Assessing the trade-off between SO1 and SO5 policy intervention through an ex-ante PMP-AB model: the case of Emilia Romagna Region

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Abstract

The flexibility granted by the new Common Agricultural Policy (CAP) Delivery Model enables EU Member States to customise the application of agricultural policy interventions according to the specific needs of each Member State. At the same time, the EU requires careful monitoring concerning the achievement of the 10 Strategic Objectives. This research aims to assess the trade-off, if existing, between the CAP objective aiming at supporting viable farm income (SO1) and the one intended to foster sustainable development (SO5). The trade-off is evaluated by conducting an ex-ante analysis to assess the potential impact of regional payments for organic conversion on both farm viability and environmental sustainability, more specifically in terms of water consumption, use of fertilisers and pesticides. The impact assessment utilises an Agent-Based Model implemented through a positive mathematical programming approach. The efficiency of policy intervention is evaluated through the "Synthesis questions and judgement criteria" set by DG AGRI as a means to assess the effectiveness of the National Strategic Plans (DG AGRI, 2023). Preliminary results on SO1 show that organic farming payment increases farm income, especially amongst the smaller farms, generally considered being the most vulnerable ones, while farm Gross Margin per Agricultural Working Unit presents a lower inequality distribution.

Keywords: CAP Specific Objectives, Agent Base Model, Farm income distribution, Envionmental impact.

JEL code: Q18, Q12, Q51, R58

1. INTRODUCTION

The environmental impact of intensified agriculture, despite the "greening" measures included in the 2014-2020 CAP, continues to harm climate, water, pollinators, biodiversity, human well-being, and cultural heritage (European Environmental Agency 2019; Nègre, 2022).

The post-2020 CAP reform started on January 1, 2023 is a new attempt to rectify these issues and align with the EU Green Deal and the goals of the Farm-to-Fork and Biodiversity strategies. In this context, the ongoing CAP architecture has introduced, on the one hand, the eco-schemes, which entitles Member States to allocate at least 25% of first pillar payments to measures beneficial for the environment and the climate. On the other hand, the New Delivery Model, outlined in Regulation (EU) 2021/2115, is a pivotal component of the CAP post-2020, and it emphasises performance and results over compliance. It redistributes responsibilities, giving EU countries more autonomy to tailor agricultural policies to their specific needs while ensuring uniform standards across the EU. The model is built around CAP Strategic Plans, allowing for targeted interventions that align with both national priorities and EU-wide objectives. Additional specifications provided in the Commission Implementing Regulation 2022/1475 mandate Member States to assess the contribution of their National Strategic Plans across dimensions such as effectiveness, efficiency, relevance, coherence, and added value, supporting a shift from a compliance-oriented approach to a more performance-based approach (EU CAP Network, 2023). The introduction of performance reports and a comprehensive set of indicators should facilitate monitoring and evaluation. This evaluation process must adhere to the Performance Monitoring and Evaluation Framework (PMEF) and must be developed by the Member State (EC, 2021) rather than the European Commission (EC). The evaluation must address several issues, such as the numerous factors affecting farm income, the complexity of assessing the CAP's net effects, the need for granular data, and the adoption of methodologies that capture the behaviour of individual farmers under various policy scenarios, thereby accounting for the heterogeneity of impacts on farm structure (EU CAP Network, 2023). Furthermore, as part of the PMEF (Article 139 of the EU 2021/2115 Regulation), Member States must conduct a preliminary assessment of their Common Agricultural Policy Strategic Plans (CSPs). The ex-ante evaluations are intended to enhance the CSP's formulation quality and set a baseline for its assessment throughout the 2023-2027 execution period. The objective of the ex-ante evaluations is to enhance the quality of the plans and to determine a baseline for its assessment throughout its implementation from 2023 to 2027.

Also at the granular level of individual policy and within a regional context, preliminary evaluations can be instrumental in quantifying the extent to which a policy contributes to the attainment of its delineated targets and in identifying prospects for methodological and procedural enhancements. Moreover, ex-ante assessments can ascertain the alignment and synergy across varied intervention mechanisms, and quantify how expected outputs will contribute to results through the use of predefined indicators.

This paper's intent is to carry out a preliminary impact analysis of the CAP specific objective aiming at supporting viable farm income (SO1) and the specific objective fostering sustainable development (SO5) using an agent-based model (ABM), based on Positive Mathematical Programming (PMP). Looking at these two CAP objectives could seem at odds due to their different primary focuses and potential for conflicting outcomes. SO1 emphasises supporting viable farm incomes and resilience within the agricultural sector to promote food security, agricultural diversity, and economic sustainability. This often involves practices that aim to maximise production and profitability, which can lead to an increase in the use of inputs such as fertilisers, pesticides, and water to ensure high yields and stable market supply. SO5, on the other hand, is centred on promoting the sustainable use of natural resources and reducing reliance on chemicals. The drive towards sustainability often requires adopting practices that may initially seem to reduce the productivity and profitability of farms, such as reducing the use of chemical inputs that are harmful to the environment.

The methodological choice is driven by the fact that PMP is widely used in agricultural policy assessment (Howitt, 1995; Britz et al., 2012; Solazzo et al., 2014; Reidsma et al., 2018; Matthews, 2022). A distinctive feature of PMP is its ability to recover important entrepreneurial decision variables, such as hidden costs related to past farming experience, risk attitude, and production expectations. In this

study we combine the PMP approach with an ABM to capture interactions between farms in the use of scarce resources and to fulfil important disaggregated specifications capturing farm heterogeneity (Reidsma et al., 2018; Berger & Troost 2014).
To measure the impact of the scenarios implemented in this model, we use some of the indicators proposed in the PMEF. This framework considers four types of indicators: output, result, impact and context indicators (Regulation (EU) 2021/2115). More specifically output indicators can be useful to assess the immediate results of the subsidy (e.g., the number of farms that adopted organic farming practices due to the subsidy). Result indicators provide information on the medium-term effects, such as changes in farm income levels or improvements in resource efficiency due to reduced chemical fertiliser usage. Impact indicators should help assess the long-term consequences of the subsidy on farm incomes and resilience, as well as the environmental outcomes. The context indicators, that provide background information that could influence the performance of the other indicators (e.g., overall trends in the agricultural sector, economic context, etc.) are not considered in this paper.
The economic effects related to SO1 are evaluated, according to PMEF, using the Agricultural Working Unit (AWU) and Fam net value added (FNVA). These indicators provide information on the actual remuneration of labor and capital from agricultural activities, reflecting the economic viability and income stability on farms, which is directly linked to the objective of supporting viable farm incomes and resilience.
To measure the environmental perspective related to SO5, the impact indicators that reflect the long-term sustainability of natural resource management and reductions in chemical dependency would be the best suited but not realistically usable as measurement, given the short time horizon (the agronomic year) used in this paper. In line with the Farm-to-Fork and Biodiversity strategies, the CAP should be key in supporting the sustainable use of fertilisers in agriculture, ensuring that farmers can maintain productivity while also reducing the harmful effects of pollution. However, the Farm-to-Fork target of a 20% reduction of the synthetic fertiliser usage is not emphasised in the CAP 2023-2027 nor reported as a specific indicator associated to SO5.
In this paper we consider of the ratio between farms gross margin (GM) and AWU, resulting from two alternative scenarios: strengthening organic farming and reducing mineral fertiliser use by 20% for conventional farms. Despite the FADN methodology switched from using Standard Gross Margin to Standard Output for measuring a farm's overall economic size (EC, 2021), in our model we use the farm GM as it better represents the internal decision-making and management process, driven by the farm holders behavioral path, helping to assess the efficiency and profitability of the different farms in the sample. Farms Standard Output, on the other hand, uses standard values to facilitate comparisons, not necessarily reflecting current market prices or individual farm cost structures.
This study is organised as follows. The methodology and data section presents the reasons why the PMP approach and the ABM method have been chosen, the structure of the AGRISP model (Agricultural Regional Integrated Simulation Package), the characteristics of the farm sample used for the analysis and the policy scenarios implemented. Section three is dedicated to analysing the results by disaggregating the sample into deciles and assessing income distribution equity by farm and by AWU, using the Gini index. The fourth section discusses these findings and concludes the study.

2. METHODOLOGY AND DATA

2.1. Agent-based models and PMP

ABMs are designed to simulate interactions among agents, thereby they can be used to describe the effects on land exchange and structural changes, considering agents' productivity, efficiency, and spatial heterogeneity within their territory (Reidsma et al., 2018). Agents can represent different individual farms, entrepreneurs, or aggregated entities, such as farm types.
The ability of ABMs to capture agents' interactions can be leveraged under the assumption of non-full rationality in production preferences, reflecting the tendency of farmers to prioritise maximising their utility function over their profit function (Nolan et al., 2009; Kremmydas et. al 2018). This is plausible when agents represent individual farm-households, in which family structure and other individual

characteristics are particularly important in determining transaction costs affecting the economic objective. Decisions are based on production factor endowment and level of technological knowledge, as well as the perception of economic and technical risks.
The literature provides some attempts to measure the effect of CAP provisions through ABM models, such as AgriPoliS (Happe et. al 2004), MP-MAS (Schreinemachers and Berger, 2011), and RegMAS (Lobianco & Esposti, 2010). For more insights into the different types of ABMs, Kremmydas et al. (2018) have conducted a systematic literature review on ABMs for evaluating agricultural policies.
Linking ABMs with Positive Mathematical Programming models offers the advantage of creating micro-level models that can depict technological variations based on the structural characteristics of the farms. This optimisation takes into consideration the unique characteristics and behaviors of individual farmers, starting from the observed optimal scenario. The cost function is hypothesised to be a quadratic functional form in output quantities: $C(x) = x'Qx/2$, where the Q matrix is symmetric and positive semidefinite. Additionally, this integration allows for the simulation of structural and technological changes, such as changes in farm size or the potential abandonment of farm activities. An ABM based on PMP can estimate these choices by simulating land exchange, the introduction of new activities and changes in agricultural management practices. Aggregating these results can provide a useful and solid insight into the general trend of the agricultural sector at regional, national, and international levels.
PMP is generally used as a straightforward calibration technique as seen in the CAPRI model, where specific technical coefficients are applied. In this study, the PMP methodology employed for calibration is based on farm marginal costs, which consider not only accounting costs but also the "transaction costs" perceived by the farmers. Calibration using the marginal costs of observed data enables the extrapolation of the social component, considering historical and attitudinal factors (referred to as hidden or latent costs), influencing a farmer's decision to produce, for instance, maize instead of tomatoes. This choice can significantly depend on factors such as the farmer's age, risk tolerance, or farm size.
Although there is no theoretical rationale requiring a specific functional form for farmers' reactions, the quadratic form is employed in this study because it is widely used in Agricultural Economics and inherently represents the cost function. Additionally, the Cholesky decomposition ensures to obtain a symmetric and positive semidefinite matrix.

2.2. The model structure

AGRISP, the model used in this paper, is a supply ABM, based on the PMP approach, which models farm-holders as agents and analyses the impact of agricultural policies on agents' behaviours related to land use, gross margin and AWU, carbon emission, and water consumption. AGRISP is implemented in GAMS (GAMS 2023) and is articulated in a calibration and a simulation module, depicted in Figure 1. The primary triggers influencing farmer behaviour and reactions to policy scenarios are the individual economic cost function and the agent-based rules steering the decisions.
The farm cost function is estimated in the calibration module using the standard PMP methodology proposed by Paris and Howitt (Paris & Howitt, 1998) and extended by Arfini (Arfini et al., 2008) for policy evaluation with FADN data. The calibration phase consists of three steps: i) Solving a positive linear programming (LP) model to obtain the dual values of a series of production constraints bounded to observed production; ii) Estimating a non-linear cost function for each observed farm based on the dual values according to the Maximum Entropy approach (Shannon, 1948; Paris e Howitt, 1998) resulting in the Q matrix; iii) Solving a non-linear programming (NLP) model that maximises the farm gross margin incorporating the non-linear cost function, represented by the *Q* matrix. This approach allows to replicate the production plan for all farms in the sample without using the calibration constraints of the first phase. The non-linear cost function returns the fundamental decision information related to the farm holder, influencing the allocation of resource endowments among various farm activities and the marginal cost within the LP model. Unlike in the SWISSland model (Möhring et al., 2016), that only considers the diagonal elements, this study represents the Q matrix of the non-linear cost coefficients considering also the elements of the triangular components of the matrix. The Cholesky' decomposition ensures the correct representation of the cost function by imposing the symmetric, positive and semidefinite structure of the matrix.

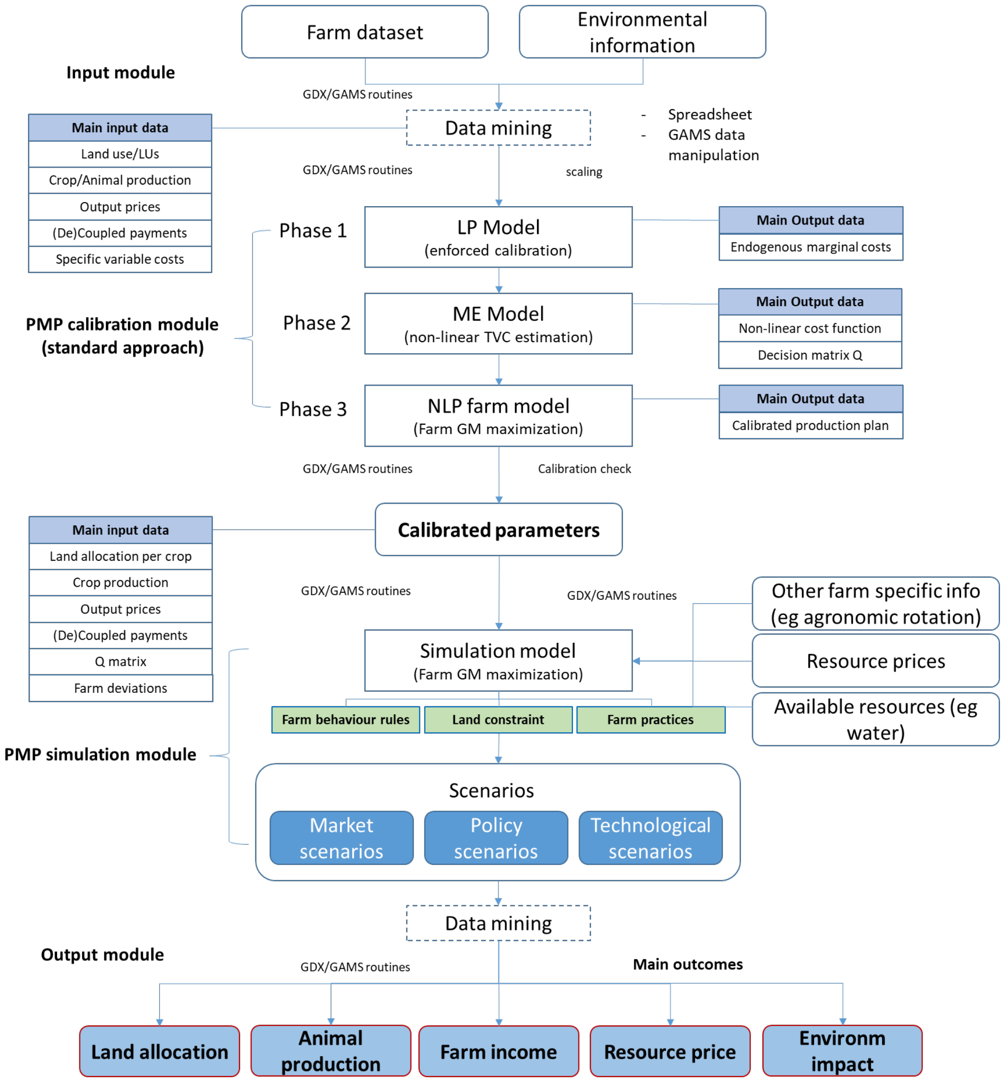

Figure 1: Figure 2. Model Structure. Source: authors' own elaboration.

The exact production level for each farm is estimated with the "self-selection". A detailed explanation of self-selection rules and a comparison between the farm and frontier cost functions can be found in Paris and Arfini (Paris & Arfini, 2000).

Within the AGRISP model, agents located in a designated agricultural regional agricultural have the capability to share and implement diverse farming methodologies or novel practices, contingent upon the accessibility of empirical technical data. This exchange is facilitated through a regional shared frontier-cost function, constructed via Positive Mathematical Programming (PMP), which incorporates the costs related to varying crops and farming techniques, as well as each farm's cost deviations. This cost function serves as a link among the farms in the sample. The deviation from the common cost function is regarded as a basis for comparing costs and profitability among the farms included in the sample.

The introduction of a subsidy, a quota or a tax, which triggers changes in output prices of variable costs, leads farms to different cost-efficiency crop or techniques combination, as result of the optimisation run in the simulation phase. This can be viewed as a form of "social learning process" or, more accurately, as an exchange of technical and economic information made available, because observed, in the sample. The interconnectedness stems from all farms being aware of the potential techniques available. The latent technologies or crops are those options that agents could potentially adopt but remain "unused" by a farm due to their lack of economic viability within a particular simulated scenario. Supports coupled to a specific technique or tied to the acreage can alter the economic ratios among various production plans. As a result, farm holders may choose to adopt a new crop or technology from the array of

agronomic techniques practiced by the farms in the sample, originally latent in their production plan, and their decision is influenced not only by the accounting cost but also by the utility cost unique to each farm.
Following calibration, the simulation module assess the repercussions of alternative policy scenarios by utilising the inherent positive data embedded in the non-linear cost function and applying a predefined set of theoretical behavioral norms. These agent-based rules offer a more realistic representation of the interactions among farms, encompassing resource exchange, as well as the choices made by the farmers regarding different agricultural practice, taking into account the specific social and family characteristics. Möhring et al. (2016) suggest a correlation between farm dynamism and demographic factors such as the age of the farm holder and the existence of successors. The underlying hypothesis posits that farmholders are prone to downscale operations upon reaching 65 years of age, and those without successors may refrain from expanding or converting to organic methods, while they rather lease out their lands, entirety or in portions. In the model, the complete rental of land is regarded as an exit from active farming operations. Conversely, younger holders, or those with potential successors, might pursue growth by leasing additional land or opt for transitioning to organic farming. It is important to highlight that each strategic decision within the model is based on the principle of cost-effectiveness, ensuring that economic considerations are at the forefront of the decision-making. Consequently, the economic cost function to be optimised reflects variables including land lease costs and the additional expenditures incurred from the transition to and maintenance of organic cultivation.
The model's core attributes are quantitatively captured through a series of equations presented herein. For an in-depth exploration of how policy tools are integrated within the model, refer to Appendix 1, which provides comprehensive details on the implementation mechanisms
Agent interactions (1-3) within the model are defined by a shared frontier-cost function (Q) with an individual deviation (u), and the application of a self-selection rule (4-5) by the n_{th} farm. This self-selection process enables farms to emulate the observed production plan by comparing the marginal cost of their current activity or technology against the average cost of a new, potentially more efficient activity or technology. The latter is characterised within the Q matrix as a latent option for an altervative activity or technology.

$$\max_{x_n \geq 0} \; (p'_n x_n - 1/2 x'_n \hat{Q}_n x_n - \hat{u}_n x_n) \tag{1}$$

$$A_n x_n \leq b_n \tag{2}$$

$$x_n \geq 0 \tag{3}$$

To account for the diversity of crop cultivation across the sample of farms, the model incorporates two sets of constraints. These constraints are intended to realistically reflect that not all farms grow every crop that is available in the region. The initial set addresses the assortment of crops that are actively cultivated, establishing the following equation for the marginal cost relationship for these crops:

$$mc_{nk} | \, x_{Rk} > 0 \;\; \lambda_{nk} + c_{nk} = Q_k x_{Rn} + u_{nk} \text{ if the } \boldsymbol{k^{-th}} \text{ activity is produced, k=1, …, J}_{\text{n}} \tag{4}$$

where $\boldsymbol{mc_{nk}}$ is the marginal cost for the $\boldsymbol{n^{-th}}$ farm associated to the $\boldsymbol{k^{-th}}$ activity.

For activities not undertaken by the $\boldsymbol{n^{-th}}$ farm, the second set of constraints imposes weak inequalities. These ensure the marginal cost relationship is less than or equal to the frontier-cost function level, reflecting the absence of production for these particular activities on the farm:

$$mc_{nk} | \, x_{Rk} = 0 : \; \bar{\lambda}_{nk} + \bar{c}_{nk} \leq Q_k x_{Rn} + u_{nk} \text{ if the } \boldsymbol{k^{-th}} \text{ activity is not produced, k} = 1, \dots, \text{Jn} \tag{5}$$

$\boldsymbol{R}$ is the level of production observed for activity **k** and the vector $\boldsymbol{u_{nk}}$ assumes the role of indexing the cost function with the farm $\boldsymbol{n}$ specific characteristics. $\boldsymbol{\lambda}$ represents the implicit component of the marginal cost associated to the production of the activity $\boldsymbol{k}$ by the farm $\boldsymbol{n}$.
Constraints (4) and (5) enable farmers to select potential production activities from the entire spectrum of regional activities, based on those observed in the preliminary phase of the PMP (Paris and Arfini, 2000). In scenarios where there is a transition to organic farming practices, the original equations (1-3) that governed conventional farming are substituted with a different set, namely Equations (6-8), to accurately reflect the changes in production dynamics.

$$\max_{x_c \geq 0, x_g \geq 0} p'_c x_c + p'_g x_g - \frac{1}{2} \begin{bmatrix} x_c & x_g \end{bmatrix} Q_{cg} \begin{bmatrix} x_c \\ x_g \end{bmatrix} \quad (6)$$

$$S.t. \;\; A_c x_c + A_g x_g \leq b \quad (7)$$

$$A_{nc} x_{nc} \cdot A_{ng} x_{ng} = 0 \quad (8)$$

Any farm using conventional technology ($\boldsymbol{c}$) can convert to organic technology ($\boldsymbol{g}$) if it is more profitable. In the Italian FADN, information regarding the agronomic management practice (organic or conventional) is provided for each farm. From this information the average costs, yield and output prices of the organic production are extrapolated. When a farm convert to organic farming those values are applied for the crops included in its production plan.
As mentioned above, with the non-linear cost component, the objective function takes advantage of the self-selection property, allowing the substitution of technology or crops based on the cost information provided in the Q_{cg} matrix. Consequently, farms that decide to convert to organic farming change their production plan and cost structure.
Equations (9-14) represent the rules related to the exchange of the land factor between agents. Setting j activities, n and m farm holdings exchange land between each other. Equation 9 indicates that the available utilised area is equal to the available area plus the rented-in land minus the rented land. Equations (9 - 14) model the land rental decisions of farmers, stipulating that the land rented must be equivalent to the land rented out at the regional level. Specifically, constraint (9) ensures that the sum of land allocated to various crops **j** (j = 1, . . . ,J) does not exceed the total available land at the **j** farm level, $\mathbf{b}_n$, adjusted for land rented ($\mathbf{Z}_n$) and rented out ($\mathbf{V}_n$).

$$A_{nj} x_n \leq b_n + Z_n - V_n \quad (9)$$

The land rented is represented as:

$$Z_n = \sum_m ZZ_{nm} \quad (10)$$

and the land rented out is represented as:

$$V_m = \sum_n VV_{nm} \quad (11)$$

where $\mathbf{ZZ}_{nm}$ and $\mathbf{VV}_{nm}$ are the matrix tracing the transfer of land for each pair of farms for renting and renting out, respectively. Additionally, equation (12) guarantees that for each pair of farms, the land rented by one must be equal to the land rented out by the other:

$$ZZ_{nm} - VV_{nm} = 0 \;\; \forall n \neq m \quad (12)$$

To avoid a given farm renting and renting out land at the same time, a specific constraint is used:

$$Z_n \cdot V_n = 0 \quad (13)$$

Finally, to maintain consistency in land exchange within the region, we stipulate that the overall amount of land rented must be equivalent to the total land leased out:

$$\sum_n Z_n = \sum_n V_n \quad (14)$$

We assume that the exchange of land is limited to the farms located in the same agrarian region. Each farm has a marginal cost level, estimated with the PMP, beyond which acquiring additional land provides no further advantage. Introducing a price shock or a policy incentive can lead to a change in the shadow price of land for a specific farm. However, the land rental price remains constant, as it is treated as exogenous to the model and is assumed to be uniform throughout the Emilia-Romagna region.
Agents' interactions are regulated by the behavioural rules already mentioned in the previous section and here summuarised: i) Conventional farmers older than 65 and without successors cannot move to organic practices; ii) Farms are only allowed to exchange land within the agrarian regions where they operate; iii) Farmers older than 65 and without successors cannot rent land.
The input level is calculated based on the spending on purchased inputs, both for crops and livestock, per hectare of UAA. The inputs are purchased fertilisers and soil improvers, plant protection products, other means for protection, bird scarers, anti-hail shells, frost protection and purchased feed.

2.3. Policy Assessment

The policy impact assessment is conducted by analysing specific results and output indicators (DG AGRI 2023) that reflect the economic farms' viable condition and their impact on natural resources before and after the introduction of the policy intervention. Thus, policy evaluation requires granular information, allowing indicators on different dimensions (by farm size) and at different scales (such as farm, hectarege, AWU). The observed distribution of GM/Farm and GM/AWU among all the farms in an area is reached by constructing the Lorenz curves and calculating the Gini index. This indicator has been used to observe income disparities between farms by highlighting the efficiency of agricultural policies in supporting fair farm income distribution of a sample of farms belonging to the FADN observatory (Allanson, 2007; Severini and Tantari, 2012; Marino et al., 2021).
In this study, using the Gini index is particularly apt for analysing the impact on all farms in the FADN sample from the Emilia Romagna Region. This analysis encompasses both the level and distribution of income, along with environmental indicators.
To provide environmental impact assessment, we integrated the Italian FADN data with environmental information on greenhouse gas (GHG) emission factors and water consumption for the different crops. GHG emissions from agricultural activities are estimated by applying the ICAAI methodology (Impronta Carbonica dell'Azienda Agricola Italiana), developed by CREA-PB, following the guidelines provided by the IPCC for establishing a national inventory of greenhouse gas emissions (Coderoni et al. 2013; IPCC 2008). This procedure, already implemented by Solazzo et al., (Solazzo et al. 2016) assumes that the amount of atmospheric emissions is linearly related to the level of economic activity, and the emission factors considered for the agricultural sector are carbon dioxide, methane and nitrous oxide, expressed in ton CO2eq per hectare or head of livestock. The conversion factors referred to the 100-year Global Warming Potential and are provided by the Fourth Assessment Report of the IPCC (IPCC 2007), following Equation (15):

$$CO_2\,eq = CO_2 + 298 \cdot N_2O + 25 \cdot CH_4 \quad (15)$$

More in detail, carbon dioxide emissions comprise emissions due to mechanical cropping operations (Ribaudo, 2011) and soil organic carbon (SOC) estimation; methane emissions are due to livestock enteric fermentation and rice cultivation; nitrogen emissions include animal manure management, synthetic fertiliser application and atmospheric deposition (Solazzo et al. 2016).

The water consumption measurement uses the Water Footprint Network, based on the extensive work of Mekkonnen and Hoekstra (Mekonnen and Hoekstra 2010) that estimates the water footprint of 147 crops and over 200 products, and which also calculates the water footprint at national and sub-national level of each crop worldwide.

2.4. Data

Emilia-Romagna plays a significant role in Italy's agricultural landscape with 1.045 million hectares of UAA in 2020 (8.36% of the national UAA), representing 46.6% of the regional area, and 53,753 active agricultural businesses. Intensive agricultural practices continue to play a crucial role in the region's agricultural output, particularly dairy farming, contributes significantly to greenhouse gas emissions.
The data used in this study are the individual farms included in the RICA (FADN) sample (CREA, 2021), of the Emilia-Romagna (NUTS2) Region. It counts 867 farms out of the 11,040 sampled farms across Italy. In the RICA sample a weight is associated to each farm to account for scaling up at the regional level for a total of 43,435 farms. This number is considerably lower than the census one as the FADN survey covers only those farms exceeding a minimum economic size. Table 1 illustrates the distribution of farms after calibration based on their agricultural practice and their utilised agricultural area.

Farms agricultural practice	Number of farms after calibration	UAA (ha)
Organic Farms	3,195	122,056
Conventional Farms	28,423	526,685
Total Farms	31,619	648,742
% of Organic Farms	10.11%	18,81%

Table 1: Number of Farms according to size class (ha) and management practices.

The set of farm data includes information on geographical location (region, province, altitude, agrarian region), household characteristics (age and gender of the farm holder, number of potential farm holder's successors), land use, specific production costs per crop (cost of seeds, fertilisers, pesticides, energy, water), gross total product, and CAP payments.
Although similar to the European sampling, the Italian FADN is notably more comprehensive, considering over 2,500 variables for each sampled farm, in contrast to the European FADN, which only takes into account approximately 1,000 variables (CREA, 2021). The "agrarian region" spatial definition is a peculiarity of the FADN and it further segments Italian provinces (NUTS3) based on geographical location and altitude range. This dimension play a crucial role in constraining the land transfer between neighbouring farms, as as explicated in the antecedent section (Equations 9 - 14).

2.5. Policy scenarios

In the AGRISP simulation module, two scenarios are implemented:
i) The "organicland" scenario, wherein payments encourage farm holders to opt for organic agricultural practices, with the objective of expanding the area under organic agriculture to 25%, in accordance with the Farm to Fork strategy target. The level of payment is assigned per crop, following the regional Rural Development Plan 2014-2020. In this scenario, an adjustment on yield and prices, going from conventional to organic, is also considered.
ii) The "fert" scenario models a decrease of 20% in the expenditure on fertilisers for conventional farms. Given that the RICA database does not distinguish between organic and chemical fertilisers, it is assumed that conventional farms utilise only chemical fertilisers. Here, a 20% reduction is applied, leaving the fertiliser expenditure for organic farms unchanged. Additionally, a very conservative approach is adopted regarding the impact on yield, estimating a yield loss of 15%, with the exception of alfalfa, where chemical fertiliser is presumed not to be used.
Both scenarios are compared to a baseline (scenario "land"), where rules permit farmers to exchange land through renting or leasing, which is a common practice to adjust farming operations without altering the proportion of land use significantly. The price of renting land is derived from the Land Market

Research of CREA-PB. The rent for arable land in Emilia Romagna in 2019 is estimated to be €607/ha (Land Market Research, CREA-PB 2021). Greening measures of the previous CAP reform are also included: crop diversification, maintenance of permanent grassland, and the establishment of Ecological Focus Areas are simulated (European Commission 2017).

3. RESULTS

3.1. Impacts on land use

Table 2 depicts the impact of the 2 scenarios on the portion of land allocated to organic farming.

Organic surface (ha)	**s_land**	**s_organicland**	**s_fert**
Organic surface	126,309	269,554	115,550
Conventional surface	522,433	379,188	533,192
Total surface	**648,742**	**648,742**	**648,742**
% of Organic surface	19.47%	41.55%	17.81%

Table 2: Impact on Organic Surface (ha).

As expected, the “organicland” scenario shows a substantial policy-driven increase in the area under organic farming, in line with the goal of reaching 25% of the total agricultural surface to align with the Farm to Fork strategy. However, the organic surface area reaches 41.55%, which exceeds the target, suggesting either an overachievement of the policy's objectives or a potential overestimation in the simulation, where the payment level assigned per crop represents a strong incentive for this significant conversion to organic farming.
Contrasting with the “organicland” scenario, the “fert” scenario reflects a reduction in expenses on chemical fertilisers by 20% for conventional farms. This scenario assumes that only chemical fertilisers are used by conventional farms, and thus the decrease in expenditure doesn't affect organic farms. Interestingly, this scenario results in a slight decrease of the percentage of organic surface area on the total agricultural surface (-1,66%), probably due to the fact that organic products prices are not yet competitive. The conservative approach taken, estimating a 15% yield loss on crops might suggest that some farmers revert to conventional methods or are less incentivised to switch to organic, given the reduced cost of conventional inputs. In other words, in the absence of subsidies, the convertion to organic farming results to be not economically convenient for conventional farms.

3.2.Structural changes

Similar trend can be noticed in the impact of the scenarios on the number of farms. Structural changes are captured by the ABM rule that allows farms to rent or lease land as a result of new market scenarios or specific policies interventions (Table 3).

Organic Farms (number)	**s_land**	**s_organicland**	**s_fert**
Organic Farms	2,856	7,113	2,904
Conventional Farms	25,292	20,363	25,017
Total Farms	**28,148**	**27,475**	**27,921**
% of Organic Farms	10.15%	25.89%	10.40%

Table 3: Impact on Number of Farms (weighted).

Organic holdings would increase from 10.15% to 25.89% of the total number of farms. However, this expansion would lead to an overall reduction, 673 farms less, at detriment of the conventional holdings. Adopting the organic technique would be conventional farms that convert to organic and increase their productive size by acquiring land from other farms that would close down. Interesting to note is that organic farms own an average area approximately double than conventional farms, as they must

guarantee enough land for crop rotations; nevertheless, in the organicland scenario a reduction in the regional average of UAA of organic farms is depicted (from 44 to 38 hectares).
The fertiliser reduction scenario does not deviate much from baseline, showing only a modest increase in the number of organic farms (+48) but would represent a substantial decrease in conventional farms (-275), probably due to the yield loss. Overall, we count 227 farms that would stop their activities by transferring whole their land to other farms, and a decrease in the regional average of UAA of organic farms (from 44 to 40 hectares).
To better understand and assess the economic and structural dynamics, we divided the sample into decilis (Table 4). The analysis of the weighted sample reflects the productive structure of the agricultural system in the Emilia-Romagna region, where 87.84% of farms are concentrated in the 1st decile. This class of holdings, comprising over 24,700 farms, representing the backbone of the regional agricultural system. The second-largest class of farms, in the second decile, represents 9.21% of farms.

Farm Decile	Farm Size (ha)	s_land	s_organicland	s_fert
1	0-55	24,726	23,995	24350
2	55-110	2,591	2,630	2650
3	110-165	518	537	608
4	165-220	122	129	122
5	220-275	36	30	0
6	275-330	30	30	66
7	330-385	80	0	80
8	385-440	12	91	12
9	440-495	16	16	16
10	495-550	18	18	18
Total		**28,148**	**27,475**	**27,921**

Table 4: Number of Farms per class.

In the "organicland" scenario we notice that the most impacted farms are the small ones (first decile) that would cede their land to other farms or increase their surface and move to an higher class (731 farms less in class 1).
The "fert" scenario report a significant decrease in class one (-351 farms) that would lead to an increase of class 2 and 3. No impact is depicted in large farm types, suggesting that the yield decrease for these farms is balanced out by the decrease in fertiliser cost.

3.3. Economic impact

The GM of the weighted sample of farms in the Emilia Romagna Region is estimated by the model at 1,125 million Euro (Table 5). The introduction of a subsidy in favour of organic farming would allow a further increase of 133 million Euro (11.82%), while the reduction in the use of fertilisers would represent only a modest increase in the regional GM (+2.08%). The distribution of the regional GM by deciles allows a deeper analysis of the economic characteristics of the companies in the sample.

Farm Decile	Farm Size (ha)	s_land	s_organicland	s_fert
1	0-55	466,642,702	488,297,279	438,878,619
2	55-110	410,492,017	456,560,976	420,820,654
3	110-165	112,331,061	155,081,649	138,680,698
4	165-220	24,328,018	28,327,777	31,051,895
5	220-275	11,795,037	11,059,807	-
6	275-330	10,276,011	10,997,140	25,412,231
7	330-385	64,817,448	-	69,087,240
8	385-440	5,749,889	89,054,242	5,521,034
9	440-495	13,290,430	13,290,430	13,727,827
10	495-550	5,357,266	5,442,698	5,324,393
Total		**1,125,079,878**	**1,258,111,997**	**1,148,504,590**

Table 5: Total Gross Margin (weighted sample) divided per class.

Under this "organicland" scenario, the GM augments for nearly all farm sizes, implying that the policy measures to foster organic farming are efficacious in enhancing the profitability of farms across the majority of size classes. This is particularly evident for larger farms (over 165 ha), which appear to

benefit markedly from the organic transition, likely due to the advantages of scale and the heightened payments per crop as stipulated by the regional Rural Development Plan.
The average GM per farm in the sample is 39,970 Euro and it reflects the structure of the FADN sample considering the high concentration of companies in the first decile. In the "organiland" scenario the average GM per farm increase by
In the GM per farm would increase by 14.56% with significant increases for all farm types up to class 8, where the increase of 99.16% is due to the shift of farms to that class from the previous one. Large farms GM does not seem to be significantly impacted (Table 6).
The reduction in fertiliser use would lead to a reduction in GM per farm in the first, eighth, and tenth deciles, where a decrease in GM/Farm of 4.5%, 3.98%, and 0.61%, respectively, is observed. Despite this decrease, result highlights an overall increase, probably due to the redistribution of farms between classes, regardless lower production levels.

	Average GM/Farm			Average GM/AWU		
Farm Decile	**s_land**	**s_organicland**	**s_fert**	**s_land**	**s_organicland**	**s_fert**
1	18,873	20,350	18,024	13,421	14,389	12,897
2	158,414	173,610	158,818	49,079	51,026	49,578
3	216,949	288,565	228,168	46,368	62,089	41,311
4	198,993	219,833	253,992	37,642	42,201	47,842
5	325,143	372,744	-	126,361	161,726	-
6	346,328	370,632	385,339	95,329	102,019	126,342
7	814,194	-	867,828	101,520	-	108,208
8	489,445	974,792	469,964	86,322	126,304	82,886
9	846,482	846,482	874,340	138,314	138,314	142,866
10	298,896	303,662	297,062	106,748	108,451	106,093
Total	**39,970**	**45,791**	**41,134**	**23,808**	**26,723**	**24,141**

Table 6: Average Gross Margin per Farm and per Annual Working Unit (weighted sample).

The GM/AWU analysis provides insight on the impact of the reforms on household income and thus on the quality of life of farmers and their families. The average GM/AWU in the reference scenario is €23,808, with considerable differences among the farm types described by the deciles. Class 1 represents the type with the lowest GM/AWU (€13,421), while class 9 represents the farm type with the highest GM/AWU (€138,314).
The introduction of the "organicland" scenario would result in a significant improvement in the GM/AWU for the majority of farms, with the exception of those in class 9, where there would be no change. The shift to greener agriculture with the reduction of fertilisers would not change much the average GM/AWU at a regional level (+1.4%), generating however a diversified effect among the farms in the sample, with a reduction for farms in the first, third, eighth, and tenth deciles. In particular, farms in the third decile would experience a significant worsening (-10.91%), while farms in this decile would find the organic scenario particularly advantageous.
In terms of subsidy distribution (Table 7), at the regional level, the average subsidies received per farm in the reference situation amount to €6,719 per farm, with significant variations among farm types where subsidies increase with farm size. Analysis of subsidy dynamics enables us to understand how direct payments to farms are the primary factor driving farms to transition to organic farming.
In the "organicland" scenario, payments per farm would increase by 67.45% for the entire sample. Certain farm types would benefit notably. Specifically, payments would rise by over 80% for farms in the 2nd, 3rd, and 4th deciles, doubling for farms in the ninth decile.
Even in the scenario involving a reduction in fertilisers, subsidies would increase, albeit to a much lesser extent than in the previous scenario (on average, the regional-scale increase is 2.5%), with varied trends among deciles. Farms in the second, and eighth deciles would experience a slight decrease in received subsidies, whereas in the sixth decile a subsidies increase by 50% due to farms relocation from the fifth to the sixth decile.

	Average Payments per Farm			Variation (%) from Baseline (s_land)	
Farm Decile	s_land	s_organicland	s_fert	s_organicland	s_fert
1	4,005	6,540	4,013	63.30%	0.18%
2	20,122	36,910	19,111	83.43%	-5.02%
3	31,814	57,331	32,572	80.20%	2.38%
4	41,281	74,730	45,315	81.03%	9.77%
5	60,147	91,449	-	52.04%	-100.00%
6	59,946	95,984	89,787	60.12%	49.78%
7	90,244	-	93,089	-100.00%	3.15%
8	58,944	15,106	58,905	-74.37%	-0.07%
9	130,912	264,900	131,227	102.35%	0.24%
10	141,738	199,770	141,738	40.94%	0.00%
Total	**6,719**	**11,251**	**6,888**	**67.45%**	**2.51%**

Table 7: Average Payments Distribution in € and Variation from Baseline.

3.4. Analysis using the Gini coefficient

The Gini coefficient measures disparities in the income level of the agricultural population by assessing the concentration of total income within the population. It quantifies the degree of statistical dispersion of transferable variables, such as income, between different units of the same population. Thus, it enables the assessment of equity in the distribution of farmers' income. The coefficient ranges from 0 (perfect fairness, all farms enjoy the same income level) to 1 (complete unfairness, where only one farm receives the entire income). Mathematically, it is defined based on the Lorenz curve, which illustrates the proportion of total population income (y-axis) cumulatively earned by the bottom x% of the population. The Gini coefficient is often calculated for various years but is used in this analysis to compare the real situation with the one simulated by the two described policy scenarios. By comparing the Gini coefficient between the reference scenario and the two policy scenarios, we can evaluate the effectiveness of the policy measures in reducing income concentration, i.e. income inequality.
The simulated situation also reveals existing income gaps between farms in different groups under the two scenarios. The analysis then considers to what extent the average support provided to various groups through different CAP interventions can narrow the income disparity gap.
The Gini index concerning the distribution of GM per farm is relatively unconcentrated (Table 8), with a value of 0.475. However, this value changes due to the two considered agri-environmental scenarios, increasing by 5.23% and 6.08% respectively.

Scenario	Gini Index (GM/Farm)	Variance %
land	0,475	-
organicland	0,500	5,23
fert	0,504	6,08

Table 8: Gini Index GM/Farm and Variance.

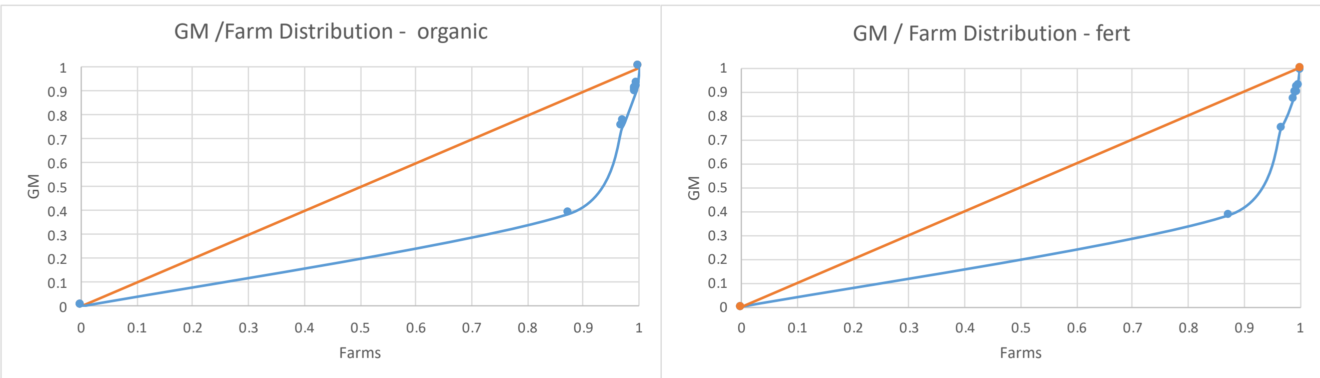

Figure 3: Gini Index GM/Farm.

Figure 3 highlights the varied capacity of farms to generate income based on their structural characteristics, economic endowment, and technological capacity. Gini index values just below 0.5 indicate an average GM/farm distribution, indicating relatively little heterogeneity in income generation ability. The fertiliser scenario, as seen from the previous data, penalises farms in certain deciles (especially the first and third), reducing their productive capacity and significantly increasing income distribution inequality. The relevant parameter for assessing the measure's effectiveness for equitable income distribution is the GM/AWU. Calculations indicate that income per employee is much more evenly distributed than income per farm. The Gini index is 0.229 in the baseline scenario, indicating uniform distribution within the first quartile. The policy scenarios analysed would worsen income distribution, concentrating it by 0.7% and 7.7% respectively. Despite this slight worsening, income distribution per employee remains within the first quartile. This finding is significant as it indicates uniformity in income-generating ability across different structural and economic characteristics, mitigating the impact of the two scenarios on income distribution (Figure 4).

Scenario	Gini Index (GM/AWU)	Variance %
land	0,229	-
organicland	0,230	0,69
fert	0,246	7,71

Table 9: Gini Index GM/AWU and Variance.

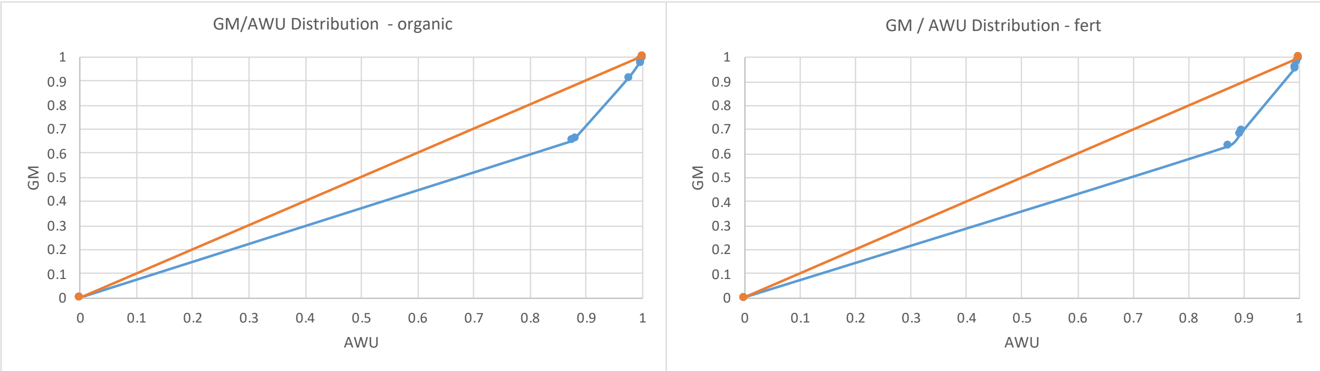

Figure 4: Gini Index GM/AWU.

Considering the role of payments in determining farm production choices, evaluating the distributional effects of scenarios in terms of payment distribution equity is interesting. The Gini index in the reference condition (land) indicates a higher concentration among firms compared to GM/AWU but remains acceptable (Table 10). The two policy scenarios increase subsidy distribution inequality between deciles (+2.43% and +37.41% respectively), exceeding the second quartile distribution threshold (Figure 5).

Scenario	Gini Index Subsidies/Farm	Variance %
land	0,367	-
organicland	0,375	2,43
fertiliser	0,503	37,41

Table 10: Gini Index Subsidies/Farm and Variance.

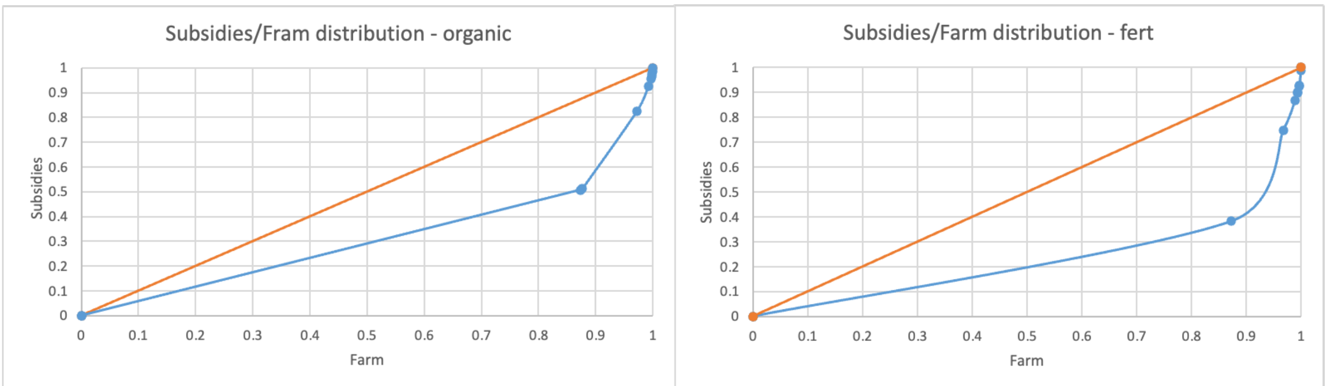

Figure 5: GIni Index Subsidies/Farm.

3.5. Environmental impacts

The environmental impact of the CAP post-2020 reform on climate change can be evaluated in terms of GHG emissions and water consumption per agricultural activity.
The "organicland" scenario shows an increase of approximately 4.20% in total carbon emissions and a decrease in total water consumption by approximately 3.34%.
The "fert" scenario shows, on the other hand, a more modest increase of approximately 1.51% in total carbon emissions and a limited impact on the water resource of approximately 0.96% (Table 11 and Figure 6).

	Surface (hectars)			**T CO2 eq/Ha**	**Carbon Emission (1,000 tCO2 eq)**			**Water FP (Million m3)**		
Product	s_land	s_organicland	s_fert	-	s_land	s_organicland	s_fert	s_land	s_organicland	s_fert
BEET	38,700	38,100	36,600	1.4457	56,000	55,100	52,800	5	5	5
CER	1,490	1,770	1,190	1.3276	1,980	2,350	1,580	8	9	6
D_WHEAT	45,900	54,100	42,900	1.6633	76,300	89,900	71,300	55	64	51
FRG	6,340	6,460	4,820	0.6700	4,250	4,330	3,230	59	61	45
C_WHEAT	68,900	63,500	66,800	1.5541	107,000	98,800	104,000	82	76	80
SUNFL	8,560	11,300	8,000	0.8188	7,010	9,270	6,550	17	23	16
PROT	13,300	12,900	10,300	1.0435	13,900	13,500	10,800	107	104	83
MAIZE	31,400	34,700	29,800	3.5235	111,000	122,000	105,000	22	24	21
ALFA	263,000	248,000	273,000	0.5026	132,000	125,000	137,000	2,470	2,320	2,550
SILAGE	13,500	14,700	18,700	1.7676	23,800	26,000	33,000	9	10	13
OIL	234	649	226	0.8188	191	531	185	3	7	3
BARLEY	11,700	9,320	9,210	0.9876	11,500	9,200	9,100	14	11	11
POTATO	4,780	4,980	5,440	2.2735	10,900	11,300	12,400	2	2	3
TOMATO	23,800	25,600	29,000	2.1134	50,400	54,200	61,300	2	3	3
GRAZ	71,200	61,800	61,000	2.2397	138,000	139,000	137,000	552	554	547
RICE	1,820	2,060	1,920	8.4969	15,400	17,500	16,300	2	2	2
SOJA	31,400	42,200	30,200	0.8096	25,400	34,100	24,400	42	57	40
SORG	8,410	13,300	16,800	1.3276	11,200	17,600	22,300	7	11	14
TOT ARABLE	644,434	645,439	645,906	-	**796,231**	**829,681**	**808,245**	**3,459**	**3,343**	**3,492**

Table 11: Environmental Impact (detailed per crop).

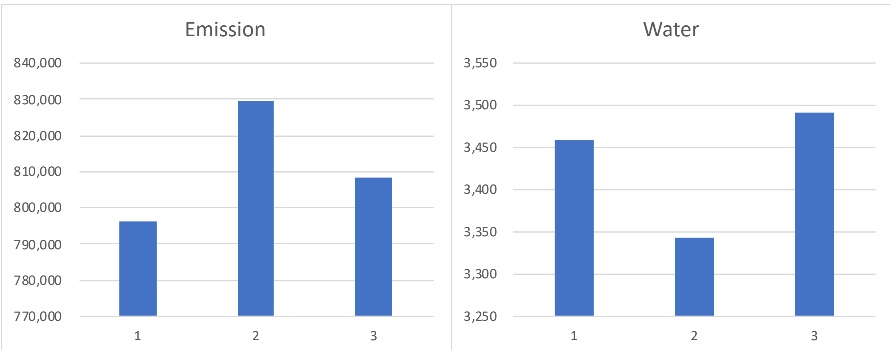

Figure 6: Environmental Impact on Emission and Water Footprint.

This analysis indicates that shifting to organic farming practices (s_organicland) increases carbon emissions slightly but reduces water consumption. On the other hand, the reduction in fertiliser usage (s_fert) leads to a minor increase in both carbon emissions and water consumption, though the increase in emissions is smaller than in the organic scenario.
To identify which crops are most impacting these results, we look at the variations in emissions and water consumption per crop for each scenario and compare them to the baseline.
For the "organicland" scenario, the crops with the most significant environmental impact are:
Oilseed which has the largest increase in both carbon emissions and water consumption, with approximately 177.73% increase in emissions and a 178.07% increase in water consumption compared to the "land" scenario, however its prodcution is very limited. Sorghum experiences a 57.14% increase in emissions and a 57.37% increase in water consumption, and soybeans shows a 34.25% increase in emissions and a 34.20% increase in water consumption. Sunflower indicates a 32.24% increase in emissions and a 32.18% increase in water consumption.
For the s_fert scenario, the crops with the most significant impact are: Again, sorghum is the most impacted with a 99.11% increase in emissions and a 100.29% increase in water consumption. Silage

records a 38.66% increase in emissions and a 38.23% increase in water consumption. Tomato has a 21.63% increase in emissions and a 21.86% increase in water consumption, while potato shows a 13.76% increase in emissions and a 14.10% increase in water consumption. Rice, the most emmitting crop in the sample, shows a 5.84% increase in emissions and a 5.64% increase in water consumption.
These crops are triggering the most significant changes in the environmental impact for each scenario. It's important to note that for both scenarios, sorghum appears to have a substantial increase in both carbon emissions and water consumption, making it a key factor in the overall environmental impact. The analysis suggests that changes in the cultivation of these particular crops have the potential to greatly influence the environmental outcomes of the agricultural practices modeled in these scenarios.

4. DISCUSSION AND CONCLUSION

Income support interventions, by strengthening farm incomes as part of the Common Agricultural Policy, play a pivotal role in achieving Specific Objective 1 (SO1). On the other hand, the application of strict environmental criteria and the support of a more sustainable agricultural system, such as organic farming, also impact farm income and its distribution among farm types, potentially reducing the effectiveness of SO1. Hence, a potential trade-off between SO1 and SO5 should be considered to find a balance between economic sustainability and environmental protection.
The purpose of this study is to determine whether changes in policy towards meeting the objectives of SO5 also align with or contradict the objectives of SO1.
To better understand the effects of agri-environmental policies, it is crucial to evaluate income distribution to assess equity and whether the analyzed policy measures (organic and fertiliser reduction) affect it, making it more or less concentrated (and therefore fairer or unfairer) in some deciles. The Gini index helps assess the equity of policy measures by determining whether they increase or decrease income distribution inequality among farmers and their households, represented by the AWU.
Overall, these scenarios indicate that financial incentives and cost reductions can have a notable impact on farming practices. The "organicland" scenario demonstrates a proactive push towards organic farming through financial incentives, while the "fert" scenario shows a reactive shift due to reduced input costs for conventional farming. Both are measured against a baseline that allows for flexibility in land management through rental agreements.
The contradiction arises when the methods to achieve SO1 potentially increase the environmental footprint of agriculture, which would be at odds with the environmental and resource efficiency goals of SO5.
Intensive farming practices that support farm income can lead to overexploitation of resources and increased chemical usage, thus harming the environment. Nutrients such as nitrogen, potassium, and phosphorus, essential for crop production, when used excessively, can be a major source of air, soil, and water pollution, and can also have negative impacts on both biodiversity and the climate.
Analysis of the model results shows that farmers, in deciding to convert to organic, also change, to some extent, their crop planning in search of greater added value, opting for more impactful crops. It is here where we must look for the cause of a 4.20 percent increase in emissions in the "organicland" scenario. In the scenario of reduced fertilizer use, this impact, although still present, decreases thanks to a shift in crop cultivation towards alfalfa, which maintains the same level of yield, as it is not subject to heavy fertilization and therefore not impacted by the scenario.

Another way of interpreting these results should be sought in the methodology applied and in some current limitations of the model that we intend to overcome in future studies. One limitation relates to the calculation of emissions using CO_2 indicators without taking into account the effect of agro-ecological practices on soil organic matter, with a consequent positive impact in terms of CO2 sequestration. Another limitation is that we do not modify the calculation of the grey water footprint for conventional production as a result of the decrease in the use of chemical fertilizers. Furthermore, an additional scenario could be added to estimate a lower yield decrease in the long term, knowing that the decrease in chemical fertilizer leads in the long run to soil enrichment.

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