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Assessing the impacts of chemicals reduction on arable farms through an integrated agro-economic model

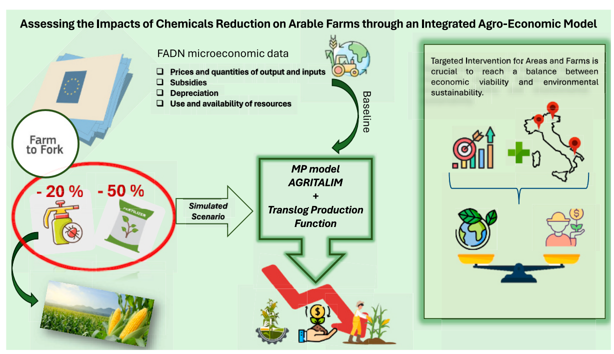
Rebecca Buttinelli, Gabriele Dono, Raffaele Cortignani *

University of Tuscia, Department of Agriculture and Forest Sciences (DAFNE) Via San Camillo de Lellis, 01100 Viterbo, VT, Italy

HIGHLIGHTS

- Farm to Fork targets on chemical reduction negatively impact Italian maize production and arable farms' economic results
- Integrating a mathematical model with an econometric production function allows for a flexible and comprehensive approach
- The decrease in production in Northern Italy potentially threatens supply chains, affecting farms' income and national output
- Medium-sized farms in the Northeast adapt better to input reductions, leveraging efficiency and crop diversification
- Specific support for vulnerable regions and areas are key for transitioning to low-input practices ensuring farms' viability

GRAPHICAL ABSTRACT



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ABSTRACT

CONTEXT: The concurrent global demands of ensuring food production, preserving the environment, and responsibly managing natural resources, shape the formulation of EU policies, influencing farmers' decision-making processes and production activities. In this context the Farm to Fork Strategy plays a crucial role, setting specific targets such as a 50 % and a 20 % reduction in pesticides and fertilizers use by 2030.

OBJECTIVE: This paper addresses the growing concern regarding the potential adverse effects of the Farm to Fork Strategy's targets on EU agricultural production, with a particular focus on Italian arable farms cultivating maize. The objectives are to analyze the impact of F2F targets on chemical reduction on Italian arable farms and maize grain production, identifying vulnerable areas and farms.

METHODS: A Farm Accountancy Data Network sample of 395 arable farms is analyzed through an integrated approach, combining an agro-economic supply model with an econometrically estimated translog production function. This integration enhances the model's flexibility, endogenizing maize grain gross saleable product, fertilizers, and pesticide quantities. This approach enables an assessment of the F2F targets' economic impacts in terms of economic variables and resource use, production output, and chemical intensity at the farm and crop level.

* Corresponding author.
E-mail address: cortignani@unitus.it (R. Cortignani).

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RESULTS AND CONCLUSIONS: Our findings indicate that reducing chemical inputs may lead to declines in agricultural production, income, and added value for Italian arable farms in the short to medium term, alongside reductions in variable costs, irrigation water, and labor. Maize grain production is particularly vulnerable in less suitable areas, such as the Central-South. However, significant impacts are also observed in more intensive regions like North-West Italy, while the North-East is less affected due to greater input efficiency and lower costs. While crop diversification helps mitigate the impact at the farm level, it does not fully offset the effects on maize production.

SIGNIFICANCE: The application of uniform targets across Europe poses a significant risk to agricultural production in the short term, especially for certain sectors. To facilitate the transition to low-input agriculture, it is crucial to develop region-specific strategies and provide support to vulnerable areas and farms. The EU Commission's reconsideration of chemical reduction targets introduces new challenges, highlighting the need for solutions that balance production and environmental sustainability. This underscores the critical role of such analyses in understanding the dynamics of production processes and the impact of such policies by identifying specific vulnerabilities of sectors, regions, and contexts and supporting policy implementation.

1. Introduction

In a global context where ensuring food production, preserving the environment, and responsibly managing natural resources are primary concerns, regulations, and policies are increasingly driving a transition toward lower-impact agriculture, aimed at reconciling these needs. Indeed, alongside market conditions, agronomic choices, and personal attitudes, the regulatory framework emerges as a central factor influencing farmers' decision-making processes and agricultural production activities (Hebinck et al., 2021). In this context, recent European Union initiatives such as the Green Deal (European Commission, 2019) and especially the Farm to Fork Strategy (European Commission, 2020), emerge as crucial drivers of change. Indeed, the Farm to Fork Strategy (F2F), designed for the agri-food sector, emphasizes a transition toward a fair, healthy, and environmentally friendly food system, and addresses pollution with a 50 % reduction in the use of chemical pesticides and a 20 % reduction in fertilizers by 2030 (Montanarella and Panagos, 2021).

Wesseler (2022), in his literature review, states that European agricultural production is expected to be affected by these restrictions, as all the studies analyzed predict a decline in EU agricultural production due to the F2F strategy. For example, Bremmer et al. (2021) assessed a reduction in production value by 2030 of around 92 billion euros and an increase of 2 or 3 million hectares in land use to balance this economic loss, while Beckman et al. (2020), Noleppa and Cartsburg (2021), and Barreiro-Hurle et al. (2021), estimated a 7–12 % decrease in agricultural output volumes. This could lead to either an expansion of agricultural land or inadequate food production, resulting in greater EU dependence on imported food.

Within this intricate web, the careful management of inputs aligns directly with the goals outlined in recent EU initiatives establishing a connection between the regulatory framework and the operational complexities of agronomic practices. However, the effectiveness of these policies is also contingent upon the need to ensure agricultural production without sacrificing the farms' viability and farmers' income. Indeed, policy objectives that limit the use of chemical fertilizers or pesticides can significantly influence the dynamics underlying the decision-making process and agricultural production affecting the response of other inputs. Understanding how the production process responds to constraints on agricultural inputs, especially chemicals, is crucial to evaluate policies' effectiveness and risks.

In this scenario, it is necessary to model these responses in an integrated and flexible approach and examine the reaction to strong direct constraints that impact production factors, also considering the relation linking them to each other (Alexander et al., 2019; Balezentis et al., 2020; Fitton et al., 2019; Malek and Verburg, 2018). The integration of such elements into agricultural economics analysis enhances the understanding of resource management while improving the adaptability of models to environmental and regulatory challenges (Godard et al., 2008). This approach provides valuable insights to guide efforts toward a critical balance between the economic sustainability of the agricultural sector and environmental protection. To this aim, the ultimate objectives of this paper are: (i) to obtain a flexible model able to provide responses not only in terms of land use but also in terms of agricultural output, fertilizers, and pesticide quantities, (ii) to analyze the impact of F2F targets on chemicals reduction on Italian arable farms and maize grain production, identifying the most vulnerable areas and farms.

For our analysis, we used as a case study a FADN sample of 395 Italian maize grain farms for the year 2020. Cereal production is expected to be among the most impacted sectors by the F2F Strategy's targets for chemical reduction (Beckman et al., 2020; Cortignani et al., 2022) and maize is likely to play a central role in the future since half of the global cereal production increase will come from this crop (Erenstein et al., 2022). Within the EU context, Italy currently is the fourth producer[1] but, over the years, the maize area has significantly decreased, leading to an increasing reliance on imported maize grain. Additionally, the potential for more frequent extreme weather events could further exacerbate maize price volatility and production risks (OECD/FAO, 2021). Indeed recently, higher temperatures and water deficit have led to the suspension of irrigation in some Italian regions, exacerbating the damage caused by pests, fungal attacks, and other sanitary issues. This trend is expected to worsen. (IPCC, 2021; Rosenzweig et al., 2014), especially in Mediterranean countries (Hristov et al., 2018; Lionello and Scarascia, 2018) including Italy (Mereu et al., 2021). In this context, limitations on the use of chemicals may pose an additional threat to the quality and safety of maize grain, thereby endangering national production and several supply chains, such as Parmigiano Reggiano (Mantovi et al., 2015).

To conduct our analysis the AGRIcultural TerritoriAL tIme economic (AGRITALIM) model, falling within the category of agro-economic supply model (such as FSSIM, EFEM, FARMIS), (Cortignani et al., 2022) has been enhanced with a flexible Translog production function. This advancement endogenizes key variables such as gross saleable product, fertilizers, and pesticide quantities, offering a more dynamic and adaptable response. By incorporating farm-specific characteristics and leveraging econometric estimates that reflect farmers' past outcomes and future expectations, the model captures non-linear interactions between inputs. This enables a more precise ex-ante analysis, grounded in observed production choices over the last decade, thereby improving the model's ability to simulate realistic policy impacts and production responses. The paper is structured as follows: Section 2 presents data and methodology, Section 3 describes the obtained results, and Sections 4 and 5 conclude with discussions and conclusions.

[1] The most specialized regions in maize grain cultivation in Italy are Lombardy, Veneto, Piedmont, and Emilia-Romagna, collectively accounting for approximately 85 % of the Italian maize grain cultivation area (CREA, 2021).

2. Material and methods

2.1. AGRITALIM model

Several studies have already estimated the economic impacts of the F2F (Farm to Fork) objectives on agricultural production in Europe.[2] Wesseler (2022), in his literature review, compares various works conducted in this area, evaluating their strengths and limitations. These studies rely on either partial equilibrium models (Barreiro-Hurle et al., 2021; Henning et al., 2021; Bremmer et al., 2021) or general equilibrium models (Noleppa and Cartsburg, 2021; Beckman et al., 2020). However, despite differences in sectoral focus, environmental impact consideration, and underlying assumptions, these models may not fully capture the impacts at the farm level (Cantelaube et al., 2012; Gocht and Britz, 2011). In contrast, AGRITALIM, an agro-economic supply model (such as FSSIM, EFEM, and FARMIS), focuses specifically on Italy and employs detailed microeconomic data to model the agricultural sector. This model has already been used to evaluate the F2F's impact on Italy's agricultural sector (Cortignani et al., 2022) and emissions reductions in the livestock sector (Dell'Unto et al., 2023). For this analysis, the AGRITALIM model was adapted to a FADN sample of 395 maize grain farms from 2020 and integrated with a translog production function. Operating within the category of agro-economic supply models, the model is based on non-linear Mathematical Programming (MP), specifically combining Leontief technology for variable costs with a quadratic cost function. The model is calibrated through the Positive Mathematical Programming (PMP) approach (Cortignani and Severini, 2012; De Frahan et al., 2016; Heckelei et al., 2012; Heckelei and Wolff, 2003; Howitt, 1995a; Paris and Arfini, 1995; Paris and Howitt, 1998). The AGRITALIM model comprehensively covers various economic, financial, productive, market, political, and structural aspects, facilitating analyses related to farm choices influenced by various factors such as agricultural and environmental policy, market conditions, climate context, and resource use. The main components and fundamental characteristics of the objective function and constraints concerning land, labor (both manual and mechanic), and water availability are shown in Appendix (A1). The model maximizes the farm operating income, considering market elements (prices of outputs and inputs), production functions (quantities of yields and inputs), agricultural policy, and depreciation costs. Depreciation costs for additional depreciable capital are annualized in the objective function by dividing the replacement value of those assets by their technical duration.

In calculating operating income, the model includes market elements, production functions, and current agricultural policy. Market prices are considered for vegetable products, crop production inputs (such as fertilizers and pesticides), and additional variables purchased from the market (such as labor and water). Leontief production functions capture the relationships between output quantities and input usage, with technical coefficients representing the quantities of inputs needed per unit of production activities. These coefficients are used to specify constraints and determine the requirements for land, labor, water, and farm structures, ensuring that total requirements align with the availability of resources, with the option for additional variables.

2.2. Modifications to the AGRITALIM model: The advantages of a mixed approach

Agro-supply models such as AGRITALIM offer highly detailed, farm-level analysis, making them ideal for targeted policy impact evaluations. Their ability to capture local agricultural practices ensures more precise predictions at the regional level, particularly in Italy, where farm structures and methods are highly heterogeneous (Gocht and Britz, 2011). AGRITALIM incorporates a Leontief technology and a quadratic cost function to ensure accurate calibration and a smooth simulation response. The advantage of using a Leontief technology in agricultural production analysis is that it establishes a direct and fixed connection between production activities and input utilization. However, the downside is that this assumption restricts flexibility in the underlying technology (Britz et al., 2007). In this model, yields and inputs like fertilizers and pesticides are exogenous parameters, lacking adjustments based on simulated scenarios. To capture modifications in input-output relationships, objective functions must incorporate endogenous productive factors and yields. To address these limitations, we have modified the AGRITALIM model and included a translog production function, as described below.

This integration of econometrics and MP offers a comprehensive approach to understanding and optimizing agricultural production.[3] By incorporating in the objective function (Eq. A1 in Appendix) the translog production function (Eq. 1), specifically estimated econometrically for a ten-year panel of 5224 Italian maize grain farms (Buttinelli et al., 2024), we develop an integrated MP model. Motivated by the need to model non-fixed and complex relationships among considered variables, the translog function provides a nuanced representation, capturing interactions among agricultural inputs. The estimated Translog production function (Eq. 1) describes the relationship between maize grain production and various agricultural inputs. The empirical estimation of the production function is expressed as:

$$lnY = \alpha + \sum_{i=1}^{n} \beta_i lnX_i + \frac{1}{2} \bullet \sum_{i=1}^{n} \sum_{j=1}^{n} \beta_{ij} ln\, X_i lnX_j + \mathrm{e} \tag{1}$$

where X represents the vector of inputs considered[4] (detailed in Table 1); β is the estimated parameters α is the intercept; and e is the error component. The selection of variables aims to be comprehensive, closely adhering to the definition of a production function, i.e. a mathematical relationship linking output to productive inputs (Christensen et al., 1975; Cobb and Douglas, 1928). It also incorporates structural and agronomic factors reflecting farm characteristics and efficiency. This approach is supported by the literature on productivity (Bierkens et al., 2019; Koundouri et al., 2014) and efficiency analyses like DEA (Latruffe et al., 2012; Skevas and Lansink, 2014) or SFA (Zhu et al., 2012; Zhu and Lansink, 2010). Unlike most studies, we separate chemical fertilizers

[2] Several studies have approached this topic using different methods. Elshaer et al. (2023) used PLS-SEM to examine how perceived economic benefits drive farmers' adoption of sustainable practices, while Heyl et al. (2023) assessed how the CAP could help achieve F2F goals through governance analysis. Reinhardt (2023) focused on the role of innovation systems in supporting these objectives. However, these studies do not specifically address farm-level economic impacts and are not directly applicable to our research questions.

[3] Most MP models are based on the Leontief production function, which represents the deterministic relationship between productive inputs (Howitt, 1995a). Some studies include more flexible functions such as Constant Elasticity of Substitution (CES) (Edwards et al., 1996; Howitt, 1995b). Among others, Howitt et al. (2012), describe includes the estimation of CES regional production functions. Graindorge et al. (2000) use a CES specification as Medellín-Azuara et al. (2010) do to obtain the agricultural water economic value. Moreover, Britz (2010) uses isoelastic functions to obtain endogenous yields in the CAPRI model and similarly, Giraldo et al. (2014), combine the estimation of a translog cost function with PMP to simulate the impact of volumetric pricing method for irrigation water in Sardinia. The papers cited in this note do not represent a complete and exhaustive overview of the thematic. However, it may be useful for readers who are more interested in the operational aspect to start working on this research topic.

[4] The inputs considered in estimating the production function are based on a comprehensive review of the relevant literature and have been adapted to fit the specific data available for our analysis. Refer to Buttinelli et al. (2024) for specific details.

Table 1
Description and Unit of Measure of variables used in the production functions estimation.

	Variables	UM	Description
Y	Production	€	Gross Output per year
L	Land	€	Return on land capital (2 % of land value) + rents
W	Water	m^3	Water Volume per year
VC	Variable Costs	€	Crop-specific costs per year (certifications. Energy. subcontracting. Marketing. seeds)
F	Fertilizers	€	Expenditure per year
P	Pesticides	€	Expenditure per year
WR	Labor	€	Expenditure on family and employed work per year
M	Machinery	€	Expenditure on owned machinery work per year
T	Temperatures	°C	Average annual temperatures at the provincial level
R	Rainfall	100 mm	Average annual rainfall volumes at the provincial level

and pesticides (Bojnec and Latruffe, 2009; Grammatikopoulou et al., 2020; Nouri-Khajebelagh et al., 2021), providing detailed insights into each input.

Estimated parameters are obtained using STATA software and are shown in the Appendix (Section A4). In addition, the empirical specification, i.e., a weighted fixed effects panel model, allows to isolate individual-specific characteristics through the intercept coefficient α, which also considers the influence of rainfall and temperature.[5] Hence, the inclusion of climatic variables (Auci and Vignani, 2020) allows for the control of climatic heterogeneity. Therefore, Maize Gross Saleable Production (MGSP) is integrated through the exponential form of Eq. 1 in the AGRITALIM objective function (shown in Appendix, section A1) as follows (Eq. 2):

$$MGSP = f(XM, XFERTM, XPESTM, l, w, vc, wr, m, t, r) \tag{2}$$

where XM, $XFERTM$ and $XPESTM$ are variables representing hectares, quantity of fertilizers and quantity of pesticides for maize grain, respectively. The parameters l, w, vc, wr, m, t and r represent land, water quantity, variable costs, work, machinery, temperatures, and rainfall respectively, as in Table 1. As each input is expressed in monetary value in Eq. 1, except for water, to obtain variables and parameters considered in Eq. 2 each input value has been decomposed in terms of price and quantity and multiplied by hectares of land per farm (See Appendix, section A.5).

In other words, the methodological advancement proposed allows for increased flexibility of the AGRITALIM model by integrating econometric estimates accounting for farm-specific characteristics and climatic influence on maize grain production. The Translog production function informs the AGRITALIM model based on past production choices and allows the model to incorporate farmers' expectations, which are shaped by previous outcomes and performances. This integration enhances the robustness and flexibility of the model, as it reflects real decision-making processes in the baseline through PMP calibration while taking into account past events, allowing us to leverage the strengths of both approaches. However, several challenges need to be considered. First, estimating flexible production functions like the translog requires detailed data, which is not always available for all crops, and is essential for robust estimations. Second, integrating these functions with MP models can lead to complexity, causing resolution issues. Additionally, input variables like fertilizers and pesticides need predefined ranges for feasible solutions. In our case, we addressed these challenges by focusing on specialized arable farms growing maize grain and setting ranges based on observed values specific to regions and altitudes. Importantly, while the econometric function provides valuable insights into past production choices, it is not used for forecasting future outcomes. Instead, it informs the AGRITALIM model, which operates with current data to simulate potential responses to policy changes and resource restrictions.

2.3. Data

As AGRITALIM is designed to consider farm-specific choices, its full potential can only be unlocked with access to detailed microeconomic data. This allows the model to provide precise, tailored responses for each farm. Data was obtained from the Italian Farm Accountancy Data Network (FADN) database, which is the only source of agricultural microeconomic data that follows standardized bookkeeping principles. FADN collects data from 68,000 farms in Italy, representing nearly 5 million farms in the European Union (EU). This data covers 90 % of the EU's total agricultural area and Standard Output. In the Italian sample, there are 11,000 farms, and their data is categorized by region, size, and type of farming (TF).[6] The collected data includes information on Gross Output, land, crop-specific variable costs, work-related costs for families and employed workers, as well as irrigation water volumes. Additionally, details on the quantity and formulations of pesticides and fertilizers used are available. To achieve the objectives of this study a sample of specialized maize grain farms in the year 2020 was selected, for a total of 395 observations across Italy. The selected farms belong to the specific TF "Specialized in Cereals and Oilseeds and Protein Crops". Consequently, livestock and livestock products are excluded from the analysis. The farms are distributed throughout the Country: 45 % are in the Northwest regions, 42 % in the Northeast regions, and 13 % in the Central-South. Moreover, 78 % of the observations are in the Plains, while 22 % are in the Hills. In terms of Farm Size, three groups are defined: Small farms (<15 ha), Medium farms (15–40 ha), and Large Farms (> 40 ha),[7] respectively representing 30.9 %, 38.2 %, and 30.9 % of the sample. Finally, 83 % of the sample consists of Specialized farms, while 17 % of Diversified farms.[8] Descriptive statistics for the sample are shown in Table 2, including information both at the farm level and at the crop level, considering the great heterogeneity of the farming system and maize production in Italy.

3. Results

This section provides an overview of some of the results obtained, offering insights into the impacts of the scenario analyzed at the farm level and on maize grain production. The simulated scenario is designed in accordance with the F2F objectives, concerning simultaneously chemical fertilizers and pesticides. However, it is important to note that the F2F strategy does not specify the territorial level at which these targets should be applied, whether at the national, regional, or farm level. Given this ambiguity, we applied these reductions at the individual farm level, aligning our approach with the available data and the capabilities of the AGRITALIM model. The reductions are implemented as maximum constraints, consisting of a 20 % decrease in mineral fertilizers and a 50 % reduction in harmful, toxic, and very toxic pesticides.

[5] The constant term α was augmented to: $\alpha_{i,t} = a + \gamma_1 T_{i,t} + \gamma_2 R_{i,t}$ With γ_1 and γ_2 are parameters that quantify the influence of average annual temperature and precipitation, respectively on agricultural production, providing a more comprehensive and nuanced analysis (see Buttinelli et al., 2024 for further details).

[6] The Types of Farms (TFs), as per EC Reg. 1242/2008, are categorized based on the predominant standard productions of cultivation and livestock. TFs are further divided into three levels with progressive ramifications: 8 classes of general TFs and 21 branches of principal TFs, further divided into 61 specific TFs.

[7] Farm size categories are defined according to FADN groupings.

[8] A diversified farm is defined as one that engages in complementary activities to agriculture, such as direct sales, agritourism, or processing. In contrast, specialized farms are solely dedicated to strictly agricultural activities.

Table 2
Description and Descriptive Statistics (Mean and St. Dev.) for the analyzed sample.

Farm	UM	Description	Mean	St. Dev.	Min.	Max.
UAA	Hectares	Total Utilized Agricultural Area per farm	41.95	48.80	3.81	474.79
Crops Output	€	Total Gross Output	69,089	85,607	6505	874,696
Operative Income	€	Operative Income	29,379	59,813	−103,051	838,690
Hired Labor	Working Units (1800 h/ unit)	Hired Working Units per farm	1.24	0.82	0.41	8.34
Family Labor	Working Units (2300 h/ unit)	Family Working Units per Farm	1.16	0.68	0.33	5.78
Maize Grain						
UAA	Hectares	Maize Utilized Agricultural Area per farm	16.92	20.49	0.31	221.79
Irrigated Land	Hectares	Farm Irrigated Area	12.93	19.91	0	221.79
Gross Margin	€	Maize Grain Gross Margin per farm	21,063	30,199	−58,264	346,468
Net Margin	€	Maize Grain Net Margin per farm	8650	28,661	−87,403	276,468
Gross Output	€/ha	Maize Grain Gross Output	1943	595	360.88	4423.73
Variable Costs	€/ha	Expenditure per hectare (seeds, energy, insurance, fuel, etc..)	320.23	170.21	53.87	2719.42
Fertilizers	100 kg/ha	Quantity of Fertilizers per hectare	5.44	33.32	0.13	79.5
Pesticides	quantity/ha	Quantity of Pesticide formulation per hectare	2.79	20.36	0	80.20
Total Labor	Hours/ha	Hours of Work per hectare, both family and hired	47.75	49.43	0	377.83
Machinery	Hours/ha	Hours of Machinery Work per hectare	26.04	33.24	0	201.51

In practical terms, each farm is required to adhere to these percentage caps on chemical usage. This approach enables the assessment of impacts both at the farm and crop levels.

The effects are analyzed using multiple indicators, which account for variations across the sample based on territorial and farm-specific characteristics. The impacts are expressed as a percentage variation from the baseline. The results at the farm level encompass economic variables such as Added Value, Variable Costs, Operative Income, and resource-use variables such as Labor (both hired and family work), Water, and Groundwater. Moreover, the translog production function, which endogenizes the quantities of fertilizers and pesticides used for maize grain, enables the quantification of variations specific to this crop. The results for maize grain production are expressed as changes in cultivated land, i.e. Utilized Agricultural Area (UAA), Gross Saleable Output, and the quantities of fertilizers and pesticides per hectare. All results are presented for the total sample and further categorized based on territorial and farm characteristics.

3.1. Impacts at the farm-level

The analysis of different groups reveals significant disparities, with some clusters being more vulnerable than others (Table 3). Overall, income is reduced by 6.8 %, while added value decreases by 4.7 %. In contrast, variable costs drop by an average of 13.4 %, and labor costs decrease by 10 %. Water usage declines by 13.3 %, with groundwater decreasing by 10.3 %. Geographically, the most affected areas in terms of Added Value are the Northwest and Centre-South (−5.4 % in both regions), while the Northeast experiences a slightly smaller reduction (−4.0 %). A similar trend is observed for other economic indicators, confirming that the Northeast is the least impacted region, with reductions of −12.1 % and − 5.4 %, respectively in Operative Income and Variable Costs. It is noteworthy that the impacts in the Centre-South occur despite their lower contribution to overall income production, as it represents a smaller portion of the sample. Nonetheless, this is also the region where Labor reductions are most pronounced (−13.1 %), as are reductions in inputs such as Water (−21.9 %) and Groundwater (−39.1 %). When looking at Altitude, Plains are more affected in terms of economic variables, while Hills experience greater variations in resource use. Specifically, Income is most impacted in Plains while Hills show a more substantial reduction in resource use, especially Water (−22.7 %) and Groundwater (−39.1 %).

Interesting results also emerge from the comparison by farm size. The sample is evenly divided, with Small farms showing more significant impacts on economic indicators, such as Operative Income (−10.1 %), as well as on resource use, including Labor (−12.8 %) and Water (−10.1 %). In contrast, the differences between medium-sized and large farms are less pronounced, with both showing similar impacts across the variables considered in the analysis. Finally, diversification helps mitigate economic impacts, as diversified farms experience a smaller reduction in income (−6.2 %). However, while the share of farms engaged in non-agricultural activities remains a minority, and their input use and income generation are significantly lower compared to specialized farms, they are not exempt from experiencing reductions similar to those faced by specialized farms, with higher impacts on Labor (−13.4 %).

Table 3
Baseline values and percentage reduction from baseline of economic and resource use variables at the farm level for the considered scenario, presented for both the total sample and categorized by territorial characteristics and farm characteristics.

		Area			Altitude		Farm Size			Diversification		
		Northwest	Northeast	Centre-South	Plains	Hills	<15	15–40	>40	Specialized	Diversified	Total
Baseline	Farms (n°)	179	164	52	310	85	122	151	122	328	67	395
	Variable Costs (€M)	4.3	4.3	0.8	8	1.4	0.8	2.4	6.3	7.7	1.7	9.5
	Added Value (M)	8.7	9.4	2.5	16.5	4	1.9	5.1	13.6	15.4	5.1	20.6
	Operative Income (€M)	5.3	6.2	1.6	10.4	2.7	1.0	3.2	8.9	9.9	3.2	13.1
	Labor (1000h)	288	264	75	514	114	117	210	301	492	136	627
	Water (1000 m^3)	1929	2836	238	4602	401	562	1461	2980	4306	697	5003
	Groundwater (1000 m^3)	30.4	68.9	38.3	99.3	38.3	35	53	49	133	5	137.6
%	Added Value	−5.4	−4.0	−5.4	−4.9	−4.4	−5.9	−4.3	−4.8	−4.8	−4.6	−4.7
	Variable Costs	−14.1	−12.1	−14.9	−12.7	−16.1	−14.5	−13.4	−13.0	−12.3	−17.3	−13.4
	Operative Income	−8.5	−5.4	−7.2	−7.1	−6.1	−10.1	−6.4	−6.6	−7.1	−6.2	−6.8
	Labor	−10	−9.1	−13.1	−10.0	−9.8	−12.8	−9.5	−9.2	−9.0	−13.4	−10
	Water	−14.2	−12.5	−21.9	−12.8	−22.7	−20.6	−10.5	−13.8	−13.6	−13.8	−13.3
	Groundwater	−10.3	−13.4	−39.1	−12.5	−39.1	−26.3	−21.3	−13.7	−19.9	−19.0	−19.8

3.2. Impacts on Maize Grain Production

Focusing on Maize Grain production, the results reveal notable differences across the considered groupings (Table 4). On average, there is an overall decline of −18.2 % in the Utilized Agricultural Area (UAA). This decline is particularly pronounced in the Centre-South (−28.0 %), though this region plays a marginal role in terms of maize land and production. A more significant difference is observed in the Northwest and Northeast regions, with the Northwest showing a reduction in maize land by −19.5 % and in maize gross saleable output by −18.5 %. In contrast, the Northeast experiences smaller reductions of −14.7 % in maize land and − 14.4 % in gross saleable output. It is important to note that the impacts on the Northern areas, while smaller than those observed in the Southern regions, pose a greater threat due to the North's significant contribution to national maize production in terms of cultivated area, yield, and intensity of pesticide use.

In terms of chemical intensity, the average reduction across the sample shows a − 2.8 % decrease in fertilizers per hectare, while pesticide use drops more sharply, by −13.0 %. The distribution of this impact across geographical and farm groupings further confirms that farms in the Northwest, being more intensive, experience greater reductions in fertilizers (−4.7 %) and pesticides (−13.8 %). In contrast, the Northeast experiences smaller reductions of −2.6 % for fertilizers, despite having higher application rates, and − 12.5 % for pesticides, where their use is less intensive. Meanwhile, the Centre-South region shows significantly higher reductions. However, this region also exhibits less pronounced reductions in chemical use, even though baseline values indicate high levels of intensity, particularly for fertilizers.

In terms of Altitude, Hills appear to be more vulnerable, especially in terms of reductions in maize UAA and Gross Saleable Output (−22.2 % and − 20.0 %, respectively). However, since Hills represent a marginal share of maize production, this decline is likely explained by the reduced suitability of these areas for maize cultivation, which probably shifts toward other crops. In terms of Farm Size, Small farms show a marked reduction in both UAA (−22.1 %) and GSP (−20.8 %). In this group, the reduction in chemical inputs is almost entirely due to pesticides (−16.8 %), which is consistent with their higher baseline intensity in pesticide use. In contrast, medium- and large-sized farms show more contained and similar changes. For medium-sized farms, the reductions are −18.0 % in UAA and − 17.1 % in GSP, while for large farms, they are −17.7 % in UAA and − 16.8 % in GSP. Interestingly, large farms exhibit an almost uniform reduction in both pesticide (−8.6 %) and fertilizer use (−8.9 %), while for medium-sized farms, the most significant reduction is once again in pesticide use, despite their lower baseline levels of pesticide intensity.

As for specialized farms, contrary to the impact described in the previous paragraph, it is the diversified farms that suffer more, even though their maize production is marginal compared to specialized farms. In fact, they exhibit larger reductions in both UAA and GSP (−22.2 % and − 19.0 %, respectively). However, the impact on chemical inputs is more evenly distributed in this group, with reductions in fertilizers (−5.0 %) and pesticides (−6.1 %). Conversely, specialized farms are more affected by the reduction in pesticide use (−15.8 %), despite their lower baseline usage.

3.3. Impacts on Northern Italy

Given the interesting findings, particularly regarding the lower impact experienced by the Northeast and the differences across farm sizes not entirely explicable when looking at the chemical intensity, we shifted our focus to Northern Italy, which accounts for 85 % of the Country's maize production. By breaking down the regions by farm size and using key indicators to represent production intensity and input use, we aimed to compare these geographically close but differently impacted areas. The selected indicators provide a comprehensive overview of both overall farm performance and specific maize production performance. Economic ones such as Total Revenues per farm, along with Operative Income on Total Revenues and per hectare, help assess these farms' profitability and efficiency. Instead, Maize GSP, Gross Margin, and Net Margin per hectare specifically evaluate the productivity of maize production and fixed cost incidence. We also considered resource intensity through indicators like Energy Consumption per hectare (used as a proxy for mechanization), Labor per Hectare, and the quantities of Fertilizers and Pesticides used. The Share of Maize Land on Total and Maize UAA per Farm highlights the relevance of maize within the overall farm structure.

Results shown in Table 5 indicate that the least impacted groups in terms of Operative Income are medium and large farms in the Northeast with reductions of −4.0 % and − 5.7 %, respectively. The same trend is observed for Added Value, with medium farms experiencing a reduction of only −3.1 %. Interestingly, labor reduction is consistent across all farm size classes. In contrast, in terms of water usage, large farms in the Northeast reduce water use less (−13.2 %) compared to those in the Northwest (−16.3 %), although they show a higher overall water usage in the baseline scenario. Cross-referencing this data with indicators in Table 7 shows that Northeast farms are characterized by larger sizes and lower energy and labor intensity, particularly among medium-sized farms. This, combined with a higher income-to-revenue ratio and consequently lower costs, may give these farms a relative advantage in offsetting the impact of the input restrictions imposed by the F2F strategy and help explain their greater capacity of offsetting these impacts. This suggests that Northeast farms are more efficient and productive in resource use, particularly in the medium-sized category, and have better water availability, which may help them mitigate reductions in other inputs, especially pesticides.

This trend is confirmed by results regarding the reduction in maize land and production (Table 6). Again, medium-sized farms in the Northeast appear to be the least affected, despite a significant reduction

Table 4
Baseline values and percentage reduction from baseline of economic and resource use variables for maize grain production, presented for both the total sample and categorized by territorial and farm characteristics.

		Area			Altitude		Farm Size			Diversification		
		Northwest	Northeast	Centre-South	Plains	Hills	< 15	15–40	>40	Specialized	Diversified	Total
Baseline	Farms (n°)	179	164	52	310	85	122	151	122	328	67	395
	Maize UAA (1000 ha)	3.3	2.5	0.4	5.1	1.1	0.6	1.7	3.9	5.0	1.2	6.2
	Maize Gross Saleable Output (€M)	7.5	4.7	0.8	11.0	2.1	1.6	0.4	0.8	10.6	2.5	13
	Maize Fertilizers (quantity/ha)	5.6	6.8	15.3	6.1	12.2	7.0	8.1	6.9	7.5	6.6	7.4
	Maize Pesticides (quantity/ha)	4.9	1.3	1.3	3.3	1.4	6.1	2.5	4.6	2.5	5	2.9
%	Maize UAA	−19.5	−14.7	−28.0	−17.3	−22.2	−22.1	−18.0	−17.7	−17.2	−22.2	−18.2
	Maize Gross Saleable Output	−18.5	−14.4	−24.5	−16.9	−20.0	−20.8	−17.1	−16.8	−17	−19	−17.4
	Maize Fertilizers	−4.7	−2.6	−0.8	−3.0	−2.5	−0.3	−0.5	−8.9	−2.4	−5	−2.8
	Maize Pesticides	−13.8	−12.5	−4.9	−13.8	−5.9	−16.8	−17.5	−8.6	−15.8	−6.1	−13

Table 5
Baseline values and percentage reduction from baseline of economic and resource use variables at the farm level for the considered scenario, presented for the Northwest and Northeast regions and categorized by Farm Size.

		Northwest				Northeast			
		< 15	15–40	>40	Total	< 15	15–40	>40	Total
Baseline	Farms (n°)	56	71	52	179	53	56	55	164
	Variable Costs (€M)	0.4	1.2	2.8	4.4	0.4	1.0	3.0	4.4
	Added Value (M)	1.0	2.6	5.2	8.8	0.8	1.9	6.7	9.4
	Operative Income (€M)	0.4	1.4	3.4	5.2	0.5	1.3	4.4	6.2
	Labor (1000 h)	69.8	111.6	106.6	288	35.1	71.9	157.1	264
	Water (1000 m^3)	404.6	716.1	808.4	1929	125.7	677.1	2032.8	2836.0
	Groundwater (1000 m^3)	12.9	6.3	11.2	30.4	0.7	46.6	21.6	68.9
%	Added Value	−7.1	−5.4	−5.1	−5.4	−4.7	−3.1	−4.2	−4.0
	Variable Costs	−14.5	−16.0	−13.3	−14.1	−14.2	−9.0	−12.8	−12.1
	Operative Income	−14.5	−8.8	−7.5	−8.5	−7.0	−4.0	−5.7	−5.4
	Labor	−13.5	−9.0	−8.7	−10	−12.9	−9.5	−8.1	−9.1
	Water	−19.7	−8.8	−16.3	−14.2	−18.0	−9.7	−13.2	−12.5
	Groundwater	−7.7	−33.9	0.0	−10.3	0.0	−19.4	−0.9	−13.4

Table 6
Baseline values and percentage reduction from baseline of economic and resource use variables for maize grain production, presented for the Northwest and Northeast regions and categorized by Farm Size.

		Northwest				Northeast			
		< 15	15–40	>40	Total	< 15	15–40	>40	Total
Baseline	Farms (n°)	56	71	52	179	53	56	55	164
	Maize UAA (1000 ha)	0.3	1.0	2.0	3.3	0.3	0.6	1.6	2.5
	Maize Gross Saleable Output (€M)	0.9	2.2	4.4	7.5	0.6	1.2	3.0	4.8
	Maize Fertilizers (quantity/ha)	6.1	5.0	5.9	5.6	8.6	6.0	5.9	6.8
	Maize Pesticides (quantity/ha)	2.0	3.9	9.2	4.9	1.6	1.2	1.1	1.3
%	Maize UAA	−22.1	−19.4	−19.2	−19.5	−20.2	−12.5	−14.7	−14.7
	Maize Gross Saleable Output	−22.1	−18.7	−17.6	−18.5	−17.4	−11.9	−14.9	−14.4
	Maize Fertilizers	−0.3	−1.1	−13.8	−4.7	−0.3	−0.5	−8.0	−2.6
	Maize Pesticides	−22.2	−20.6	−7.8	−13.8	−10.0	−11.7	−16.8	−12.5

in UAA (−12.5 %) and production (−11.9 %). Large farms also experience greater reductions (−14.7 % and − 14.9 %, respectively) but are less impacted than those in the Northwest. Conversely, small farms experience higher impacts in both regions, though more significantly in the Northwest. When examining the impact on chemical inputs, small and medium-sized farms in the Northeast show a reduction in pesticide use of −10.0 % and − 11.7 %, respectively despite their relatively low baseline values. The same is true for large farms, although in this case, the reduction in fertilizers is also significant (−8.0 %). In the Northwest, however, similar size groups experience nearly double the impact of pesticide reductions, with small farms facing a decrease of −22.2 % and medium-sized farms −20.6 %. This is attributed to a higher pesticide intensity per hectare. In contrast, large farms see a higher reduction in fertilizer use (−13.8 %) and a lower reduction in pesticide use (−7.8 %), which is the opposite of the trends observed in large farms in the Northeast. Maize indicators in Table 7 offer further insights, as Northeast farms show a higher percentage of income over total revenues across all groups, despite similar income per hectare. The average farm size, particularly for larger farms, is also significantly larger (94.4 vs 72.9) and their labor intensity and costs are lower, yet they generate comparable income per hectare. In other words, at the farm level, the smaller overall impact on income in Northeastern farms can be explained by their higher income-to-revenue ratio, lower labor intensity, and larger farm sizes, particularly in the medium and large classes.

Table 7
Economic and performance indicators selected to assess efficiency and profitability outcomes at both the farm and crop levels, specifically for the Northwest and Northeast regions, as well as across different farm size categories.

	Northwest				Northeast			
	< 15	15–40	>40	Total	< 15	15–40	>40	Total
Farms (n°)	56	71	52	179	53	56	55	164
Total revenues (1000€/farm)	1.4	3.7	8.0	13.0	1.2	2.9	9.7	13.7
Land (ha/farm)	10.9	24.5	72.9	34.3	10.2	28.6	94.4	44.7
Operative Income on Total Revenues (%)	32.9	38.8	42.3	40.5	45.9	45.7	54.8	49.7
Energy (kWh/ha)	15.5	10.4	5.9	8.1	15.5	7.7	5.2	6.5
Operative Income per hectare (€/ha)	725.1	825.1	891.8	863.2	858.9	827.3	854.5	845.8
Labor per Hectare (1000 h/ha)	114.4	64.2	28.1	46.9	65.1	44.9	30.3	36.0
Share of Maize Land on Total (%)	0.55	0.56	0.53	0.54	0.47	0.39	0.31	0.34
Maize UAA (ha/farm)	6.0	13.7	38.9	18.4	4.8	11.1	29.3	15.2
Maize Gross Saleable Output (€/ha)	2721.2	2279.8	2184.5	2272.7	1903.6	1861.6	2267.4	1880.0
Fertilizers (quantity/ha)	6.1	5.0	5.8	5.6	8.6	6.0	5.9	6.8
Pesticides (quantity/ha)	2.0	3.9	9.2	4.9	1.6	1.2	1.1	1.3
Maize Gross Margin (€/ha)	1431.7	1433.4	1246.1	1332.0	1116.2	1125.6	1503.4	1360.5
Maize Net Margin (€/ha)	−292.7	160.9	319.5	454	63.2	182.3	457.7	649.3
Maize Labor costs (€/ha)	896.6	467.5	279.2	498.0	413.0	278.4	214.3	362.3
Maize Machinery Costs (€/ha)	1331.7	599.0	268.8	666.5	560.9	500.0	437.0	599.2

These factors reduce cost incidence, especially for labor, leading to lower fixed costs.

At the maize level, the reduced impact on Northeast farms can be attributed to several factors. First, maize occupies a smaller share of their total UAA (0.34 on average, compared to 0.54 in the Northwest), which naturally reduces the impact of maize-specific restrictions. Second, lower labor costs per hectare of maize contribute to higher net margins across all farm sizes. Additionally, Northeast farms show lower pesticide intensity but greater access to water, enabling them to implement agronomic techniques that reduce dependency on chemical inputs or compensate for lower pesticide use through efficient management of fertilizers and water. Consequently, while production levels may be slightly lower, their higher margins help offset the impact of the restrictions. The different behavior observed in large farms suggests that, even with lower pesticide intensity, their reduction is accompanied by a decrease in fertilizer use. This may reflect a more integrated and strategic resource management, where large farms are able to adopt practices that allow for a joint reduction of inputs, optimizing production. In contrast, small farms do not show the same effect on fertilizers: they primarily reduce pesticide use, both in areas of high and low intensity, displaying greater rigidity in adjusting fertilizer use.

3.4. Sensitivity analysis

The hypothesized scenario aligns with the F2F strategy, implementing simultaneous reductions of 20 % in fertilizers and 50 % in pesticides at the farm level. To further evaluate the robustness and sensitivity of the model, we conducted additional analyses introducing variations in both scenarios and methodologies. Specifically, we tested two alternative scenarios with single-factor reductions: one with a 20 % reduction in fertilizers only and another with a 50 % reduction in pesticides only. Moreover, all scenarios were evaluated both with and without the integration of the translog production function. This allowed us to assess how the inclusion of this function, which endogenizes chemical input quantities for maize production, influences the model's output. In other words, while the main analysis examines the combined effects of reductions in pesticides and fertilizers, the sensitivity analysis provides insights into the individual contributions of each input to the observed changes and the role of the production function in shaping the outcomes. Results for the main and alternative scenarios are presented in Table 8, focusing on the overall sample. Due to space constraints, detailed results by regions are not included here.

The results show that, when the production function is not included, the impact is mainly "absorbed" in terms of land use, which shows a greater reduction in all observed scenarios compared to the integrated model. In this case, since chemical inputs are exogenous variables, the variation in the use of these inputs cannot be evaluated. Conversely, in the scenarios that integrate the translog production function, the scenario involving only a 20 % reduction in pesticides shows more contained impacts on maize UAA and GSP, with an average impact of −4.0 % and − 4.7 % respectively. In contrast, the fertilizer reduction scenario shows a greater impact than the other scenarios (−7.6 %), while pesticides remain relatively stable (−0.5 %). On the other hand, the scenario with a 50 % reduction in pesticides shows a greater impact on both UAA (−16.8 %) and GSP (−16.2 %). Interestingly, in this case, the reduction in pesticides (−15.1 %) is partially offset by a smaller impact on fertilizers (−2.1 %). This dynamic is also evident in the scenario with reductions in both inputs.

Table 8
Impact of different scenarios on maize grain with and without the integration of the Translog production function.

	Fertilizers&Pesticides	Fertilizers	Pesticides
With Translog			
Maize UAA	−18.2	−4.0	−16.8
Maize Gross Saleable Output	−17.4	−4.7	−16.2
Maize Fertilizers per ha	−2.8	−7.6	−2.1
Maize Pesticides per ha	−13.0	−0.5	−15.1
Without Translog			
Maize UAA	−23.7	−11.7	−23.0
Maize Gross Saleable Output	−20.4	−9.5	−19.9
Maize Fertilizers per ha	0.0	0.0	0.0
Maize Pesticides per ha	0.0	0.0	0.0

This highlights how the model's flexibility in accounting for interactions between inputs can reveal dynamics that would otherwise go unnoticed. In particular, the reduction of pesticides tends to have the most significant impact, whereas reducing fertilizers alone shows a more limited effect on the crop. When both inputs are reduced simultaneously, fertilizers seem to act as a buffer, helping to mitigate the losses caused by the pesticide reduction. This suggests that the response is more sensitive to pesticide reductions, which appear to drive most of the decreases in UAA and production. At the same time, the smaller reduction in fertilizers when pesticides are lowered indicates that farmers may adjust their use of fertilizers to maintain production. This emphasizes the challenge of reducing both inputs together, as farmers seem to adapt their input management to sustain productivity.

We can conclude that the model responds appropriately to different scenarios and constraints providing a more nuanced understanding of how individual farms react to pesticide reductions. Farms clearly employ offset strategies, such as increasing fertilizer use, which can only be identified when using flexible production functions. This becomes especially relevant when analyzing impacts involving the use of chemical inputs, particularly when the goal is to obtain more detailed, region-specific results. Flexible functions are thus essential for capturing the complex interactions between inputs and offering insights that are tailored to the specific characteristics of the farms and regions under study, as shown by the heterogeneity of the results shown in the previous sections.

4. Discussion

Our analysis underscores the impacts of the F2F objectives on Italian arable farms, particularly concerning maize grain production. The study provides in-depth insights into how changes in agricultural practices and input availability affect farms based on size, geographical location, altitude, and degree of specialization. The findings reveal a notable decrease in added value and income resulting from the implemented scenario of a 20 % reduction in fertilizers and a 50 % reduction in pesticides, indicating a substantial economic impact on these farms. The contraction in production is linked to a decrease in variable costs and a significant reduction in resource use. These changes could have serious social implications, with a pronounced decrease in employment affecting both family and hired labor in the Central-South regions and smaller farms. While Northern regions exhibit a more contained impact regarding these variables, their combined effect remains significant due to their substantial contribution to national maize grain production. Diversified farms manage to contain the impact on Operative Income, likely due to alternative income sources offsetting production reductions. Furthermore, the reduction in chemicals affects other inputs, as already noted by Cortignani et al. (2022). Water, and particularly Groundwater, emerges as the most affected input at the farm level. The analysis indicates a stronger impact in Southern areas, which are more susceptible to water scarcity, and where the decrease in agricultural and maize grain production is higher. Given these regions' limited contribution to maize grain production, it is likely they will increasingly transition to less water-intensive crops, such as durum wheat. This shift implies that policies limiting chemical inputs may "filter out" less suitable areas for maize grain cultivation, particularly in marginal production zones.

The response of maize grain production to the hypothesized scenario supports this hypothesis indicating an overall -18.2 % reduction in maize grain UAA. However, this loss is counterbalanced by an average reduction of −6.8 % in income. This dynamic can be attributed to the fact that already efficient farms can maintain income levels despite reduced chemical inputs, or due to increased land allocation to less chemical-demanding crops within their crop rotations, particularly in regions less suited for maize production. In fact, a decrease in less favorable and less productive areas is observed, i.e. the Central-South and Hills regions, as well as in diversified farms. However, the Northern regions collectively exhibit significant losses that could have severe consequences for the supply chain. This is why we chose to focus on the confrontation between Northwest and Northeast, trying to figure out why the latter appears to be less affected by the F2F scenario, especially when examining farm size subgrouping.

Medium-sized farms in the Northeast are the least affected and they benefit from higher total revenues, lower labor reliance, and better input management, which help maintain profitability. This is attributed to specific farm characteristics, such as input efficiency and lower labor intensity. As noted by Beckman et al. (2020), the potential for labor to substitute for other agricultural inputs varies with crop type and farm scale. Although slightly less productive than their Northwest counterparts, these farms encounter lower costs, resulting in higher profit margins. The reduced impact in the Northeast is also linked to greater crop diversification and less reliance on maize, which represents a smaller share of total land, enabling them to prioritize more profitable crops or crops eligible for CAP coupled subsidies. Their larger average size further enhances adaptability, allowing better absorption of input reduction effects through diversification. In contrast, high specialization or greater production intensity may limit flexibility in adjusting to input availability, making it more challenging to transition to less chemical-demanding crops. Mixed farms, particularly those combining crops and livestock, not considered in this analysis, could have an even higher advantage in reducing fertilizer and pesticide use through diversification of agricultural activities (Czyżewski and Kryszak, 2023). Indeed, Li et al. (2023) state that in these farms transitioning from chemical to organic fertilizers is not straightforward, as maize cultivation can negatively impact the substitution effect between organic and chemical fertilizers, confirming this crop's "inflexibility" in terms of chemical requirements.

The reliance on chemical inputs in current agronomic practices for maize grain is especially evident for fertilizers, which show an overall lower reduction across the sample, likely to offset the higher decrease shown by pesticides. In accordance with Robu et al. (2023), it is evident that regional variations in pesticide use exist, not only across the EU but also within a single Country. Farms experiencing the most significant decrease in the quantity of fertilizers and pesticides per hectare are those characterized by more intensive production, specifically in the Northwest and Plains. In contrast, Northeast farms, characterized by lower pesticide and labor usage, seem to compensate with higher productivity, utilizing resources more efficiently. This efficiency is likely supported by greater reliance on mechanization and better overall management as confirmed by their higher profit margins. These findings align with the conclusions of Gadanakis et al. (2015) and Speelman et al. (2008), who emphasized the necessity for farmers to develop economies of scale to achieve cost savings in input use. However, larger farms exhibit comparable impacts on both fertilizers and pesticides, even in areas with lower intensity. Yet, the effects on income and maize production are more moderate in this group, since maize occupies a smaller portion of their land. This outcome can also be attributed to the varying efficiency levels across farm sizes (Latruffe, 2010). Additionally, fertilizers and pesticides have an "insurance" effect on production, and sometimes, due to factors external to production itself, farmers may tend to overuse these inputs (Nave et al., 2013; Singbo et al., 2015). This tendency may be particularly true for smaller or those where income or production losses would be challenging to mitigate through other crops or organizational changes. In essence, smaller farms may resort to using more inputs, potentially less efficiently, to secure their income, while larger farms, with better structures, manage these aspects more effectively (Guo et al., 2022). This highlights significant differences in agricultural input management strategies between the two types of farms. Furthermore, higher water availability allows Northeast farms to compensate for lower input intensity. Being characterized by a higher water supply, they can maintain production even with reduced chemical inputs. The flexibility in water management, supported by a higher incidence of groundwater, may enable them to sustain production levels more effectively.

Overall, the analysis reveals several insights into the impacts of transitioning to low-input agriculture in specialized arable farms. Regional disparities are evident, highlighting the need for region-specific strategies to achieve the targets for reducing chemical intensity in agriculture. This is particularly important given that the F2F strategy does not specify the territorial level at which Member States should apply these reductions. The observed differences in impacts suggest that a "one-size-fits-all" approach would be inappropriate, emphasizing the importance of tailoring reductions to regional characteristics. Lower intensity in terms of pesticide and labor use, as well as more efficient resource and cost management, allow for the maintenance of higher profit margins, especially in medium-sized farms. However, this is not true for smaller farms, highlighting the role that scale plays in mitigating the effects of F2F targets. Small-sized farms emerge as the most vulnerable, particularly to reductions in pesticide usage, facing not only production contractions but also occupational consequences. The presence of other crops also helps lessen maize's impact on total farm income penalizing more specialized farms and areas contributing the most to maize production.

5. Conclusions

Our analysis, which integrates an agro-supply model, i.e. AGRITALIM (Cortignani et al., 2022), and an econometrically estimated translog function (Buttinelli et al., 2024), highlights the potential impacts of the F2F strategy on Italian arable farms and maize grain production. This integration represents a significant methodological advancement, capturing interactions between inputs, individual farm effects, and broader climatic influences on maize grain production. It enhances AGRITALIM's ability to simulate realistic responses to policy changes based on farmers' expectations making it a flexible tool responding not only in terms of land use change but also variations in maize production and chemical quantities.

The findings suggest short- to medium-term reductions in agricultural production, income, and added value, with significant social implications, especially for smaller and diversified farms. Maize grain shows limited adaptability to chemical restrictions, particularly in the short term. The results indicate a shift toward less input-intensive practices and crops primarily affecting areas less suited for maize grain production, such as the Central-South and Hills regions, as well as more diversified farms. The regions characterized by higher specialization and greater production, such as the Northwest, experience significant losses that they are not able to offset. With Italy being the EU's fourth-largest maize producer (Erenstein et al., 2022), a contraction in production could increase reliance on imports, and lead to economic losses across various sectors (Barreiro-Hurle et al., 2021). Nevertheless, reduced pesticide and labor intensity, along with efficient resource management, water availability, crop diversification, and effective cost management, help mitigate these impacts in medium-sized farms in the Northeast. The observed reductions in chemical use and their variability highlight the varying vulnerabilities of farms to reductions in fertilizers and pesticides. This underscores the need for further investigation, as Staniszewski et al. (2023) note, stressing that farm structure plays a crucial role in the success of intensifying sustainable production in agriculture.

Our results support these assertions, revealing different scenarios at both regional and size levels. We can conclude that impacts vary based on farms' internal management, primarily driven by input organization and their ability to operate efficiently while reducing costs and choosing their crop patterns. Considering unique agricultural characteristics, such as existing production practices, territorial features, and market and policy framework, this analysis contributes to a deeper understanding necessary to guide targeted interventions.

However, it is essential to acknowledge some limitations. Our study does not take into account the impacts deriving from the new CAP reform, i.e. internal convergence. (Pierangeli et al., 2023; Solazzo et al., 2015), or Eco-schemes. Additionally, our model operates considering current agronomic techniques, crop rotations, and technologies, and some results may be influenced by external factors such as technical efficiency, outcome uncertainty, and socio-demographic features, possibly leading to input overuse. (Bontemps et al., 2021; Nave et al., 2013). We also do not assume adjustments in input or output prices and repercussions due to contractions in international production. Finally, a reduced pesticide coverage could exacerbate risks due to drought, and fungal or pest attacks jeopardizing production (Leggieri et al., 2020; Medina et al., 2015; Wu et al., 2010), especially in the Mediterranean region (Hristov et al., 2020; Lionello and Scarascia, 2018; Rosenzweig et al., 2014).

In conclusion, our research highlights the importance of adopting region-specific strategies when transitioning to low-input agriculture, as a uniform approach could jeopardize production and disproportionately impact entire regions. As we plan this transition, it is crucial to recognize the limitations of current policies and promote sustainable practices that balance environmental goals with farm economic viability. The recent withdrawal of the Sustainable Use Regulation (SUR) on pesticide usage by the European Commission underscores the importance of carefully considering the future of EU agricultural policies. Collaborative efforts are needed to develop balanced policies that address both environmental and economic challenges.

CRediT authorship contribution statement

Rebecca Buttinelli: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Gabriele Dono:** Conceptualization, Validation, Writing – review & editing. **Raffaele Cortignani:** Funding acquisition, Project administration, Resources, Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix A. Mathematical representation of the AGRITALIM model

A.1. Objective function

$$maxZ = \mathbf{GPS} + \mathbf{CAP} + \mathbf{RCA} - \mathbf{VC} - \mathbf{QC} - \mathbf{EXL} - \mathbf{FP} - \mathbf{PW} - \mathbf{DRO} - \mathbf{DRNI}$$

Operating income $= \boldsymbol{Z}$
Gross Saleable Production $= \mathbf{GPS} = \boldsymbol{pc} * \boldsymbol{yc} * \boldsymbol{XC}$
CAP payments $= \mathbf{CAP} = \boldsymbol{dp} + \boldsymbol{cpc} * \boldsymbol{XC}$
Revenues from Complementary Activities $= \mathbf{RCA}$
Variable Costs $= \mathbf{VC} = \boldsymbol{pfp} * \boldsymbol{qfp} * \boldsymbol{XC} + \boldsymbol{acc} * \boldsymbol{XC}$
Quadratic Costs $= \mathbf{QC} = \frac{1}{2}\boldsymbol{XC}' \, \boldsymbol{Q} \, \boldsymbol{XC}$
External Labour $= \mathbf{EXL} = \boldsymbol{ph} * \boldsymbol{XH}$
Pumped Water $= \mathbf{PW} = \boldsymbol{pw} * \boldsymbol{XW}$
Depreciation Rates Observed $= \mathbf{DRO}$
Depreciation Rates New Investments $= \mathbf{DRNI} = \boldsymbol{drtc} * \boldsymbol{ADTC}$

Variables
XC = hectares of crops
XH = hours of labour
XW = quantity of water pumping
ADTC = additional area of tree crops

Market
pc = prices of crops
pfp = prices of factors of production (fertilizers, pesticides)
ph = prices of external labour
pw = prices of water pumped

drtc = depreciation rates of new investments (tree crops)
Production function
yc = yields of crops
qfp = quantities of factors of production (fertilizers, pesticides)
Common Agricultural Policy payments
dp = decoupled payments
cpc = coupled payments for crops
Revenues and average costs
acc = average costs for crops (per hectare)

A.2. General constraints

$$\sum_{j} \boldsymbol{XC}_{j,n} \leq \boldsymbol{ald}_n \forall \boldsymbol{n}$$

$$\sum_{j} \boldsymbol{ml}_{j,n} {}^* \boldsymbol{XC}_{j,n} \leq \boldsymbol{alb}_n \forall \boldsymbol{n}$$

$$\sum_{j} \boldsymbol{mw}_{j,n} {}^* \boldsymbol{XC}_{j,n} \leq \boldsymbol{awt}_n \forall \boldsymbol{n}$$

$$\sum_{jt} \boldsymbol{XC}_{jt,n} \leq \boldsymbol{atc}_n + \boldsymbol{ADTC}_n \forall \boldsymbol{n}$$

Sets shown in the mathematical representation
j = types of crops
n = farms
jt = tree crops
Other sets (not shown in the mathematical representation): geographical area [NUTS 2 and NUTS 3], altimetric level, types of cultivation (field, vegetable garden, greenhouse), following crops, main vegetable product, time.
Matrix coefficients
ml = labour (manual and mechanical) needs per each crop
mw = water needs per each irrigated crop
Availabilities
ald = land availability per each farm
alb = labour availability per each farm
awt = water availability per each source (e.g. water unit association, well) and farm
atc = tree crops area per farm

A.3. Constraints on use of chemical inputs

$$\sum_{j,tf} \boldsymbol{qfp}_{j,tf,n} {}^* \boldsymbol{XC}_{j,n} \leq \boldsymbol{QF}_n^0 {}^* \boldsymbol{0.8} \forall \boldsymbol{n}$$

$$\sum_{j,tp,tc} \boldsymbol{qfp}_{j,tp,tc,n} {}^* \boldsymbol{XC}_{j,n} \leq \boldsymbol{QP}_n^0 {}^* \boldsymbol{0.5} \forall \boldsymbol{n}$$

$$\boldsymbol{QF}_n^0 = \sum_{j,tf} \boldsymbol{qfp}_{j,tf,n} {}^* \boldsymbol{XC}_{j,n}^0 \forall \boldsymbol{n}$$

$$\boldsymbol{QP}_n^0 = \sum_{j,tp,tc} \boldsymbol{qfp}_{j,tp,tc,n} {}^* \boldsymbol{XC}_{j,n}^0 \forall \boldsymbol{n}$$

Sets
tf = types of fertilizers (e.g. solid minerals)
tp = types of pesticides
tc = toxicological classes (e.g. very toxic, toxic, and harmful)
Matrix coefficients, availabilities, and variables
qfp = quantities of factors of production (fertilizers, pesticides)
QF^0 = quantity of fertilizers used in the baseline
QP^0 = quantity of pesticides used in the baseline
XC^0 = hectares of crops observed in the baseline

A.4. Maize grain specification

Table A.4.1
Weighted fixed effects model estimates for the translog production function and their Standard Errors (St. Err.) and significance levels.

	Parameter	St. Err.	
Land	0.143	0.111	
Water	−0.065	0.025	***
Variable Costs	0.120	0.167	
Fertilizers	0.879	0.143	***
Pesticides	0.370	0.130	***
Work	0.340	0.091	***
Machinery	−0.028	0.034	
Land×Water	−0.005	0.004	
Land×Variable Costs	−0.043	0.026	*
Land×Fertilizers	−0.019	0.027	
Land×Pesticides	−0.081	0.025	***
Land×Work	−0.013	0.016	
Land×Machinery	−0.004	0.006	
Water×Variable Costs	0.004	0.009	
Water×Fertilizers	0.027	0.008	***
Water×Pesticides	−0.026	0.008	***
Water×Work	0.011	0.005	**
Water×Machinery	0.002	0.002	
Variable Costs×Fertilizers	−0.089	0.049	*
Variable Costs×Pesticides	−0.170	0.046	***
Variable Costs×Work	−0.090	0.029	***
Variable Costs×Machinery	0.005	0.012	
Fertilizers×Pesticides	−0.033	0.043	
Fertilizers×Work	−0.080	0.029	***
Fertilizers×Machinery	−0.007	0.010	
Pesticides×Work	0.070	0.024	***
Pesticides×Machinery	0.015	0.010	
Work×Machinery	0.000	0.009	
Land^2	0.088	0.014	***
Water^2	0.003	0.003	
Variable Costs ^2	0.196	0.030	***
Fertilizers ^ 2	0.015	0.033	
Pesticides ^2	0.092	0.027	***
Work ^2	0.020	0.011	*
Machinery^2	0.000	0.003	
Temperatures	−0.026	0.030	
Rainfall (100 mm)	−0.007	0.006	
Constant	−0.054	0.734	

*Note: *p < 0.1; **p < 0.05; ***p < 0.01. Obs.: 5224. Adjusted R-Sq: within = 0.50, between = 0.78, overall = 0.73. All the variables are expressed in logarithms, except for Temperatures and Precipitations. Source:* Buttinelli et al., 2024.

A.5. Maize grain production

Maize Gross Saleable Production = MGSP $= \alpha_i + \beta_{temperatures} \cdot t + \beta_{rainfall} \cdot r + \beta_{land} \cdot XM \cdot l + \beta_{water} \cdot XM \cdot w + \beta_{variable\ costs} \cdot XM \cdot vc + \beta_{fertilizers} \cdot XM \cdot XFERTM \cdot pfp + \beta_{pesticides} \cdot XM \cdot XPESTM \cdot pfp + \beta_{work} \cdot XM \cdot wr + \beta_{machinery} \cdot XM \cdot m + \frac{1}{2}\beta_{lw} \cdot XM \cdot l \cdot XM \cdot w + \ldots + \frac{1}{2}\beta_{wrm} \cdot XM \cdot wr \cdot XM \cdot m + \frac{1}{2}\beta_{l2} \cdot XM \cdot l \cdot XM \cdot l + \ldots + \frac{1}{2}\beta_{m2} \cdot XM \cdot m \cdot XM \cdot m$[9]

Variables
XM = hectares of maize grain
XFERTM = quantity of fertilizers for maize grain
XPESTM = quantity of pesticides for maize grain
Market
pfp = prices of factors of production (fertilizers, pesticides)
Production function
t = temperatures
r = rainfall
l = land interest
w = water
vc = variable costs
f = fertilizers
p = pesticides
wr = work
m = machinery

[9] Where β_{lw} is the parameter for the interaction between land and water, β_{wrm} is the parameter for the interaction between work and machinery. Moreover β_{l2} is the parameter for the land quadratic term and β_{m2} is the parameter for the machinery quadratic term. Each interaction and quadratic term are associated with the respective linear term in the equation, contributing to the overall representation of MGSP.

Sets shown in the mathematical representation.

j = types of crops

n = farms

Other sets (not shown in the mathematical representation): geographical area [NUTS 2 and NUTS 3], following crops.

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