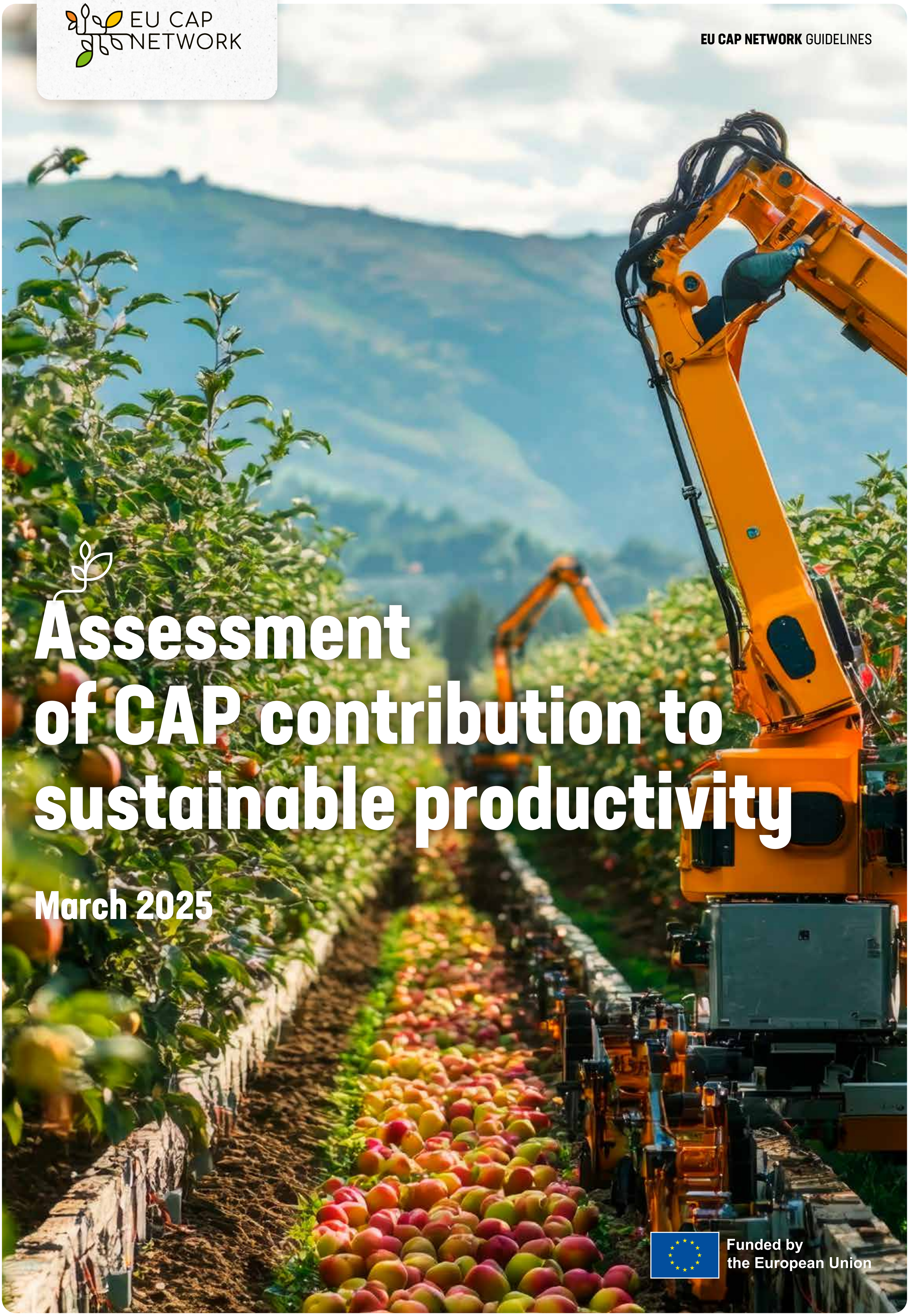

EU CAP NETWORK GUIDELINES

Assessment of CAP contribution to sustainable productivity

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EU CAP NETWORK

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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
DME-DIB	data for monitoring and evaluation - disaggregated data on interventions and beneficiaries
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

Acknowledgements

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Questions and suggestions regarding the content of the publication can be addressed to the European Evaluation Helpdesk for the CAP at evaluation@eucapnetwork.eu.

1. Introduction

CAP contribution to productivity

As stated in Article 39 under the section of "Union Policies and Internal Actions of the Treaty of the European Union", one of the CAP objectives is to "increase agricultural productivity by promoting technical progress and by ensuring the rational development of agricultural production and the optimum utilisation of the factors of production, in particular labour". CAP Strategic Plans can foster farm productivity by supporting modernisation, technologies and innovative solutions (e.g. farm precision farming), knowledge transfer and even infrastructures. Implementing Regulation (EU) 2022/1475 recommends that Member States examine the CAP Strategic Plans' contribution to capital, labour and land productivity when assessing its effectiveness towards Specific Objective 2 (SO2) (see Annex I of Reg.). In addition, Annex I of Regulation (EU) 2021/2115 lays down indicators for the multi-annual assessment of the performance of the policy associated with SO2 impact indicator I.6 measuring the changes in Total Factor Productivity in agriculture by comparing agricultural output to the total inputs used.

Farm productivity and sustainability

The 2024 'Strategic Dialogue' report on the future of EU agriculture emphasises the need to optimise benefits in terms of sustainability, resilience, profitability and greater responsibility. Whereas CAP Strategic Plans should contribute to increasing farm productivity, notably through technologies and innovative solutions, they also aim at "fostering sustainable development and efficient management of natural resources such as water, soil and air, including by reducing chemical dependency" (Specific Objective 5 (SO5)) and "improve the response of Union agriculture to societal demands on food and health, including high-quality, safe and nutritious food produced in a sustainable way" (Specific Objective 9 (SO9)). Consequently, the different interventions supported by CAP Strategic Plans targeted towards farm productivity and/or other SOs can also improve sustainable productivity of the agricultural sector. This suggests that measuring agricultural sustainable productivity could provide interesting insights into the achievements of CAP Strategic Plans in regard to the well-being of farmers and rural communities. This involves assessing, for example, to which extent the economic productivity gains supported/achieved were accompanied by improved protection of environmental resources and the consideration of societal demands.

Challenges associated with the assessment of sustainable productivity

The impact of the CAP on farm productivity has been studied by the scientific community in a number of academic articles over the past decade, revealing the challenges associated with the assessment of CAP effects on productivity, notably the sensitivity of the different types of results observed in relation to the methodology used and the difficulty in establishing a proper counterfactual. Moreover, literature reviews reveal that the calculation of productivity indicators, such as total factor productivity (TFP), also faces methodological and data challenges.

When assessing productivity, several methods make it possible to account for environmental outcomes associated with agricultural outputs, although with various degrees of complexity. For example, a reduction in greenhouse gas emissions (GHG) or any other type of pollution can be considered as a gain to be reflected in the measurement of farm productivity. Since 2017, the Organization of Economic Co-operation and Development (OECD) Network on Agricultural Total Factor Productivity and the Environment has gathered experts working on methods and addressing challenges associated with the assessment of sustainable productivity in the agricultural sector.

Purpose of the guidelines

Member States can benefit from guidance to carry out evaluations considering the effects of CAP Strategic Plans on farm productivity and/or sustainable productivity over the 2023-2027 programming period. These guidelines present different quantitative approaches that can be implemented to examine the net contribution of CAP interventions to farm sustainable productivity. Given the diversity of existing approaches, the guidelines focus on a set of selected methods with different characteristics that highlight in what conditions they could be applied and what they can demonstrate. **These examples of methods are indicative and it should be noted that Member States can implement any other method deemed more appropriate to their needs/context**.

Target groups for these guidelines

The guidelines are addressed to Managing Authorities. They provide an overview of how to measure farm sustainable productivity, showing examples of existing approaches and how they can be used to reflect on the policy choices in CAP Strategic Plans. In parallel, the guidelines aim to be a reference document for evaluators wishing to assess the choices made by their Member State and the contribution of CAP Strategic Plans' interventions. The information provided on existing methods, their characteristics and application, will contribute to raising technical knowledge and capacity for assessing the CAP's net effect on sustainable productivity. For that purpose, the guidelines are complemented with technical annexes, providing additional (theoretical and technical) information on the methods presented and their implementation.

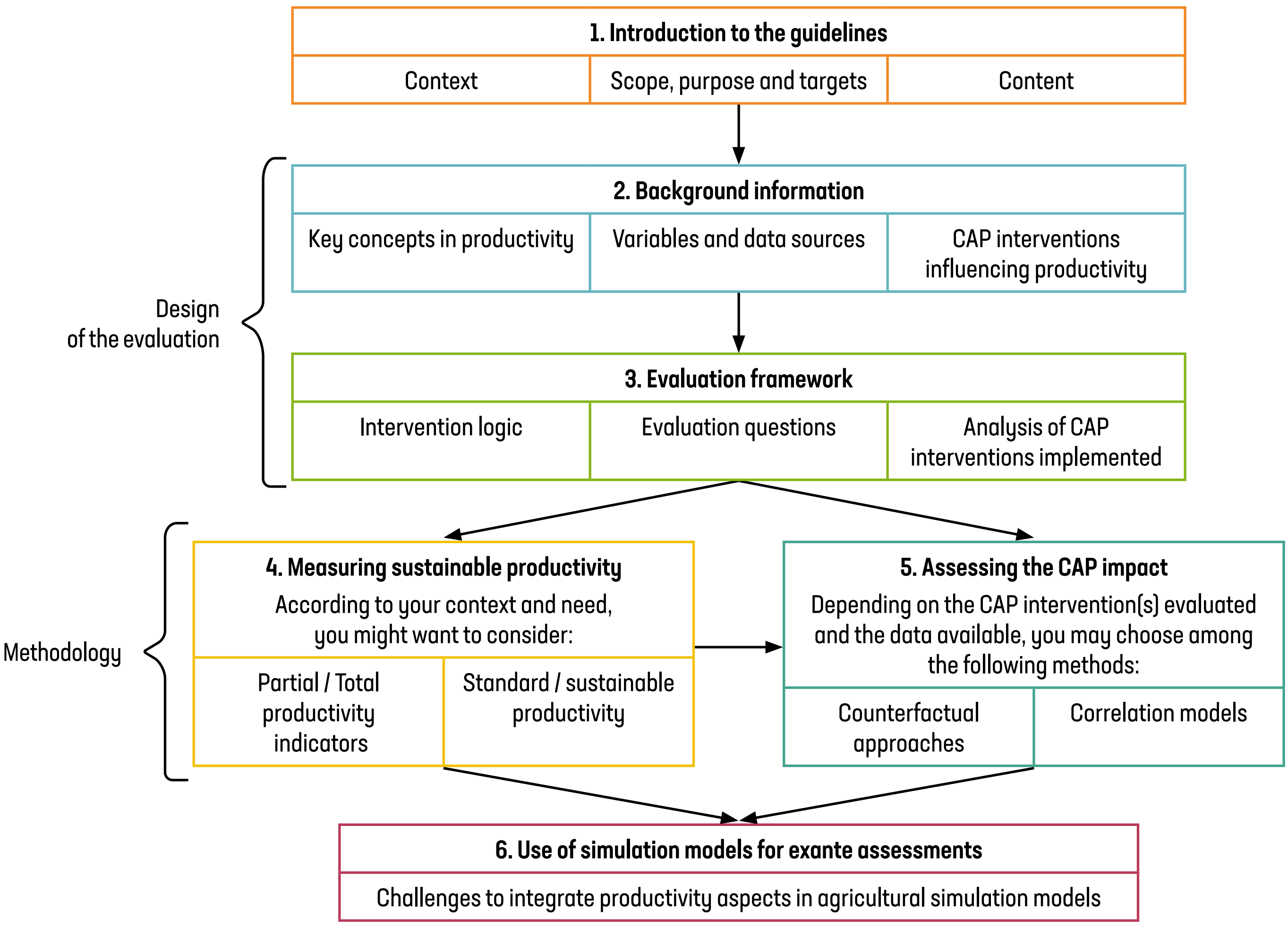
Scope and structure of the guidelines

The guidelines present quantitative methods to measure farm productivity and/or sustainable productivity and asses the net contribution of CAP interventions on changes in productivity observed in the studied farms. The recommended methods allow for the assessment of CAP income support interventions, investment support, environmental interventions (i.e. eco-scheme and ENVCLIM interventions), as well as sectoral interventions benefitting farmers from Producer Organisations (e.g. support for farm investments or support for environmental-friendly practices). Support directly provided to farms through sectoral policies could indeed be considered, albeit with caution, considering the heterogeneity of these measures. Data referring to support not directly targeting farms, such as the European Innovation Partnership (EIP) (Article 127) and sectoral support provided to Producer Organisations (Article 46), are not considered in the guidelines.

The guidelines are structured in six chapters:

- Chapter 1 is the introduction, which presents the scope and objectives of the guidelines.
- Chapter 2 aims to provide background information, i.e. on the key concepts and key variables associated with the measurement of productivity and introduces the necessary references to the CAP framework.
- Chapter 3 focuses on the evaluation framework for assessing the CAP impact on productivity. It gives examples of the intervention logic and evaluation questions to be adjusted by Member States according to their context and needs.
- Chapter 4 presents different options to measure farm productivity and sustainable productivity by considering partial and total indicators reflecting the economic, environmental and social performance of farms.
- Chapter 5 then describes different approaches to assess (ex post) the CAP's contribution to productivity.
- Chapter 6 focuses on the potential use of simulation models to assess (ex ante) the effects of CAP Strategic Plans on productivity.

Figure 1. Content of the guidelines



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

Chapters 2 and 3 provide all the necessary information to understand the topic of the CAP and productivity, and to design an evaluation framework examining the impact of CAP interventions on standard and sustainable productivity. These chapters will be particularly useful for Managing Authorities planning to launch an evaluation on this topic.

Chapters 4 and 5 reflect the two-step approach generally implemented for assessing the CAP's impact on productivity, implying to first measure changes in productivity and then assess the CAP's impact on the observed changes. These chapters provide a list of indicators and methodologies to be used by Member States, according to their specific interests and needs (e.g. partial vs total indicators, one specific vs several CAP interventions) and the available data. They will be particularly useful to evaluators and should help them structure the appropriate methodological approach in line with the evaluation scope and objectives.

Chapter 6 outlines how simulation models might be used to estimate the potential impact of the CAP on productivity and highlights the actual challenges that need to be addressed at Member State level to achieve this.

2. Background information

2.1. Concepts and definitions

This chapter introduces key topics related to productivity. Readers will be introduced to the traditional concepts and informed about topics recently developed to capture the complex relationships between agricultural production, the natural environment and societal demands. It is then complemented with a glossary providing useful definitions at the end of the chapter.

2.1.1. Farm productivity

In a production process, one or several inputs are transformed through a technology to generate one or several outputs.

Traditionally, farm productivity is defined as the **ratio between the amount of output produced from agricultural activities and a given amount of inputs** (land, labour, capital, etc.) of a farm. It can be simply seen as the ratio of outputs to inputs.

Inputs [1] reflect all the means that are intentionally and non-intentionally used in production processes. The inputs of labour, capital, livestock (sometimes included in capital) and land are complemented by intermediate inputs (such as fertilisers, plant protection products, seeds, feed, water, and other raw materials and purchased services, such as transportation) to be combined during production to obtain outputs. Some authors differentiate between man-made inputs (e.g. synthetic fertilisers, plant protection products and seeds), and non-man-made inputs (e.g. water and land).

The outputs of agricultural production are typically a good, such as wheat and milk or a service, such as on-farm sales, accommodation or a meal for a guest [2]. These goods and services are usually traded on markets and therefore have a price.

The **production-possibility frontier** shows the 'optimal' input-output combinations that are technically efficient and feasible, while the **production function** is a mathematical representation of this technological relationship between the inputs used and the output produced.

Farm productivity can vary according to the implemented production processes for transforming inputs into outputs. Higher farm productivity can be obtained either by using a lower quantity of inputs but producing the same quantity of outputs or by using the same quantity of inputs but obtaining a higher quantity of output. This may be due to higher **efficiency of resource use (i.e. higher farm efficiency) and/or better performing technology (i.e. technological progress)**. Higher productivity may imply higher profitability for farmers.

Farm productivity is influenced by a variety of drivers. Technological innovations (e.g. precision farming, efficient irrigation systems, etc.) play a crucial role in productivity through technological progress, while the adoption of improved farming practices (e.g. precision farming) and efficient resource management increase productivity through higher farm efficiency. The motivation, entrepreneurial and managerial skills, and education of farmers are additional drivers impacting productivity. Externally, government policies and regulations, access to markets and credit, research and education systems, and infrastructure development including transportation and irrigation systems, could potentially constitute key drivers. Moreover, pedoclimatic conditions also play a significant role in shaping farm productivity.

2.1.2. Environmental and social outputs of agricultural production

Farm productivity growth is becoming increasingly important in the context of increased global food demand, while agricultural land is limited and natural resources are threatened by intensive farming practices. Increasing farm productivity is also necessary for EU farmers to remain profitable in a more competitive environment.

As highlighted by Fuglie, Morgan & Jelliffe [3], "agricultural output increased nearly fourfold, while the global population grew by 2.6 times, leading to a 53-percent increase in agricultural output per capita between 1961 and 2020. [...] Most of the growth in agricultural production was achieved by raising productivity [...] global agricultural land area increased by 8 percent to 4.76 billion hectares [...] the total number of people working on farms peaked in 2003 at just over 1 billion and then declined to 841 million by 2020". This productivity growth was made possible by an increased use of resources such as synthetic fertilisers, pesticides, irrigated areas, machinery, etc. and the implementation of specific farm practices (e.g. monocultures on large areas, frequent tillage, etc.).

However, while the increase in man-made inputs has enabled the production of food for a growing population, intensive agriculture is also putting pressure on the very resource that sustains it – healthy and productive soils [4]. Overall, intensive agricultural practices in agriculture have resulted in excess nutrients in water bodies and water over-abstraction, chemical pollution, loss of landscape diversity and features (e.g. ponds and hedgerows), loss of soil health and fertility and biodiversity loss, including pollinator decline [5]. By contrast, agriculture has also positive impacts on the environment, such as landscape and habitat preservation through hedges and other natural infrastructures in fields, landscape maintenance in remote areas and carbon sequestration [6].

1 Frequently also called 'factors of production'.

2 Sometimes the terms 'output' and 'good' are used interchangeably, implicitly accounting for services.

3 Fuglie, K.O., Morgan, S., Jelliffe, J., *Department of Agriculture. Economic Research Service, World Agricultural Production, Resource Use, and Productivity*, 1961-2020, Economic Reserach Service, Washington, D.C., February 2024. http://www.ers.usda.gov/publications/pub-details/?pubid=108649.

4 EEA, 2019a, *Land and soil in Europe – why we need to use these vital and finite resources sustainably*, EEA Signals, European Environment Agency. https://www.eea.europa.eu/publications/eea-signals-2019-land. Accessed 29 August 2024.

5 See previous footnote and EEA, 2019b, *The European environment – state and outlook 2020*, European Environment Agency. https://www.eea.europa.eu/publications/eea-signals-2019-land. Accessed 29 August 2024.

6 OECD, *Multifunctionality in Agriculture: Evaluating the Degree of Jointness, Policy Implications*, OECD, 2008. https://doi.org/10.1787/9789264033627-en.

Furthermore, the social dimension must also be taken into account. Changes in the agricultural production processes can impact farmers, consumers and rural inhabitants' quality of life e.g. through the provision of safe and affordable food, the contribution to the dynamism and attractiveness of rural areas, the preservation of traditions, local employment, etc. Regarding the latter, the progressive replacement of labour by capital in the agricultural sector has had side effects on the social organisation within the farm, the working conditions of farmers and generally on rural employment patterns. By contrast, in some areas, agriculture is the major employer with limited or no employment alternatives.

In other words, agriculture not only produces agricultural outputs that are traded on the market but also produces environmental and social outputs (externalities). **Accounting as much as possible for these (negative and positive) environmental and social outputs of agricultural production provides a complete picture of farm productivity** that is useful when drawing comparisons [7] or when assessing the influence of specific agricultural subsidies.

2.1.3. Sustainable productivity

In the context of these guidelines, **sustainable productivity is defined as farm productivity that accounts for not only the agricultural outputs but also the environmental and social outputs generated by the production process**.

Assessing sustainable productivity in agriculture involves evaluating how efficiently farm resources are used to generate agricultural outputs while considering that environmental and social outputs are also produced by these resources. Similarly to standard productivity that accounts only for agricultural goods and services, the assessment of sustainable productivity can be done for a given farming system at farm or sectoral level. Computing sustainable productivity accounts for all outputs produced by the farm, not only agricultural goods (e.g. wheat or milk) or services (e.g. tourist accommodation), but also environmental and social outputs. The latter are not traded on the market, while typical agricultural outputs are traded on the market. The environmental and social outputs are often not aimed at by farmers and are therefore sometimes referred to as 'by-products'. They may be desirable, relating to positive impacts of agriculture on the environment or the society (e.g. high biodiversity, good working conditions), or not desirable, relating to negative impacts of agriculture (e.g. GHG emissions, high animal mortality rate). In the latter case of negative impacts, we also speak of 'bads' to denote these types of environmental or social outputs.

2.1.4. Graphical summary

The figure below illustrates how the increased use of one input (e.g. nitrogen fertiliser) can positively influence crop yields (which is one possible measure of productivity, as further detailed in Chapter 4), while generating negative environmental outputs.

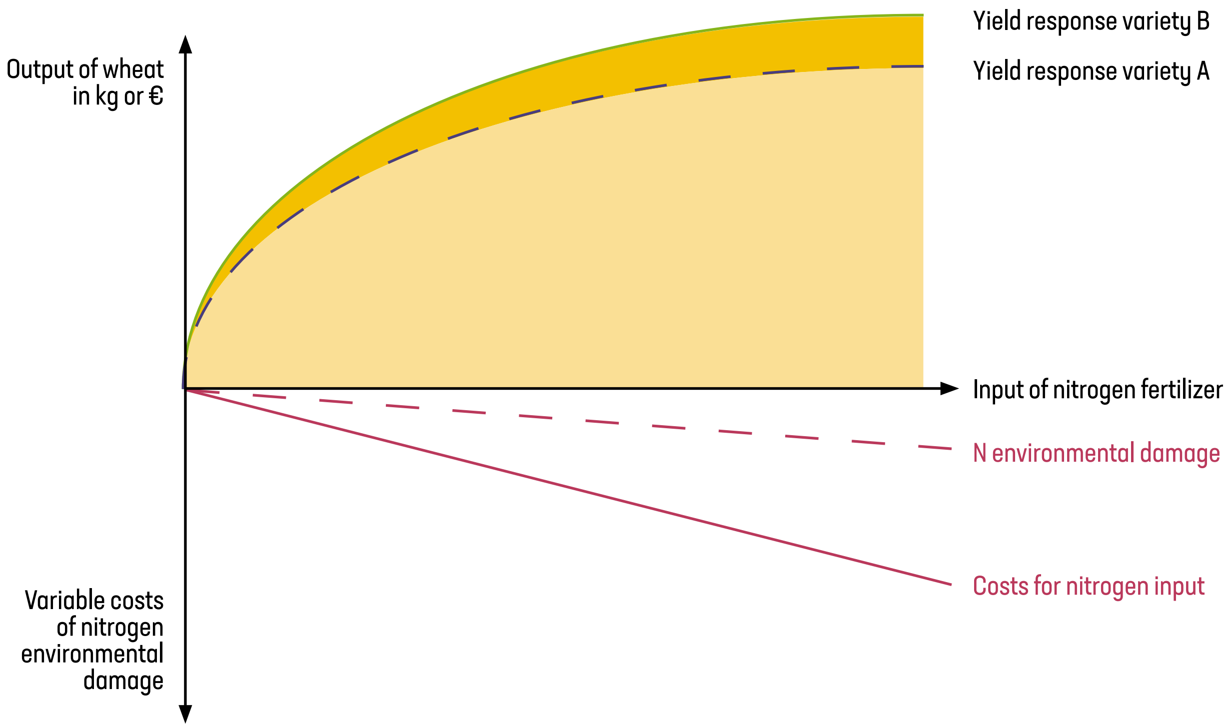
- The vertical axis represents the produced agricultural output of a specific crop, e.g. wheat measured in physical terms (kg or tonnes) or monetary terms (euros). The horizontal axis represents the quantity of inputs (in physical or monetary terms) used to produce this crop. Here, only one input is considered, i.e. nitrogen fertiliser. All other inputs are assumed to be the same across farms or time.
- The two curves on the positive vertical axis (dashed blue and solid green lines) represent two possible yield responses, i.e. the different input-output combinations that are technically efficient for two genetically different varieties of wheat and are known as the production frontiers [8]. Both curves are going upward since using more fertiliser increases the quantity of wheat produced, but at some point stagnate [9].
- Variety B (solid green line) is more productive than variety A, for the same amount of fertiliser used (all other inputs are assumed not to vary). The two curves therefore show different technologies: farms adopting the more productive technology B will exhibit technological progress, which is one component of productivity growth.
- A farm is on the frontier (i.e. on the curves) when it produces the highest possible (or maximum attainable) output with a given level of input. Farms growing varieties A or B may not achieve the highest output. As a result, they may not be on the frontier (i.e. they will be neither on the dashed blue nor solid green curves) but below it, meaning that they use the technology less efficiently and thereby exhibit technical inefficiency. This is another component of productivity growth.

7 Consider two farms F and G using the same amount of inputs. Farm F produces only agricultural goods, while farm G produces a smaller amount of agricultural goods, but also produces environmental biodiversity and landscape goods. If only agricultural goods are taken into account for the productivity calculation, then farm F would appear to be more productive than farm G. However, if all goods (economic and environmental) are considered, then G could be ranked higher than F.

8 If, for instance, fertiliser is not spread optimally across the field, the maximum yield for a given amount of fertiliser will not be attained.

9 In other words, the production functions satisfy some standard neoclassical economic assumptions; the more nitrogen fertiliser is applied, the more wheat is produced (i.e. positive marginal productivity). The production functions have diminishing marginal returns; the increment of crop yield is very high for the first 10 kg of nitrogen fertiliser (to the left of the horizontal axis), while the increment is very low for the last 10 kg (on the right side of the horizontal axis).

Figure 2. The production of wheat with one single input (nitrogen fertiliser)



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

- The cost of nitrogen fertiliser (in euros) is plotted in the same graph (the red solid line) on the negative scale of the vertical axis. The cost curve is a straight line because each additional kilogramme of nitrogen fertiliser costs the same amount. It is a downward-sloping curve as the increasing scale is downward, which indicates that costs are increasing the more fertiliser is used. The second line (red dashed) represents the environmental costs, the costs of the environmental impacts of producing wheat. Indeed, nitrogen fertiliser is not only an essential input for producing crops. When applied on a field and not taken up by plants, it may become nitrous oxide (N_2O), a gas that contributes to global warming, or may generate nitrates and leach into water streams. The environmental damage can be quantified on the same scale as the nitrogen fertiliser costs. The environmental costs of excessive N (dashed red line) increase the same amount with each kg of fertiliser.

2.1.5. Useful definitions

The box below provides definitions of key terms to consider when measuring productivity. The terms, frequently used and referred to throughout the guidelines, are introduced here to help the reader understand and/or clarify key aspects associated with productivity measurement.

Box 1. Definitions of some methodological terms

Component: productivity change can be decomposed into two components, namely technical efficiency change and technological change. Decompositions resulting in different components are possible (e.g. scale efficiency change, resource allocation, increase in output value, etc.).

Decision-making unit (DMU): an entity or agent (e.g. individual, farm, company, public authority, etc.) at the level at which production decisions are made. Also called the unit of observation.

Driver: an element that has an influence on an outcome. Here we are interested in the drivers of productivity, e.g. CAP subsidies or farm size. Drivers can be assessed with a regression analysis where they are explanatory variables.

Factor: the term is used in these guidelines as 'production factor', meaning an input in a production process; see 'Inputs'.

Frontier or production frontier or production possibility frontier: it shows trade-offs, that can be described as the maximum attainable output with given combinations of inputs or the combinations of different goods using the same inputs.

Heterogeneity: unobserved heterogeneity occurs when the farms (or, more generally, the DMUs) differ in many aspects that are difficult to observe and measure, such as managerial skills, land quality and microclimate conditions.

Inputs: all the means that are intentionally and non-intentionally used in production processes. Furthermore, some inputs are man-made (e.g. machines, mineral fertiliser) while others are non-man-made (e.g. water, land). They are also called factors of production.

- **Fixed inputs:** inputs whose quantity cannot be changed in a short period, e.g. capital, land, etc. Labour may be considered as a fixed or quasi-fixed input.
- **Variable inputs:** inputs that are produced elsewhere before being used in production processes, e.g. fertiliser, plant protection products, seeds, feed water, other raw materials and purchased services. Such inputs are also called **intermediate inputs**.

Output: a good or service that is obtained from combining inputs in a production process through a technology.

- **Desirable output or good output:** an output from a production process that is favourable or beneficial to the farmer or the society as a whole, e.g. wheat, milk, biodiversity and landscape amenities. Agricultural desirable goods are traded on markets and have a price. Other desirable outputs, such as biodiversity or landscape amenities, are (intentional or unintentional) by-products of farming and a market for them does not exist.
- **Non-desirable output or undesirable output or bad output or 'bad'**: an output that is associated with negative impacts and is therefore not beneficial to the farmer or society, such as work accidents, livestock mortality, greenhouse gases, nitrate leaching, nitrate runoff and soil erosion.

Production function: a mathematical representation of the production technology. The main functional forms are Cobb-Douglas, translog or quadratic [10]. See Section 4.7.1 in the Technical Annexes.

Productivity: an important indicator to measure performance. A general definition of productivity is the ratio of output(s) produced and input(s) used. Changes in productivity can be decomposed into several components.

Sustainable productivity: in the context of these guidelines, it is understood as farm productivity that accounts for the environmental and social outputs generated by agricultural production.

Technological progress: is one component of productivity change. It refers to the improvement of technology through innovation and scientific advances. It can be represented as shifts in outputs without changes in inputs.

Technical efficiency: the effectiveness with which a given set of inputs is used to produce an output.

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

10 Coelli, T.J., D.S. Prasada Rao, C.J. O'Donnell, and G.E. Battese, *An Introduction to Efficiency and Productivity Analysis*, Springer-Verlag, New York, 2005, p.98. http://link.springer.com/10.1007/b136381.

2.2. Key variables and data sources for assessing productivity

Data availability determines the type of analysis that can be done and, thus, the ability to demonstrate the CAP's effects based on sound and robust findings.

2.2.1. Key variables for assessing productivity

Outputs and inputs

The assessment of productivity requires data that contains information on farms' production processes, namely **outputs and inputs**. In general, the inputs included in productivity assessments are disaggregated into four (or five) main inputs: **land, labour, capital, livestock (sometimes included in capital) and intermediate inputs**. These main inputs can be further decomposed; for example, instead of intermediate inputs one can use fertilisers, crop protection products and other intermediate inputs. Output can be included as a single output (which can be partial, e.g. wheat or milk, or total, aggregated) or as several disaggregated outputs. Many options of disaggregation are possible, but it is important that what is included fully describes the production process (e.g. total output may be replaced by crop output, livestock output and other farm output).

The **choice of the level of disaggregation of outputs and inputs**, that is to say the choice of the number of outputs and inputs included in the assessment of productivity, is based on the available data, the type of farming (e.g. for dairy specialist farms two outputs may be included, namely milk produced and the other – aggregated – output), the model used (e.g. data envelopment analysis may easily incorporate several outputs contrary to stochastic frontier analysis) and the number of observations in the sample used. Indeed, while disaggregating outputs and inputs allows approaching a more realistic production process, using too many inputs and outputs compared to the sample size may reduce the degrees of freedom in the analysis, thereby reducing the robustness of statistical results.

Note that capital can be intended as a stock (e.g. total assets) or as a flow (i.e. recognising that capital services represent ongoing contributions to production over time). Productivity measurements typically use the flow measure of capital. Capital productivity is defined by the OECD as the ratio between the flow of output and the flow of capital (capital services) [11].

Quantities vs monetary values

In theory, the assessment of productivity requires information on (physical) **quantities of outputs and quantities of inputs** e.g. tonnes of wheat produced and kilogrammes of fertilisers used. However, databases, such as the Farm Accountancy Data Network (FADN), with quantities of all outputs and all inputs are usually unavailable. Instead, more frequently monetary values are available. For inputs, these values are costs (sometimes called expenses or expenditures) as in the case of intermediate inputs, or estimated values as can be in the case of buildings or machinery. For outputs, the monetary values are typically revenues from sales and other transfers (e.g. farm use, farmhouse consumption). In productivity assessments, inputs such as land (measured in hectares), labour (in units like hours or full-time workers), livestock (number of heads) and occasionally specific outputs (e.g. milk) are quantified, which means they are informed in physical measurements. Other outputs, as well as capital and intermediate inputs, are typically expressed in monetary terms. However, productivity should reflect variations in physical quantities (profitability, in contrast, captures changes in monetary values, such as revenues relative to costs).

To cope with this issue, researchers and practitioners often resort to **quantity indices, which are designed to measure changes in the physical quantities of inputs and outputs, independent of price fluctuations**. These indices allow for a more accurate assessment of productivity by standardising units across different inputs and outputs, thus focusing purely on the efficiency of resource use. By isolating quantity changes from price effects, these indices provide a clearer picture of how much output is produced per unit of input, which is essential for distinguishing productivity gains from profit-driven outcomes influenced by market prices. In practice, when using FADN data, input expenses and output revenues can be typically converted into constant currency (e.g. constant euros) by applying relevant price indices. These indices, which are generally available at the national level, cover both agricultural inputs and outputs, allowing for **inflation-adjusted** comparisons over time. When conducting cross-country comparisons, adjustments for purchasing power differences must also be considered. Information on annual price indices and **purchasing power** parities (PPP) for Member States can be obtained via the Eurostat website [12].

11 Rizov, M., Pokrivcak, J., and Ciaian, P., *CAP subsidies and productivity of the EU farms*, Journal of Agricultural Economics, 64(3), 2013, pp. 537-557. https://doi.org/10.1111/1477-9552.12030.
12 Another issue regards the adjustment needed for capital productivity because it is necessary to correct capital productivity while considering opportunity cost. Note that the cost opportunity is not available on FADN, but it is possible to use the interest rates of country bonds from Eurostat. Note that this interest rate depends on the bond's duration, which can be approximated by the inverse of the depreciation rate of fixed assets, representing their expected duration.

While inflation-corrected inputs and outputs provide stability for comparisons over time, they introduce several issues in productivity assessments. First, monetary values, even when adjusted for inflation, may not accurately reflect physical quantities, potentially distorting productivity estimates. General price indices can also lead to inaccuracies if they do not match specific agricultural inputs or outputs. Additionally, regional price differences, technological advancements and the omission of non-market factors (e.g. unpaid labour, ecosystem services) may further distort the results. Finally, inflation adjustments may not fully account for price volatility in agricultural markets, complicating comparisons. Nevertheless, where the only data available are input expenses and output revenues, inflation-adjusted comparisons are considered the best way forward, provided that potential distortions are acknowledged and examined.

As outputs are typically quantified in monetary terms, this allows the aggregation of diverse outputs in a total output and therefore adequately considers multiproduct farms [13]. **Total output** may be measured in terms of **revenue from sales**, however, the monetary value of the aggregated output may also be represented through **value added** [14]. Gross value added refers to the net output of the agricultural sector, which is obtained after subtracting from the revenue the value of intermediate goods and services consumed in the production process. Net value added implies deducting depreciation from gross value added. **The choice between revenue and value added significantly influences the interpretation and implications of productivity measurements**.

Output and input quality

A word of caution should be given relating to quality. In general, databases containing the necessary information on outputs and inputs **do not account for output or input quality** when outputs and inputs are measured in physical terms. For example, the land input is commonly measured in terms of the number of hectares used for production. However, such a measurement does not integrate information on the quality of land (e.g. in terms of the quantity of organic matter in the soil). The labour input does not integrate the quality of labour (e.g. in terms of education level).

Quality is however generally accounted for in costs or revenues. For example, a higher quality wheat attains a higher price. A high-skilled worker will be paid more than a low-skilled worker. As regards to land input, it can be tempting to use land rental prices (if available) instead of land area, but such prices may not only reflect land quality but also local policies (e.g. land prices may be regulated) or buyers' and sellers' negotiating power. The reliability and representative nature of the available data is often questionable too. Therefore, the simplest practice is to use land and labour (and livestock) in quantities for productivity assessment in agriculture, and the potential differences in land and labour qualities across farms or countries should be kept in mind when interpreting the results.

Treatment of data

As in all cases where data are used, a thorough **data cleaning** to deal with outliers, correct errors and ensure data accuracy is needed. **Outliers** can significantly distort the results of productivity calculation and regression analysis, leading to biased and inaccurate conclusions. Methods such as visual inspection, statistical tests (e.g. Z-scores) and advanced data screening techniques (e.g. BACON algorithms) should be employed to detect and mitigate the impact of outliers. Properly addressing outliers ensures that the analysis accurately reflects the true relationship between the variables. The simplest way to deal with outliers is to remove them. However, several factors should be considered before taking this step.

1. Investigate the cause of the outliers, such as data entry errors (e.g. misplaced decimals or incorrect units) and understand the context (e.g. unusual production outcomes in agricultural data may result from severe weather events and could still be valid observations).
2. Assess the impact of the outliers by performing sensitivity analyses to understand how they influence the results.
3. When handling outliers, there are several options: retain them while using robust statistical techniques, transform the data (e.g. through winsorizing, which is a method to substitute extreme values) or remove the observations altogether. If you choose to remove them, it is essential to document the criteria used to ensure transparency. Additionally, be cautious, as removing too many outliers can result in the loss of meaningful data, especially when they represent rare but valid events.

Sometimes data are not complete (i.e. missing data) and it may be relevant to address it. **Missing data can introduce several challenges in the analysis**, potentially leading to biased estimates and reduced statistical power. Techniques such as imputation, sensitivity analyses or methods that can accommodate unbalanced panels can be used to handle missing data, ensuring that the analysis remains robust and reliable. Ignoring missing data can skew results as the characteristics of the missing values may differ significantly from those observed. Therefore, a careful consideration of the nature of the missing data and the application of appropriate methods for handling it are crucial to ensure the validity of the results.

In 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. This may have consequences for output data particularly since, in some databases, negative output values exist to account for stock variations. Some recent data transformation techniques (e.g. inverse hyperbolic sine transformation) have been suggested to handle negative and zero values in this context.

It is essential to **standardise variables when they are measured on very different scales**. This process helps prevent numerical instability in the regression analysis and ensures that the coefficients can be compared on a like-for-like basis.

13 For the full reference for Coelli et al. (2005) check footnote 10.

14 FAO, *Productivity and Efficiency Measurement in Agriculture Literature Review and Gaps Analysis*, Food and Agriculture Organization of the United Nations, Rome, February 2017, p.14. https://www.fao.org/3/ca6428en/ca6428en.pdf.

2.2.2. Data sources

This section presents different data sources available to measure productivity and sustainable productivity. These indicators can be assessed at regional level or farm level. More details on methods to measure productivity are provided in Chapter 4.

Combining databases for a regional or state level assessment of productivity

To conduct analyses at the regional level (NUTS 1 or NUTS 2), one can use aggregated data from sources such as Eurostat (e.g. Economic Accounts for Agriculture (EAA)) or REAA (regional EAA) that provide detailed and harmonised information about outputs and inputs of the whole agricultural industry carried out in countries or by regions), national statistical agencies, and international organisations like the Food and Agriculture Organisation (FAO) and the OECD. Several sources can be combined to obtain the necessary information for sustainable productivity assessment (aggregated data on agricultural output, land, agricultural labour etc. and countries' GHG emissions from the agricultural sector).

Box 2. Indicator C.29/I.6 Total Factor Productivity based on Eurostat

An annual total factor productivity (TFP) index and percentage changes for each Member State are published and regularly updated on the Commission's Agri Food Data Portal [15].

In the cover note on context and impact indicators [16], the Commission services recommend using data from Eurostat to calculate TFP in agriculture at national level (indicator C.29/I.6 in the PMEF and C.27 in the CMEF).

For this purpose, relevant datasets available on Eurostat for the calculation of TFP are:

- EAA – Indices: volume, price, values of crop output, animal output, agricultural output and detailed and total intermediate input (aact_eaa05) [17]
- EAA – values at real prices of crop output, animal output, agricultural output and detailed and total intermediate inputs (in terms of national accounts: intermediate consumption) (aact_eaa04) [18]
- Agricultural labour input statistics - absolute figures of total labour force, non-salaried and salaried labour input (1 000 annual work units) (aact_ali01) [19]
- Farm structure - Tenure of agricultural holdings (e.g. owned, rented) by utilised agricultural area, sex and age of farm manager (ef_mp_tenure) [20]
- Agricultural production - Crop production in national humidity for cultivated area by crop types at national (apro_cpnh1) [21]

Concerning the use of Eurostat sources, EAA, being a satellite account of national accounts, follow the basic concepts, principals and rules based on the European System of Accounts (ESA 2010), taking into consideration the specific requirements of agriculture. Inputs provided in EAA are measured by their prices. For the productivity compilation, the best is to use their volume indices, which are calculated from data at real prices. In the case of labour, the changes are measured in an annual work unit (AWU), detailing both paid and unpaid work. However, due to its national accounting approach, the EAA reflects in its generation of income account the compensation of employees (i.e. that concerns only the part of paid work). Hence, using the latter as weight in the productivity indicator needs to deal with the two types of labour input differently: using the compensation of the employees for the paid labour input at AWU and preparing an adjustment estimation based on the latter to derive the correct weight for non-salaried labour. This helps ensure that family farms are properly covered. Similarly for land, other Eurostat statistics provide the changes in hectares covering both owned and rented by farmers, while the EAA (following the concept of ESA 2010) reflects only the rents paid for land.

To overcome this, the cover note on context and impact indicators requests the use of additional bridge tables to derive the share of salaried AWU against the total, and the share of rented land against the total. This enables dividing salaries by the share of paid AWU and rents by the share of rented land to come up with correct weights, assuming that the implicit cost of owned land is the same as rented land and that the implicit cost of unpaid work corresponds to salaries for paid work. In reality, this assumption may not hold and (complex) methodologies exist to estimate the cost of implicit (owned) inputs.

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

15 Agri Food Data Portal: https://agridata.ec.europa.eu/extensions/IndicatorsSectorial/AgriculturalProductivity.html. Accessed 10 September 2024. Agri Food Data Portal. https://agridata.ec.europa.eu/extensions/IndicatorsSectorial/AgriculturalProductivity.html; https://agridata.ec.europa.eu/extensions/IndicatorsSectorial/AgriculturalProductivity.html. Accessed 10 September 2024.
16 Context and Impact indicators 07/03/2024 – Version 9.0: https://agriculture.ec.europa.eu/common-agricultural-policy/cap-overview/cmef_en.
17 See more at: https://ec.europa.eu/eurostat/databrowser/view/aact_eaa05/default/table?lang=en&category=agr.aact.aact_eaa. Accessed 10 September 2024.
18 See more at: https://ec.europa.eu/eurostat/databrowser/view/aact_eaa04/default/table?lang=en&category=agr.aact.aact_eaa. Accessed 10 September 2024.
19 See more at: https://ec.europa.eu/eurostat/databrowser/view/aact_ali01/default/table?lang=en&category=agr.aact.aact_ali. Accessed 10 September 2024.
20 See more at: https://ec.europa.eu/eurostat/databrowser/view/ef_mp_tenure/default/table?lang=en&category=agr.ef.ef_mp. Accessed 10 September 2024.
21 See more at: https://ec.europa.eu/eurostat/databrowser/view/apro_cpnh1/default/table?lang=en&category=agr.apro.apro_crop.apro_cp.apro_cpnh. Accessed 10 September 2024.

At the farm level, bookkeeping databases are adequate for standard productivity assessment

At the farm level, the most useful and commonly used data is from the **FADN**, whether the EU level FADN or national strands that feed the EU FADN. The FADN data are bookkeeping data from a sample of representative commercial farms in each Member State and, as such, include detailed information on outputs (quantities and monetary terms, in particular, total output), inputs (quantities and costs) and other characteristics of farms that may help explain the variations in productivity across time or farms (e.g. location of the farm, farmer age), including detailed information on subsidies received by farms.

FADN data are reported each year for a rotating sample of farms. However, some delays can occur before the data are made available to evaluators. Given that specific analyses and methods (e.g. to consider productivity growth) require observations over a significant period of time to accurately reflect the trends observed, before launching an evaluation, it is important to consider when the required data will be available. One possibility to overcome issues associated with data availability is to examine data from previous programming periods.

Other local data may also be used to assess productivity e.g. data obtained from a specific bookkeeping agency, a group of farms or collected from dedicated surveys [22].

Strategies to assess farm-level sustainable productivity with bookkeeping databases

The above-mentioned databases are useful to assess standard productivity (accounting only for agricultural goods and services) but are usually not sufficient to assess sustainable productivity (i.e. productivity accounting for agricultural outputs as well as environmental and social outputs) as they do not contain much information on environmental and social outputs (e.g. GHG emissions, nutrient surpluses, pesticide impacts, animal welfare, working conditions, etc.). The ambition of FSDN (Farm Sustainability Data Network (FSDN)) [23] to extend the FADN to social and environmental sustainability dimensions is a way to a more robust assessment of sustainable productivity. However, FSDN data is not expected to be available until 2027. In some Member States, some scarce environmental or social information is available in the national strand of the FADN. In general, however, such information is not included in national nor EU FADN. Therefore, at present, there are two strategies to assess farm-level sustainable productivity:

1. **Using bookkeeping databases and approximate environmental and social outputs** with available information in the bookkeeping databases. This is described in detail for the specific case of FADN in Section 2.2 of Technical Annex 3.

2. **Complementing bookkeeping databases with outside information**. When possible, the bookkeeping database (FADN or local bookkeeping data) could be merged with other databases with information for the same farms, or at least for some of them. For example, the Land Parcel Identification System (LPIS) and the integrated administrative and control system (IACS) could provide information on ecological focus areas and therefore habitats (e.g. hedges) for most of the farms in the FADN database, bringing together economic and environmental data in a single database. This will be possible if LPIS, IACS and FADN are linked together, for instance with the unique beneficiary identifier (Variable B010 of DME-DIB) [24] [25]. Another example of complementing databases comes from the Netherlands, with the Minerals Policy Monitoring Programme (LMM) monitoring water quality for a large number of farms in the FADN sample.

Technical Annex 1 provides a list of FADN variables and upcoming FSDN variables that can be used for assessing the CAP contribution to sustainable productivity. Technical Annex 3 gives more detail on environmental and social indicators.

Other data

Pedoclimatic information can be included as control variables in assessing the impact of CAP measures on productivity (see Chapter 5). This information is freely available in databases on climatic variables from the Commission's Joint Research Centre (JRC) or Copernicus (observational such as E-OBS, or reanalysis data such as ERA5, EURO CORDEX), or soil quality (LUCAS) now dynamic from the JRC.

22 In this respect, two deliverables of the LIFT project can serve as examples.
1) The general questionnaire with detailed questions on practices (https://zenodo.org/records/5075706);
2) The specific questionnaire on working conditions (https://zenodo.org/records/5075571). Accessed on 5 December 2024.

23 Regulation (EU) 2023/2674 of the European Parliament and of the Council of 22 November 2023 amending Council Regulation (EC) Nº 1217/2009 as regards conversion of the Farm Accountancy Data Network into a Farm Sustainability Data Network. https://eur-lex.europa.eu/eli/reg/2023/2674/oj. Accessed 28 November 2024.

24 As stated in Annex IV of Implementing Regulation (EU) 2022/1475 on "Rules on disaggregated data on interventions and beneficiaries referred to in articles 9(3) and 10(3)".

25 Further provisions relating to the data to be extracted from the different datasets will be set out in the forthcoming Commission Implementing Regulation laying down rules for the application of Council Regulation (EC) Nº 1217/2009 setting up the Farm Sustainability Data Network.

2.3. Sustainable productivity and the CAP

2.3.1. CAP interventions with direct effects on farm productivity

As stated in Regulation (EU) 2021/2115, CAP Strategic Plans can foster farm productivity by supporting modernisation, technologies and innovative solutions (e.g. precision agriculture), knowledge transfer and even infrastructure. Member States can implement the following CAP interventions to support investments, practices and/or innovations contributing to farm productivity [26]:

- **Support for investments (INVEST)** (Article 73 and 74) can foster farm restructuring, modernisation, innovation, and uptake of new practices and technologies, etc. (Recital 28). Investment allows farmers to adopt new technologies (e.g. precision agriculture and automation systems) and re-organise or scale up their operations, which may facilitate the adoption of more advanced and capital-intensive technologies or the adoption of organic practices for which specific machinery and large area(s) are needed. These on-farm changes can improve productivity by increasing yields or supporting the efficient use of resources (e.g. nutrients, fertilisers or energy), which also contributes to the sustainability of farm practices. Studies have generally reported the positive effects of investment subsidies on increasing farm productivity.
- **Cooperation intervention (COOP)** (Article 77) helps improve the productivity of the agricultural sector, notably through research, innovations and knowledge transfer supported by EIPs (Article 127). Other forms of cooperation promoted under Article 77 can also have positive effects on agricultural productivity (e.g. through LEADER, quality schemes) [27].
- **Sectoral types of interventions** (Article 42-68) can foster investments contributing to the optimisation of production costs and the development of innovative practices and production techniques in supported sectors.
- **Coupled income support (CIS)** can aim to improve productivity (e.g. by encouraging economies of scale, requiring certain infrastructures or a more optimal age of plantation, etc.), and/or reduce negative impacts (e.g. through a more efficient use of resources). Before 2023, voluntary coupled support (VCS) only aimed to compensate for the identified difficulty of the targeted sector or production. As of 2023, Member States can grant CIS to improve the competitiveness, sustainability or quality in certain sectors and productions that are particularly important for social, economic or environmental reasons (Article 32(2)). For this purpose, Member States can add specific eligibility criteria to targets e.g. some productivity levels, farms engaged in performance controls, quality value chains, etc.
- **Knowledge exchange and dissemination of information (KNOW)** (Article 78): Member States may grant support for actions to promote innovation, training and advice, and other forms of knowledge exchange and dissemination of information.
- **Farm advisory services (FAS)** (Article 15) as defined by Member States in their CSPs, advise farmers and other CAP beneficiaries on land and farm management. These services address economic, environmental and social dimensions, taking into account existing farming practices, and deliver up-to-date technological and scientific information developed by means of research and innovation projects. The provided assistance includes the support for changing production needed to address consumer demand and the implementation of innovative practices.

Support for setting up young farmers and new farmers (Article 75) can also be seen as contributing to improving agricultural productivity, as it requires applicants to submit a business plan to ensure the performance of the farms supported.

26 This section presents all CAP interventions with intended direct effects on productivity, as indicated in the regulation. Not all of them may have been implemented for this purpose by the Member States, which have defined interventions that should contribute to the productivity-related priority (SO2) in the intervention logic of their CAP Strategic Plan. See Chapter 3.2 on intervention logic.
27 The COOP type of intervention is excluded from the scope of the guidelines, which focus on assessing farm productivity and only consider the effects of CAP interventions directly delivered to farms. COOP interventions are project based which makes it difficult to identify their effects at the farm level. At the same time, with COOP interventions it is difficult to identify farms that did or did not participate in COOP projects, which limits the application of the proposed methods in these guidelines.

2.3.2. CAP interventions with indirect effects on farm productivity

Other CAP interventions can influence farm productivity, although this is not their primary objective.

- **Decoupled income support interventions (DIS)** include the following interventions: basic income support for sustainability (BISS) (Article 21), payments for small farmers (PSF) (Article 28), complementary redistributive income support for sustainability (CRISS) (Article 29) and complementary income support for young farmers (CIS-YF) (Article 30). Support delivered to **areas facing natural or other specific constraints (ANC) (Article 71) or areas with specific disadvantages (ASD) (Article 72)** is considered in these guidelines as decoupled income support as it aims to support farmers in areas with natural handicaps, such as mountainous areas or other challenging farming conditions. This is intended to maintain agricultural activity and sustainable land use in these areas. Unlike coupled income support, decoupled payments are not linked to sectors/productions/farm types, but are based on eligible hectares and, in some cases, entitlements. While providing income support to farmers, this category of interventions generally does not directly induce the production of specific outputs. However, it can have indirect effects due to changes in risk perception or financial constraints that may impact production decisions, resource allocation and investment capacity.
- **Eco-schemes (Article 31) and ENVCLIM interventions (Article 70)** are designed to encourage farmers to adopt or continue environmentally friendly farming practices that go beyond the mandatory standards (GAECs and SMRs). These interventions can impact productivity in different ways, especially in the sustainability dimension. Standard productivity can increase even when the produced marketed output level decreases because of a relatively higher reduction of costs/inputs due to more efficient farming practices.

2.3.3. Expected effects on environmental and social aspects

These CAP interventions are designed to address economic, environmental or social dimensions or a combination of these. By supporting practices, innovations or investments targeting higher farm efficiency or technological progress, they enable reducing the amount of inputs used for a given output, lowering the negative impacts (e.g. investment support or EIP can help farmers get equipped with precision spraying systems based on real-time sensors, which can reduce the volume of pesticides as the site of application is limited to points where the presence of plants is detected, with no differences in the average crop yield as the recommended doses are not affected) [28].

These CAP interventions can also positively influence social aspects. For instance, they can improve animal welfare and employment conditions by supporting investments in equipment for improving livestock housing conditions and reducing work arduousness or long working hours (e.g. transition from conventional to robotic milking). Specifically, Regulation (EU) 2021/2115 states among objectives for certain sectoral types of interventions as "the improvement of conditions of employment and enforcement of employer obligations as well as occupational health and safety requirements" [29].

However, as some conflicts can exist between the economic and social or environmental dimensions, negative effects can also occur, e.g. by encouraging increased input use (e.g. water used for irrigation purposes or higher livestock numbers with increased GHG emissions), with detrimental effects on the environment. There is often a trade-off between the positive and negative impacts related to the various dimensions.

28 Zanin, A., R., A., Neves, D., C., Teodoro, L., P., R., da Silva Júnior, C., A., da Silva, S., P., Teodoro, P., E., Baio, F., H., R., *Reduction of pesticide application via real-time precision spraying*, Sci Rep, Apr 4;12(1):5638, 2022. doi: 10.1038/s41598-022-09607-w.

29 In accordance with Directives 89/391/EEC, 2009/104/EC and (EU) 2019/1152.

3. Evaluation framework

3.1. Legal basis for assessing the CAP's impact on productivity

The increase of agricultural productivity is based on optimal utilisation of the factors of production, respecting social objectives and integrating environmental protection requirements, as fostered by the Treaty of the European Union [30].

In the context of the CAP, the increase in productivity is embedded in Specific Objective 2 (SO2) as defined in Regulation 2021/2115 [31]. At the same time, the **assessment of productivity is a key element when evaluating SO2**. Implementing Regulation (EU) 2022/1475 recommends examining the **CAP Strategic Plans' contribution to capital, labour and land productivity** when assessing its effectiveness towards Specific Objective 2 (see Annex I). As shown in the table below, the factor of success (FoS) recommended for the assessment of the key evaluation element 'farm competitiveness' looks at the impact of the CAP on farm productivity. This factor of success is disaggregated further below (when developing evaluation questions) in order to operationalise its use in line with the methods proposed in these guidelines.

Table 1. Indicative framework for assessing SO2 according to Regulation (EU) 2022/1475

Specific objective	Key evaluation elements	Factors of success
SO2 – To enhance market orientation and increase farm competitiveness both in the short and long term, including **a greater focus on research, technology and digitalisation**	**Enhanced market orientation** Based on agri-food trade balance (import-export).	Agri-food trade is increasing due to CAP support
	Farm competitiveness Based on increased capital, labour and land productivity through innovation.	**Productivity** in farms supported is increasing due to CAP support

Source: Annex I of Implementing Reg. (EU) 2022/1475

In addition, the Performance and Monitoring Framework (PMEF) includes indicator **I.6 for the calculation of the total factor productivity in agriculture**, by comparing agricultural output to the total inputs used. This indicator can also be used to observe the changes in the productivity of agricultural production factors [32].

Although Member States are required to calculate indicator I.6 and assess the CAP contribution to farm productivity in the context of SO2, they are not required to consider the CAP effects on sustainable productivity. However, as already stated in the introduction of these guidelines, the different interventions of CAP Strategic Plans that contribute to improving productivity can also have a potential effect on the other dimensions of sustainability, as the economic gains can (or cannot) be accompanied by environmental and social gains.

From a methodological perspective, improving the measurement of environmental and social inputs and outputs is crucial. As pointed out by the OECD, productivity indicators that do not account for environmental and social inputs and outputs "give a biased picture of the evolution of technology, for example by ignoring the effects of agriculture on the environment. In particular, certain forms of production use resources that are free but not renewable or beyond the capacity for renewal. This results in Total Factor Productivity (TFP) indicators that omit inputs that should logically be included. If output growth was accompanied by a degradation of natural capital, and which was not counted as an input, TFP growth might have been overstated. The measurement will also be biased if, for example, the investment in pollution control equipment to prevent leakage of ammonia in the air is counted as input and the reduction in pollution is not counted at all. Understandably, performance indicators that do not account for the destruction of natural capital and other environmental impacts of farming are unlikely to be seen as credible. In short, productivity discussions and indicators can no longer limit themselves to consider only marketed inputs and outputs" [33].

30 See Article 39 of the section of Union Policies and Internal Actions, Article 3 of the Treaty and Article 11 of the section on Provisions Having General Application of the Treaty.
31 Article 6, 1(b) of Regulation (EU) 2021/2115.
32 See the corresponding indicator fiche here: https://agriculture.ec.europa.eu/common-agricultural-policy/cap-overview/cmef_en. Accessed 10 September 2024.
33 OECD, *Agricultural Total Factor Productivity and the Environment - A guide to emerging best practices in measurement*, Paper n° 17. 2022.

From a policy perspective, there are various reasons to recommend the assessment of sustainable productivity and expand the scope of the evaluation:

- Sustainability is at the core of the general objectives of the CAP, by improving the sustainable development of farming, food and rural areas.
- The granting of income support to farmers has become increasingly conditioned to the adherence to some specific requirements related to environmental aspects.
- The objectives of sectoral interventions stress both the economic and environmental sustainability [34] and the improved sustainability of production systems and processes [35].
- Investment support is also related to environmental sustainability objectives [36].
- All of the above interventions are targeted towards farm productivity, but because of their contribution to sustainability objectives, they can also improve sustainable productivity.
- Finally, the recently published EU analytical brief on measuring agricultural productivity [37], concludes with suggestions on how TFP could evolve into a more meaningful measurement that addresses the evolving policy objectives toward sustainability, resilience and competitiveness. It recommends expanding the scope of TFP to include sustainability dimensions that would allow obtaining an indicator more suited for measuring sustainable productivity growth.

3.2. Intervention logic of CAP interventions affecting productivity

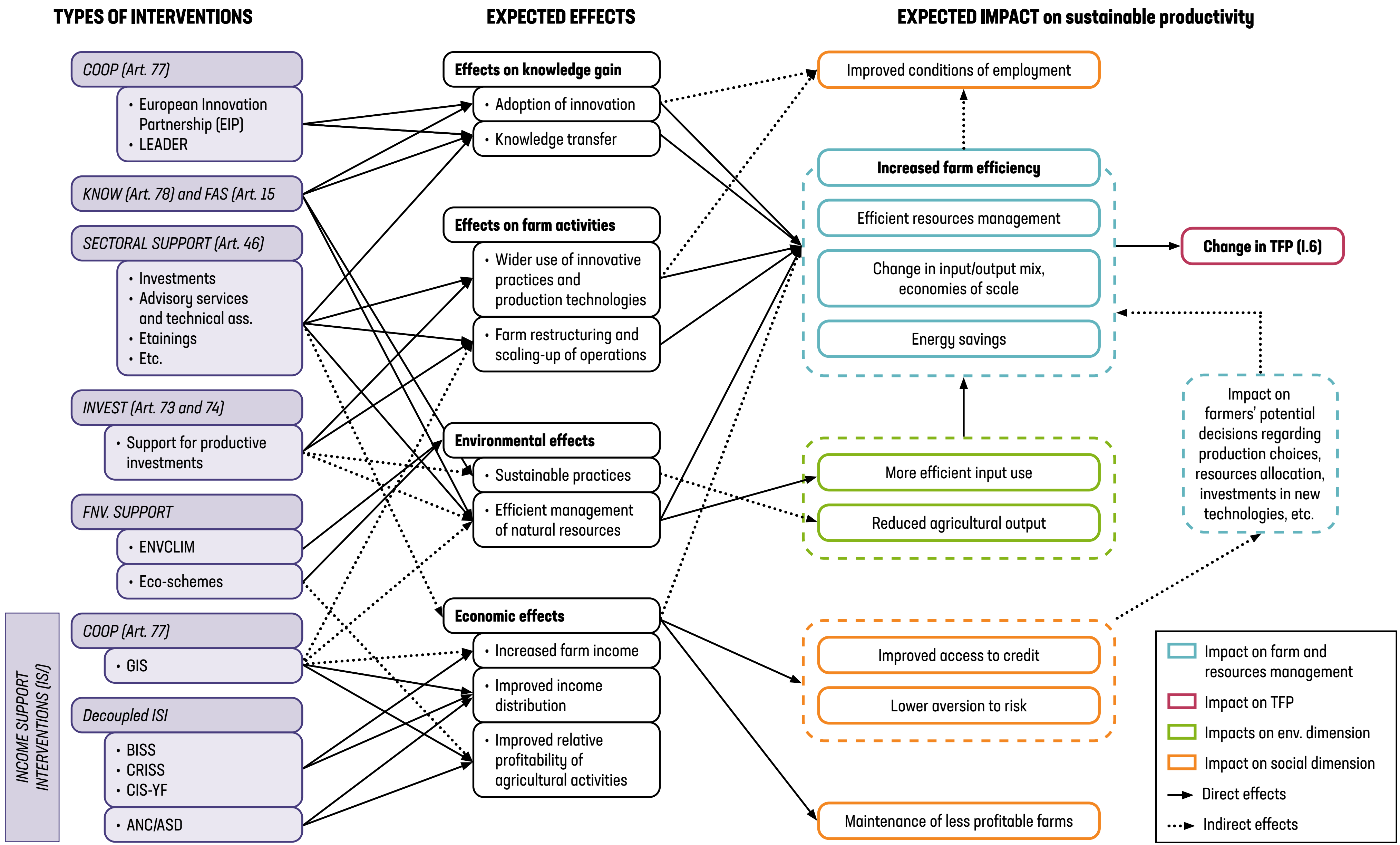
The starting point of any evaluation is the review of the intervention logic. The diagram below illustrates the general intervention logic of CAP interventions with direct and indirect effects on productivity and therefore linked to the impact indicator I.6 'total factor productivity in agriculture'. It is the task of each evaluator to review it and adapt it to the context and reality of the Member State.

This general intervention logic highlights the expected effects of CAP interventions supporting restructuring, modernisation, technologies and innovative solutions, knowledge transfer and exchange, as well as those with environmental and economic effects expected to affect farm productivity. As highlighted in the diagram, the increase in knowledge, the adoption of innovative solutions and the modernisation of farms should ultimately improve technological progress and/or farm efficiency, thus improving productivity. At the same time, income support interventions can influence production decisions and indirectly impact productivity. Furthermore, environmental support interventions may trigger the use of more efficient and sustainable farming practices and therefore increase productivity. Further side-effects on social and environmental aspects are suspected but are not systematic.

Note: The intervention logic presented here focuses on the CAP's impact on standard productivity, although the diagram also includes a few green and yellow boxes that reflect the corresponding impact on the social and environmental dimensions. This is because it is not possible to illustrate in a single diagram all the expected effects of CAP interventions on the economic, social and environmental dimensions (unless the diagram is extremely simplified).

34 For example, the wine sector (Article 57 of Regulation (EU) 2115/2021) or fruit and vegetables sector (Article 46).
35 Article 60 (4) of Regulation (EU) 2115/2021.
36 Article 73 (4)(a)(i) of Regulation (EU) 2115/2021.
37 EC (2024), *Measuring agricultural productivity, Insights into yields and Total Factor Productivity in the EU*, October 2024. European Commission, DG Agriculture and Rural Development. https://agriculture.ec.europa.eu/cap-my-country/performance-agricultural-policy/studies-and-reports/analytical-briefs_en. Accessed 02 December 2024.

Figure 3. Intervention logic of CAP interventions affecting productivity



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

It should be noted that the objective of the guidelines is to recommend quantitative methods to assess the CAP effects on sustainable productivity. Therefore, **the guidelines only take into account the CAP interventions whose effects can be quantified** in terms of increased or decreased productivity (also see Chapter 4, which presents a range of productivity indicators for that purpose). Consequently, COOP types of interventions are excluded from the scope of the guidelines, which focus on assessing farm productivity and only consider the effects of CAP interventions directly delivered to farms. COOP interventions are project-based which makes it difficult to identify their effects at farm level. At the same time, with COOP interventions, it is difficult to identify farms that did or did not participate in a COOP project, which limits the application of the methods, as proposed in these guidelines.

This intervention logic could be enriched in the future to account for potential improvements of downstream processes that can be supported by the CAP. The rationale can be found in the recent EU Analytical Brief that argues the average global agricultural productivity needs to increase by 28% over the next decade to address food insecurity. In this context, TFP could be estimated beyond primary agriculture, to allow the measurement of the overall efficiency of the food value chain, looking at the productivity of downstream processes, where better storage, more efficient logistics, and reduced food waste and loss could all help to improve agricultural productivity.

3.3. Examples of evaluation questions

This section presents examples of evaluation questions (EQs) that (a) consider the effects of the selected CAP interventions on sustainable productivity and (b) can be addressed through the quantitative approaches developed in these guidelines (methods for evaluating are presented in Chapters 4 and 5). Therefore, the factor of success for farm productivity proposed in the regulation [38] is disaggregated further to reflect aspects related to sustainable productivity and to help answer the evaluation questions. Two examples of EQs are suggested here, whether the evaluation examines the effects of a specific CAP intervention or a set of different CAP interventions (as a whole).

EQ1. To what extent has a specific (targeted) CAP intervention affected farm productivity?

This evaluation question can be asked by Managing Authorities willing to assess the role of specific and targeted CAP interventions. It should refer to specific interventions not taken up by all farms (i.e. there are some counterfactual farms) and that clearly affect farm production, such as investment support, agri-environmental payments and support for organic farming.

This evaluation question can either consider the effect of the CAP intervention on (a) farm productivity or (b) sustainable productivity. In line with the rationale provided in these guidelines for assessing sustainable productivity and not just productivity, additional (to what is in the Implementing Regulation) factors of success and indicators are proposed.

38 Annex I of Implementing Regulation (EU) 2022/1475.

Figure 4. Example of evaluation framework considering the effects of a specific (targeted) CAP intervention on sustainable productivity

Factors of success	Indicators	Data sources	Recommended method(s)
Standard productivity in supported farms is increasing due to CAP support (included in Annex I of Regulation (EC) 1475/2022)	Standard productivity indicators: › partial productivity (PP) (Section 4.2) › TFP (Section 4.3)	Elaborations on individual farm FADN data or other databases containing bookkeeping information	Assessment performed by means of a counterfactual impact evaluation, such as propensity score matching (Section 5.4.1) and/or difference-in-difference (Section 5.4.2) where **the outcome is the standard productivity indicator**
Negative environmental impacts of farms are lower (and/or positive social impacts are higher) in beneficiary farms/regions than in non-beneficiary farms/regions (suggested new factor of success)	Environmental and/or social sustainable indicators (Section 4.2)	Elaborations on individual farm FADN data or other databases containing bookkeeping and environmental/social information	Assessment performed by means of a counterfactual impact evaluation such as propensity score matching (Section 5.4.1) and/or difference-in-difference (Section 5.4.2) where **the outcome is the environmental or social indicator**
Sustainable productivity in supported farms is increasing due to CAP support (suggested new factor of success)	Sustainable productivity indicators: › eco-productivity indices (Section 4.3) › environmentally-adjusted productivity indices (Section 4.3)	Elaborations on individual farm FADN data or other databases containing bookkeeping and environmental/ social information	Assessment performed by means of a counterfactual impact evaluation such as propensity score matching (Section 5.4.1) and/or difference-in-difference (Section 5.4.2) where **the outcome is the sustainable productivity indicator**

Source: EU CAP Network supported by the European Evaluation Helpdesk for the CAP (2024)

Note: Standard productivity refers to the traditional productivity concept accounting only for the marketed agricultural goods, while sustainable productivity includes also environmental and social goods. See Chapter 4.

EQ2. To what extent have a set of different CAP interventions affected farm productivity?

This evaluation question can be asked by Managing Authorities willing to assess the contribution of a set of different CAP interventions as it (and corresponding approaches suggested) enables an assessment of the effects of a relatively large array of interventions, including those which benefit a large share of farms, even if at different levels (e.g. BISS). Hence, the recommended methods, developed in these guidelines and indicated in the table, can include those interventions where it is not possible to have a large enough group of non-beneficiary farms to implement a counterfactual evaluation impact.

This evaluation question can either consider the effect of the set of CAP interventions on (a) farm productivity or (b) sustainable productivity. In line with the rationale provided in these guidelines for assessing sustainable productivity and not just productivity, additional (to what is in the Implementing Regulation) factors of success and indicators are proposed.

Figure 5. Example of evaluation framework considering the effects of a set of different CAP interventions on sustainable productivity

Factors of success	Indicators	Data sources	Recommended method(s)
Farm standard productivity is positively and significantly correlated to the amount of support provided by the considered CAP interventions (based on FoS included in Annex I of Regulation (EC) 1475/2022)	Standard productivity indicators: › partial productivity (PP) (Section 4.2) › TFP (Section 4.3)	Elaborations on individual farm FADN (or other) panel data	Assessment based on correlation models: ordinary least-squares (OLS) (Section 5.5.1)
	PP and TFP calculated over some years		Assessment based on correlation models: fixed effects model (FE) (Section 5.5.2)
	PP and TFP calculated over a relatively long number of years		Assessment based on correlation models: dynamic panel method (SYS-GMM) (Section 5.6.1)
Environmental impacts of farms are negatively and significantly (and/or social impacts are positively and significantly) correlated to the amount of support provided by the considered CAP interventions (new factor of success)	Environmental and social indicators (Section 4.2)	Elaborations on individual farm FADN (or other) panel data	Assessment based on correlation models: ordinary least-squares (OLS) (Section 5.5.1)
	Environmental and social indicators calculated over some years		Assessment based on correlation models: fixed effects model (FE) (Section 5.5.2)
	Environmental and social indicators calculated over a relatively long number of years		Assessment based on correlation models: dynamic panel method (SYS-GMM) (Section 5.6.1)
Sustainable productivity is positively and significantly correlated to the amount of support provided by the considered CAP interventions (new factor of success)	Sustainable productivity indicators: › eco-productivity indices (Section 4.3) › environmentally-adjusted productivity indices (Section 4.3)	Elaborations on individual farm FADN (or other) panel data	Assessment based on correlation models: ordinary least-squares (OLS) (Section 5.5.1)
	Sustainable productivity indicators calculated over some years		Assessment based on correlation models: fixed effects model (FE) (Section 5.5.2)
	Sustainable productivity indicators calculated over a relatively long number of years		Assessment based on correlation models: dynamic panel method (SYS-GMM) (Section 5.6.1)

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

Note: Standard productivity refers to the traditional productivity concept accounting only for agricultural goods marketed, while sustainable productivity includes also environmental and social goods. See Chapter 4.

These questions and the corresponding methods indicated in the tables focus on farm productivity. Hence, they do not consider other aspects that may explain the changes in productivity observed, for example:

- effects of the CAP on productivity drivers (e.g. modernisation, innovative technologies, management skills and knowledge, access to capital, etc.); and
- effects of the CAP on productivity components (e.g. resource allocation, increase in output value, etc.).

These aspects are necessary to consider for understanding the findings of the quantitative analyses presented in these guidelines. They should be inquired through other means, notably through interviews with stakeholders, focus groups, case studies, etc., which are not addressed in these guidelines. Specific PMEF indicators can be particularly relevant for complementing the information, i.e. R.9 (farm modernisation), R.3 (digitalising agriculture) and I.1 (sharing knowledge and innovation) (see also Section 3.6 on other relevant indicators).

In addition, a benchmarking analysis of productivity scores can also be of interest to describe the background context in which the CAP interventions have been implemented and identify strengths, weaknesses, opportunities and areas for improvement. It can allow farmers to compare their performance against industry standards or similar farms, helping them understand where they stand in terms of productivity and sustainability.

3.4. Level of analysis

Analysis of the impact of the CAP on productivity can be carried out at farm level and/or at regional level, depending on the objective of the evaluation and the type of data available. Both levels of analysis are valid but have different advantages.

Figure 6. Different levels of analysis to assess the CAP impact on productivity

	Farm level analysis	Regional level analysis
When is it appropriate?	Farm level analyses reflect the direct impact of CAP on individual farms' productivity. They explicitly account for the individual situation of each farm, characterised by a specific set of CAP interventions. A farm level analysis allows for a more in-depth evaluation of the impact of CAP interventions on productivity because it allows for comparison of the effect of many variables (e.g. input) and different groups according to specific farm characteristics (e.g. economic size). A farm level analysis should be favoured for analyses focusing on the effect of one CAP intervention (e.g. INVEST, ENVCLIM) for which specific groups of beneficiaries and non-beneficiaries must be established. A farm level scale indicator can provide more in-depth evidence about the link between productivity, farming practices, land features and agroclimatic conditions [39].	Regional (that also includes national) level analyses involve aggregated data on CAP interventions, i.e. CAP support is measured as the sum of the CAP support received by all farms, which can include a variety of different CAP interventions in a given region or country. A regional-level analysis is relevant for considering CAP interventions that benefit (almost) all farms yearly, as for BISS, or for considering all CAP support as a whole in the analysis. When the analysis is carried out based on regional/national aggregated data, it is possible to obtain valuable comparisons by using time-invariant control variables or selecting regions and countries that are comparable in relevant aspects. To achieve this, significant efforts must be made to ensure that the groups being compared are as similar as possible, thereby allowing for a more accurate assessment of the effects of CAP interventions.

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

39 EU Analytical Brief Nº 5. Measuring agricultural productivity. Insights into yields and total total factor productivity in the EU, October 2024.

3.5. Descriptive analysis supporting the assessment of productivity

Before embarking on an evaluation method to answer the EQs, evaluators should carry out a descriptive analysis of the uptake of CAP interventions and the distribution of support across farms. Such an analysis will set the context on the number of beneficiaries supported by the relevant interventions affecting productivity and how these are distributed across different types of farms or sectors.

If the uptake is low, significant effects are not expected and cannot be quantified. In this case, the quantitative methods proposed in these guidelines cannot be implemented and the evaluator might choose a less robust evaluation approach. For example, the naïve group comparison or qualitative assessments based on experts' and stakeholders' opinions. A naïve group comparison can be supported by qualitative methods such as in-depth interviews and focus groups, the method for impact assessment of programmes and projects (MAPP) [40], and Delphi methods. The use of such qualitative techniques is useful for obtaining some informed views on the effects or potential effects of CAP interventions on productivity, even if these relate only to a small number of beneficiaries. At the same time, however, such techniques may involve some selection bias, which should be taken into account in the interpretation of calculations. If the uptake is sufficient, the evaluator can apply advanced evaluation approaches described in Chapter 5.

3.6. Other relevant indicators

Other context and result indicators may be used to further contextualise the impact indicator I.6 (total factor productivity) and help answer the evaluation questions. Given that farm productivity is mainly dependent on the evolution of three types of inputs (land, labour, capital), it is pertinent to examine, where possible, the evolution of PMEF indicators reflecting these inputs. It must be noted that land productivity, which is not presented here, is extensively examined under Chapter 4.2 on partial indicators.

The labour input in particular is critical, as the TFP indicator is very sensitive to any variation of this input. Relevant PMEF indicators to specifically examine labour are:

- **Farm labour force (PMEF context indicator C.13)**. This indicator shows the labour force directly employed by the agricultural holding and working regularly (can also be differentiated by sex), and the temporary labour force. It can be obtained by Eurostat (farm structure survey and integrated farm statistics). This context indicator can give an indication of the quantity of the labour input (e.g. number of persons or AWU) that has contributed to a change in output.
- **Labour productivity (PMEF context indicator C.30)**. This indicator consists of three specific indicators: labour productivity in agriculture, labour productivity in forestry and labour productivity in the food industry. For each specific indicator labour productivity is calculated as gross value added (GVA) per unit of labour input. It shows how much value the labour force creates per hour worked and the evolution of this indicator gives an indication of the competitiveness of the agricultural or forestry holding or the food industry company.

Capital is another input which can be examined specifically to explain the effects of investments on productivity. A relevant context indicator is:

- **Gross fixed capital formation in agriculture (PMEF context indicator C.28)**. It measures the producer's investments, deducting disposals, in fixed assets during a given period, plus certain additions to the value of non-produced assets realised by the productive activity of the producer. Gross fixed capital formation in agriculture is a key element of competitiveness as it indicates the capacity of the holding to become more competitive through investments.

Then, intermediate inputs such as pesticides, fertilisers, feed, etc. can be considered to assess the changes as regards the share of land which is farmed with low, medium and high intensity:

- **Farming intensity (PMEF context indicator C.34)**. This indicator is expressed as the percentage of UAA that is farmed with low, medium or high input intensity. The indicator measures the level of inputs used by the farm per unit of production factor (in general land). Intensification is defined as the increase in farm intensity, while extensification describes the opposite trend. The inputs considered are fertilisers, pesticides, other crop protection products and purchased feed, covering both crop and livestock productions. Farms are classified into intensity categories according to an estimate of input volume per hectare of UAA. This indicator offers a useful perspective by allowing the assessment of the drivers of the changes in productivity observed. In particular, it can help determine whether an increase in land productivity can be associated with growing intensification of agriculture.

40 For the MAPP method see 'Quick Guide #8: How to apply the MAPP in the assessment of environmental impacts' of the Guidelines for assessing RDP achievements and impacts in 2019. The recommended steps are the same for any type of impact, their detail only needs to be adapted to the types of beneficiaries of the relevant interventions.

There are also some result indicators whose value can give useful information to answer the EQs. For instance:

- **Farm modernisation (PMEF result indicator R.9)**. It measures the share of farms receiving investment support to restructure and modernise, including to improve resource efficiency. It is pertinent for EQ1 to examine the effects of investment interventions. A higher share of farms receiving investment support to restructure and modernise may trigger a boost in productivity. This may be interesting to examine for a certain sector or region for instance, where productivity has been low and where CAP investments are expected to make a difference.
- **Enhancing performance through knowledge and innovation (PMEF result indicator R.1)**. It measures the number of persons benefiting from advice, training, knowledge exchange or participating in EIP Operational Groups supported by the CAP, in order to enhance sustainable economic, social, environmental, climate and resource efficiency performance. It is a pertinent indicator to examine the effects of COOP interventions, notably EIP ones [41], especially given that these interventions have important effects on outcomes related to knowledge gains (see the intervention logic in Section 3.2). Therefore, as COOP interventions are excluded from the scope of these guidelines, this result indicator offers the opportunity to examine the potential of the EIP interventions to contribute to knowledge gains and, as a consequence, increased farm efficiency.
- **Digitalising agriculture (PMEF result indicator R.3).** It measures the share of farms benefitting from support for digital farming technologies through the CAP. Modernisation, leading to improved productivity, cannot be achieved without the adaptation of farmers to the digital transition. Digitalisation can enable farmers to adapt to the digital transformation and adopt innovative digital solutions that help modernise and improve productivity. Digitalisation can be boosted by investment support, advisory services, EIP projects and support to different sectors through sectoral interventions e.g. in the fields of fruit and vegetables, apiculture and wine. This indicator is therefore pertinent for providing further information on how the combination of these interventions (relevant for EQ2) contributes to digitalisation and consequently to improved productivity. In addition, as COOP interventions are excluded from the quantification methods of these guidelines, this indicator can provide information on how EIP projects (as part of COOP interventions) enable farmers to adopt digital solutions that improve their farm technical efficiency.

41 Art. 77, 1(a) of Regulation (EU) 2021/2115.

4. Measuring sustainable productivity

4.1. Selecting the right indicators

Depending on the scope of your evaluation, the technical resources available to you or the data available in your country, you might want to consider the CAP impact on:

- the productivity of single inputs (e.g. capital, land, labour) taken separately, or of single environmental or social themes taken separately → **partial indicators**

OR

- on total productivity (i.e. referring to all inputs used in the production of all outputs) → **total indicators**.

Partial indicators focus on a single issue and can highlight specific outcomes; for example, how one input performs, a specific environmental impact of agriculture or a specific social aspect. Total indicators aim to give a complete picture of productivity in agriculture, considering all possible combinations of inputs, the possible product mixes, and the possible joint processes of economic and other (environmental or social) production.

Moreover, the analysis can focus on:

- productivity considering only the agricultural outputs, i.e. the output that is aimed to be produced by farmers and sold at a specific price → **standard productivity**

OR

- productivity i.e. considering not only agricultural output, but also environmental and social impacts generated by the production process → **sustainable productivity**.

Standard productivity is measured with widely used indicators that can be calculated with various approaches, all with pros and cons, which have been well-tested. By contrast, sustainable productivity is based on recent approaches that are still evolving and that require information that is usually complex to obtain or integrate into the analysis (i.e. some necessary information is not available in classic bookkeeping data; no price exists for the environmental and social goods). It is important to underline that the limited availability of relevant data may make it difficult to precisely calculate sustainable productivity. Therefore, the integration of environmental and social outputs in the calculation of sustainable productivity may vary according to Member States, depending on data available and Member State choices associated with specific contexts, which may prevent further aggregation of the indicators at the EU level.

As a summary, the table below presents the different indicators suggested for the analysis.

Table 2. Productivity indicators

		Productivity indicators focusing on:	
		A single issue (one input, or one environmental or social aspect)	**All inputs and outputs**
And accounting for:	**Standard productivity** (i.e. agricultural goods only)	Partial productivity indicators [see Chapter 4.2 and Technical Annex 2]	Total factor productivity (TFP) [see Chapter 4.3 and Technical Annex 4]
	Sustainable productivity (i.e. env. and social aspects integrated in the analysis)	Environmental and social indicators of agriculture [see Chapter 4.2 and Technical Annex 3]	Eco-productivity indices and environmentally adjusted productivity indices [see Chapter 4.3 and Technical Annex 5]

Increased data needs

Increased methodological complexity

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

Each of these indicators is presented in the next chapters. According to preferences, the reader can go directly to the relevant chapter (as indicated in the table).

The degree of methodological complexity increases with the integration of multiple inputs and outputs (partial productivity being less complex than multiple productivity (i.e. TFP)) and also increases in terms of data needed with the integration of environmental and social impacts (standard productivity is less complex than sustainable productivity).

4.2. Partial indicators

Why use partial indicators?

Partial indicators focus on a single issue. Generally, they relate an output to one of the inputs used in producing that output. The output may be either:

- **agricultural**
  → in this case, we speak about **partial productivity**. Examples of partial productivity are yield (output per unit of land area) and agricultural output produced per unit of labour.
- **environmental**
  → in this case, we speak about **environmental indicators**. Examples of environmental indicators are emission intensity (i.e. the amount of GHG emissions per amount of product, e.g. per livestock unit) and biodiversity per ha of land.
- **social**
  → in this case, we speak about **social indicators**. Examples of social indicators are number of outdoor hectares per 100 heads of poultry, number of work accidents per worker and farmers' sick leave or mortality rate.

Although here environmental and social indicators do not include the term 'productivity', they are in fact partial productivity indicators since they relate a measure of impacts (e.g. amount of GHG emissions) to product (e.g. livestock units). The term 'environmental productivity' is not used in these guidelines, as it has a specific meaning in some scientific studies, which is close to the 'sustainable productivity' defined in Section 2.1.3. Note also that in some studies, the terms 'environmental indicators' and 'social indicators' denote the measurement of impacts only, without relating them to inputs.

Pros and cons of partial indicators:

- **Pros** – Partial indicators highlight the role of a specific input. When looking at several partial indicators together (e.g. plotting them on a radar chart), it can point towards a specific weakness.
- **Cons** – Partial indicators give only a partial picture of productivity, as (i) only one input is considered and (ii) the three dimensions of sustainability (economic, environmental, social) are considered separately. Several partial indicators could be used in combination to give a broad picture of productivity. However, the picture would still be incomplete as this does not account for input substitution, contrary to total indicators [42].

How to calculate partial indicators?

Step 1: Decide on the level of analysis

- Comparing farms → Use farm-level data in one or several years
- Comparing sectors → Use sectoral data if available in one or several years, or aggregate farm-level data per sector
- Comparing regions → Use regional data in one or several years, or aggregate farm-level data per region
- Assessing the evolution over time → Use the same data as above depending on your level of analysis, but make sure that you have several years of past observations (at least five years, for example from previous programming periods)

When aggregating, be aware of the aggregation bias (see Section 4.7 Issues in productivity estimation in the Technical Annexes). When possible, use farm level data over aggregated data, as the former includes more information than the latter.

Step 2: Check what data you have

- If you have data over several years, you need to adjust the monetary values for inflation. If you have data for several countries, you need to adjust the monetary values for purchasing power (see Section 2.2.1).
- **Partial productivity:** The calculation of partial productivity requires information on outputs and inputs (see Section 2.2.1).
- **Environmental and social indicators:** The calculation of environmental and social indicators necessitates diverse and complex data, and is often limited by available data. It is therefore necessary to start with knowing the data you have at hand in order to select the environmental and social indicators that you can calculate (see Section 3.3 of the Technical Annexes).

See Section 2.2 for further information on the data needs and sources, and Technical Annex 1 for examples of information in the FADN database.

Step 3: Calculate the partial indicators

- **Partial productivity:** These indicators are straightforward ratios:

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

42 Moreover, partial indicators cannot always be aggregated into a single value for agriculture as a whole and can only be analysed for individual commodities (e.g. yields).

As presented in Section 3.6, the PMEF indicator C.30 'Labour Productivity' is a partial indicator, as it relates to gross value added (GVA) per unit of labour input [43].

Learn more about the partial productivity indicator in Technical Annex 2.

- **Environmental and social indicators:** These indicators are more complex.

Some environmental and social indicators can be directly retrieved from FADN data or other bookkeeping data (see Technical Annex 1). Other indicators need to be calculated with bookkeeping and other data (e.g. GHG emissions) or collected through specific surveys (e.g. working conditions).

Learn more about the environmental and social indicators in Technical Annex 3.

Step 4: Read the results from the partial indicators

- **Partial productivity:** A higher value of partial productivity indicates a more efficient use of the input in generating output. For example, higher labour productivity (output per work unit) suggests that labour is being used more efficiently.

Example of application from literature

An interesting example of the use of partial productivity is the analysis by Garrone et al. [44] which investigated the relationship between EU agricultural subsidies and agricultural labour productivity.

These authors used labour productivity, which is measured as the annual growth in gross agricultural value added (VA) per worker in real terms. The gross agricultural VA, an indicator of the output, includes the productivity effect induced by coupled CAP payments.

The study used a comprehensive regional-level dataset covering 213 EU regions from 2004 to 2014, utilising the Clearance Audit Trail System (CATS) dataset which includes detailed information on all farm subsidies received by farmers in every region. The study concluded that an increase in productivity was driven by decoupled subsidies, specifically Pillar I decoupled payments and certain Pillar II payments. In contrast, coupled Pillar I subsidies hinder productivity growth. It is important to clarify that these conclusions were drawn earlier for the previous CAP 'reforms'. This does not question the applied methodology of the analysis or its conclusions as 'historical knowledge', but it makes these conclusions potentially obsolete for the CAP today.

- **Environmental and social indicators:** There is no single interpretation for environmental and social indicators, it depends on the way the indicator is calculated. For example, a higher value of GHG emissions per ha is not desired; therefore, farms (or regions) are said to be performing better when this indicator is lower. By contrast, a higher value of a biodiversity index indicates better environmental performance.

Example of application from literature

Scope of the study

Based on a sample of 3 074 French dairy farms, Lambotte et al. [45] compared the carbon footprint of milk production between organic and conventional farming methods.

Methodological approach

The carbon footprint was assessed using four different measures of GHG emissions per litre of milk produced. These emissions are calculated through a cradle-to-farm-gate life cycle analysis, which also accounts for soil carbon changes linked to land use management.

Main findings

The study found that the carbon footprint of organic milk is 19%, or 0.185 $kgCO_2e.L^{-1}$, lower than that of conventional milk. However, when including the effects of indirect land use changes, the advantage of organic milk decreased to 11%, or 0.133 $kgCO_2e.L^{-1}$.

Checklist

What the evaluator needs for partial indicators

- Clarify the rationale for using partial indicators
- Decide the level of analysis
- Check what data you have, ensuring access to the necessary data sources
- Collect additional data if needed
- Make the necessary adjustments to data
- Calculate the partial indicators
- Interpret the results of the partial indicators, taking into account the type of indicator (e.g. a high value is not always desirable)
- Take into account other available information (results from other sources, contextual information, other indicators) to triangulate the results and better explain the value of the partial indicator.

See also Technical Annexes 2 and 3 for the technical description and details on partial indicators.

43 For more information see: https://agriculture.ec.europa.eu/common-agricultural-policy/cap-overview/cmef_en. Accessed 10 September 2024.
44 Garrone, M., Emmers, D., Lee, H., Olper, A., and Swinnen, J., *Subsidies and Agricultural Productivity in the EU*, Agricultural Economics, Vol. 50, N° 6, November 2019, pp. 803-817. https://doi.org/10.1111/agec.12526.
45 Lambotte, M., De Cara, S., Brocas, C., and Bellassen, V., *Organic farming offers promising mitigation potential in dairy systems without compromising economic performances*, Journal of Environmental Management 334:117405, 2023. https://doi.org/10.1016/j.jenvman.2023.117405.

4.3. Total indicators

Why use total indicators?

Total indicators aim at relating all outputs to all inputs used in producing that output. The outputs considered may be either:

- **agricultural outputs only**

  → in this case, we speak about **standard productivity or Total Factor Productivity (TFP)**.

- **agricultural, environmental and social outputs**

  → in this case, we speak about **sustainable productivity** [46].

Pros and cons of total indicators:

- **Pros** – Total indicators give a complete picture of productivity in agriculture. They account for the whole production process and the possible combinations of inputs, the possible product mixes, and the possible joint processes of agricultural and other (environmental or social) production. Various 'total' indicators could be calculated depending on the focus, e.g. a specific indicator accounting for agricultural and environmental production but not social production.
- **Cons** – It is generally not possible to account for all outputs and, therefore, the term multi-factor productivity is used instead of TFP. Environmental and social outputs are often poorly monitored and therefore the lack of information, along with the complexity of valuing and aggregating such outputs, implies that only a few of them are included in analyses. Another important challenge relates to quality adjustments in TFP, which has been recognised as essential for improving the accuracy of productivity assessments in agriculture [47]. Similarly, the residual nature of TFP in agriculture does not allow a distinction between the effects of agricultural technologies, farming practices, research and development, knowledge sharing initiatives and policy measures. Therefore, it's important to keep in mind the limitations of total indicator.

How to calculate total indicators?

Step 1: Decide on the level of analysis

- Comparing farms → Use farm-level data in one or several years
- Comparing sectors → Use sectoral data if available in one or several years, or aggregate farm level data per sector
- Comparing regions → Use regional data in one or several years, or aggregate farm level data per region
- Assessing the evolution over time → Use the same data as above depending on your level of analysis, but make sure you have several years of observations (at least five years)

When aggregating, be aware of the aggregation bias (see Section 4.7 Issues in productivity estimation in the Technical Annexes).

Step 2: Check what data you have

- If you have data over several years, you need to adjust the monetary values for inflation. If you have data for several countries, you need to adjust the monetary values for purchasing power (see Section 2.2.1).
- **TFP:** the calculation of TFP requires information on outputs and inputs, as well as prices (in some cases).
- **Sustainable productivity:** the calculation of sustainable productivity necessitates the same information as for TFP (outputs, inputs, prices) as well as information on environmental and social aspects. For these, data availability may be limited. For example, as market prices are generally not available for environmental and social outputs, these need to be estimated (shadow prices). Therefore, sustainable productivity may not be complete in terms of environmental and social aspects. It may only focus on a specific theme for which you have the data. To understand which themes will be considered in sustainable productivity, it is therefore necessary to start with knowing the data you have at hand.

See Section 2.2 for further information on the data needs and sources, and Technical Annex 1 for examples of information in the FADN database.

Step 3: Calculate the total indicator

- **Total Factor Productivity (TFP)**

TFP may be obtained by various methodologies depending on whether it is calculated with respect to a production frontier and whether the method accounts for statistical uncertainty (stochastic method) or not (deterministic method).

46 The USDA-ERS International Agricultural Productivity dataset employs the growth accounting method to estimate TFP growth. TFP is calculated as the difference between the value-share-weighted growth of aggregated agricultural inputs (land, labour, capital and materials) and output growth (crop and livestock production). This methodology captures efficiency improvements and technological advancements in agriculture, enabling cross-country comparisons of productivity trends while maintaining consistency in data sources and assumptions. This methodology is not considered in this guideline because it is specific to the United States.

47 For instance, the USDA-ERS incorporates quality elements such as adjusting land inputs to reflect differences between irrigated and rainfed croplands, while labour inputs are refined based on demographic factors like education and age. Similarly, the OECD emphasises the need to harmonise methodologies by including environmental outcomes, such as reductions in GHG, and adjusting for input quality changes to align TFP measures with sustainability goals.

Table 3. Available methodologies for TFP estimation

	Deterministic methodologies	Stochastic methodologies	
		Parametric	Semi-parametric
Non-frontier	**Index numbers (Laspeyres, Paasche, Fisher, Törnqvist index)** TFP = **ratio of all outputs divided by all inputs**, where both outputs and inputs can be aggregated through different ways	**Dynamic panel data (DPD)** TFP = **residual of output growth not due to growth of inputs**, in regression of production function with endogeneity accounted for with the lagged output	**Control function estimator (CFE)** TFP = **residual of output growth not due to growth of inputs**, in regression of production function with endogeneity accounted for with a control function
Frontier	**Malmquist or Färe-Primont index with data envelopment analysis (DEA)** TFP = **change in output due to shift of frontier** and to increased efficiency, using linear programming	**Malmquist or Färe-Primont index with stochastic frontier analysis (SFA)** TFP = **change in output due to shift of frontier and to increased efficiency**, accounting for noise in the analysis	

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

The Commission's PMEF indicator C.29 'Total factor productivity' is for example calculated with the Fisher index [48].

Note that DPD and CFE are usually adopted at the individual farm level as this level enables the use of datasets with sufficient observations. The use of DPD and CFE at the regional or national level is discouraged even if possible, given the low number of observations that may compromise the robustness of the results.

Learn more about TFP in the Technical Annex 4.

› Sustainable productivity

Contrary to TFP, where the output is only the agricultural output (i.e. monetary value of production), sustainable productivity accounts for environmental and social goods in the output produced by the farm.

While methods for TFP calculation are proven and widely used methods, methods for calculating sustainable productivity are more recent and still evolving. They currently include two main streams of approaches:

- eco-productivity index: a ratio of aggregated agricultural, environmental and desirable social outputs to the aggregated value of undesirable outputs. That is to say, inputs are not considered.
- environmentally-adjusted productivity index: a ratio of aggregated desirable outputs to aggregated and undesirable outputs.

As in the case of standard TFP, these indices can be computed with methods relying on a frontier or not, and methods that are deterministic or stochastic.

Table 4. Available methodologies for sustainable productivity estimation

	Deterministic methodologies	Stochastic methodologies
Non-frontier	**Index numbers (Laspeyres, Paasche, Fisher, Low, Geometric Young index)** productivity = **ratio of aggregated desirable outputs to the aggregated value of undesirable outputs and inputs**, where outputs can be aggregated through different ways	
Frontier	**Malmquist or Färe-Primont index with data envelopment analysis (DEA)** productivity = **change in output due to shift of frontier** and to increased efficiency, using linear programming	**Malmquist or Färe-Primont index with stochastic frontier analysis (SFA)** productivity = **change in output due to shift of frontier and to increased efficiency**, accounting for noise in the analysis

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

48 For more information see: https://agriculture.ec.europa.eu/common-agricultural-policy/cap-overview/cmef_en. Accessed 10 September 2024. More details are also available in the EU Analytical Brief N°5: Measuring agricultural productivity. https://agriculture.ec.europa.eu/cap-my-country/performance-agricultural-policy/studies-and-reports/analytical-briefs_en.

Learn more about sustainable productivity in the Technical Annex 5.

Step 4: Read the results from the total indicators

› **TFP**

TFP grows when production grows at a faster rate than the quantity of inputs. Hence, TFP values greater than one indicate productivity growth, suggesting technological progress or improved efficiency. By contrast, values lower than one show a decrease in productivity. For example, a TFP of 1.02 indicates a 2% growth in productivity [49].

Example of application from literature

Scope of the study

Comparing the total factor productivity for five main sectors of French agriculture namely field crop, dairy, beef cattle, sheep and goat, and mixed (field crop and grazing), between 2002 and 2015 [50].

Methodological approach

Data Envelopment Analysis and the Färe-Primont productivity index.

Main findings

The main results suggest a productivity increase for all sectors. The productivity indices are 1.25, 1.08, 1.23, 1.17 and 1.17 for field crop, dairy, beef cattle, sheep and goat, and mixed farms. This means the TFP growth over the period is 25%, 8%, 23%, 17% and 17%, respectively.

› **Sustainable productivity**

In the case of Index Numbers, values greater than one indicate that the numerator is greater than the denominator. That is to say, desirable outputs have grown more than undesirable outputs. In the case of Malmquist or Färe-Primont index, similar to TFP, index values greater than one indicate sustainable productivity growth.

Example of application from literature

Scope of the study

Measuring GHG adjusted TFP of a balanced sample of 49 French suckler cows between 1990 and 2013 [51].

Methodological approach

An extension of the Färe-Primont productivity index that included bad outputs. Estimations were conducted using a Data Envelopment Analysis.

Main findings

The Färe-Primont productivity index for the period is 0.946 indicated a 5.4% decrease in GHG-adjusted TFP. In contrast, the standard TFP at 1.006 showed no change.

Checklist

What the evaluator needs for total indicators

- Clarify the rationale for using total indicators
- Decide on the level of analysis
- List all the data requirements of TFP and/or sustainable productivity and check what data you have
- For the TFP and/or the sustainable productivity estimation, familiarise yourself with the different available methodologies
- Decide on the methodology to use and why
- Calculate the indicator with the selected method and interpret the results
- Triangulate the results with information from other sources, other indicators or other methods and therefore better explain the indicator value obtained

See also Technical Annexes 4 and 5 for the technical description and details on total indicators.

49 While it is theoretically possible to compare TFP across different farms, regions or production techniques, it is generally not recommended. This is because TFP values can be influenced by a variety of factors such as differences in input quality, environmental conditions and local economic contexts, which may not be fully comparable across different entities. As a result, comparing static TFP values between farms or regions may lead to misleading conclusions.

50 Dakpo, K.H., Desjeux, Y., Jeanneaux, P., and Latruffe, L., *Productivity, technical efficiency and technological change in French agriculture during 2002-2015: a Färe-Primont index decomposition using group frontiers and meta-frontier*, Applied Economics 51, 2018, 1166-1182. https://www.tandfonline.com/doi/abs/10.1080/00036846.2018.1524982.

51 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 24, 2019, 625-639. https://doi.org/10.1007/s10666-019-09656-y.

5. Assessing the CAP's impact on sustainable productivity

5.1. Introduction

This section addresses the issue of how to assess the impact of the CAP on productivity, whether standard productivity accounts only for agricultural output, or sustainable productivity that also integrates environmental and social impacts.

This assessment is clearly challenging for many reasons, including that the impact of the different interventions of CAP can vary according to the nature of these measures and that several factors other than CAP affect productivity.

Different models can be used to assess the impact of CAP interventions on sustainable productivity and to overcome methodological issues.

This guideline document proposes different models that can be classified into the following three main categories:

- counterfactual impact models [52]
- correlation static models
- correlation dynamic models

Each approach has its own pros and cons, areas of application and data and analytical needs to be applied as described in Sub-sections 5.4, 5.5 and 5.6.

Several aspects should be taken into consideration to decide which method is more appropriate for specific evaluation conditions. However, the next section provides a simple discussion of the main elements driving the choice of the model.

5.2. Selecting the right approach

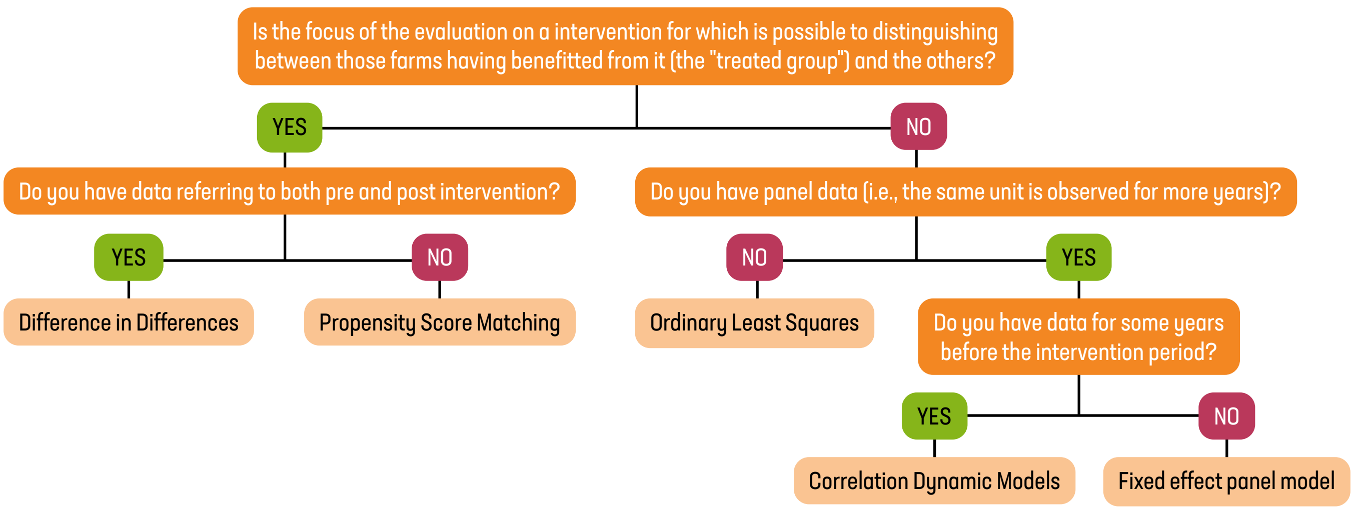
To select the most suitable approaches, the following main aspects can be considered:

1. It is not always possible to distinguish farmer beneficiaries and non-beneficiaries of CAP interventions in available databases.
2. Farmers often participate in several types of interventions at the same time; these can interact with each other and, depending on the set of interventions, generate different effects on productivity.
3. Productivity has a dynamic nature, i.e. past productivity is expected to have an effect on current productivity.

The choice between correlation and counterfactual approaches is mainly driven by the possibility of distinguishing between farmers benefitting and not benefitting from the considered policy measure, as shown in Figure 7 below. It reports a simplified decision tree that is consistent with what has been developed in a previous publication by the European Evaluation Helpdesk for Rural Development [53]. This simplified decision tree is based on the idea that the approach to be used should be selected according to different aspects, including data availability.

It should be noted that the choice of the best possible method, given the evaluation's specific context and objectives, will require sufficient knowledge and skills from the evaluators. Although presenting different levels of complexity, the selected approaches (and presented in more detail in the next chapters) demand specific skills in econometrics and statistics in order to be implemented.

Figure 7. Simplified decision tree for choosing the method to assess the impact of CAP on productivity



Source: EU CAP Network supported by the European Evaluation Helpdesk for the CAP (2024)

52 There is a large body of literature on the use of counterfactual impact models. In these guidelines, we refer only to those most commonly used in agricultural economics. For a more detailed explanation, refer to: Abadie, A., Cattaneo, M.D., *Econometric Methods for Program Evaluation,* Annual Review of Economics, 10:465-503, 2018. https://doi.org/10.1146/annurev-economics-080217-053402; and Imbens, G.W., *Causal Inference in the Social Sciences. Annual Review of Statistics and Its Application,* 11:123-152, 2024. https://doi.org/10.1146/annurev-statistics-033121-114601.
53 EU CAP Network, *Interactive Decision Tool for I.01, I.02, I.03. Publication - Guidelines and tools*, 01 Apr 2020. https://eu-cap-network.ec.europa.eu/publications/interactive-decision-tool-i01-i02-i03_en. Accessed 9 October 2024.

It is important to underline that some CAP interventions concern almost all farms (e.g. BISS), whereas others enable clearly distinguishing beneficiaries from non-beneficiaries (e.g. ENVCLIM). In this latter case, it is possible to rely on counterfactual impact models such as propensity score methods and difference-in-difference. **Difference-in-difference is preferred when data for both pre- and post-intervention are available as it can provide robust findings**.

However, the counterfactual approaches adopted in this document are difficult to apply for assessing the impact of a set of policy at the same time. This can be a relevant issue provided that farmers often benefit from more than one measure at the same time. CAP interventions can interact with each other and other interventions in ways that may lead to unintended consequences or synergistic effects. A typical case regards the interactions between BISS and INVEST interventions. BISS provides a stable income base, so farmers may be more willing to invest in new technologies and equipment as the financial risk associated with such investments is mitigated. This can lead to a synergistic effect with INVEST intervention.

Under these circumstances, **correlation models, even if they have a different scope, can be used to explain the separated impact of more measures at the same time** using different explanatory variables, one for each main policy measure.

However, different correlation models exist. If panel data are not available, ordinary least squares (OLS) models have to be used [54] (Figure 7). **If panel data are available, more complex models can be used, including fixed effect and dynamic panel models.** The latter can be used only if data spans for a large enough number of years (i.e. a sufficiently long panel) and if adequate econometric skills are available. If this is not the case, fixed effect regression models can be used.

The table below shows the characteristics of the different approaches for each of the aspects mentioned above.

Methods	Focus on the impact of one/several CAP interventions	Require the distinction of beneficiaries VS non-beneficiaries	Account for the dynamic nature of productivity
Counterfactual impact models	One CAP intervention	✓ Yes	PSM could DiD - ✓ Yes
Correlation static models	Several CAP interventions	✗ No	✗ No
Correlation dynamic models	Several CAP interventions	✗ No	✓ Yes

In this document, correlation refers to a statistical association between two variables, indicating that as one variable changes, another tends to change in a specific direction. This relationship can be positive, negative or zero. However, correlation alone does not imply that one variable causes the other to change. This is a critical distinction because **relying solely on correlation can lead to misguided conclusions and ineffective or harmful actions**. Causation, on the other hand, implies a cause-and-effect relationship between variables. **Establishing causation requires demonstrating that changes in one variable directly result in changes in another**. This is much more challenging to prove and typically requires well-designed experiments that control for other potential drivers.

More details on these methods are provided in the next chapters.

54 Note that correlation methods do not directly identify causation, but only correlation.

5.3. Useful definitions

The box below provides definitions of key terms to consider when assessing the CAP impact on farm productivity, whether standard or sustainable. The terms, frequently used and referred to throughout this chapter, are introduced here to help the reader understand and/or clarify key aspects associated with causal inference.

Box 3. Definitions of some methodological terms encountered when assessing the impact of CAP on productivity

Association or correlation: a statistical relationship between two variables (e.g. productivity and CAP intervention) can be detected using statistical methods by analysing observations; see also 'causality'.

Causality: causality refers to the relationship between causes and effects. It implies that a change in one variable (the cause or explanatory variable) directly brings about a change in another variable (the effect or dependent variable). Establishing causality is a central goal in many scientific and social science studies.

Endogeneity: endogeneity occurs when explanatory variables are correlated with the error term (see definition below), often due to omitted variables, measurement errors or simultaneity. This can lead to bias, resulting in inaccurate results. Endogeneity can be corrected using variables that are not correlated to the error term. They are called instruments or instrumental variables.

Error term: the error term is a residual variable that accounts for a lack of perfect goodness of fit (see definition below) of a statistical model assessing the drivers of a dependent variable (e.g. how productivity is correlated to the level of CAP support and other variables) (see for example regression model). The error term appears in a statistical model, like a regression model, to indicate the uncertainty in the model. It captures the variation in the dependent variable unexplained by the variation in the explanatory variables.

Goodness of fit: it implies a comparison of the observed data with the data expected under the model using some fit statistic. There are different statistical tests to determine whether a set of observed values matches those expected under the applicable model. Generally, these are based on the analysis of the error terms; high error terms suggest a low goodness of fit.

Growth rate or change: in the literature, productivity is considered in terms of changes or growth rates from the previous period and not absolute levels. This aspect is important in empirical applications and different approaches can be used. In these guidelines the terms changes and growth rates are used interchangeably to underline that the model does not use the level of productivity.

Heterogeneity: unobserved heterogeneity is when the farms (or more generally, the DMUs) differ in many aspects that are difficult to observe or measure, such as managerial skills, land quality and microclimate conditions. Observed heterogeneity, on the other hand, refers to characteristics that can be directly observed by researchers, such as farm size, age or region, which may influence the output differently.

Omitted variable bias: this type of bias arises in statistical models when a relevant explanatory variable (i.e. that influences the dependent variable) is not included in the model. This omission can lead to incorrect estimates of the effects of other explanatory variables in the model. When modelling productivity, an example of omitted variable bias is e.g.not accounting for weather conditions, farm characteristics, managerial abilities or any other important drivers of productivity.

Ordinary least squares (OLS): a common method in a regression analysis. It relies on a linear model and aims at minimising the sum of squared residuals.

Panel data (or longitudinal data): data that have both spatial and time dimensions. In these data, individuals (e.g. farms or regions) are observed at several points in time. Panel data can be balanced panel data, where each individual is observed each time period, or unbalanced panel data where individuals are observed over a different number of time periods.

Regression analysis or regression model: statistical methods applied to a mathematical equation in order to identify the relationship between a dependent variable and one or several explanatory variables.

Most regression models state that a dependent variable is a function of a set of explanatory variables and regression coefficients (or parameters) to be estimated, with representing an error term:

$$Y_i = f(X_i, \beta) + e_i$$

The main goal is to estimate the function, that is to say, to estimate the value of the regression coefficients and the error terms. For example, a simple single-variable regression has the following structure:

$$Y_i = \beta_0 + \beta_1 X_i + e_i$$

Regression models allow for an assessment of whether these relationships are statistically significant.

R-squared is a statistic used to evaluate the model goodness of fit in regression models. It provides an indication of the proportion of variance in the dependent variable explained by the model and is based on the value of the error term.

Statistical significance: this refers to the likelihood that an observed relationship in a data set is not due to random chance. Statistical significance is commonly assessed using a p-value, where a lower p-value (typically less than 0.05), indicates that the observed relationship is unlikely to be due to random chance alone. Estimating a regression model involves estimating the value of the coefficients as well as their statistical significance.

Variable: something that varies, a quantity that can change.

- **Explanatory variables** explain variation in a dependent variable. In the regression model, they are on the right-hand side of the equation. The main explanatory variables of interest in the context of these guidelines relate to CAP intervention.
- **Control variables or covariates** are controlled or unchanged during a study. They are part of the explanatory variables but are not the primary interest of the study. A control variable could be where the farm is located or the age of the farmer.
- **Dependent variables** are explained in a regression analysis. It is on the left-hand side of the regression model. For example, productivity is the dependent variable in a regression used to assess productivity drivers.
- **Lagged dependent variables** explain a specific dependent variable in a regression model where the value of the dependent variable in the previous period may be included as an explanatory variable. We call this value the lagged dependent variable. This approach helps capture the dynamic effects and temporal dependencies in the data.

Selection bias: this occurs when the sample used in a study or analysis is not representative of the whole population from which it was drawn. This can lead to results and conclusions that do not accurately reflect the reality of the broader population [55].

Example of selection bias; a policy intervention is introduced to increase productivity, but only the largest farms choose to participate in it. If an evaluation of the programme only considers these participating farms, it might incorrectly conclude that the subsidy significantly boosts productivity across all farms. This is because the evaluation fails to account for smaller farms that did not participate, leading to an overestimation of the subsidy's overall impact. To avoid this bias, it is crucial to include a representative sample of all farms, both participants and non-participants, in the analysis.

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

5.4. Counterfactual impact evaluation

Counterfactual impact evaluation (CIE) methods aim to estimate the causal effects of one CAP measure (or eventually a given set of policy measures) on productivity. These methods are developed in general, in this context, using individual farm data.

According to the JRC [56], counterfactual impact evaluation is "a method of comparison which involves comparing the outcomes of interest of those having benefitted from a policy or programme (the 'treated group') with those of a group similar in all respects to the treatment group (the 'comparison/control group'), the only difference being that the comparison/control group has not been exposed to the policy or programme. The comparison group provides information on 'what would have happened to the members subject to the intervention had they not been exposed to it,' the counterfactual case. The case for counterfactual impact evaluation is based on the need to collect evidence and determine whether policy objectives have been met and, ultimately, whether the resources were used efficiently. These answers feed back into the design and implementation of future interventions and budgetary decisions".

The following CIE methods can be used to assess the contribution of CAP interventions on productivity and are described in detail below:

- propensity score matching
- difference-in-difference

5.4.1. Propensity score matching

What's propensity score matching and what can it demonstrate?

Propensity score matching (PSM) is a statistical technique used to estimate the causal effect of a treatment by accounting for the covariates that predict the probability of receiving the treatment. In the context of evaluating the CAP interventions and their impact on productivity, PSM helps to **disentangle the causality between CAP interventions and productivity outcomes by matching DMUs (e.g. farms or regions) receiving CAP interventions with similar DMUs that do not**. This is done based on the likelihood (i.e. propensity score) that each DMU has to receive the treatment (i.e. the CAP interventions).

55 It is crucial to identify an appropriate control group for the comparison with the treatment group, ensuring that the control group closely resembles the treatment group in all relevant aspects. Additionally, it is important to emphasise that the treatment group itself may not be representative of the overall population, further complicating the possibility to generalise the findings.
56 Joint Research Centre – Counterfactual impact evaluation. https://joint-research-centre.ec.europa.eu/scientific-activities-z/counterfactual-impact-evaluation_en#:~:text=CIE%20-%20Counterfactual%20impact%20evaluation%20-%20is%20a,not%20been%20exposed%20to%20the%20policy%20or%20programme. Accessed 21 August 2024.

PSM allows to measure the treatment effect in two different ways:

- The **average treatment effect (ATE)** is a measure used to estimate the average effect of a treatment (or CAP intervention) over the entire population or sample of interest. It indicates the average difference in outcome (e.g. productivity) between DMUs that received the treatment and DMUs that did not, across the entire population or sample used. This measure is particularly useful in understanding the overall impact of treatment when applied to a broad population.
- The **average treatment effect on the treated (ATT)** focuses on the subset of the population or sample that received the treatment (or CAP intervention). It measures the average effect of the treatment among those DMUs that were treated, providing insight into the impact of the treatment on those DMUs who received it. ATT is then calculated as the average of the individual treatment effects for those DMUs who received the treatment, relative to the average outcome of the matching units that did not, making it a useful measure for evaluating the effectiveness of treatment among the treated group.

PSM is widely used in policy evaluation, including assessing the impacts of agricultural policies like the CAP, where **it is crucial to control for covariates that could influence both the allocation of policy measures and the outcomes of interest**. This method helps to mimic a randomised control trial by creating a balanced dataset where the treated and control groups have similar distributions of the covariates, thus isolating the effect of the treatment from other factors. It is important to ensure that the variables chosen for PSM account for the variability between the treated and untreated groups, allowing for sufficient overlap between them. Moreover, it is important to consider the assumption that treatments do not depend on unobservable variables.

When to use it?

Use PSM to:

- Assess the effects on farms' productivity of a given CAP intervention (e.g. investment support, ENVCLIM) targeted toward farms with specific features.
- Control for covariates that could influence both the allocation of CAP interventions and the outcomes of interest (e.g. farm size, production specialisation, organic farming, etc.).

Example of relevant information conveyed by PSM (for policymakers)

The implementation of PSM will reveal the ATE and the ATT. These two scores can be examined separately or compared with each other to draw useful conclusions about the effects of the policy.

- **ATE** indicates the average difference in outcomes between DMUs that received the treatment and units that did not, across the entire population (or sample).
  For example, if the ATE of participating in the INVEST intervention on farm productivity is estimated to be 10%, it means that on average, farms that received investment support had 10% higher productivity compared to farms that did not receive any investment support.
- **ATT** indicates the average difference in outcomes between treated DMUs and their matched controls.
  For instance, if the ATT of participating in the ENVCLIM intervention on farm productivity is estimated to be 8%, it means that farms that participated in the ENVCLIM scheme had on average 8% higher productivity compared to similar farms (matched or weighted based on propensity scores to allow to assess comparable treated-untreated farms) that did not participate.

In addition, the **direction of the effects** (positive or negative) is indicated by the sign of the ATE or ATT scores. Positive effects (i.e. ATE > 0) suggest that the treatment improves the outcome (i.e. productivity), while negative effects (i.e. ATE < 0) suggest the considered measure worsens the outcome.

The **magnitude of effects** informs about the practical significance of the treatment. Even a statistically significant effect (i.e. statistically different from zero) might be too small to be of practical importance.

Comparing the values and significance of ATE and ATT can provide valuable insights. When both ATE and ATT are statistically significant and similar in magnitude, it suggests that the treatment effect is consistent across the entire population or sample. Conversely, if ATE and ATT differ significantly, it may indicate that the treatment effect varies between the subgroup that received the treatment (ATT) and the broader population or sample (ATE).

For example:

- If both ATE and ATT are positive and significant → Recommend maintaining the policy or expanding the treatment to more units.
- If ATE is significant but ATT is not (or vice versa) → Suggest revising the treatment criteria or target the strategy to maximise the benefits.
- If neither ATE nor ATT are significant → Consider discontinuing the treatment or revising the policy substantially.

Box 4. Example of an application

Scope of the study

The study of Nilsson [57] investigated the effects of CAP investment support on the labour and TFP of agricultural firms in Sweden during the 2007-2013 programming period. These subsidies aimed to modernise agricultural holdings, improve competitiveness and promote rural development.

Methodological approach implemented

The study conducts an individual (micro-level) analysis using detailed firm-level data on 34 300 agricultural firms in Sweden and the coarsened exact matching method (a method similar to PSM) to handle selection bias.

Main findings

The key finding note that CAP investment support has had a positive and significant effect on the productivity of small agricultural firms. The effects of the investment support became more pronounced over time, with the most substantial improvements in productivity observed several years after the initial investment. This indicates that the benefits of the subsidies accumulated gradually as farms adjusted and implemented the supported investments. The positive effects of investment support vary across different agricultural sectors. The dairy and animal farming sectors showed the most significant improvements in productivity and turnover, while the effects were less pronounced in other sectors such as forestry and mixed farming. The study did not find significant additional benefits from receiving larger amounts of support or investment support more than once.

How to implement PSM?

Data required

The data and the procedure differ according to the level of analysis:

- Individual level: most common in PSM, where each DMU (e.g. a farm) is analysed to assess the impact of the treatment on an individual basis.
- Regional level: the analysis might be conducted to understand the effects of a policy across different regions. Aggregated regional level (e.g. NUTS2 or NUTS1) should be used for the analysis.
- National level: similar to regional, but on a larger scale. This might involve more complex adjustments to account for national-level policy design or characteristics and could benefit from a stratified or clustered sampling approach.

Generally, it is better to use an individual level because it reduces estimation errors due to aggregation bias.

Step-by-step approach

Step 1: Selection of covariates

Include all relevant variables affecting the treatment assignment and the outcome. This selection should be based on an in-depth analysis of how the policymaker decides the treatment (subsidies) and what type of farms participate or do not in the treatment.

Step 2: Estimation of propensity scores

For each unit (e.g. individual farm), the probability of receiving the treatment (i.e. CAP interventions) is estimated based on observed covariates (see Box 3 for definition of covariates). This probability is the propensity score, typically estimated using a logistic regression model (as explained in Technical Annex 6.1).

Step 3: Matching of similar units

DMUs, or units, in the treatment group (i.e. units that received CAP interventions) are matched with units in the control (untreated) group that have similar propensity scores. Matching can be done through various methods, such as nearest neighbour, calliper matching, or kernel matching (as detailed in Technical Annex 6.1).

Step 4: Comparison of outcomes

After matching, the treated units' average outcome (e.g. productivity) is compared to the average outcome of the control units to estimate the treatment effect.

Step 5: Estimates of ATT and ATE

The latter step yields estimates of the ATE or the ATT.

57 Nilsson, P., *Productivity Effects of CAP Investment Support: Evidence from Sweden Using Matched Panel Data*, *Land Use Policy*, Vol. 66, July 2017, pp. 172-182. https://doi.org/10.1016/j.landusepol.2017.04.043.

To go further

The recent advancements in the PSM methodology introduced new perspectives and tools that enhance its robustness and applicability.

- Double robust: this method combines two powerful tools, for example PSM with a regression-based adjustment, to provide a more precise estimation about the effects of different treatments [58].
- Generalised propensity matching: traditional methods for comparing treated and untreated groups only work well when there are just two groups. This method can handle more complex situations, like comparing farms that use different amounts of treatment or that use it at different times [59].
- Genetic matching: this method uses a special algorithm to find the best matches between treated and untreated groups. It helps find the most similar farms or plots, so we can make more accurate comparisons [60].
- Machine learning: many of these methods can be implemented using machine learning, for example generalised propensity matching with boosting allows a more precise evaluation of the propensity score [61].

If other approaches can be used to assess the impact of CAP interventions on productivity, it could be useful to compare the results to triangulate these.

See also Technical Annex 6.1 for the technical description and details of this method.

Checklist

What the evaluator needs for PSM

- Clarify the rationale for selecting PSM as the preferred method for estimating causal effects on productivity
- Ensure a good understanding of the different ways to measure the treatment effect (ATE and ATT) and what the scores mean for policy
- Identify when you want to use PSM, e.g. for assessing one intervention that clearly benefits some farms but no other farms
- Decide on the level of analysis
- Identify the data needed for the selected level of analysis
- Follow the recommended steps for implementing the PSM method
- Interpret the results
- Triangulate the results with information from other sources, other indicators or other methods and therefore better explain the values obtained

5.4.2. Difference-in-difference

What is difference-in-difference (DiD) and what can it demonstrate?

Difference-in-difference (DiD) also belongs to the group of CIE methods. DiD is a powerful method used to evaluate the causal impact of policy interventions by comparing changes in outcomes over time between a treatment group (e.g. farms benefitting from a CAP intervention) and a control group (e.g. non-participating farms).

For instance, if certain farms participate in a specific CAP intervention while others do not, DiD can be used to assess the impact of this intervention on agricultural productivity by comparing changes over time between these groups. This helps to establish a causal relationship between the considered CAP measure and productivity changes. This method has the relevant advantage that it isolates the effect of the treatment by controlling for common trends affecting both the treated and control groups.

Note that, as in all models using panel data (e.g. FE and DPD models, see Sections 5.5.2 and 5.6.1) that, as already explained, refer to different years, it is important to consider that CAP evolves over time [62]. Therefore, if a significant change occurred for a specific intervention or a set of interventions during the considered period, the results should be analysed with caution.

58 Bang, H., and Robins, J.M., *Doubly Robust Estimation in Missing Data and Causal Inference Models*, Biometrics, Vol. 61, N° 4, December 2005, pp. 962-973. https://doi.org/10.1111/j.1541-0420.2005.00377.x.

59 Hirano, K., and Imbens, G.W., *The Propensity Score with Continuous Treatments*, in A. Gelman and X. Meng (eds.), Wiley Series in Probability and Statistics, 1st ed., Wiley, 2004, pp. 73-84. https://doi.org/10.1002/0470090456.ch7.

60 Diamond, A., and Sekhon, J.S., *Genetic Matching for Estimating Causal Effects: A General Multivariate Matching Method for Achieving Balance in Observational Studies*, *Review of Economics and Statistics*, Vol. 95, N° 3, July 2013, pp. 932-945. https://doi.org/10.1162/REST_a_00318.

61 McCaffrey, D.F., Griffin, B.A., Almirall, D., Slaughter, M.E., Ramchand, R., and Burgette, L.F., *A Tutorial on Propensity Score Estimation for Multiple Treatments Using Generalized Boosted Models*, Statistics in Medicine, Vol. 32, N° 19, August 30, 2013, pp. 3388-3414. https://doi.org/10.1002/sim.5753.

62 Fixed effects and DiD methods are closely related and can sometimes be identical, particularly when using a two-way fixed-effects model, which is a common form of DiD. This approach includes fixed effects for individuals and time, treating the variable of interest as a dummy indicating treatment.

When to use it?

Use DiD for:

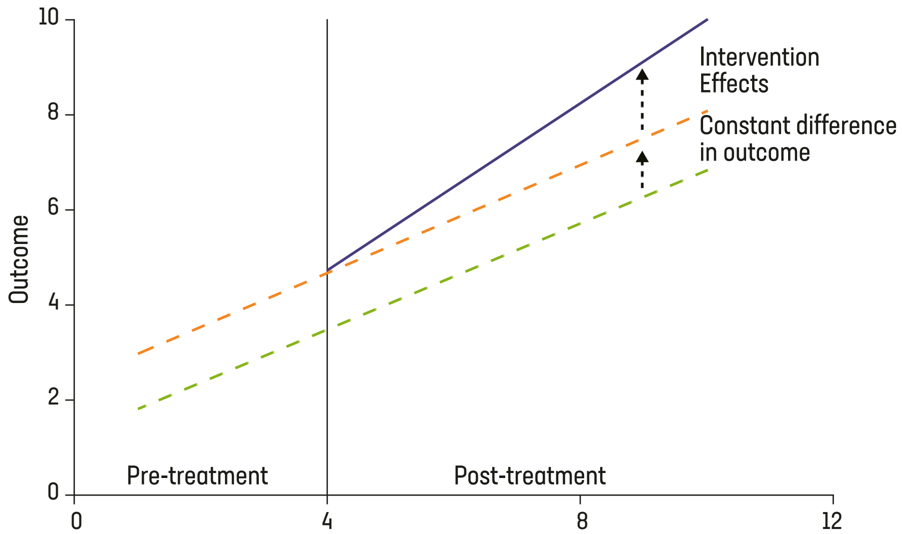
- Assessing the impact of policy changes: it can be used to evaluate the effect of the CAP interventions on farm productivity by comparing farms that adopted specific interventions with those that did not.
- Pre- and post-intervention analyses: it makes it possible to observe the effects of policy changes as they unfold. For instance, DiD can be used to study the impact of new CAP policies on farm productivity by comparing farmers who implemented the policy with those who did not before and after the policy's introduction.

However, DiD is applicable when farmers unaffected by the intervention can be clearly observed, serving as a control group. For example, it is difficult to use it to assess the impact of decoupled direct payments, because it is difficult to find a group of farms that do not benefit from this support. DiD also requires a series of data over a period of more years.

Example of relevant information conveyed by DiD (for policymakers)

A critical assumption in DiD is that, in the absence of treatment, the average outcomes for the treatment and control groups would have followed the same trajectory over time (i.e. constant difference in outcome). This assumption is crucial for attributing any post-treatment differences in outcomes to the treatment itself (i.e. parallel trend assumption (PTA)). Different tests exist to assess the satisfaction of PTA [63]. Note that, if these tests are not satisfied, the DiD can generate misleading results.

Figure 8. DiD estimation



Source: Introduction to Difference-in-Differences Estimation 64

The DiD estimator indicates the additional change in outcomes for the treated group relative to the control group after the intervention. This is interpreted as the causal effect of the intervention on the outcome.

For example, suppose the DiD estimator for the ENVCLIM intervention on farm productivity is estimated to be 5%. In that case, it implies that the productivity of farms participating in the intervention increased by 5% more than those that did not receive the intervention). Unlike the ATT obtained using PSM, DiD effectively controls for pre-existing differences in productivity without the need to specify the variables causing these differences. For instance, if farmers who participate in ENVCLIM initially have lower productivity due to lower machinery intensity, this factor would affect the ATT, but not the DiD estimate, as the latter isolates the impact of the ENVCLIM intervention itself, taking into account the pre-existing difference between the farms that participate at ENVCLIM and ones that don't participate.

For example, the effects, positive or negative, are indicated by the DiD estimator. Positive effects suggest that the treatment increases productivity, while negative effects suggest the treatment worsens the outcome. The magnitude of effects informs us of the practical significance of the treatment:

- if the DiD estimator is positive and significant, it suggests that the intervention had a beneficial effect, recommending the continuation or expansion of the policy;
- if the DiD estimator is not significant, it may suggest revising the treatment criteria or targeting strategy to maximise benefits; and
- if the DiD estimator is negative or insignificant, consider discontinuing the treatment or revising the policy substantially.

63 Arkhangelsky, D., Imbens, G., *Causal models for longitudinal and panel data: a survey*, The Econometrics Journal, November 2024. https://doi.org/10.1093/ectj/utae014.
64 Introduction to Difference-in-Differences Estimation: https://www.aptech.com/blog/introduction-to-difference-in-differences-estimation/. Accessed 20 December 2024.

Example of an application

Scope of the study

The study by Baráth, Fertő, and Bojnec [65] investigated the impact of various types of CAP subsidies on different components of TFP in Slovenia.

Methodological approach implemented

The study employed a comprehensive methodological approach to evaluate the impact of CAP subsidies on farm productivity using data from the Slovenian FADN covering the period from 2006 to 2013. Initially, a stochastic frontier production model was used to estimate TFP. To address the non-random assignment of aid allocation, the study utilised a DiD estimator. This approach helped to isolate the causal impact of CAP subsidies by comparing changes in productivity over time between subsidised (treated) farms and non-subsidised (control) farms while accounting for common trends and pre-existing differences.

Main findings

The results indicated that CAP subsidies did not have a significant effect on TFP or its components in Slovenian FADN farms. Additionally, there were no notable effects of subsidies on fertiliser adoption or intensification. Despite the relatively large share of less favoured areas (LFA) subsidies among rural development subsidies for Slovenian farms, their influence on improving TFP was not significant. Agri-environmental subsidies are less likely to contribute to TFP improvements.

How to implement DiD?

Data required

Applying DiD requires specific data. Hence, before starting the analysis, make sure to gather the following:

- Panel data: DiD analysis requires panel data that tracks the same DMUs (farms, regions) over time, before and after the implementation of CAP interventions. This data should include both DMUs affected by the new CAP interventions (treatment group) and those not affected (control group).
- Time periods: Data must span sufficient time before and after the policy implementation to observe potential changes and trends. This includes having multiple time periods (i.e. years) to establish trends and control for seasonal and annual variations in agricultural productivity. Hence, at least three years before and after the implementation are recommended to have a robust estimation.
- Control variables: Data on variables that could influence productivity independently of CAP interventions, such as weather conditions, technological changes and market conditions, is crucial. These help in controlling for external drivers that might affect the outcomes.

Step-by-step approach

Step 1: Clarify the level of analysis

DiD can be used on farms, regions or countries. The level of focus depends on the availability of the data. For example, farm level is more precise but some variables may not be available, such as the technological infrastructures, unemployment rate and weather conditions. These can be available only at the regional or county levels.

Step 2: Extract data from the database

In general, DiD is particularly usable at the farm level. In case the parallel trend assumption is already verified, without the use of covariates, it is not necessary to extract other variables from the database.

Step 3: Define the objective and select units

Clearly define the objective of the study, such as assessing the impact of a specific CAP intervention on farm productivity. Identify the farms to be analysed (i.e. units), ensuring a clear distinction between the treatment group (farms benefitting from the CAP intervention) and the control group (farms not benefitting from the CAP interventions).

Step 4: Select covariates and collect data

Identify and collect data on covariates that influence parallel trends. For example, in the evaluation of INVEST, more intensive farms generally exhibit higher productivity trends compared to less intensive farms. Additionally, more intensive farms tend to have a greater propensity to participate in INVEST compared to less intensive ones because they necessitate making more investments. Due to this, the productivity trends before joining INVEST diverge between treated and untreated farms. Therefore, it is necessary to introduce farm intensity level (e.g. farm net value added/UAA) as a control variable to achieve parallel trends before treatment.

Step 5: Estimate the DID 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 (for example, individual, regional or country fixed effect).

Step 6: Estimate treatment effects

Calculate the DID estimator to determine the causal impact of the CAP measure on the outcome variable. Interpret the estimated treatment effect in the context of the evaluation study objective.

65 Baráth, L., Fertő, I. and Bojnec, Š. (2020), *The Effect of Investment, LFA and Agri-environmental Subsidies on the Components of Total Factor Productivity: The Case of Slovenian Farms*, J Agric Econ, 71: 853-876. https://doi.org/10.1111/1477-9552.12374.

To go further

Recent advancements in the DiD methodology have introduced new perspectives and tools that enhance its robustness and applicability [66].

- New perspectives in DiD: after 2020, the DiD methodology has seen significant developments. These include the ability to account for variations in treatment effects over multiple periods, such as different programme phases or years following the initial implementation of a policy.
- Synthetic DiD and limited treatment groups: new tools like synthetic DiD have been developed to handle scenarios to easily obtain parallel trend assumptions, making the treated and untreated groups more comparable using weights.
- Robust estimators and selection bias: the introduction of robust estimators, such as double robust or double debiased machine learning, aims to reduce selection bias. These methods integrate machine learning techniques to improve the estimation of causal effects, addressing potential biases that may arise from non-random treatment assignments.
- DiD methods could be used in combination with PSM. This more advanced approach has been presented by the EU CAP Network's publication *Propensity score matching-difference in differences (PSM-DiD) method* [67].

See also Technical Annex 6.2 for the technical description and details of this method.

Checklist

What the evaluator needs for DiD

- Clarify the rationale for selecting DiD as the preferred method for estimating causal effects of CAP on productivity
- Ensure a good understanding of what DiD means for policymaking
- Decide on when to use DiD e.g. for assessing the impact of policy changes
- Ensure you have the specific data required for DiD (e.g. enough years of data and a large enough sample for both treated and control groups)
- Identify the level of analysis
- Follow the recommended steps for implementing the DiD method
- Interpret the results in the context of your evaluation
- Triangulate the results with information from other sources, other indicators or other methods and therefore better explain the values obtained

5.5. Correlation static models

Correlation models aim to estimate the drivers of productivity, where CAP interventions are included among the drivers. Correlation models are divided into two groups:

- Static models – where the dependent variable's past values are not included in the model i.e. the productivity of farms in the previous years is not considered for the analysis.
  The following correlation static models can be used to assess the contribution of CAP interventions on productivity:
  - ordinary least squares (OLS)
  - fixed effects (FE)
- Dynamic models – where the dependent variable's past (lagged) values are incorporated to explain the current values of the dependent variable i.e. the productivity of farms in the previous years is seen as the driver influencing the actual productivity in the current year and is taken into account for the analysis.

5.5.1. Ordinary least squares

What is the ordinary least squares model and what can it demonstrate?

OLS regression is a statistical method used to estimate the relationships between a dependent variable (e.g. productivity) and one or more explanatory variables (e.g. CAP intervention, farm size and farmer age).

OLS is particularly useful in analysing the impact of CAP interventions on productivity because OLS allows to quantify how the support provided by specific CAP interventions, (e.g. DIS, CIS, etc.) is correlated to the productivity of specific DMUs such as individual farms.

The extent and significance of this correlation are assessed by estimating the regression coefficients, namely one coefficient for each explanatory variable. The term OLS refers to a specific approach for estimating the regression coefficients, based on minimising the sum of the squares of the errors. An extensive set of statistical packages, including common spreadsheet software or R or Stata commands, can be used to develop an OLS estimation.

The main advantages of OLS are the relative simplicity of the method and the possibility to use data referring to a single year (i.e. cross-sectional data).

When to use it?

OLS can be used to assess how much the dependent variable (e.g. productivity) is correlated with the support provided by a set of CAP interventions accounting for other drivers affecting the level of the dependent variable.

66 See footnote 52 for Abadie, A., & Catteneo, M.D., (2018) and Imbens, G.W., (2024).
67 EU CAP Network, Online learning portal: https://eu-cap-network.ec.europa.eu/training/evaluation-learning-portal/learning-portal-propensity-score-matching-difference-differences-psm-did-method_en. Accessed 9 October 2024.

This method is suitable in contexts where several explanatory variables (e.g. different CAP interventions) affect the level of productivity and when the amount of support provided by each CAP intervention can vary between the considered units (e.g. individual farms).

Several conditions need to be verified to apply OLS:

1. The relationship between the variables needs to be linear, which assumes that:
   - a linear relationship exists between the dependent and explanatory variables; and
   - the explanatory variables are not perfectly multicollinear (i.e. not fully correlated with each other).
2. The error terms have a mean of zero, constant variance, and are uncorrelated with each other or with the explanatory variables [68]. This means the errors are randomly distributed and do not follow any pattern.

Example of relevant information conveyed by OLS (for policymakers)

Magnitude and direction of effects:

The size and sign of the regression coefficient associated with the CAP intervention explanatory variables provide insights into the correlation of this CAP intervention on productivity.

Each regression coefficient in the OLS model represents **the expected change in the dependent variable (i.e. productivity level) for a one-unit increase in the corresponding explanatory variable** (i.e. the amount of support provided by the policy measure), holding all other variables constant.

Examples of OLS Interpretation:

1. Suppose an OLS model yields an estimated regression coefficient of 2.0 for a policy subsidy, with a p-value of 0.01. This suggests that all else being equal, an increase of one unit in this subsidy (e.g. EUR 1) increases productivity by 2.0 units. The low p-value indicates that this effect is statistically significant. If the R^2 is 0.75, it indicates that the model explains 75% of the variance in productivity. This is a high goodness of fit.
2. Now, consider another CAP measure with an estimated coefficient of -1.5 and a p-value of 0.03. This negative coefficient suggests that all else being equal, an increase of one unit in this CAP measure (e.g. EUR 1) decreases productivity by 1.5 units. The p-value of 0.03 indicates that this effect is also statistically significant.
3. Finally, let us examine a third CAP measure with a coefficient of 0.5 but a p-value of 0.25. This positive coefficient suggests that all else being equal, an increase of one euro of this CAP measure increases productivity by 0.5 units. However, the high p-value indicates that this effect is not statistically significant, meaning that there is not sufficient evidence to conclude that this CAP measure has a real impact on productivity.

The estimated coefficient of a specific CAP intervention can be non-significant or significant. This can be assessed using the probability value (p-value) associated with each coefficient and provided directly by the utilised software.

- A p-value < 0.05 (i.e. less than 5%) is considered to support the idea that the relationship is statistically significant, which means statistically different from zero. This means that we can trust the fact that the coefficient is different from zero and therefore that the impact of the explanatory variable on the dependent variable is non-zero.
  Note that in this case, the sign of the coefficient can be positive or negative. In the first case, the result indicates that the correlation is positive, suggesting an increase of the support could exert a productivity enhancing role (and vice versa).
- A p-value > 0.05 is considered non-significant and suggests that the CAP intervention is not correlated with the dependent variable (e.g. productivity). We cannot be certain that the effect of the CAP intervention is not zero.

Comparative analysis

By comparing the coefficients of different CAP interventions, policymakers can identify which measures are substantially correlated with productivity and which are not. If the objective is to understand the correlation with farm productivity, those CAP interventions that have significant and positive coefficients could be reinforced. The opposite applies to those interventions that are found to have significant and negative coefficients. Hence, these pieces of information provide suggestions on how to reallocate policy resources among policy measures if the only policy objective is to enhance farm productivity.

Note that the model also provides coefficients for the other non-policy explanatory variables included in the model (also known as covariates or control variables). Similar considerations apply to these coefficients.

68 In cases where errors are correlated, robust standard errors can be used to obtain valid inference.

Example of an application

Scope of the study

Hu & Antle [69] focused on whether agricultural policy, specifically the level of taxation or subsidisation, significantly impacts aggregate agricultural productivity.

The study investigated the impact of nominal protection coefficients (NPC), which measure the agricultural sector's degree of taxation or subsidisation. The NPC is used as a proxy for the level of government intervention in agricultural markets.

Analysis conducted

The analysis uses cross-sectional data from the years 1960, 1970 and 1980 at country level. The study conducted a macro-level analysis, examining aggregate data across multiple countries. It estimated the aggregate agricultural production function and a political model to understand the broader impacts of agricultural policies on productivity.

Main findings

The econometric results strongly support the hypothesis that agricultural policy significantly impacts productivity. The productivity effect is large and statistically significant in countries with moderate levels of taxation (NPC between 0.7 and 1) or subsidisation (NPC between 1 and 1.15). In countries with high levels of taxation (NPC less than 0.7) or high levels of subsidisation (NPC greater than 1.15), marginal policy changes do not significantly affect productivity. High levels of intervention distort incentives, reducing the effectiveness of policy changes.

How to implement OLS?

Data required

OLS can use both farm-level and regional/national data. Regional/national aggregated data can be used especially when farm-level data is not available.

Before starting the analysis, make sure to gather the following for each individual unit (i.e. farm or region):

- productivity levels or growth rates (which will be the dependent variable);
- levels of support provided by each CAP intervention considered (e.g. DIS, CIS, etc.) (which are the main explanatory variables of interest); and
- levels of other explanatory variables (the control variables) that may exert an effect on farm productivity (e.g. farm size, age of farmers, other gainful activities etc.).

Such data should refer to the same year. However, if data are available, it could be useful to also get data on the amount of support provided one year before the one in which the productivity is estimated (and eventually two years before, too). These can be included as explanatory variables to whether the policy interventions have effects on productivity after one year (and eventually two years later). Indeed, it is important to acknowledge that the impact of CAP interventions on productivity may not be immediate in the same year (year t) they are implemented, but rather manifest in subsequent periods, such as the following year (year $t+1$). Consequently, Member States should, where data permits, also examine the influence of interventions from the previous year (year $t-1$) on the productivity outcomes of the current year (year t). This approach aligns with the understanding that timing and information set assumptions are crucial in estimating production functions and can affect the precision of productivity estimates [70].

Step-by-step approach

Step 1: Identify the level of analysis according to data availability.

OLS can be used at both farm, regional and country levels.

Step 2: If the analysis is developed at individual farm level, extract data from the database.

It is important to take into account the distribution of dependent variables and that the explanatory variables cannot be correlated (i.e. no multicollinearity issues) because this can lead to misleading interpretations of the outcomes. The analysis will be more robust if there are more observations. It is required to pay attention to the variables that present anomalies in the data (for example, caused by erroneous insert).

Step 3: Calculate or estimate the productivity indicator that is perceived most appropriate.

Step 4: Identify the explanatory variables including both those related to the support provided by the relevant CAP interventions and control variables.

The choice of control variables should be grounded in relevant literature that has tackled similar issues.

Step 5: Estimate the OLS model and critically assess the goodness of the estimate.

Step 6: Robustness checks

It is essential to perform robustness checks, for example, by using alternative model specifications, including additional control variables and lagged explanatory variables (if available) to ensure the reliability of the results.

Step 7: Analyse the estimation results to draw policy implications.

69 Hu, F., and Antle, J.M., *Agricultural Policy and Productivity: International Evidence*, Review of Agricultural Economics, Vol. 15, N° 3, September 1993, p. 495. https://www.jstor.org/stable/1349484.
70 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.

To go further

Note that the overall quality of the OLS estimation could turn out to be not satisfactory at the end of Step 5 (assessment of the goodness of the estimate). For example, the estimated model could have a poor explanatory power (e.g. a low R^2) or additional econometric issues such as multicollinearity. Under these circumstances, a different configuration of the model should be attempted, for example, by adding or removing some explanatory variables or treating these to account for nonlinearity (for example using the squared values).

The OLS method can also be used with panel data, by simply pooling all data and using this as a cross section. However, this approach does not take full advantage of the panel structure of the data. In particular, it does not control for the time-invariant differences among the DMUs. Hence, if panel data are available, it is suggested that the FE model be used, as described in the next section. This approach allows the definition of the analysis and results from different methods, enabling triangulation.

See also Technical Annex 6.3 for the technical description and details of this method.

Checklist

What the evaluator needs for OLS

- Clarify the rationale for selecting OLS as the preferred method for estimating drivers of productivity
- Ensure a good understanding of the advantages of OLS and what it means for policymaking
- Verify you fulfil all the conditions necessary for applying OLS
- Ensure there is the necessary expertise to analyse the information derived from OLS: interpret the magnitude and direction of the effects or carry out comparative analyses of different CAP interventions
- Ensure you have the data required for OLS
- Identify the level of analysis
- Follow the recommended steps for implementing the OLS method
- Interpret the results in the context of your evaluation
- Ensure the necessary flexibility to apply a different configuration of the OLS model in case the estimate is not deemed satisfactory
- Complement the results with information from other sources, other models or methods and therefore triangulate and better explain the values obtained

5.5.2. Fixed effects

What are fixed effects and what can they demonstrate?

The FE model is an approach similar to OLS that provides estimates of coefficients used to assess whether a set of explanatory variables are significantly correlated to a dependent variable and the direction of this correlation (positive or negative). It can be estimated with a time or individual fixed effect or both (two way fixed effect (TWFE)).

However, the FE method is more advanced than OLS and is particularly useful when analysing the **impact of variables that vary over time**. The main advantage in comparison to OLS is that the FE model, relying on panel data, allows **for control of unobserved time-invariant individual-specific characteristics** that could influence the dependent variable. These individual-specific characteristics (or effects) are assumed to be constant over time (time-invariant) but varying across DMUs (e.g. gender, regions and altitude). By focusing on within-DMU variations, the FE model effectively controls for all time-invariant differences among DMUs, thereby providing a robust estimate of the impact of time-varying explanatory variables (e.g. CAP interventions) compared to standard OLS, which does not account for such unobserved heterogeneity.

When to use it?

This model is extensively used in agricultural economics to evaluate the impact of policy measures on various outcomes, including productivity [71].

This model is particularly useful for assessing **the impact of policy changes** where the policies are expected to influence productivity within the same farm or region across different time periods. For instance, examining **how shifts from coupled to decoupled payments in CAP influence farm productivity** over several years within the same farms.

Therefore, FE requires panel data (i.e. data for the same units for several years). In other words, the data involves multiple observations (time periods) for the same individual DMUs (e.g. farms, regions or countries).

Example of relevant information conveyed by FE (for policymakers)

When using a FE estimator to analyse the relationship between CAP interventions and productivity in agricultural economics, it is crucial to understand how to interpret the results effectively.

The interpretation of the coefficients (and related p-values) is similar to the case of OLS (described earlier – see Section 5.5.1). The impact of time-invariant characteristics of the DMUs (e.g. altitude) are not directly estimated but are controlled for in the FE model [72]. This means that the coefficients of the explanatory variables reflect the

71 Latruffe, L., and Desjeux, Y., *Common Agricultural Policy Support, Technical Efficiency and Productivity Change in French Agriculture*, Review of Agricultural, Food and Environmental Studies, Vol. 97, N° 1, June 2016, pp. 15-28. https://doi.org/10.1007/s41130-016-0007-4. Weber, J.G., and Key, N., *How Much Do Decoupled Payments Affect Production? An Instrumental Variable Approach with Panel Data*, *American Journal of Agricultural Economics*, Vol. 94, N° 1, January 2012, pp. 52-66. https://doi.org/10.1093/ajae/aar134.

72 Note that this is also true for explanatory variables measuring CAP support. If there is little or no variation in the policy variable (e.g. when only post-treatment is included), then FE may not be suitable.

impact of changes within DMUs over time, net of any time-invariant characteristics. It is relevant to note that using the FE estimator removes the not-observable time-invariant characteristics, reducing the omitted variable bias.

CAP evaluators will thus rely on an FE model to verify:

- Magnitude and direction of effects: the size and sign of the regression coefficients provide insights into the effectiveness of CAP interventions. For instance, a positive and significant coefficient for a CAP intervention suggests that increasing subsidies is associated with higher productivity.
- Comparative analysis: by comparing the coefficients of different CAP interventions, policymakers can identify which measures substantially impact productivity and which do not.

Performing robustness checks is crucial to ensure that the results of a model are reliable and not dependent on a specific set of assumptions. This can be done by trying different model specifications, such as using quadratic, polynomial or interaction terms. The latter model captures more complex relationships between variables. Additionally, extra control variables can help account for other drivers that might influence the results. By testing these alternatives, you can confirm that the findings hold true under various conditions, thus strengthening the confidence in the model's conclusions.

Example of an application

Scope of the study

Latruffe & Desjeux [73] investigated how various changes in the CAP and different types of CAP interventions affected the technical efficiency and productivity change of farms in France between 1990 and 2006. The study encompasses multiple CAP reforms, including the 1992 MacSharry reform, the Agenda 2000 reform, and the 2003 Luxembourg reform. It analysed three distinct CAP interventions: investment subsidies, production subsidies and rural development subsidies.

Methodological approach

The study conducted an individual-level analysis considering separately three types of farming: field crops, dairy and beef cattle. By using FE models, Latruffe and Desjeux controlled for time-invariant characteristics of the farms, allowing them to isolate the impact of different types of CAP subsidies on technical efficiency and productivity change. This approach helped to disentangle the complex relationship between CAP interventions and farm performance, providing valuable insights for policy analysis.

Main findings

The findings indicated a significant reduction in efficiency following the first CAP reform (1992 MacSharry reform) but an improvement in efficiency change. The econometric results using FE models and OLS provided ambiguous findings, with the effect of subsidies varying depending on the sample's production orientation and the performance considered. The study provided several methodological recommendations for future research, emphasising the need for careful consideration of the type of subsidy and the specific context of the farms being analysed.

How to implement FE?

Data required

Applying FE requires panel data. Two main types of panels can be found:

- in a balanced panel, all DMUs (farms, regions, etc.) are observed in all periods;
- in the unbalanced panel, DMUs are not always observed in all periods; this means that the groups of DMUs can change according to the considered year.

Both types can be used, but balanced panels are often preferred for simplicity and consistency. However, to achieve this, it is necessary to exclude the DMUs that are not present in all the years [74]. Hence, the sample is generally smaller, as it refers only to these farms and not the whole sample.

As in the case of OLS, the FE model can use both farm level and regional/national data.

Before starting the analysis, make sure to gather the following for each individual unit (i.e. farm or region):

- Productivity indicators.
- Levels of support provided by each CAP intervention (e.g. CIS, DIS, etc.).
- Levels of other control variables that may exert an effect on farm productivity (e.g. farm size, investments and so on)

In contrast with OLS, it is important to have this data for more years. Hence, the data should be structured to account for the year the variables refer to.

73 See footnote 71 for Latruffe, L., & Desjeux, Y., (2016).

74 Note that the exclusions of farms also lead to the elimination of many important available information. This should be done only after careful consideration of alternatives.

Step-by-step approach

Step 1: Identify the level of analysis according to data availability.

Step 2: If the analysis is developed at the individual farm level, extract data from the FADN.

Step 3: Calculate or estimate the productivity indicator that is perceived as the most appropriate.

Step 4: Identify the explanatory variables including both those related to the support provided by the relevant policy measures and control variables.

Step 5: Estimate the FE model and critically assess the goodness of the estimate.

Step 6: Robustness checks: It is essential to perform robustness checks, for example by using alternative model specifications (e.g. using quadratic, polynomial or interaction terms) or including additional control variables to ensure the reliability of the results.

Step 7: Analyse the estimation results to draw policy implications.

To go further

Productivity has often been found to exhibit a dynamic nature, that is, its value is influenced by past values. This is not accounted for in FE models. Hence, it could be useful, if data and adequate statistical expertise are available, to also analyse the relationship between policy measures and productivity using dynamic panel model described in the next section. This allows one to look at the problem from another angle and to triangulate the information coming from two different models.

See also Technical Annex 6.4 for the technical description and details of this method.

Checklist

What the evaluator needs for the FE model

- Clarify the rationale for selecting FE as the preferred method for estimating drivers of productivity
- Ensure a good understanding of the advantages of FE, especially in comparison with OLS, and what it means for policymaking
- Ensure there is the necessary expertise to analyse the information derived from the FE model; interpret the magnitude and direction of the effects or carry out comparative analyses of different CAP interventions
- Ensure you have the panel data required for FE
- Identify the level of analysis
- Follow the recommended steps for implementing the FE method
- Interpret the results in the context of your evaluation
- **Verify** you have adequate expertise to complement FE with a dynamic panel model and information from other sources and therefore triangulate the results obtained from FE

5.6. Correlation dynamic model

5.6.1. Dynamic panel data model

What is the dynamic panel data model (DPD) and what can it demonstrate?

The DPD model aims to account for the dynamic nature of productivity i.e. it considers how past values influence the current value of productivity.

Among the various dynamic panel models, these guidelines focus on SYS-GMM, which has been widely employed to analyse the impact of CAP interventions on farm productivity. It is a robust econometric technique where:

1. There is a need to control for unobserved individual effects that could bias the results.
2. The relationship between variables is dynamic, meaning that past values of productivity and CAP interventions influence current values.
3. Past productivity levels potentially influence the granting of CAP support.

When to use it?

Use DPD to:

- Explore the relationship between productivity and CAP interventions, acknowledging the dynamic nature of productivity (i.e. incorporating its past values in the analysis).
- Mitigate issues related to omitted variable bias by controlling for unobserved heterogeneity.
- Recognise the dynamic relationship between CAP and productivity, where past values of productivity may be correlated with their current values.

Example of relevant information conveyed by DPD (for policymakers)

Most results of this model can be interpreted as those of previous methods (e.g. OLS and FE regression). However, some differences exist between SYS-GMM and previous methods.

- Coefficients: the estimated regression coefficients can be read as in previous models. Each coefficient represents the estimated impact of an explanatory variable (e.g. a specific CAP intervention) on the dependent variable (e.g. productivity).
  For instance, a positive coefficient for a subsidy variable indicates that an increase in these subsidies is associated with an increase in productivity. Check the p-values to determine the statistical significance of the coefficients. Typically, a p-value less than 0.05 indicates the coefficient is statistically significant.
- Lagged dependent variable: this is a feature of the dynamic model as SYS-GMM. The coefficient of the lagged dependent variable (e.g. lagged productivity) indicates the **persistence effect** of productivity over time. A significant positive coefficient suggests that past productivity levels positively influence current productivity. Understanding the persistence effect helps in designing policies that consider the long-term impacts of CAP interventions.

  For example, GMM results show:

  - A coefficient of 0.5 for decoupled subsidies (e.g. DIS) with a p-value of 0.01 → this means that decoupled subsidies have a significant positive impact on productivity.
  - A coefficient of 0.3 for the lagged productivity with a p-value of 0.02 → this means that past productivity levels positively influence current productivity.
  - A large positive coefficient (0.1 to 1) for decoupled subsidies suggests a strong positive impact on productivity.
    If decoupled subsidies enhance productivity significantly, policymakers might consider increasing such subsidies if increasing productivity is a policy priority.

Additional estimation results are available for assessing the validity of the model and providing information about the issue at stake (see Box 5 for additional outputs of the SYS-GMM model estimation).

Box 5. Additional outputs of the SYS-GMM model estimation

- **Hansen J test** checks the validity of the instruments used in the GMM estimation. Note that in some cases, we may have too many or too few instrumental variables; the test allows us to understand if the variables used are correct. A high p-value (typically above 0.05) indicates that the instruments are valid and not over-identified.
- **AR(1) and AR(2) tests** check for the differenced residuals' first-order and second-order serial correlation. The absence of second-order serial correlation (p-value > 0.05 for AR(2)) is crucial for the validity of the GMM estimator.
- **Wald tests** assess the joint significance of the explanatory variables. A significant Wald test (p-value < 0.05) indicates that the model as a whole is statistically significant.

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

Example of DPD application

Scope of the study

Mary [75] analysed the impact of CAP subsidies on TFP using a FADN dataset of French crop farms between 1996 and 2003.

Methodological approach implemented

A production function was estimated using a system GMM approach, and farm-level TFP was recovered. The analysis covered the years from 1996 to 2003 and an individual level analysis using farm level data from the French FADN was conducted.

Main findings

The key finding is that several CAP subsidies, particularly set-aside premiums, LFA payments and livestock subsidies, significantly and negatively impacted farm productivity. The CAP reforms, such as the Agenda 2000 reform, positively impacted TFP in French crop farms.

75 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.

How to implement DPD?

Step-by-step approach

Step 1: Clarify the level of analysis

This analysis is adapted to evaluate the dynamics of productivity or the relation to the past value. It is necessary to use panel data.

Step 2: Extract data from the databases

A balanced panel dataset i.e. tracking the same farms or DMUs over time, is better but not essential.

A sufficiently long period for the dataset, to capture the dynamics of productivity changes and policy impacts. At least one period for the covariates and two periods for the dependent variable are necessary to have a dynamic panel; then it is necessary to have at least two or three more lags to build the instrumental variables.

Step 3: Select covariates and collect data

Identify and collect data on covariates that influence both the likelihood of receiving CAP subsidies and productivity outcomes.

Step 4: Estimation

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

Step 5: Assess model quality

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

Step 6: Perform sensitivity analysis

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

Step 7: 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 any potential areas for policy improvement.

To go further

See also Technical Annex 6.5 for the technical description and details of the DPD method.

Checklist

What the evaluator needs for the DPM

- Ensure a good understanding of the advantages of the DPM for analysing the impact of CAP interventions on farm productivity and what it means for policymaking
- Ensure there is a good understanding of when the DPM can be used and how it differs from OLS or FE models
- Ensure there is the necessary expertise to implement the DPM, analyse the information derived from it and interpret its results
- Ensure you have and/or collect the required data for the DPM
- Identify the level of analysis
- Follow the recommended steps for implementing the DPM
- Interpret the results in the context of your evaluation
- Triangulate the results obtained from the DPM with information from other sources or other methods and therefore better explain the results

6. Further information

6.1. Use of simulation models to assess ex ante the CAP impact on productivity

6.1.1. Context

While the previous chapters propose methodologies to assess past effects of CAP measures on observed productivity (ex post analysis), future effects (ex ante analysis) could be anticipated with simulation models. Simulation models are widely used in ex ante analyses and frequently support decision-making by exploring potential consequences of counterfactual situations or different hypothetical scenarios. In some Member States, simulation models were used in ex ante assessments of the likely consequences of the CAP Strategic Plans and they will be widely used tools for supporting decision-making in the follow-up policy reforms.

The topic of this section is to explore in more detail how productivity can be taken into account by such models and when they are useful to compensate for the lack of data to measure past effects. Furthermore, challenges and limitations for assessing the likely effects of the CAP on productivity are covered. As such, it examines the potential use of simulation models for the assessment of CAP Strategic Plans and briefly explains how to use simulation models to estimate the effects of CAP Strategic Plans on farm productivity.

As each simulation model has idiosyncratic features, it is not possible to show how farm productivity enhancements are implemented in each model, but the general mechanisms are presented here. Furthermore, a discussion explains how simulation models that are not (yet) augmented with a productivity module could be enhanced. It should be stressed here that developing these models and applying them at national level requires specific expertise, which is not always available in all Member States.

6.1.2. A short non-exhaustive overview of simulation models

6.1.2.1. A short overview of essential terminology

This section presents a collection of simulation models used in agricultural policy analyses at the EU level and in several Member States. Before going into details, it is helpful to characterise what simulation models essentially are.

- **Model**: a model is a representation of reality that serves a particular purpose. A production function, as shown in Section 2.1, is a typical model. Such a conceptual model is very useful because it shows how certain mechanisms operate. However, due to its simplicity, it is, in many cases, not sufficient to answer important policy statements, such as implementing a nitrate tax of 50% will reduce crop supply by X %. Therefore, such models are frequently called qualitative or conceptual models that are capable of showing the direction of change but not quantifying the change.
- **Empirical models**: such models use observations to uncover relationships and if possible, causal effects between variables (see Section 5.3). A typical empirical model is one that estimates TFP based on specific data and functional forms [76] or indices (see Section 4). They are used to analyse counterfactual situations **ex post**.
- **Simulation models**: such models are based on theoretical or technical concepts and used to analyse 'what-if' situations (counterfactuals and/or scenarios) **ex ante**. Apart from technical and theoretical relationships, they use parameters to fit the model to given situations. Some models can be 'calibrated', which means that an algorithm fits a model to actual observations. Once a model is fitted, changing one or more parameters will yield a new equilibrium. Changes in policies, market situations or environmental conditions can be analysed one by one or simultaneously, depending on the scenario.
- **Scenario**: a scenario is a set of well formulated assumptions that are used as inputs for a quantitative model to carry out simulation analyses. Scenarios can be purely fictional (e.g. the abandonment of CAP Strategic Plans) or related to small changes in observed/projected situations (e.g. increase in the level of support in areas with natural constraints).
- **Forecast models**: these models are basically empirical models that use high frequency data to make forecasts. They are typically not based on coefficient estimates that are fitting a theoretical model but are data driven (e.g. time series models and machine learning algorithms). These models show expected outcomes (e.g. prices in the future) but cannot explain why the algorithms come to a specific result because they are ignorant of causality. Models are typically selected based on their forecasting capabilities and not because of their underlying superior theory.

There are two important classes of parameters:

- An **exogeneous** variable in a causal model or causal system is determined in advance before running a simulation. A typical exogeneous parameter is a tariff rate that raises border prices. Such parameters are sometimes called 'policy variables' because policymakers can control them explicitly.
- An **endogenous** variable value is determined by other factors within the model or system. It is influenced by internal drivers and dynamics within the model, making it a key component in understanding the behaviour and relationships within the system. Land use changed after imposing a tariff represents a typical endogenous variable. Another endogenous variable might be income.

76 An example of such an analysis is on the impact of CAP pillar II payments on agricultural productivity; European Commission, Joint Research Centre, Dudu, H., Smeets Kristkova, Z., *Impact of CAP pillar II payments on agricultural productivity*, Publications Office, 2017. https://data.europa.eu/doi/10.2760/802100.

There is a trade-off between model complexity (many endogenous parameters) and their usability. Elegant models are based on a few equations with few parameters that are easy to grasp. More detailed, and therefore less easy to grasp, models are necessary to simulate complex policies such as CAP Strategic Plans. Useful models strike a balance between complexity and relevance for policy analysis i.e. they abstract from details that are not policy relevant.

6.1.2.2. A short overview of simulation models in agriculture

Simulation models can assess a wide array of economic, social and environmental topics. The focus here is on agriculture and its economic and environmental impacts. Tool #61 of the Better Regulation Toolbox presents an overview of generic simulation models and how they are used to evaluate policies (see Chapter 8) [77].

In many cases, models need to be integrated or combined to evaluate complex outcomes of policies. Therefore, some agricultural models have GHG modules and others are combined with elaborate models that focus on specific topics such as soil carbon accumulation, biodiversity or water pollution.

Box 6. Synthesis of Chapter 8 of Tool #61 of the Better Regulation Toolbox

This section of the Better Regulation Toolbox focuses on simulation models for analysing impacts in impact assessments, evaluations and fitness checks. Simulation models are quantitative tools used to represent complex systems and predict their behaviour under different scenarios. They are particularly useful for estimating the potential impacts of policy interventions across various domains, including economic, social and environmental spheres. Key points from this chapter include:

- Types of simulation models: The toolbox discusses different types of models, such as macroeconomic models, microsimulation models and sector-specific models. Each type has its strengths and is suitable for different policy areas and research questions.
- Application in policy analysis: Simulation models can be used to assess the potential effects of policy options, compare alternative scenarios and identify unintended consequences. They are valuable for both ex ante impact assessments and can also be used for ex post evaluations.
- Data requirements: The data needs for different types of models are presented, emphasising the importance of high-quality, up-to-date inputs for reliable results.
- Limitations and uncertainties: The toolbox discusses the limitations of simulation models, including assumptions, simplifications and uncertainties inherent in modelling complex systems. Understanding these limitations is crucial for interpreting and communicating results.
- Best practices: The toolbox provides guidance on using simulation models in policy analysis, such as transparency in model documentation, sensitivity analysis and validation techniques.
- Integration with other tools: The chapter explains how simulation models can be combined with other analytical tools, such as cost-benefit analyses or multi-criteria analyses, to provide a comprehensive assessment of policy impacts.
- Reporting and communicating results: Guidance on effectively presenting model results to policymakers and stakeholders, including the importance of clearly stating assumptions and limitations, is likely included.

By providing this comprehensive overview of simulation models, Chapter 8 of Tool #61 aims to equip policymakers and analysts with the knowledge to effectively use these powerful tools in the context of better regulation and evidence-based policymaking.

Source: Chapter 8 Tool #61 of the Better Regulation Toolbox.

The main purpose of simulation models in agriculture is to analyse the effects of parameter changes on outcomes. They help to explain why certain outcomes (e.g. change in organic farming area) may be expected when a policy changes (e.g. a higher rate of support for organic farming). Depending on their complexity, such models can be very specific (e.g. show where farmers switch to organic farming, how output-prices are affected) or show only rudimentary results (e.g. show the output change of organic farming in the whole economy).

77 Better Regulation Toolbox: https://commission.europa.eu/law/law-making-process/planning-and-proposing-law/better-regulation/better-regulation-guidelines-and-toolbox_en. Accessed 10 June 2024.

There are two broad classes of economic simulation models:

- **Computable general equilibrium** (CGE) models try to capture the economic relationships and interactions of all sectors in an economy including households, the state and foreign trade. They are useful to show how resources (e.g. labour, and capital) are allocated across economic activities. Some models are used to analyse the world economy while many others are focussing on one country or a group of countries or regions. Among the most well-known models that are used for agricultural policy analyses is GTAP [78], which is a core model that is implemented in many variants (among them MAGNET) [79].
- **Partial equilibrium models** focus on one element of the economy e.g. the farm sector or a sub-sector, such as the dairy industry. When large scale, they are modelling the whole sector either globally or nationally. Small scale models are frequently focusing on one type of farm or the agricultural sector in a region. CAPRI [80], AGMEMOD [81], GLOBIOM [82] and Aglink-Cosimo are among the many models of this variant.

Within these two classes, there are two variants to model economic behaviour:

- **Agent-based models** and **micro-simulation models**: Such models simulate the economic behaviour of individual farms/firms and households. The model results crucially depend on endowments, interactions among agents and preferences among other factors. Frequently, such models are designed to show the path of dynamic adjustment to a new equilibrium situation.
- **Representative models**: The unit of modelling is a whole economy, a regional economy, a sector or a group of representative farms. The result is the final equilibrium situation. The path to get there is frequently not of interest. More complex models are capable of modelling the interaction of represented units explicitly by determining market clearing prices endogenously, simpler models take prices as given.

6.1.3. The representation of productivity in simulation models

6.1.3.1. Modelling technological change

Productivity is a topic of great importance, not only in agriculture. Many economic disciplines analyse its rate of change in different settings and strive to measure it, to understand the causes of its slowdown and to explore remedies to increase its rate of change. The framework for such analyses is the issue of technological change, and there are several ways of exploring its relevance and the drivers influencing it.

This section builds heavily on Naqvi and Stockhammer [83], who provide an elaborated survey on various economic schools of thought and their treatment of technological change. Their study explores a wide range of models assessing the impact of climate change. This section focuses on the neo-classical approach that underlies most models used in agricultural policy analysis.

In neo-classical economics, technological change is introduced as either exogenous or endogenous.

- In exogenous technological change models, a positive exogenous productivity shock of the overall production function or specific inputs (e.g. labour augmenting technological change) shifts the production possibility frontier outwards, resulting in higher productivity for the same input.
- Endogenous technological change models attempt to explain how factors like prices, investment levels, and investments in research and development (R&D), explain input-specific productivity gains within a given model. The underlying theory states that inputs with rising costs will see higher R&D investment to improve input-specific productivity gains, which, for profit-maximising firms, result in lower costs.

A widely cited model of the first class is the DICE framework [84]. It is the backbone of an integrated assessment model (IAM). It assumes that economic activity results in emissions that cause temperatures to increase, negatively feeding back on the economy through an environmental damage function. That describes the negative effects on productivity.

Models of the second type [85] are more complex but essential in identifying the underlying causes of technological change and understanding the processes and interactions. Private and public investments in research and development and the incentives to make them possible are among the elements of such models. They can be used to analyse whether public investments are crowding out private ones among others. There is a growing body of empirical studies, that investigate the direction and intensity of climate policies in inducing technological change towards a greener economy [86].

78 Details are available here: GTAP Models: Current GRAP Model: https://www.gtap.agecon.purdue.edu/models/current.asp. Accessed 10 June 2024.
79 Details are available at: The MAGNET Model Module: https://www.magnet-model.eu/. Accessed 10 June 2024.
80 Details are available here: CAPRI Modelling System – Common Agricultural Policy Regionalised Impact Modelling System: https://capri-model.org/. Accessed 10 June 2024.
81 Details are available here: AGMEMOD – Agri-food projections: https://agmemod.eu/. Accessed 10 June 2024.
82 Details are available here: Global Bioshpere Management Model (GLOBIOM): https://iiasa.ac.at/models-tools-data/globiom. Accessed 10 June 2024.
83 Naqvi, A., and Stockhammer, E., *Directed Technological Change in a Post-Keynesian Ecological Macromodel*, *Ecological Economics*, Vol. 154, December 2018, pp. 168-188. https://doi.org/10.1016/j.ecolecon.2018.07.008.
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86 Aghion, P., Dechezleprêtre, A., Hémous, D., Martin, R., and Van Reenen, J., *Carbon Taxes, Path Dependency, and Directed Technical Change: Evidence from the Auto Industry*, *Journal of Political Economy*, Vol. 124, Nº 1, February 2016, pp. 1-51. https://doi.org/10.1086/684581.

6.1.3.2. A short overview of productivity in agricultural simulation models

As elaborated in more detail in Section 2.1, TFP reflects the not (yet) explained gains in productivity in empirical analysis. The ultimate sources of TFP growth are outside of the direct control of farmers and may be beyond the reach of agricultural policy – it emanates from the domains of innovation and research policy. What farmers can do to become more productive, and what the CAP Strategic Plans support, is the adoption of digitalisation, innovative technologies and practices, and to participate in training and knowledge sharing. Some aspects of that can be captured in simulation models.

A recent non-exhaustive overview of agricultural models is presented in an assessment of the potential of existing and innovative modelling tools by Gonzalez-Martinez, et al. [87]. The authors surveyed how suitable simulation models are to quantitatively answer the accomplishment of CAP Specific Objectives. Figure 9 gives an overview of a range of models and whether they are suitable to analyse various aspects of competitiveness. Gonzalez-Martinez et al. explored the suitability of models for the assessment of other Specific Objectives of CAP Strategic Plans as well, but they did not focus on productivity which is closely linked to competitiveness. An overview is shown in Figure 9 which shows that only a few models are designed to evaluate aspects of gains on competitiveness over various relevant domains. As indicated in the list of models, some of them are modelling only the farm sector or parts of it at a single Member State level, while 'large scale models' can model policies for a range of countries.

It is important to highlight that the use of large-scale models or farm-level models serves different purposes and offers complementary insights. Large-scale models, such as CAPRI and GLOBIOM, are particularly valuable for assessing the broader impacts of CAP policies across multiple countries and sectors, providing insights into trade-offs and synergies at the regional or global scale. In contrast, farm-level models are essential for capturing the nuanced, micro-level impacts of policies on individual farm types, production systems and local conditions. Combining these approaches allows for a more comprehensive analysis, bridging the gap between macroeconomic impacts and localised effects of policy.

One model stands out, FARMDYN, a dynamic mixed integer bio-economic farm scale model. It was created by Britz et al. [88] and it is currently being actively developed. New modules are added from time to time. Special features of this model include that it can be calibrated to fit observed farms, it is fully dynamic and simulations can typically cover several decades, but it can also be used for comparative-static analyses or short-run simulations. As indicated in Figure 9, this model is suitable to simulate the adoption of technology and the consequences of investment support measures in its current implementation. Due to its modular structure, the model can also be used to analyse environmental aspects, such as the marginal climate change abatement cost [89].

Figure 9. An overview of the capacities of typical agricultural models to represent competitiveness

Models	Increasing Competitiveness (Productivity)			
	Market shares	Age of Asset	Technology Adoption	Investment support
Large-scale models				
AGMEMOD				
CAPRI				
GLOBIOM				
MAGNET				
MITERRA				
Small-scale models				
Eco-Scheme Farm simulation tool (NL)				
FAPRI Ireland Model				
Farm-Dyn				
FARMIS (DE)				
Farm income FADN-based calculation tool (NL)				
IMF-CAP				
KOBALAMI (NL)				
SiTFarm tool (Slovenian typical farm model tool)				

Source: adapted from Gonzalez-Martinez et al. (2024)

*Note: red: not modelled; yellow: potentially modelled, green: modelled.

87 Gonzalez-Martinez, A., Jongeneel, R., & van Asseldonk, M., & Donnellan, T., Witzke, P., & Rac, I., & Dillon, E., Havlik, P., *Assessment of the potential of existing and innovative modelling tools*, Deliverable D 2.1 of Tolls4CAP, 2024. https://www.tools4cap.eu/publications/. Accessed 10 June 2024.

88 Britz W., Lengers, B,.Kuhn, T. and Schäfer, D., *A highly detailed template model for dynamic optimization of farms - FARMDYN*, University of Bonn, Institute for Food and Resource Economics, 2014.

89 Huber, R., Tarruella, M., Schäfer, D., and Finger, R., *Marginal Climate Change Abatement Costs in Swiss Dairy Production Considering Farm Heterogeneity and Interaction Effects*, *Agricultural Systems*, Vol. 207, April 2023. https://doi.org/10.1016/j.agsy.2023.103639.

Box 7. Capabilities and features of the FARMDYN model

FARMDYN provides a flexible, modular template to simulate farms with different productions e.g. dairy, mother cows, beef fattening, pig fattening, piglet production, arable farming and biogas plants.

- Fully dynamic simulations typically cover several decades, alternatively comparative-static or short-run versions.
- Integer variables capture returns-to-scale investments (e.g. machinery and buildings based on convex combinations over a concave set) and indivisibilities in labour use.
- Selected farm management decisions (e.g. feeding, manure management and labour use) depicted with a sub-annual temporal resolution, partially bi-weekly.
- Deterministic or stochastic programming version. The latter treats all variables as state dependent, allows for scenario tree reduction and covers different risk measures (value at risk, MOTAD, etc.).
- Farm labour, machinery and stable use are modelled in rich detail.
- Arable cropping can be differentiated by system (conventional or organic), tillage type and intensity.
- For dairy farming, the model distinguishes several herds by number of lactations and lactation phase.
- Beef fattening can be depicted in several phases, linked to different grazing options, considering crossbreeding and sexing.
- The machinery park is available at different mechanisation levels.
- Detail in grassland management (number of cuts, bales/silo/hay etc.).
- Highly differentiated modules for nitrogen fate while covering country specific legislation on fertiliser use (requires adaptation to national standards).
- A range of economic, social and environmental indicators, including life-cycle assessment derived ones.

Source: adapted from Uni Bonn[90]

6.1.4. The way ahead

This chapter provides an overview of how productivity is addressed in simulation models. It confirms that productivity elements are already implemented in many of them, although at varying degrees, which is to be expected since a model is designed to answer specific questions (and overloading models with features risks turning them into a 'black box').

Based on the elaboration presented above, one can conclude that most agricultural simulation models are not (yet) well suited in their current state to help Member States assess ex ante the impact of the CAP on productivity. Firstly, the set of adequate existing tools (i.e. simulation models) is very limited. Secondly, many of them require data that cannot be easily extracted from publicly available datasets. Thirdly, a competent team of researchers would need to be assigned to carry out the analysis because even if open-source models are available, the skills to modify them and adapt them to a given country's situation might often not be available (i.e. it is not only the CAP Strategic Plan interventions that need to be implemented in the model, but also all interventions from the previous CAP programming period).

The data and model availability for each Member State differs. For a few Member States (e.g. Germany, France and the Netherlands), all types of models are available, as well as teams of experts with the necessary skills for actively using them in farm policy analyses. In such situations, simulation models may be useful research tools to analyse the effects of interventions on productivity and trade-offs between the intended production of goods for which markets exist and the non-intended production of goods or bads for which markets do not exist.

For other Member States, country specific (and therefore CAP Strategic Plan specific) models are not yet readily available (or only specific types of models with limitations in representing productivity). In these situations, it may be advisable to invest in capacity-building and additional data collection in order to catch up and be able to provide simulation model results at least when the ex post evaluation is due.

90 See more at: Uni Bonn: https://www.ilr1.uni-bonn.de/en/research/research-groups/economic-modeling-of-agricultural-systems/farmdyn. Accessed 12 June 2024.

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