3. Advantages and disadvantages

Table 17. Pros and cons of panel fixed effects

Pros	Cons
Control for time-invariant characteristics The FE model effectively controls for all time-invariant characteristics of the entities (e.g. farms, regions), which could otherwise make the results biased. This is particularly useful in agricultural economics where unobserved heterogeneity (e.g. soil quality, climate) can significantly influence productivity.	**Exclusion of time-invariant variables** One major limitation of the FE model is that it cannot estimate the effects of time-invariant variables (e.g. geographic characteristics, long-term soil quality) because these are absorbed by the fixed effects. This can be problematic if these variables are important determinants of productivity.
Focus on within-entity variations By focusing on within-entity variations, the FE model isolates the impact of time-varying CAP interventions on productivity, providing a clearer picture of how changes in policy affect productivity over time within the same farm or region.	**Potential bias in small panels** The FE estimator can suffer from bias, especially in small panels (small number of entities or time periods). This bias arises because the model removes time-invariant characteristics by demeaning the data, which can lead to biased estimates if the panel is not sufficiently large.
Reduction of omitted variable bias The FE model reduces the risk of omitted variable bias by controlling for unobserved, time-invariant factors that could correlate with both the independent variables (CAP interventions) and the dependent variable (productivity).	**Loss of degrees of freedom** Including fixed effects for each entity reduces the degrees of freedom, which can be particularly problematic in small samples. This can lead to less precise estimates and wider confidence intervals.
Handling endogeneity FE models can address endogeneity issues by including entity-specific effects, which is crucial when policy measures are not randomly assigned but are influenced by the characteristics of the entities themselves.	**Endogeneity concerns** Endogeneity can arise if the CAP interventions are correlated with unobserved factors that also affect productivity. For example, policy measures might be implemented in response to changes in productivity, leading to reverse causality. Addressing endogeneity often requires instrumental variable techniques, which can be challenging to implement.
	Limited external validity The results of a FE model are based on within-entity variations and may not generalise well to other contexts. This limitation in external validity means that the findings might not be applicable to entities that do not exhibit similar within-entity changes.
	Complexity in interpretation Interpreting the results of an FE model requires careful consideration of the within-entity variations. The coefficients represent the average effect of changes in the independent variables within the same entity over time, net of any time-invariant characteristics. This can be complex and may require additional explanation to policymakers.

Source: EU CAP Network supported by the European Evaluation Helpdesk for the CAP (2025)

6.5. Details on dynamic panel

Dynamic panel data (DPD) is also a correlation model that, in contrast with OLS and FE models, explicitly addresses the dynamic aspects. DPD models are particularly effective for estimating the impact of the CAP on productivity in agricultural economies. These models account for the dynamic nature of agricultural production processes, control for unobserved heterogeneity, and address endogeneity issues. The SYS-GMM estimator is commonly used in this context due to its ability to handle these complexities.

6.5.1. Technical explanation

The general form of a dynamic panel data model can be represented as:

$$y_{it} = \rho y_{it-1} + \beta X_{it} + \alpha_i + \gamma_t + \epsilon_{it}$$

Where:

- y_{it} is the dependent variable (e.g. productivity) for unit i at time t
- y_{it-1} is the lagged dependent variable
- X_{it} is a vector of explanatory variables (e.g. CAP subsidies, farm characteristics)
- α_i represents unobserved individual effects
- γ_t represents time effects
- ϵ_{it} is the error term

The SYS-GMM estimator addresses endogeneity by using lagged values of the dependent variable and other endogenous variables as instruments (see also Annex 1).

Methodological steps for implementing the dynamic panel data model

Define the objective and select units

- Clearly define the objective of the study, which is to estimate the impact of CAP on productivity.
- Select the units of analysis, such as farms from the FADN database.

Select covariates and collect data

- Identify and collect data on covariates that influence both the likelihood of receiving CAP subsidies and productivity outcomes. Common data sources include FADN individual farm data sets, national statistical agencies and other relevant databases.

Estimation

- Use the SYS-GMM estimator to estimate the relationship between productivity and CAP measure(s).

Assess model quality

- Evaluate the quality of the model by checking specification tests for the SYS-GMM model.
- Perform tests for autocorrelation i.e. the Sargan test for the suitability of the instruments and Wald tests for the specification of the model.

Perform sensitivity analysis

- Conduct a sensitivity analysis to assess how robust the estimated treatment effects are to potential hidden biases.

Interpret results

- Interpret the results of the quantitative analyses and their implications in policy terms. This includes understanding the impact of CAP subsidies on productivity and identifying potential areas for policy improvement.

6.5.2. Estimation

Software Implementation: Implement the model using statistical software such as R or Stata. These platforms offer packages and functions specifically designed for dynamic panels (e.g. 'plm' in R, 'xtabond2' in Stata).

6.5.3. Advantages and disadvantages

Table 18. Pros and cons of DPD

Pros	Cons
Addresses endogeneity The dynamic panel system GMM effectively handles endogeneity issues by using lagged values of the variables as instruments, which is crucial when policy measures and productivity may influence each other.	**Complexity** The implementation of SYS-GMM is complex and requires a careful specification of the model, including the selection of appropriate instruments and lag lengths.
Controls for unobserved heterogeneity This method accounts for unobserved individual effects that could make the results biased, ensuring more reliable estimates.	**Instrument proliferation** There is a risk of instrument proliferation, which can overfit the model and lead to biased results. This requires a careful management of the number of instruments used.
Dynamic relationships It captures the dynamic nature of the relationship between productivity and CAP interventions, considering how past values influence current outcomes.	**Assumption sensitivity** The validity of the results in the SYS-GMM dynamic panel estimator hinges on two crucial assumptions: the absence of second-order serial correlation and the validity of the chosen instruments. To ensure the robustness of the findings, these assumptions must be rigorously tested. The robustness of the findings depends on the careful selection and validation of instrumental variables, as well as the thorough testing of the underlying assumptions. A detailed description of the instruments used may also be helpful for replication.
Efficient estimation By combining level and differenced equations, SYS-GMM provides more efficient and consistent estimates compared to the other econometric tools indicated in these guidelines.	**Data requirements** SYS-GMM requires a large panel dataset with sufficient time periods and cross-sectional units to provide reliable estimates, which may not always be available.
Robustness to measurement errors The method is robust for the measurement of errors in the explanatory variables, which is often a concern in agricultural data.	**Interpretation challenges** The results can be difficult to interpret, especially when dealing with multiple lags and complex dynamic relationships.

Source: EU CAP Network supported by the European Evaluation Helpdesk for the CAP (2025)

References

1. Abad, A., *An Environmental Generalised Luenberger-Hicks-Moorsteen Productivity Indicator and an Environmental Generalised Hicks-Moorsteen Productivity Index*, Journal of Environmental Management, Vol. 161, September 2015, pp. 325-334. https://doi.org/10.1016/j.jenvman.2015.06.055.

2. Ackerberg, D., Benkard, C.L., Berry, S., and Pakes, A., *Chapter 63 Econometric Tools for Analyzing Market Outcomes*, Handbook of Econometrics, Vol. 6, Elsevier, 2007, pp. 4171-4276. https://doi.org/10.1016/S1573-4412(07)06063-1.

3. Ackerberg, D.A., *Timing Assumptions and Efficiency: Empirical Evidence in a Production Function Context*, The Journal of Industrial Economics, Vol. 71, Nº 3, September 2023, pp. 644-674. https://doi.org/10.1111/joie.12340.

4. Ackerberg, D.A., Caves, K., and Frazer, G., *Identification Properties of Recent Production Function Estimators*, Econometrica, Vol. 83, Nº 6, 2015, pp. 2411-2451. https://doi.org/10.3982/ECTA13408.

5. Ait Sidhoum, A., Mennig, P., and Sauer, J., *Do Agri-Environment Measures Help Improve Environmental and Economic Efficiency? Evidence from Bavarian Dairy Farmers*, European Review of Agricultural Economics, Vol. 50, Nº 3, June 13, 2023, pp. 918-953. https://doi.org/10.1093/erae/jbad007.

6. Aldanondo-Ochoa, A.M., Casasnovas-Oliva, V.L., and Almansa-Sáez, M.C., *Cross-Constrained Measuring the Cost-Environment Efficiency in Material Balance Based Frontier Models*, Ecological Economics, Vol. 142, December 2017, pp. 46-55. https://doi.org/10.1016/j.ecolecon.2017.06.006.

7. Ang, F., Kerstens, K., and Sadeghi, J., *Energy Productivity and Greenhouse Gas Emission Intensity in Dutch Dairy Farms: A Hicks-Moorsteen By-production Approach under Non-convexity and Convexity with Equivalence Results*, Journal of Agricultural Economics, Vol. 74, Nº 2, June 2023, pp. 492-509. https://doi.org/10.1111/1477-9552.12511.

8. Baldoni, E., and Esposti, R., *Agricultural Productivity in Space: An Econometric Assessment Based on Farm-Level Data*, American Journal of Agricultural Economics, Vol. 103, Nº 4, August 2021, pp. 1525-1544. https://doi.org/10.1111/ajae.12155.

9. Baldoni, E., Coderoni, S., and Esposti, R., *The Complex Farm-Level Relationship between Environmental Performance and Productivity: The Case of Carbon Footprint of Lombardy Farms*, Environmental Science & Policy, Vol. 89, November 2018, pp. 73-82. https://doi.org/10.1016/j.envsci.2018.07.010.

10. Baležentis, T., Blancard, S., Shen, Z., and Štreimikienė, D., *Analysis of Environmental Total Factor Productivity Evolution in European Agricultural Sector*, Decision Sciences, Vol. 52, Nº 2, April 2021, pp. 483-511. https://doi.org/10.1111/deci.12421.

11. Ball, V.E., *Output, Input, and Productivity Measurement in U.S. Agriculture 1948-79*, American Journal of Agricultural Economics, Vol. 67, Nº 3, August 1985, pp. 475-486. https://doi.org/10.2307/1241066.

12. Baráth, L., Bakucs, Z., Benedek, Z., Fertő, I., Nagy, Z., Vígh, E., Debrenti, E., and Fogarasi, J., *Does Participation in Agri-Environmental Schemes Increase Eco-Efficiency?*, Science of The Total Environment, Vol. 906, January 2024. https://doi.org/10.1016/j.scitotenv.2023.167518.

13. Biagini, L., Antonioli, F., and Severini, S., *The Impact of CAP Subsidies on the Productivity of Cereal Farms in Six European Countries: A Historical Perspective (2008-2018)*, Food Policy, Vol. 119, August 2023. https://doi.org/10.1016/j.foodpol.2023.102473.

14. Blundell, R., and Bond, S., *Initial Conditions and Moment Restrictions in Dynamic Panel Data Models*, Journal of Econometrics, Vol. 87, Nº 1, November 1998, pp. 115-143. https://doi.org/10.1016/S0304-4076(98)00009-8.

15. Blundell, R., and Bond, S., *GMM Estimation with Persistent Panel Data: An Application to Production Functions*, Econometric Reviews, Vol. 19, Nº 3, January 2000, pp. 321-340. https://doi.org/10.1080/07474930008800475.

16. Blundell, R., Bond, S., and Meghir, C., *Econometric Models of Company Investment*, in L. Mátyás and P. Sevestre (eds.), The Econometrics of Panel Data, Vol. 28, Springer Netherlands, Dordrecht, 1992, pp. 388-413. https://doi.org/10.1007/978-94-009-0137-7_27.

17. Breunig, R., & Wong, M., *Estimation of total factor productivity. Quantitative Tools for Microeconomic Policy Analysis*, December 2005, pp. 195-214. https://researchportalplus.anu.edu.au/en/publications/estimation-of-total-factor-productivity.

18. Buckley, C., Wall, D.P., Moran, B., and Murphy, P.N.C., *Developing the EU Farm Accountancy Data Network to Derive Indicators around the Sustainable Use of Nitrogen and Phosphorus at Farm Level*, Nutrient Cycling in Agroecosystems, Vol. 102, Nº 3, July 2015, pp. 319-333. https://doi.org/10.1007/s10705-015-9702-9.

19. Buckley, C., Wall, D.P., Moran, B., O'Neill, S., and Murphy, P.N.C., *Farm Gate Level Nitrogen Balance and Use Efficiency Changes Post Implementation of the EU Nitrates Directive*, Nutrient Cycling in Agroecosystems, Vol. 104, Nº 1, January 2016, pp. 1-13. https://doi.org/10.1007/s10705-015-9753-y.

20. Bureau, J. C., & Antón, J., *Agricultural Total Factor Productivity and the environment: A guide to emerging best practices in measurement*, Organisation for Economic Co-operation and Development, 2022. https://doi.org/10.1787/6fe2f9e0-en.

21. Callois, J.-M., and Aubert, F., *Towards Indicators of Social Capital for Regional Development Issues: The Case of French Rural Areas*, Regional Studies, Vol. 41, Nº 6, August 2007, pp. 809-821. https://doi.org/10.1080/00343400601142720.

22. Chamberlain, G., *Multivariate Regression Models for Panel Data*, Journal of Econometrics, Vol. 18, Nº 1, January 1982, pp. 5-46. https://doi.org/10.1016/0304-4076(82)90094-X.

23. Chambers, R.G., Serra, T., and Lansink, A.O., *On the Pricing of Undesirable State-Contingent Outputs*, European Review of Agricultural Economics, Vol. 41, Nº 3, July 1, 2014, pp. 485-509. https://doi.org/10.1093/erae/jbu018.

24. Coelli, T., Lauwers, L., and Van Huylenbroeck, G., *Environmental Efficiency Measurement and the Materials Balance Condition*, Journal of Productivity Analysis, Vol. 28, Nº 1, October 1, 2007, pp. 3-12. https://doi.org/10.1007/s11123-007-0052-8.

25. Cobourn, K., O'Donnell, C., Antón, J., Henderson, B., *An Index Theory Based Approach to Measuring the Environmentally Sustainable Productivity of Agriculture*, OECD Food, Agriculture and Fisheries Papers Working Papers, No.213, Paris, 2024. https://www.oecd.org/en/publications/an-index-theory-based-approach-to-measuring-the-environmentally-sustainable-productivity-performance-of-agriculture_bf68fb78-en.html.

26. Cropper, M.L., and Oates, W.E., *Environmental Economics: A Survey*, Journal of Economic Literature, Vol. 30, Nº 2, 1992, pp. 675-740. https://www.jstor.org/stable/2727701.

27. Dakpo, K.H., and Lansink, A.O., *Dynamic Pollution-Adjusted Inefficiency under the by-Production of Bad Outputs*, European Journal of Operational Research, Vol. 276, Nº 1, 2019, pp. 202-211. https://doi.org/10.1016/j.ejor.2018.12.040.

28. Dakpo, K.H., and Ang, F., *Modelling Environmental Adjustments of Production Technologies: A Literature Review: Externalities and Environmental Studies*, in T. Ten Raa and W.H. Greene (eds.), The Palgrave Handbook of Economic Performance Analysis, Springer International Publishing, Cham, 2019, pp. 601-657. https://doi.org/10.1007/978-3-030-23727-1_16.

29. Dakpo, K.H., Jeanneaux, P., and Latruffe, L., *Greenhouse Gas Emissions and Efficiency in French Sheep Meat Farming: A Non-Parametric Framework of Pollution-Adjusted Technologies*, European Review of Agricultural Economics, Vol. 44, Nº 1, February 2017, pp. 33-65. https://doi.org/10.1093/erae/jbw013.

30. Dakpo, K.H., Jeanneaux, P., and Latruffe, L., *Modelling Pollution-Generating Technologies in Performance Benchmarking: Recent Developments, Limits and Future Prospects in the Nonparametric Framework*, European Journal of Operational Research, Vol. 250, Nº 2, 2016, pp. 347-359. https://doi.org/10.1016/j.ejor.2015.07.024.

31. Dakpo, K.H., Jeanneaux, P., and Latruffe, L., *Pollution-Adjusted Productivity Changes: Extending the Färe-Primont Index with an Illustration with French Suckler Cow Farms*, Environmental Modeling & Assessment, Vol. 24, Nº 6, December 1, 2019, pp. 625-639. https://doi.org/10.1007/s10666-019-09656-y.

32. Del Gatto, M., Di Liberto, A., and Petraglia, C., *MEASURING PRODUCTIVITY*, Journal of Economic Surveys, Vol. 25, Nº 5, December 2011, pp. 952-1008. https://doi.org/10.1111/j.1467-6419.2009.00620.x.

33. Ding, S., Guariglia, A., and Harris, R., *The Determinants of Productivity in Chinese Large and Medium-Sized Industrial Firms, 1998-2007*, Journal of Productivity Analysis, Vol. 45, Nº 2, April 2016, pp. 131-155. https://doi.org/10.1007/s11123-015-0460-0.

34. Dolman, M.A., Sonneveld, M.P.W., Mollenhorst, H., and De Boer, I.J.M., *Benchmarking the Economic, Environmental and Societal Performance of Dutch Dairy Farms Aiming at Internal Recycling of Nutrients*, Journal of Cleaner Production, Vol. 73, June 2014, pp. 245-252. https://doi.org/10.1016/j.jclepro.2014.02.043.

35. Ebert, U., and Welsch, H., *Environmental Emissions and Production Economics: Implications of the Materials Balance*, American Journal of Agricultural Economics, Vol. 89, Nº 2, May 2007, pp. 287-293. https://doi.org/10.1111/j.1467-8276.2007.00997.x.

36. Elmiger, B.N., Finger, R., Ghazoul, J., and Schaub, S., *Biodiversity indicators for result-based agri-environmental schemes - Current state and future prospects*, Agricultural Systems, 204:103538, 2023. https://doi.org/10.1016/j.agsy.2022.103538

37. Eder, A., Salhofer, K., and Scheichel, E., *Land Tenure, Soil Conservation, and Farm Performance: An Eco-Efficiency Analysis of Austrian Crop Farms*, Ecological Economics, Vol. 180, February 2021. https://doi.org/10.1016/j.ecolecon.2020.106861.

38. European Commission, Directorate-General for Internal Market, Industry, Entrepreneurship and SMEs, *Corporate Social Responsibility, Responsible Business Conduct, and Business & Human Rights: Overview of Progress*, Publications Office, 2019. https://ec.europa.eu/docsroom/documents/34482.

39. European Commission, Directorate-General for Research and Innovation, Veerman, C., Pinto Correia, T., Bastioli, C. et al., *Caring for soil is caring for life - Ensure 75% of soils are healthy by 2030 for food, people, nature and climate - Report of the Mission board for Soil health and food*, Publications Office, 2020. https://data.europa.eu/doi/10.2777/821504.

40. FAO and ITPS, *Global soil organic carbon map (gsocmap) technical report, Food and Agriculture Organization of the United Nations*, Rome, 2018. https://www.fao.org/global-soil-partnership/pillars-action/4-information-and-data-new/global-soil-organic-carbon-gsoc-map/en/.

41. Färe, R., and Primont, D., *Multi-Output Production and Duality: Theory and Applications, Springer Netherlands, Dordrecht*, 1995. https://doi.org/10.1007/978-94-011-0651-1.

42. Färe, R., and Grosskopf, S., *Intertemporal Production Frontiers: With Dynamic DEA*, Springer Netherlands, Dordrecht, 1996. https://doi.org/10.1007/978-94-009-1816-0.

43. Färe, R., Grosskopf, S., and Hernandez-Sancho, F., *Environmental Performance: An Index Number Approach*, Resource and Energy Economics, Vol. 26, N° 4, December 2004, pp. 343-352. https://doi.org/10.1016/j.reseneeco.2003.10.003.

44. Färe, R., and Grosskopf, S., *A Comment on Weak Disposability in Nonparametric Production Analysis*, American Journal of Agricultural Economics, Vol. 91, N° 2, 2009, pp. 535-538. https://doi.org/10.1111/j.1467-8276.2008.01237.x.

45. Fleming, A., O'Grady, A.P., Stitzlein, C., Ogilvy, S., Mendham, D., and Harrison, M.T., *Improving Acceptance of Natural Capital Accounting in Land Use Decision Making: Barriers and Opportunities*, Ecological Economics, Vol. 200, October 2022. https://doi.org/10.1016/j.ecolecon.2022.107510.

46. Førsund, F.R., *Multi-Equation Modelling of Desirable and Undesirable Outputs Satisfying the Materials Balance*, Empirical Economics, Vol. 54, N° 1, February 2018, pp. 67-99. https://doi.org/10.1007/s00181-016-1219-9.

47. Førsund, F.R., *Good Modelling of Bad Outputs: Pollution and Multiple-Output Production*, International Review of Environmental and Resource Economics, Vol. 3, N° 1, August 13, 2009, pp. 1-38. http://dx.doi.org/10.1561/101.00000021.

48. Førsund, F.R., *Performance Measurement and Joint Production of Intended and Unintended Outputs*, Journal of Productivity Analysis, Vol. 55, N° 3, June 2021, pp. 157-175. https://doi.org/10.1007/s11123-021-00599-9.

49. Fox, K.J., *Efficiency at Different Levels of Aggregation: Public vs. Private Sector Firms*, Economics Letters, Vol. 65, N° 2, November 1999, pp. 173-176. https://doi.org/10.1016/S0165-1765(99)00147-0.

50. Guesmi, B., and Serra, T., *Can We Improve Farm Performance? The Determinants of Farm Technical and Environmental Efficiency*, Applied Economic Perspectives and Policy, Vol. 37, N° 4, December 2015, pp. 692-717. https://doi.org/10.1093/aepp/ppv004.

51. Hailu, A., and Veeman, T.S., *Non-Parametric Productivity Analysis with Undesirable Outputs: An Application to the Canadian Pulp and Paper Industry*, American Journal of Agricultural Economics, Vol. 83, N° 3, 2001, pp. 605-616. https://doi.org/10.1111/0002-9092.00181.

52. Henderson, B., Lankoski, J., Flynn, E., Sykes, A., Payen, F., MacLeod, M., *Soil Carbon Sequestration by Agriculture: Policy Options*, OECD Publishing, number 174, 2022. https://doi.org/10.1787/63ef3841-en.

53. Henningsen, A., Czekaj, T.G., Forkman, B., Lund, M., and Nielsen, A.S., *The Relationship between Animal Welfare and Economic Performance at Farm Level: A Quantitative Study of Danish Pig Producers*, Journal of Agricultural Economics, Vol. 69, N° 1, February 2018, pp. 142-162. https://doi.org/10.1111/1477-9552.12228.

54. Hoang, V.-N., *A Frontier Functions Approach to Optimal Scales of Sustainable Production*, Environment and Development Economics, Vol. 19, N° 5, 2014, pp. 566-584. https://doi.org/10.1017/S1355770X14000023.

55. Hoang, V.-N., and Rao, D.S.P., *Measuring and Decomposing Sustainable Efficiency in Agricultural Production: A Cumulative Exergy Balance Approach*, Ecological Economics, Vol. 69, N° 9, July 2010, pp. 1765-1776. https://doi.org/10.1016/j.ecolecon.2010.04.014.

56. Hoang, V.-N., and Alauddin, M., *Assessing the Eco-Environmental Performance of Agricultural Production in OECD Countries: The Use of Nitrogen Flows and Balance*, Nutrient Cycling in Agroecosystems, Vol. 87, N° 3, July 2010, pp. 353-368. https://doi.org/10.1007/s10705-010-9343-y.

57. Hoang, V.-N., and Alauddin, M., *Input-Orientated Data Envelopment Analysis Framework for Measuring and Decomposing Economic, Environmental and Ecological Efficiency: An Application to OECD Agriculture*, Environmental and Resource Economics, Vol. 51, N° 3, March 2012, pp. 431-452. https://doi.org/10.1007/s10640-011-9506-6.

58. Hoang, V.-N., and Coelli, T., *Measurement of Agricultural Total Factor Productivity Growth Incorporating Environmental Factors: A Nutrients Balance Approach*, Journal of Environmental Economics and Management, Vol. 62, N° 3, November 2011, pp. 462-474. https://doi.org/10.1016/j.jeem.2011.05.009.

59. Hoang, V.-N., and Nguyen, T.T., *Analysis of Environmental Efficiency Variations: A Nutrient Balance Approach*, Ecological Economics, Vol. 86, February 2013, pp. 37-46. https://doi.org/10.1016/j.ecolecon.2012.10.014.

60. Dillon, E.J., Hennessy, T., Buckley, C., Donnellan, T., Hanrahan, K., Moran, B., and Ryan, M., *Measuring Progress in Agricultural Sustainability to Support Policy-Making*, International Journal of Agricultural Sustainability, Vol. 14, N° 1, January 2, 2016, pp. 31-44. https://doi.org/10.1080/14735903.2015.1012413.

61. Karagiannis, G., *More on the Fox Paradox*, Economics Letters, Vol. 116, N° 3, September 2012, pp. 333-334. https://doi.org/10.1016/j.econlet.2012.04.002.

62. Kortelainen, M., *Dynamic Environmental Performance Analysis: A Malmquist Index Approach*, Ecological Economics, Vol. 64, N° 4, February 2008, pp. 701-715. https://doi.org/10.1016/j.ecolecon.2007.08.001.

63. Kuosmanen, N., and Kuosmanen, T., *Modeling Cumulative Effects of Nutrient Surpluses in Agriculture: A Dynamic Approach to Material Balance Accounting*, Ecological Economics, Vol. 90, June 2013, pp. 159-167. https://doi.org/10.1016/j.ecolecon.2013.03.016.

64. Kuosmanen, T., *Measurement and Analysis of Eco-efficiency: An Economist's Perspective*, Journal of Industrial Ecology, Vol. 9, N° 4, February 2008, pp. 15-18. https://doi.org/10.1162/108819805775248025.

65. Kuosmanen, T., *Weak Disposability in Nonparametric Production Analysis with Undesirable Outputs*, American Journal of Agricultural Economics, Vol. 87, N° 4, 2005, pp. 1077-1082. https://doi.org/10.1111/j.1467-8276.2005.00788.x.

66. Kuosmanen, T., and Kortelainen, M., *Measuring Eco-efficiency of Production with Data Envelopment Analysis*, Journal of Industrial Ecology, Vol. 9, N° 4, October 2005, pp. 59-72. https://doi.org/10.1162/108819805775247846.

67. Lamkowsky, M., Oenema, O., Meuwissen, M.P.M., and Ang, F., *Closing Productivity Gaps among Dutch Dairy Farms Can Boost Profit and Reduce Nitrogen Pollution*, Environmental Research Letters, Vol. 16, N° 12, December 1, 2021. https://research.wur.nl/en/publications/closing-productivity-gaps-among-dutch-dairy-farms-can-boost-profi.

68. Lauwers, L., *Justifying the Incorporation of the Materials Balance Principle into Frontier-Based Eco-Efficiency Models*, Ecological Economics, Vol. 68, N° 6, April 2009, pp. 1605-1614. https://doi.org/10.1016/j.ecolecon.2008.08.022.

69. Lebacq, T., Baret, P.V., and Stilmant, D., *Sustainability Indicators for Livestock Farming. A Review*, Agronomy for Sustainable Development, Vol. 33, N° 2, April 2013, pp. 311-327. https://doi.org/10.1007/s13593-012-0121-x.

70. Levinsohn, J., and Petrin, A., *Estimating Production Functions Using Inputs to Control for Unobservables*, Review of Economic Studies, Vol. 70, N° 2, April 2003, pp. 317-341. https://doi.org/10.1111/1467-937X.00246.

71. Lin, N., *Social Capital: A Theory of Social Structure and Action*, 1st ed., Cambridge University Press, 2001. https://doi.org/10.1017/CBO9780511815447.

72. Mary, S., *Assessing the Impacts of Pillar 1 and 2 Subsidies on TFP in French Crop Farms*, Journal of Agricultural Economics, Vol. 64, N° 1, February 2013, pp. 133-144. https://doi.org/10.1111/j.1477-9552.2012.00365.x.

73. Meng, Y., Shen, Z., Štreimikienė, D., Baležentis, T., Wang, S., and Zhang, Y., *Investigating the Impact of Agricultural Informatization on the Carbon Shadow Price*, Journal of Cleaner Production, Vol. 445, March 2024. https://doi.org/10.1016/j.jclepro.2024.141330.

74. Meuwissen, M.P.M., Feindt, P.H., Spiegel, A., Termeer, C.J.A.M., Mathijs, E., Mey, Y.D., Finger, R., et al., *A Framework to Assess the Resilience of Farming Systems*, Agricultural Systems, Vol. 176, November 2019, p. 102656. https://doi.org/10.1016/j.agsy.2019.102656.

75. Mosnier, C., Benoit, M., Minviel, J.J., and Veysset, P., *Does Mixing Livestock Farming Enterprises Improve Farm and Product Sustainability?*, International Journal of Agricultural Sustainability, Vol. 20, N° 3, May 4, 2022, pp. 312-326. https://doi.org/10.1080/14735903.2021.1932150.

76. Murray, A., *Partial versus Total Factor Productivity Measures: An Assessment of their Strengths and Weaknesses*, International Productivity Monitor, Centre for the Study of Living Standards, vl. 31, 2016, pp. 113-126. https://ideas.repec.org/a/sls/ipmsls/v31y20168.html.

77. Murray, A., Sharpe, A., *Partial versus Total Factor Productivity: Assessing Resource Use in Natural Resource Industries in Canada*, CSLS Research Reports 2016-20, Centre for the Study of Living Standards, 2016. https://ideas.repec.org/p/sls/resrep/1620.html.

78. Murty, S., and Russell, R.R., *Bad Outputs, in S.C. Ray, R. Chambers, and S. Kumbhakar (eds.), Handbook of Production Economics*, Springer Singapore, Singapore, 2020, pp. 1-53. https://doi.org/10.1007/978-981-10-3450-3_3-1.

79. Murty, S., Russell, R.R., and Levkoff, S.B., *On Modeling Pollution-Generating Technologies*, Journal of Environmental Economics and Management, Vol. 64, N° 1, July 2012, pp. 117-135. https://doi.org/10.1016/j.jeem.2012.02.005.

80. Njuki, E., Bravo-Ureta, B.E., and Cabrera, V.E., *Climatic Effects and Total Factor Productivity: Econometric Evidence for Wisconsin Dairy Farms*, European Review of Agricultural Economics, Vol. 47, N° 3, June 15, 2020, pp. 1276-1301. https://doi.org/10.1093/erae/jbz046.

81. O'Donnell, C., *How to Build Sustainable Productivity Indexes*, CEPA Working Papers Series WP102022, School of Economics, University of Queensland, Australia, 2022. https://ideas.repec.org/p/qld/uqcepa/182.html.

82. O'Donnell, C.J., *Measuring and Decomposing Agricultural Productivity and Profitability Change**, Australian Journal of Agricultural and Resource Economics, Vol. 54, N° 4, October 2010, pp. 527-560. https://doi.org/10.1111/j.1467-8489.2010.00512.x.

83. O'Donnell, C.J., *Nonparametric Estimates of the Components of Productivity and Profitability Change in U.S. Agriculture*, American Journal of Agricultural Economics, Vol. 94, N° 4, July 2012, pp. 873-890. https://doi.org/10.1093/ajae/aas023.

84. O'Donnell, C.J., *Productivity and Efficiency Analysis: An Economic Approach to Measuring and Explaining Managerial Performance*, Springer Singapore, Singapore, 2018. https://doi.org/10.1007/978-981-13-2984-5.

85. OECD, 2001a, *Measuring Productivity - OECD Manual: Measurement of Aggregate and Industry-level Productivity Growth*, Organisation for Economic Co-operation and Development. https://doi.org/10.1787/9789264194519-en.

86. Olley, G.S., and Pakes, A., *The Dynamics of Productivity in the Telecommunications Equipment Industry*, Econometrica, Vol. 64, N° 6, November 1996. https://doi.org/10.2307/2171831.

87. Pham, M.D., and Zelenyuk, V., *Weak Disposability in Nonparametric Production Analysis: A New Taxonomy of Reference Technology Sets*, European Journal of Operational Research, Vol. 274, N° 1, April 2019, pp. 186-198. https://doi.org/10.1016/j.ejor.2018.09.019.

88. Picazo-Tadeo, A.J., Castillo-Giménez, J., and Beltrán-Esteve, M., *An Intertemporal Approach to Measuring Environmental Performance with Directional Distance Functions: Greenhouse Gas Emissions in the European Union*, Ecological Economics, Vol. 100, April 2014, pp. 173-182. https://doi.org/10.1016/j.ecolecon.2014.02.004.

89. Picazo-Tadeo, A.J., Gómez-Limón, J.A., and Reig-Martínez, E., *Assessing Farming Eco-Efficiency: A Data Envelopment Analysis Approach*, Journal of Environmental Management, Vol. 92, N° 4, April 2011, pp. 1154-1164. https://doi.org/10.1016/j.jenvman.2010.11.025.

90. Picazo-Tadeo, A.J., Beltrán-Esteve, M., and Gómez-Limón, J.A., *Assessing Eco-Efficiency with Directional Distance Functions*, European Journal of Operational Research, Vol. 220, N° 3, August 2012, pp. 798-809. https://doi.org/10.1016/j.ejor.2012.02.025.

91. Piot-Lepetit, I., Vermersch, D., *Pricing Organic Nitrogen Under The Weak Disposability Assumption: An Application to the French Pig Sector*, Journal of Agricultural Economics, Vol. 49, N° 1, March 1998, pp. 85-99. https://doi.org/10.1111/j.1477-9552.1998.tb01253.x.

92. Pittman, R.W., *Issue in Pollution Control: Interplant Cost Differences and Economies of Scale*, Land Economics, Vol. 57, N° 1, February 1981. https://doi.org/10.2307/3145748.

93. Porter, M.E., Linde, C.V.D., *Toward a New Conception of the Environment-Competitiveness Relationship*, Journal of Economic Perspectives, Vol. 9, N° 4, November 1, 1995, pp. 97-118. https://www.jstor.org/stable/2138392.

94. Reinhard, S., Lovell, C.A.K., and Thijssen, G., *Econometric Estimation of Technical and Environmental Efficiency: An Application to Dutch Dairy Farms*, American Journal of Agricultural Economics, Vol. 81, N° 1, February 1999, pp. 44-60. https://doi.org/10.2307/1244449.

95. Rizov, M., Pokrivcak, J., and Ciaian, P., *CAP subsidies and productivity of the EU farms*, International Association of Agricultural Economists 2012 Conference, Foz do Iguacu, Brazil, August 18-24, 2012. https://doi.org/10.1111/1477-9552.12030.

96. Robling, H., Abu Hatab, A., Säll, S., and Hansson, H., *Measuring Sustainability at Farm Level - A Critical View on Data and Indicators*, Environmental and Sustainability Indicators, Vol. 18, June 2023. https://doi.org/10.1016/j.indic.2023.100258.

97. Roshdi, I., Hasannasab, M., Margaritis, D., and Rouse, P., *Generalised Weak Disposability and Efficiency Measurement in Environmental Technologies*, European Journal of Operational Research, Vol. 266, N° 3, May 2018, pp. 1000-1012. https://doi.org/10.1016/j.ejor.2017.10.033.

98. Roy, N., K., and Das, A., Prospects of Renewable Energy Sources, in Islam, M., R., Roy, N., K., and Rahman, S., (eds.), *Renewable Energy and the Environment, Singapore, Springer Singapore*, 2018, pp. 1-39. https://doi.org/10.1007/978-981-10-7287-1_1.

99. Ryan, M., Hennessy, T., Buckley, C., Dillon, E.J., Donnellan, T., Hanrahan, K., and Moran, B., *Developing Farm-Level Sustainability Indicators for Ireland Using the Teagasc National Farm Survey*, Irish Journal of Agricultural and Food Research, Vol. 55, N° 2, December 1, 2016, pp. 112-125. https://doi.org/10.1515/ijafr-2016-0011.

100. Severini, S., Tantari, A., and Di Tommaso, G., *The Instability of Farm Income. Empirical Evidences on Aggregation Bias and Heterogeneity among Farm Groups*, Bio-Based and Applied Economics, April 13, 2016, pp. 63-81. https://doi.org/10.13128/BAE-16367.

101. Simar, L. and Wilson, P.W., *Estimation and Inference in Two-Stage Semi-parametric Models of Production Processes*, Journal of Econometrics, Vol. 136, N° 1, January 2007, pp. 31-64. https://www.sciencedirect.com/science/article/abs/pii/S0304407605001594.

102. Skevas, I., Lansink, A.O., and Skevas, T., *Analysing Inefficiency in a Non-parametric Spatial-dynamic By-production Framework: A k -nearest Neighbour Proposal*, Journal of Agricultural Economics, Vol. 74, N° 2, June 2023, pp. 591-607. https://doi.org/10.1111/1477-9552.12522.

103. Skevas, T., and Lansink, A.O., *Reducing Pesticide Use and Pesticide Impact by Productivity Growth: The Case of Dutch Arable Farming*, Journal of Agricultural Economics, Vol. 65, N° 1, January 2014, pp. 191-211. https://doi.org/10.1111/1477-9552.12037.

104. Slijper, T., De Mey, Y., Poortvliet, P.M., and Meuwissen, M.P.M., *Quantifying the Resilience of European Farms Using FADN*, European Review of Agricultural Economics, Vol. 49, N° 1, January 10, 2022, pp. 121-150. https://doi.org/10.1093/erae/jbab042.

105. Solow, R.M., *Technical Change and the Aggregate Production Function*, The Review of Economics and Statistics, Vol. 39, N° 3, August 1957, p. 312. https://doi.org/10.2307/1926047.

106. Trang, N.T., Tu, V.H., Son, L.T., and Son, N.P., *Is Super-Intensive Shrimp Farming More Environmentally Friendly? An Application of Material Balance Principle in the Mekong Delta*, Environment, Development and Sustainability, Vol. 25, Nº 3, March 2023, pp. 2670-2687. https://doi.org/10.1007/s10668-022-02156-2.

107. Van Beveren, I., *Total Factor Productivity Estimation: A Practical Review*, Journal of Economic Surveys, Vol. 26, Nº 1, February 2012, pp. 98-128. https://doi.org/10.1111/j.1467-6419.2010.00631.x.

108. Wang, S., Ang, F., and Lansink, A.O., *Mitigating Greenhouse Gas Emissions on Dutch Dairy Farms. An Efficiency Analysis Incorporating the Circularity Principle*, Agricultural Economics, Vol. 54, Nº 6, November 2023, pp. 819-837. https://doi.org/10.1111/agec.12804.

109. Woolcock, M., and Narayan, D., *Social Capital: Implications for Development Theory, Research, and Policy*, The World Bank Research Observer, Vol. 15, Nº 2, August 1, 2000, pp. 225-249. https://doi.org/10.1093/wbro/15.2.225.

110. Wooldridge, J.M., *On Estimating Firm-Level Production Functions Using Proxy Variables to Control for Unobservables*, Economics Letters, Vol. 104, Nº 3, September 2009, pp. 112-114. https://doi.org/10.1016/j.econlet.2009.04.026.

111. Yang, H., and Pollitt, M., *The Necessity of Distinguishing Weak and Strong Disposability among Undesirable Outputs in DEA: Environmental Performance of Chinese Coal-Fired Power Plants*, Energy Policy, Vol. 38, Nº 8, August 2010. https://doi.org/10.1016/j.enpol.2010.03.075.

112. Zaim, O., *Measuring Environmental Performance of State Manufacturing through Changes in Pollution Intensities: A DEA Framework*, Ecological Economics, Vol. 48, Nº 1, January 2004, pp. 37-47. https://doi.org/10.1016/j.ecolecon.2003.08.003.

113. Zhou, P., Ang, B.W., and Poh, K.L., *A Survey of Data Envelopment Analysis in Energy and Environmental Studies*, European Journal of Operational Research, Vol. 189, Nº 1, August 2008, pp. 1-18. https://doi.org/10.1016/j.ejor.2007.04.042.

EU CAP Network *supported by*
European Evaluation Helpdesk for the CAP
Avenue des Arts 46,
1000 Brussels, Belgium
+32 2 808 10 24
evaluation@eucapnetwork.eu

Funded by
the European Union