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Assessing The Economic Relevance and Productivity of Agricultural Inputs in Italian Farms Through Quantitative Analyses

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Tesi di dottorato di:

Dott.ssa Rebecca Buttinelli

Coordinatore del corso

Prof. Giulio Guarini

Firma (Signature) …………..

Tutore

Prof. Raffaele Cortignani

Co-tutore

Prof. Gabriele Dono

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1. Introduction

Agriculture faces the dual challenge of feeding the growing global population and actively contributing to the environment's safeguarding. With the world's population expected to reach 9.7 billion by 2050 (UN, 2022) the demand for food is rising amidst an increase in the intensity and frequency of extreme weather events in a context where Climate Change (CC) is and will represent the primary threat to agricultural sustainability in this century (Beach et al., 2015; Tack et al., 2015). Indeed, CC makes adverse weather events more violent, frequent, and less predictable, amplifying climate-related risks and creating new ones (IPCC, 2022). Altered climate patterns can disrupt traditional growing seasons, impact crop yields, and affect livestock, potentially leading to crop failures and economic instability for farmers. The intricate relationship between agriculture and the environment underscores the urgency of adopting sustainable practices, which enhance the already fundamental role of agriculture in environmental preservation. Following the definition provided by Pretty and Bharucha (2014), Sustainable Intensification (SI) is the path to follow, i.e. increasing crop and livestock yields and associated economic returns reducing at the same time impacts on soil and water resources (Cassman and Grassini, 2020). According to Baulcombe et al. (2009) and Pretty (2008) sustainable production systems should prioritize high-productivity crop varieties and livestock breeds, minimize the unnecessary use of external inputs, promote agroecological processes like nitrogen fixation, reduce the use of environmentally harmful technologies, leverage human capital for knowledge and innovation. Additionally, these systems aim to minimize the adverse impacts of management on externalities, including water pollution, carbon sequestration, and the dispersal of pests.

Agriculture plays a key role in preserving landscapes, biodiversity, and territories, not only produces food but also contributes to the provision of public goods and environmental services. Pretty (2008) defines "sustainable agriculture" as practices aligned with current and future societal needs, underscoring the crucial role agriculture plays in society. In this context, greater sustainability leads to resource conservation, i.e., an improvement in the stocks and use of natural resources. Over the past two decades, Europe has made efforts to enhance the positive role of agriculture in preserving the environment through targeted policies and laws. These efforts inevitably affect the use of agricultural inputs in the production method and farmers' decision-making process. Regarding water resources, for example, the European Union (EU) has promoted their more rational use, by focusing on the preservation and restoration of water quality and encouraging a more efficient utilization of this resource since the beginning of the century. This intention led to the Water Framework Directive 2000/60 (WFD) whose objective was to encourage water conservation and cost recovery across various sectors throughout the EU, including agriculture, following the "polluter pays" principle. Furthermore, Article 9 of the WFD mandated Full Cost Recovery (FCR), meaning that pricing should have incentivized the efficient use of the resource and, thus, include all associated costs[1]. Italy, in this regard, introduced the obligation of measuring and estimating irrigation volumes, as well as assessing environmental and resource costs in 2015 (Guidelines DM 15th of February 2015, no. 39).

Aware of the road ahead, in December 2019, the EU Commission introduced the European Green Deal, closely tied to the UN 2030 Agenda (European Commission, 2019), an ambitious strategic plan aimed at transforming Europe into a low-carbon and environmentally sustainable continent by 2050. The primary objective of the Green Deal is to address the challenges of CC, biodiversity loss and environmental sustainability in an integrated way while promoting economic growth and job creation. Some key objectives of the EU Green Deal concern Climate Neutrality, Clean Energy, a Circular Economy, Sustainable Mobility, Biodiversity Protection, Sustainable Building and finally Sustainable Agriculture. In this vision, agriculture is hence a crucial component of the transition, and this is why the European Commission specifically shaped a strategy for the agricultural and food sector. In fact, in May 2020, the Farm to Fork (F2F) Strategy strengthened the Green Deal vision by focusing on building a fair, healthy, and environmentally friendly food system (European Commission, 2020). Key objectives are sustainable food production, reducing food waste, promoting healthy diets, enhancing food security and transparent food information. One of the F2F Strategy's main goals directly affecting the agricultural production process, is to promote the efficient use of natural resources in agriculture and reduce the environmental impact of agriculture. This will especially concern the reduction of antibiotic use, the protection of biodiversity and ecosystems and finally the reduction of the use of chemical input. This last objective will require a 50% reduction in chemical pesticide use, and a 20% reduction in fertilizer leading to a 50% decrease in nutrient losses by 2030.

Europe’s commitment, spanning over two decades, to ensure that agriculture not only adheres to but actively contributes to environmental protection, is undeniable. Furthermore, this process is progressively intensifying, also introducing specific targets regarding the reduction of chemicals, i.e. fertilizers and pesticides. Europe is hence actively addressing agricultural challenges by promoting sustainable practices, placing increased emphasis on reducing harmful inputs and optimizing the

[1] Bennett et al., (1991) define Full Cost Recovery (FCR) as comprising three main components: Real Use Value, derived from the current use of the resource; Option Value, representing the potential value for future generations; and Existence Value, reflecting the intrinsic value associated with the mere existence of the resource, irrespective of its current or future use.

utilization of natural resources. Yet, while promoting sustainable agricultural practices and preserving natural resources is desirable, it is equally important to acknowledge that such alterations may pose several challenges and involve potential trade-offs. In other words, limitations deriving from these policies could lead to modifications in the relationship among agricultural inputs, with impacts on yields that will vary across agricultural sectors and areas. This is why these ambitions require adequate economic and political support (Agovino et al. 2019).

In this context, farmers are called to face challenges such as adapting to new regulations, modifying crop selection, and managing heightened costs linked to the adoption of environmentally friendly practices. These multiple requirements must be encountered, all while sustaining production and income, ensuring crop quality, adapting to reduced access to chemicals, and preserving natural resources. Additionally, farmers are also required to meet market standards, fulfil consumers' demands, and operate in a competitive market. These challenges may potentially impact farmers' income and livelihoods, especially in the short term, not only having impacts on production, but also socioeconomic implications for farms and rural areas including changes in work organization, farm profitability, and farmers' decision-making processes. In essence, the delicate equilibrium lies in recognizing that while preserving the environment and natural resources is crucial, this objective must be achieved in a way that sustains the economic viability of agriculture and safeguards farmers' welfare. The path forward demands more than regulatory measures; it necessitates financial incentives, technical support, and capacity-building for farmers to transition to new practices. A transition that fails to consider the social and economic impacts of reducing agricultural inputs along with the threats posed by CC could jeopardize both European social cohesion and agricultural production. Indeed, in February 2024, the European Commission announced the withdrawal of the Sustainable Use Regulation (SUR), i.e. a proposal aiming to establish legally binding targets at the EU level to reduce the use and risk of chemical pesticides by 50% (Regulation of the European Parliament and of the Council on the sustainable use of plant protection products, COM (2022) 305 final 2022/0196), following widespread farmer protests across Europe. This Regulation, which had already been rejected by the European Parliament, was considered divisive by Commission President Ursula Von der Leyen. She acknowledged that the proposal had not progressed smoothly through the legislative process and committed to proposing a new formulation, likely to come after the elections and the formation of the new European Parliament.

In this context, analyses focused on the impacts of these policies and research that consider the diverse production individualities among areas, productive sectors, and supply chains are more necessary than ever. Over the years, numerous studies have explored the impacts of policies aimed at conserving the environment and natural resources, including those that influence the accessibility and constraints on the quantities of agricultural inputs used in agricultural production, especially irrigation water and chemicals. In fact, one of the most extensively researched topics has been the application of the WFD, potentially altering water-related costs and hence accessibility to irrigation water, on farmers' income and employment in agriculture (Bazzani et al., 2005; Latinopoulos, 2008; Gómez-Limón et al., 2002)[2]. The findings highlighted differentiated impacts among farm types (Bartolini et al., 2007; Cortignani et al., 2018), groups of farmers (Gómez-Limón and Riesgo, 2004) and depending on the policy framework (Viaggi et al., 2010). More recently, several studies have highlighted the potential risk for F2F objectives to cause a decline in agricultural production, both in the short and long term (Barreiro-Hurle et al., 2021; Beckman et al., 2020; Noleppa and Cartsburg, 2021). Wesseler (2022) conducted a comprehensive review of academic literature on the assessment of F2F strategy's impact on agriculture production, assessing that the reviewed studies uniformly predict a decrease in agricultural output, both in terms of value and volume. This trend could result in agricultural expansion into non-agricultural areas and insufficient food production, possibly leading to greater reliance on imports and compromising sustainability efforts in Europe.

The impact assessments of the F2F strategy mentioned earlier consider the European Union as a whole. However, it is crucial to account for regional variations influenced by climatic, geographic, and productive factors, particularly concerning specific crops. Robu et al. (2023) emphasize the existence of regional patterns in pesticide use across Europe, underscoring the importance of regional analyses that recognize the influence of socioeconomic factors. Climate also plays a pivotal role, with the Mediterranean area identified as one of the most vulnerable regions to climatic variations (Williges et al., 2017; Lionello & Scarascia, 2018; Hristov et al., 2020). Agriculture in this region is already facing significant threats, primarily driven by rising temperatures and scarce precipitation. These factors contribute to a growing demand for irrigation water while simultaneously limiting water availability (Wada et al., 2010; Cramer et al. 2018; Gorguner and Levent, 2020). This poses the risk of creating a cycle that increases the frequency and severity of drought events, extending to areas that traditionally do not experience water scarcity (Malek et al., 2018; Nerantzaki et al., 2019; FAO, 2022). Recent studies, such as Beillouin et al. (2020) highlight the negative impact of drought on European yields with losses tripling between 1964 and 2015 (Brás et al., 2021), consequently, farmers in these regions must cope with the heightened risk of drought to safeguard their incomes and

[2] See Mirra et al. (2021) for a review of the literature focusing on water pricing following the WFD requirements.

maintain production levels (García-León et al., 2021) while also committing to a path of reducing chemicals as required by the new EU policies.

In other words, agricultural production depends on the relation between yields and various agricultural inputs, with the relationship among them directly impacting the outputs. This is why alterations in this delicate equilibrium could lead to different outcomes influenced by several factors. Therefore, it is crucial to examine the economic impacts of such limitations on the agricultural sector (Alexander et al., 2019; Balezentis et al., 2020; Fitton et al., 2019; Malek and Verburg, 2018). The specific focus of this thesis is to assess the relevance of chemical inputs and irrigation water on agricultural production across diverse systems and areas, in order to identify the most vulnerable farms and regions. In this context, the objectives of this thesis aim to take a step towards modeling based on reliable data, providing detailed results at territorial, sectoral, and even farm levels. This methodological approach could represent an initial effort to inform policymaking with tools capable of offering reliable information and empirical evidence, thus enhancing the efficiency of the policy formulation process. This is crucial in the context of formulating new objectives, as mentioned earlier, and in shaping a Common Agricultural Policy (CAP) increasingly oriented towards choices voluntarily undertaken by farmers such as eco-schemes. It is indeed essential to understand the pros and cons of these strategies, which otherwise risk being inefficient and may not support a low-input transition but rather impose constraints that could disproportionately affect already exposed areas, such as regions where agriculture serves as a means of territorial protection and a vital economic activity for small farms relying on local or family labor, thereby posing risks to their incomes. By recognizing and addressing the challenges faced by farmers, this thesis aims to foster a balanced and conscious approach that supports both environmental preservation and agricultural productivity.

2. Research Objectives and Design

Building upon the concepts introduced in the previous paragraph, the general objective of this thesis is to evaluate and quantify the economic impacts on Italian farms resulting from modifications in the relationship among various agricultural inputs. By integrating diverse empirical analyses within its framework, the thesis provides a structured approach to understanding the complexities of agricultural production and policy impact evaluation. Therefore, the specific research objectives are pursued through a structured approach aimed at framing and integrating diverse empirical analyses. This methodology ensures internal coherence and addresses the inherent complexities of evaluating agricultural production and policy impacts. This thesis is structured around two key components: understanding the dynamics between agricultural inputs and outputs and evaluating the economic impacts of policies that could alter these relationships.

The component focusing on the dynamics of agricultural inputs and outputs aims to understand the interdependencies among various inputs, with particular emphasis on irrigation water, fertilizers, and pesticides. This analysis assesses their relevance and contribution to agricultural production, considering variations across different sectors to highlight the heterogeneity of Italian agriculture. Each sector requires detailed analysis of its production processes to capture specific territorial and productive characteristics. The methodological approach adopted enables the identification of potential downsides of policies aiming at a transition towards low-input agriculture, ensuring economic impacts are not underestimated, especially regarding employment and the vitality of areas where agriculture is significant for both employment and territorial safeguarding. These insights guide strategies to optimize resource use and support the path toward more sustainable agriculture without sacrificing economic viability. Specifically, the specific objectives of this thesis are to:

1. **Identify and analyze the relationships among agricultural inputs**, with a focus on diverse case studies encompassing broader-scale contexts as well as more specific and representative crops. This approach facilitates a thorough examination of the economic implications arising from alterations in input relationships across different scales, thereby encouraging a comprehensive understanding of the scenario.
2. **Quantify the economic impact of the European F2F Strategy goals on Italian agriculture**, especially considering a 50% reduction in chemical pesticide use and a 20% reduction in fertilizers.

3. **Evaluate the relevance and quantify the contribution of irrigation water** to crop production in Italy to determine how fluctuations in its availability and productivity can impact yields and to identify the most vulnerable areas throughout the Country.

By focusing on both the broader Italian context and specific sectors and crops, our objective is to reveal the complexity of the agricultural production process. This dual focus allows us to highlight the repercussions of changes in input availability on Italian agriculture, enabling the identification of vulnerable sectors, regions, and crops. The underlying theme that unifies the specific objectives, i.e. the identification of inputs interdependencies, the economic relevance of irrigation water in agriculture, and the analysis of F2F targets' impacts on farms is the deepening of our comprehension of the intricate dynamics shaping agricultural production.

To achieve the objectives of this research, the following steps were implemented:

1. **Formulation of Research Hypotheses and Conceptual Framework**: Research hypotheses were developed in response to the specific research objectives and framed within a robust conceptual framework suitable for addressing the complexity of research objectives.

2. **Data Extraction:** The necessary data for analysis were extracted from the Italian Farm Accountancy Data Network (FADN) database. These data constitute the empirical basis for the research and allow for comprehensive analyses at the farm level as well as more detailed analyses for individual crops. Moreover, these detailed data enable a realistic reconstruction of the production structure of farms and a focused examination of every single input employed.

3. **Methodologies:**

- *Mathematical Programming (MP):* The use of MP to model the behavior of agricultural producers has a long tradition in agricultural economics. These methods enable a prospective (ex-ante) analysis of the evolving phenomena that characterize the agricultural sector or a retrospective (ex-post) analysis, providing a measure of the efficiency and effectiveness of agricultural policy tools. Positive Mathematical Programming (PMP) is a specialized modeling technique within agricultural economics that falls under the broader category of MP (Howitt, 1995a). Positive models assume that the observed farm reality is already in an economic optimum. Therefore, the model must demonstrate its ability to precisely reproduce the structure of revenues, costs, and observed production choices, aiming to capture the system of preferences that led the farmer to choose a specific arrangement over others. Specifically, these positive models are employed to optimize resource allocation by replicating the structure of revenues and costs while capturing observed production choices (Paris and Arfini, 1995; Paris and Howitt, 2000, 1998). PMP is widely used for ex-ante analysis, and in the context of this thesis, it serves to offer valuable insights into the potential repercussions of the Farm to Fork (F2F) strategy on Italian farms. Additionally, it aids in understanding how alterations in one production factor may impact other agricultural inputs, it can provide insights into the potential impacts of the F2F strategy on Italian farms and on the influence of modifications in one production factor on the other agricultural inputs.

- *Econometric Estimation of Production Functions:* After identifying the most vulnerable farms and sectors, econometric estimation techniques were employed to explore the production processes of specific crops. Both rigid production functions, such as the Cobb-Douglas (Cobb and Douglas, 1928), and flexible production functions, like the Translog (Christensen et al., 1975) were estimated. By leveraging the properties of production functions and advanced econometric techniques, it becomes possible to quantify the effects of changes in input levels on agricultural output. This approach also aids in identifying complementarity and substitution effects among inputs, offering insights that inform subsequent analyses on the impact assessment of policies affecting input-output balance. Specific emphasis is placed on irrigation water to determine its economic value and contribution to agricultural production. Estimating its value and productivity poses several challenges (Young, 2005), especially in Mediterranean regions where water scarcity is a significant threat to agricultural production (Cammalleri et al,, 2020). Employing econometric techniques to estimate the shadow price of irrigation water allows for highlighting its significance for crop production and identifying vulnerable areas susceptible to water scarcity (Bierkens et al., 2019). This approach is also useful to pinpoint opportunities where improved water management could enhance economic outcomes and mitigate environmental impacts. Additionally, production functions also allow for assessing the efficiency with which farms utilize agricultural inputs, using analyses such as Stochastic Frontier Analysis (SFA). This approach can incorporate the influence of exogenous factors potentially leading to input overuse. In other words, by employing various empirical specifications tailored to each specific objective and analysis, and leveraging production function properties it becomes feasible to evaluate the Marginal Productivity (MP) of inputs and estimate farms' Technical Efficiency (TE) (Battese and Coelli, 1995), in an attempt to analyze the agricultural production process as comprehensively as possible.

- *Integrated Mathematical Programming*: Relying on the methodologies utilized in the preceding analyses, the introduction of a PMP model, incorporating the Translog production function properties in the objective function and the optimization process, brings increased flexibility necessary to assess the impact of F2F objectives on the agricultural sector. Most PMP models are based on a Leontief technology, establishing a fixed connection between productive activities and agricultural inputs (Howitt, 1995a). However, incorporating a more flexible econometrically estimated production function into the objective function is beneficial to enhance the model's stability and make production and input quantities (such as fertilizers and pesticides) endogenous (Britz, 2010; Howitt, 1995b; Howitt et al., 2012). Indeed, several studies have adopted more adaptable functions like the Constant Elasticity of Substitution (CES) (Edwards et al., 1996; Howitt, 1995b). Howitt et al. (2012), for example, detail several calibration methods for agricultural production water use models, including the estimation of CES regional production functions. Similarly, Graindorge et al. (2000) and Medellín-Azuara et al. (2010) employed CES specifications to determine the economic value of agricultural water. The application of flexible functions in these studies underscores the necessity of capturing the complex interrelationships within agricultural systems. Furthermore, Britz (2010) utilized iso-elastic functions to derive endogenous yields responsive to price variations in the CAPRI model, while Giraldo et al. (2014) combined a translog cost function estimation with PMP to simulate the effects of volumetric and cost-recovery pricing for irrigation water in Sardinia. In our research, a similar methodology is adopted, integrating MP with econometric estimation to thoroughly address the challenges and research questions to address in this thesis. This methodological advancement not only facilitates the accurate representation of farm planning decisions but also enables the simulation of detailed responses to constraints in the use of chemicals, making the quantity of chemicals endogenous and providing results not only in terms of land use.

The ultimate goal of these analyses is to evaluate the economic impacts of policies like the F2F Strategy on Italian agriculture, and to propose insights in the management of natural resources, i.e. irrigation water, considering that the latest regulatory framework is provided by the WFD 2000/60. This ambition requires a comprehensive approach, including ex-ante evaluations of EU targets, to develop empirical tools for assessing the impacts of these policies (Godard et al., 2008). Econometric estimation of production functions with different purposes, such as MP estimation or TE estimation, offers empirical insights into input productivity and interdependencies, grounding the analysis in real-world data. PMP models simulate farm-level responses to policy changes, offering prospective analysis of economic impacts from input modifications. Integrating econometrically estimated production functions into PMP models enhances their flexibility and realism, enabling detailed simulations of input use and policy impacts. This integration represents a methodological advancement, addressing the flexibility of these models as a significant area of research interest. This approach ensures the complementarity and interdependence of diverse methodologies applied in this thesis, providing a comprehensive and coherent analysis of agricultural production.

By grounding the analysis in empirical data and leveraging advanced modeling techniques, the research evaluates the immediate economic impacts of policy interventions and anticipates implications for agricultural productivity, sustainability, and socio-economic outcomes. Both MP and Econometrics methodologies rely on detailed microeconomic data, offering deep insights into agricultural practices and farmers' expectations. This comprehensive approach ensures that the research addresses current challenges and contributes to shaping informed, forward-thinking agricultural policies. Integrating these perspectives with ex-ante simulations reconstructs current agricultural conditions and future scenarios, providing a powerful tool for evaluating policies and designing new strategies. This methodological integration bridges the gap between ex-post analysis and ex-ante policy assessments, enhancing the robustness and applicability of findings. This dual approach is compelling in the current landscape where agricultural policies experience reassessment and structural modifications. In this context, this thesis contributes to advancing this methodological approach by demonstrating its application in evaluating the economic impacts of agricultural policies and input modifications.

The final aim of this work is to provide policymakers with actionable insights supporting sustainable agricultural development and resilience amidst future uncertainties. This conceptual model supports the policy process by offering evidence-based comprehension of the economic impacts of agricultural input modifications through detailed analysis of agricultural production specificities. Focusing on sectors affected by changes in input availability, it recognizes the interconnected nature and inevitable repercussions on other agricultural inputs. Understanding stems from a comprehensive analysis of the production system, considering geographical, sectoral, regulatory, and market processes influencing farmer decisions. In conclusion, placing agricultural economics at the center of policy formulation requires underscoring the importance of evidence-based decision-making in complex policy environments. Integrating detailed microeconomic data with advanced modeling techniques enhances the precision of analysis. This positions agricultural economics not only at the forefront of policy evaluation, but also in a key role in supporting new policy formulations to support agricultural production, especially during the transition to lower-input agriculture.. The methodology adopted in this thesis offers a rigorous framework to evaluate trade-offs and optimize resource use effectively, exposing interconnected dynamics of agricultural inputs, outputs, and policy interventions, and proposing methodological options not only to evaluate policy impacts but also to guide the formulation of new policies tailored to the specific sectors and territories of each Country. Through empirical results and reliable assessments, this thesis represents an initial step towards identifying the necessary analyses that should guide future policies. It aims to provide a methodological contribution that translates into empirical evidence supported by data useful for better calibrating policies, even if based on specific case studies. The thesis is structured as follows: each chapter represents a scientific contribution, complete with an introduction, methodology, presentation of results, discussion, and conclusion section. Each chapter is also preceded by a brief specific introduction that clarifies the role of each paper within the thesis, explaining how the contribution addresses the specific research objectives outlined in the previous section. Subsequently, a concluding section is provided to blend the work, highlighting commonalities across various analyses and summarizing key points emphasized using several methodologies aimed at framing the study context from different perspectives.

3. Farm to Fork strategy and restrictions on the use of chemical inputs: Impacts on the various types of farming and territories of Italy

This study stands as a significant step in the research agenda, offering a comprehensive evaluation of the intricate relationships linking agricultural inputs within the context of Italian agriculture. By accurately analyzing the extensive Italian FADN dataset, covering approximately 40,000 farms over four years from 2015 to 2018, this study serves as the foundational and comprehensive attempt to identify the types of farms, crops, and geographic regions that are most vulnerable to fluctuations in chemical inputs, specifically due to European policies. Crucial to this research is the Agricultural Territorial Time (AGRITALIM) agro-economic supply model. AGRITALIM offers a detailed analysis of production choices, including elements considering current production conditions, and political framework. Moreover, it provides a highly detailed territorial analysis that considers both geographical area and altitude, providing precise and in-depth insights. Various analyses have previously assessed the impacts of the F2F Strategy on European agriculture. According to Wesseler (2022), European agricultural production is anticipated to be significantly influenced by the reduction in chemical usage. For example, Bremmer et al. (2021) estimated a decrease in production value by approximately 92 billion euros by 2030 and predicted that an additional 2 to 3 million hectares of land would be required to compensate for this economic loss. Similarly, studies by Beckman et al. (2020), Barreiro-Hurle et al. (2021) Noleppa and Cartsburg (2021) projected a 7-12% decline in agricultural output volumes. However, these studies mainly consider the EU as a whole and often overlook the specific conditions of each Member State. As a result, they might underestimate the impacts of such policies or fail to identify the most affected sectors, farms, and regions. Conversely, regional differences in pesticide usage have been highlighted (Robu et al., 2023), demonstrating the necessity for a more detailed approach.

The primary research objective of this chapter is to analyze the entire agricultural sector in Italy, taking into account the existing variations across sectors, regions, and farms. By acknowledging and incorporating these differences, this study aims to pinpoint the most susceptible areas and provide a more accurate assessment of the F2F Strategy's impacts at a regional level. This approach intends to contribute to a more detailed and specific understanding of the effects of agricultural policies on different parts of the sector. Within the broader context of the research agenda, this study effectively addresses the following specific research objective:

- **Quantify the economic impact of the European F2F Strategy goals on Italian agriculture**: A particular emphasis is placed on assessing the economic consequences of significant reductions in the use of pesticides and fertilizers. However, our analysis is not limited to economic factors such as added value and income, but it also considers social factors like employment and environmental indicators such as fertilizer and pesticide intensity, as well as impacts on natural resource use. The hypothesis is that the effects of the F2F strategy can vary based on various elements and aspects considered and that limitations in the use of chemicals could generate repercussions on other inputs, such as water. This in-depth understanding of agricultural dynamics directly addresses our third research objective by providing key insights into the economic and environmental implications of the F2F Strategy.

These policy-driven transformations carry profound economic, social, and environmental implications. In the context of our general research objective, this study assumes the crucial role of being the first step, aiming to clearly identify the types of farms, crops, and geographic territories most susceptible to reductions and modifications among agricultural input relations. The obtained results are crucial to guide the subsequent steps of this research. Moreover, this work aims to deepen the comprehension of the economic and environmental consequences associated with sustainability policies, offering several insights for future analyses and providing useful insights for policymakers and stakeholders. The scientific paper resulting from this study, titled “Farm to Fork Strategy and restrictions on the use of chemical inputs: Impacts on the various types of farming and territories of Italy”, was published in 2022 in the journal "Science of The Total Environment”.

Farm to Fork strategy and restrictions on the use of chemical inputs: Impacts on the various types of farming and territories of Italy

Raffaele Cortignani[a*], Rebecca Buttinelli[b], Gabriele Dono[a]

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

[b] University of Tuscia, Department of Economics, Engineering, Society and Business Organization (DEIM), 01100 Viterbo, Italy

[*]Corresponding author at University of Tuscia, Department of Agriculture and Forest Sciences (DAFNE), Via San Camillo de Lellis, 01100 Viterbo, Italy. E-mail address: cortignani@unitus.it (R. Cortignani).

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3.1. Abstract

This study evaluates the impacts of reduction in chemical inputs use, as defined by the Farm to Fork strategy, on the Italian agricultural sector based on current production practices and technologies, as well as market and political framework. The impacts are evaluated in terms of some economic, environmental and social indicators, and are shown and discussed in both geographic areas and types of farming. The analysis was conducted on all Farm Accountancy Data Network (FADN) sample of Italian farms in various years, about 40,000 farms, by using the AGRITALIM model.

The main results show an improvement in the environmental sustainability of agricultural production in terms of lower use of chemicals. Negative socio-economic and productive impacts are observed overall in the national territory, but some areas are more affected. The reduction of income could especially affect some types of farming and smaller farms.

In conclusion, the Farm to Fork strategy could be a fundamental impetus to review some failings and weaknesses of European agriculture. Our analysis shows that targeted and forward-looking interventions are especially important for some types of farming, production sectors and territories. New research is needed to support the choices of stakeholders regarding policy support and innovation in agriculture. Political interventions are needed to incentivize farmers to adopt environmentally friendly agricultural practices and limit income losses. Genetic and technological innovations could play a fundamental role in limiting the reductions of agricultural production and modernizing farms.

Keywords: Farm to Fork Strategy; Chemical Inputs; Mathematical Programming Model; Sustainability; Common Agricultural Policy

JEL Classification codes: C61, Q15

3.2. Introduction

In December 2019 the EU Commission presented the European Green Deal as directly connected with the Commission's strategy to implement the United Nation's 2030 Agenda (European Commission, 2019). More recently, the Communication from the Commission of 20 May 2020 on the Farm to Fork Strategy strengthened further the efforts for building a fair, healthy and environmentally friendly food system (European Commission, 2020). More specifically, the Farm to Fork Strategy addresses pollution with a 50% reduction in the use of chemical pesticides by 2030 and aims 20% reduction in fertilizer use plus a decrease of nutrient losses by at least 50% (Montanarella and Panagos, 2021). The impacts of the strategy application can be significant in terms of production of agricultural products and food, use of natural resources (land, water) and chemical inputs (e.g. nitrogen), as well as socio-economic impacts on farms and rural territories. Integrated analyses are necessary to take into account the various aspects regarding the use of natural resources but at the same time the productive and socio-economic ones (Rounsevell et al., 2014; Alexander et al, 2019; Fitton et al, 2019; Balezentis et al., 2020; Malek and Verburg, 2020; Prudhomme et al, 2020).

Economic models can provide these types of evaluation and, specifically, the micro-economic approach of mathematical programming models allows the technical aspects of agricultural production and resource uses to be taken into account (Godard et al., 2008). Various types of models have been developed over the years that can be grouped into three groups: a. agro-economic supply models (e.g., FSSIM, EFEM, FARMIS); b. Partial Equilibrium models (e.g., CAPRI, GLOBIOM, ESIM); c. Computable General Equilibrium models (e.g., GTAP, MAGNET). Some of these models use data provided by the Farm Accountancy Data Network (FADN), such as FSSIM, EFEM, FARMIS and CAPRI models (Angenendt et al, 2018).

In this research context, the main objective of this study is to evaluate the possible impact of the Farm to Fork Strategy in the agricultural sector in Italy, using the AGRIcultural TerritoriAL tIme economic (AGRITALIM) model. This model belongs to the group of agro-economic supply models, uses FADN data and is based on non-linear mathematical programming, which combines Leontief technology for variable costs with a non-linear cost function (such as the CAPRI model). Compared to models already found in literature, the AGRITALIM model has some innovative aspects. Specifically, the model considers several years and then the same or similar farm is homogeneous from a structural and productive orientation point of view, but different states of nature in terms of market (prices of outputs and inputs) and production conditions (quantities of outputs and inputs) are observed. Furthermore, the AGRITALIM model is very detailed from a territorial point of view, considering NUTS2 and NUTS3 areas, and altimetric levels. All these characteristics are important in the simulation phase and in terms of information for stakeholders.

The simulated scenarios consider the obligation to reduce in use of chemical inputs (20% of fertilizers and 50% of more hazardous pesticides) in each farm. In other words, each single farm is obliged to reduce the use of chemical inputs according to the percentages defined by the strategy. The hypothesis of acting at the farm level allows for quantification of the relevance of chemical inputs for all farms based on the current conditions of the market, political framework and technologies. However, the simulations carried out have no intention of proposing political actions and measures. The impacts are evaluated in terms of some economic, environmental and social indicators (e.g., added value, income, uses of mineral fertilizers and pesticides, family and external labour), land use and production quantities of crops, milk and meat.

The crucial question of the research is to understand what might involve the achievement of the objectives set by the Farm to Fork strategy regarding the use of chemical inputs. The assessment is based on current market conditions, political framework and technologies, in order to comprehend which sectors and territories are most in need of political support, research and innovation.

The main research hypotheses consider that the impacts can be differentiated depending on the various elements and aspects of different nature (economic, environmental and social). Furthermore, it should be considered that the impacts may differ by geographic areas, altimetric levels and types of farming. Compared to recent research about the impacts of the Farm to Fork strategy (Beckman et al., 2020; Noleppa and Cartsburg, 2021; Barreiro-Hurle et al., 2021), this paper offers some innovative aspects that can further stimulate discussion and future research on this issue. Our analysis considers results of different natures and is distinguished by territories and sectors, therefore the results can provide useful information to national and local stakeholders and policymakers. Moreover, in the coming months, important decisions on the new agricultural policy will be taken, as well as relevant political and scientific questions concerning genetic improvement and technologies 4.0 use will be discussed. Our research fits well into this whole scientific and political context.

3.3. Material and Methods

3.3.1. Data and characteristics of farm sample

The database on which the model is built totals 40,408 Italian farms of the FADN sample, about 10,000 for each year of the period considered 2015-2018 (9,569 farms for the 2015 year; 10,153 farms for 2016 year; 10,380 farms for 2017 year; 10,306 farms for 2018 year). The sample isn't constant and represents all Italian farms observed in the FADN sample. Therefore, some farms are observed for several years, and others don't. For farms observed for more years, the overall sample captures the differences in terms of market and production aspects. In any case, the farms not observed for more years, add observations to the overall sample, similar or not to those present in other years.

We outline the main features of the farm sample, first considering the resources used in its geographical districts and territorial areas, then the productive activities carried out.

The Utilized Agricultural Area (UAA) approximately equals 1.254 kha, with 43.6% located in Northern Italy, 19.6% in Central Italy and 15.1% in the South and Islands (Table 1a). About the altimetric level, 41.7% of the UAA is located in the hills, 35.2% in the plains and 23.2% in the mountains. 56% of the Added Value is produced in Northern Italy, 28.4% in South and Islands, and the remainder, 15.7%, in Central Italy. 48.2% of the Added Value is obtained in the plains and 36.2% in the hills

Table 1a. Use of resources and inputs in Italy, per geographical area and altimetric level.

	Italy	Northwest	Northeast	Centre	South	Islands	Plain	Hill	Mountain
Farms (n°)	40,408	8,070	9,070	7,286	11,507	4,475	12,670	18,647	9,091
UAA (kha)	1,254	302	244	246	272	190	441	522	291
Added value (MM €)	3,384	846	1,047	531	715	246	1,631	1,226	527
Family labour (kh)	73,115	11,906	18,679	13,780	21,141	7,609	22,515	32,452	18,148
External labour (kh)	23,151	2,395	4,903	2,595	10,837	2,421	11,297	8,767	3,088
Feeds (ktons)	2,076	830	821	159	204	62	1,378	486	213
Total Water (kmc)	360,250	115,756	100,728	23,009	86,653	34,104	245,474	79,268	35,507
Groundwater (kmc)	72,115	5,805	16,096	6,765	35,853	7,596	51,578	17,659	2,879
Mineral fertilizers (tons)	190,190	57,105	57,430	27,638	33,038	14,980	117,111	59,608	13,471
Manure (tons)	253,731	64,507	102,083	20,907	44,362	21,873	125,694	81,767	46,271
Pesticides classified (tons)	4,451	1,891	1,421	359	677	103	2,381	1,565	506
I	445	86	174	86	87	13	210	210	25
II	842	142	477	77	132	14	380	251	210
III - IV	3,165	1,664	771	196	458	76	1,790	1,104	271
Pesticides unclassified (tons)	4,802	2,758	768	437	706	132	3,588	1,044	170

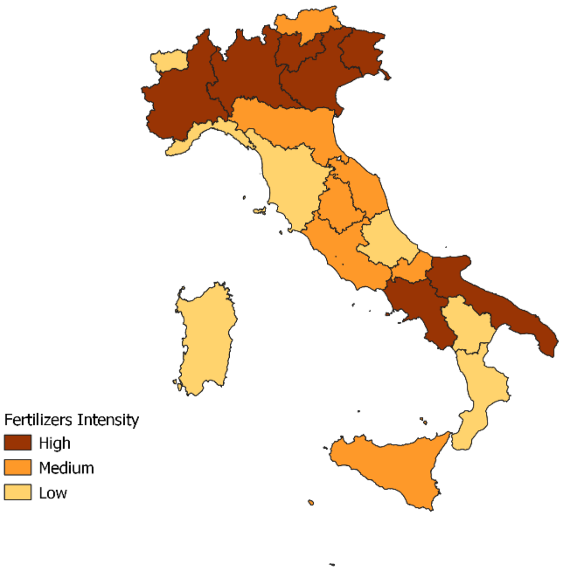
The percentages of observed family work employment are roughly in line with the percentage of the number of farms, thus denoting a substantial homogeneity of hours per farm (h/farm) in the various territories.

The presence of livestock obviously conditions the purchase and use of feed, which is concentrated for 80% in Northern Italy, where about 72% of the livestock units (LSU) are located, and for 66.4% in the lowland areas, where about 63% of LSU are raised. Also, for these productive factors, the use in the lowlands is much more intensive than in the hills and mountains.

The use of water in the entire sample reaches 287 m3/ha, with average values of 396 m3/ha in Northern Italy and 557 m3/ha in the plains. Of this total, the groundwater use in the entire sample is 58 m3/ha (20% of the total), with average values of 132 m3/ha in Southern Italy and 117 m3/ha in the plains (41.4% and 21% of the respective totals).

The use of mineral fertilizers and manure reaches values of 52 kg/ha and 202 kg/ha respectively on the whole sample. However, there are very marked differences compared to the average, since in the Northeast the applications of fertilizers reach 235 kg/ha, while the use of manure reaches 418 kg/ha. In the plains, these applications reach respectively 266 kg/ha and 285 kg/ha. The FADN database distinguishes pesticides on the basis of their degree of toxicity: the group of classified pesticides includes very toxic and toxic (I), harmful (II) and irritants (III and IV); then there is the whole group of unclassified (0). It is interesting to note that the overall physical use of classified and unclassified pesticides is basically the same, while irritants are prevalent among the former, while very toxic and toxic have a limited weight.

Figure 1 shows the intensity of chemical inputs used for the various Italian regions. The data used are the quantity per hectare of fertilizers and pesticides and these variables were associated with the 21 Italian regions (Coordinate Reference System: WGS84 / UTM zone 33N) in order to obtain thematic maps. For each variable analysed, the values were divided into 3 quantiles (or tertiles) within each of which there are 7 regions. A low intensity of chemical inputs used is represented with the lighter colour, and vice versa (a higher intensity with the darker colour).



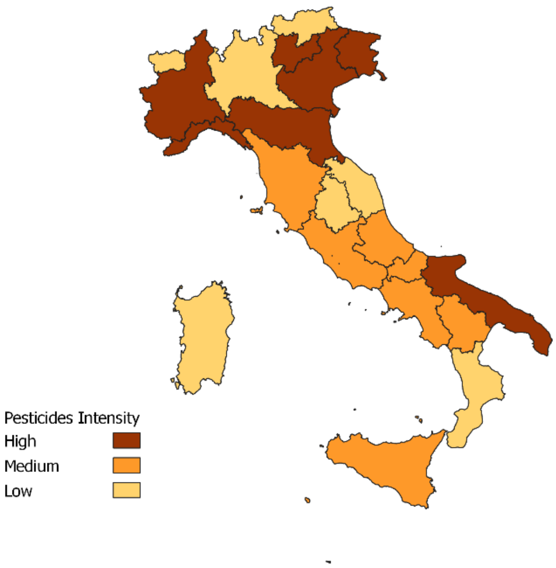


Figure 1: Use of fertilizers and pesticides (quantity per hectare) in the Italian regions.

In other words, the average use per hectare of fertilizers and pesticides was calculated for each region, and three groups of seven regions were obtained based on the average use. Therefore, in the first group (darker colour) there are the seven regions that have higher values, while in the third group (lighter colour) there are the regions that have lower values, passing through the group of seven regions that have intermediate values.

In general, the regions that have a greater intensity of chemical inputs used are the regions of Northern Italy and as regards Southern Italy, Campania and Puglia. Table 1b shows the crop and animal production, distinguishing for tons of crops sold and reused, tons of milk, and number of heads of livestock raised for meat. It can be noticed that more than 55% of the wheat, fresh fruit, tubers and roots produced for sale come from Northern Italy and more than 60% from the plains.

Table 1b. Plant and animal production in Italy and for geographical area and altimetric level.

		Total	Northwest	Northeast	Central	South	Islands	Plain	Hill	Mountain
Sold crops (ktons)	Grain	2,409	898	739	441	267	65	1,549	769	91
	Fresh fruit	1,930	377	694	162	574	123	1,166	470	294
	Grapes	743	72	279	98	204	90	309	396	39
	Tubers and roots	567	37	351	17	154	7	377	59	131
	Leafy vegetables	238	24	29	38	146	2	74	88	77
	Olives	211	8	1	36	150	16	65	121	26
	Dried fruit	19	5	2	6	5	2	3	14	2
Reused crops (ktons)	Silage	1,404	382	511	91	299	122	1,087	242	75
	Hay	934	224	279	150	163	118	295	339	300
	Pasture	537	115	22	66	134	200	29	204	304
	Grain	314	167	81	27	29	10	226	69	18
Milk (ktons)	Bovine	1,408	495	527	114	168	105	765	325	317
	Buffalo	76	0	0	8	68	0	47	27	2
	Sheep	76	1	0	27	6	42	12	52	12
	Goat	7	2	1	0	1	3	1	3	3
Meat (kn°)	Poultry	9,569	646	6,159	516	1,380	868	3,922	5,074	573
	Swine	3,001	2,255	491	172	37	47	2,605	344	53
	Bovine	580	217	183	56	63	60	294	156	130
	Sheep	324	18	10	102	104	90	27	179	118

The grapes are obtained mainly in the north (47.3%) and in the South of Italy (39.6%), in the hills (53.2%) and in the plains (41.6%). Much of the production of leafy vegetables (62.1%) and olives (78.7%) is concentrated in Southern Italy and the Islands. Olives are mainly produced in the hills (57.2%), while the production of leafy vegetables is divided almost equally between the three altimetric levels. The production of dried fruit is also distributed in almost equal parts between North, Center, South Italy and the Islands, and is concentrated in the hilly areas (73.4%). Most of the crops reused in farm activity are produced in Northern Italy (63.6% silage and 78.9% wheat) and in the plains (over 70%). Hay production is more or less equally divided between Northern Italy (53.9%) and Central South (46.1%) and between the three altimetric levels. Grazing is mainly practiced in southern Italy (including the islands) with a percentage of 62.3%, and in the mountains (56.6%). 90% of the milk produced in Italy is from cows: 72.6% of it is obtained in Northern Italy and 54.3% in the plains. 89% of buffalo milk is produced in Southern Italy and about 62% in the plains. More than half of sheep's milk (54.7%) is obtained in the Islands but production in the Center is also large (35.8%). 68.4% of this milk is obtained in the hilly areas. Finally, goat's milk is mainly produced in the South (52.3%) and Northern Italy (41.2%) and in the mountain areas (45.5%).

As regards the number of heads of meat, poultry, pig and cattle farms are concentrated in Northern Italy with percentages higher than 69% and reach 91.5% in the case of pigs. As for the altimetric areas, 86.8% of pigs and 50.7% of cattle are raised on the plain; the rest of the cattle are divided between hills and mountains. Poultry are raised in the hills (53%) and in the plains (41%). Finally, sheep are mainly raised in the South (59.8%) and in Central Italy (31.5%), especially in the hilly areas (55.2%) and in the mountains (36.3%).

3.3.2. AGRITALIM model

The AGRIcultural TerritoriAL tIme econoMic (AGRITALIM) model is an agro-economic supply model that represents the entire FADN sample of Italian farms in various years (2015, 2016, 2017, 2018), distinguishing by geographical areas (NUTS-1 NUTS-2, NUTS-3) and altimetric levels (plain, hill, mountain). The model is calibrated using the Positive Mathematical Programming (PMP) approach (Arfini and Paris, 1995; Howitt, 1995; Paris and Howitt, 1998; Heckelei and Wolff, 2003; Cortignani and Severini, 2012; Heckelei et al., 2012; de Frahan, 2016). This approach not only automatically and exactly calibrates the model to observed activity levels, but also avoids adding ad-hoc constraints and over-specialised responses of the model to policy changes. As all economic models represented with mathematical programming, there are certain methodological limitations that need to be considered when introducing explicit technologies and management practices: without data on the current adoption of these technologies and practices, the calibration of the model becomes challenging, and zero adoption has to be assumed in the baseline.

The model uses a large part of FADN data concerning economic, financial, productive, market, political, and structural aspects. This allows for carrying out different types of analysis as regards the farm's choices induced by agricultural and environmental policy, market conditions and climate change, and use of resources such as, for instance, irrigation water management. The model has some dynamic elements, as can consider structural changes (e.g., tree crops, number of animals and related areas) by way of the annualization of the investments made (depreciation rates).

The general mathematical representation of the AGRITALIM model is shown in the Appendix.

To follow, the main components and fundamental characteristics of the objective function (Table 2) and constraints (Table 3) are shown.

The model maximizes the operating income of the various farms, considering elements of the market (prices of outputs and inputs), production function (quantities of yields and inputs), agricultural policy, and depreciation costs (Table 2).

Table 2. The main components of the objective function: are parameters (market, production function, policy) and variables.

Components	Market	Production function	Policy	Variables
Gross Saleable Production - crops	prices	yields		hectares of crops
Gross Saleable Production - animals	prices	yields		number of animals
CAP coupled payments			payments	hectares of crops, number of animals
CAP decoupled payments			payments	
Complementary activities	total revenues			
Variables cost - crops	prices	quantities		hectares of crops
Variables cost - animals	average costs			number of animals
External labour	prices			hours of labour
Feed purchased	prices			quantity of feed
Pumped water	prices			quantity of water pumping
Depreciation rates observed	costs			
Depreciation rates - tree crops	costs			an additional area of tree crops
Depreciation rates - animals	costs			additional area of stables and facilities

Model variables include crop hectares, number of animals, hours of labour, quantities of feed, water pumped from wells, additional areas of tree crops, and additional areas of stables and structures.

The costs related to the additional depreciable capital (tree area, stables and animal facilities) are annualized in the objective function as depreciation costs. The latter is obtained by dividing the replacement value of those depreciable capitals by the years of their technical duration indicated by the FADN. For tree crops, it is assumed that the variation of the surface involves investments both in the planting of orchards and in harvesting machinery. The variation in the size of herds and flocks is associated with investments in stables and farming facilities.

The model is subject to different types of constraints (Table 3) concerning land, labour and water availability, tree crops area (including the additional area), stables and facilities area (including the additional area), animal nutrition (in terms of the ratio between reused crops and animals) and ratios between categories of animals (productive and not).

Table 3. Structure of the constraints: left-hand and right-hand sides, involved variables.

Types	Matrix coefficients	Availabilities	Variables
Land		farmland	hectares of crops
Labour	manual and mechanical labour needs	family labour, permanent employment temporary employment, external labour	crops (hectares), animals (number), external labour (hours)
Water	water needs	WUA, natural, artificial, pumped waters	crops (hectares), quantity of water pumping
Tree crops		tree crops area	tree crops (hectares), additional area of tree crops
Stables and facilities	area per animal	area of stables and facilities	animals (number), additional area of stables and facilities
Feeding	feed needs	feed produced on the farm	crops (hectares), animals (number), purchased feed (quantity)
Productive and non-productive animals	ratio		productive and non-productive animals (number)

In other words, the mathematical model maximizes operating income by choosing productive activities (hectares of crops and number of animals) and is constrained by the resource's availability (land, labour, water). As for labour and water, the model allows additional variables (hours of labour and quantity of water pumping). Other variables of the model concern the possibility of purchasing external feeds and additional areas of fixed capital. As for the feed, in fact, the model considers that the animals are fed with crops produced on the farm and with feed purchases on the market.

The additional areas of tree crops and animals are possible in the simulation phase, to foresee some expansions in terms of farm structures; if this occurs, additional depreciation rates are considered in terms of costs. The calculation of the operating income considers elements of the market, production function and policy. Market prices refer to animal and vegetable products, to some crop production inputs (e.g. fertilizers and pesticides), and to all the additional variables purchased on the market (labour, feed, water). Production functions consider relationships between quantities of output and inputs used. For some production activities is not possible to distinguish between price and quantity, and the average cost is used (e.g., for animals). The quantities of inputs needed per unit of production activities (matrix of technical coefficient) are used in the specification of the constraints and determine the needs in terms of land, labour, water, feeding and structures. Total needs must respect resource availability, with the possibility of additional variables.

3.3.3. Simulated scenarios

Table 4 reports the simulated scenarios which consider the obligation to reduce the use of chemical inputs (20% of fertilizers and 50% of pesticides) and apply it as a maximum constraint at a single farm level. To manage the reduction of pesticides, the various toxicological classes involved were considered. Specifically, two scenarios were considered. The Sim1 scenario acts only on chemical fertilizers, reducing the possible use at the farm level by 20% compared to the baseline, and the Sim2 scenario also considers the reduction of pesticides classified as very toxic, toxic and harmful. The scenario regarding pesticide reduction alone is not relevant in terms of the results and information to be provided. From the point of view of the mathematical formulation, the constraints are shown in the Annex (A.3. Constraints on use of chemical inputs).

Table 4. Simulated scenarios with a % reduction of chemical inputs.

	Fertilizers	Pesticides
Sim1	20%	0%
Sim2	20%	50%

The simulations carried out have no intention of proposing political actions and measures but to quantify the relevance of chemical inputs for each farm, based on current conditions of the market, political framework and technologies.

The scenarios were chosen to distinguish the impact of fertilizers and pesticides, considering that the productivity of chemical inputs is different for the various cropping activities. In general, fertilizers have lower productivity in less profitable crops, and the pesticides are especially essential to obtain high-income crops (e.g., fruit and vegetables

The impacts are evaluated in terms of some economic, environmental and social indicators (e.g., added value, income, uses of mineral fertilizers and pesticides, family and external labour), land use and production quantities of crops, milk and meat. Generally, a worsening of socio-economic results and an improvement of environmental ones are expected. This general trend could differ for the various geographical areas considering the different levels of agricultural practices intensity.

3.4. Results

This section describes the results of the simulations under the two scenarios of reduction in the use of chemical inputs. The impacts are presented in terms of variation in the resources and use of inputs, and vegetables/animal production, over the baseline values, reported in Tables 1a and 1b. The impacts are shown and discussed for total area and, as regards the Sim2 scenario, by geographical area and altimetric level. The presentation of the results will first concern the impacts on the of resources and use of inputs, then move on to the impacts on production activities.

Furthermore, the impacts on operating income are shown, both for the total and for size classes (UAA and economic). The section ends with some simulation results shown on maps, regarding the use of nitrogen, income and total labour hours.

3.4.1. General impacts on resources and use of inputs

The Sim1 scenario requires reducing the farm use of mineral fertilizers by 20%. Table 5a shows that this restriction modifies the production activities, also leading to a reduction in the use of pesticides, -9.5% for classified and -12.2% for unclassified, and in the use of manure, -6.3%. Evenly, Sim2 simulation that also reduces the use of very toxic, toxic and harmful pesticides by 50%, affects the use of all the other chemical inputs. In fact, there is a 19.4% decrease for irritating pesticides that, combined with the 50% cut for toxic and very toxic, reduces of 28.4% the whole use of classified pesticides. Also, there is a 13.1% decrease for unclassified pesticides, a 25.0% reduction for mineral fertilizers and 13.0% for manure. This occurs because crops require different chemical inputs at the same time, and therefore the reduction in the use of one input affects the cultivation activity, and indirectly the other inputs. To consider that the productivity of chemical inputs is different for the various cultivation activities, and in general, fertilizers have lower productivity in less profitable crops, and pesticides are especially essential to obtain high-income crops (e.g., fruit and vegetables). This involves a differentiated reduction for the various chemical inputs.

Table 5a. Impacts on resources and use of inputs for the total area (Sim1 and Sim2 scenarios) and at the geographical area and altimetric level (Sim2 scenario). Percentage variations with respect to baseline.

	Sim1	Sim2	Northwest	Northeast	Central	South	Islands	Plain	Hill	Mountain
UAA	-4.7	-7.6	-8.7	-9.3	-7.6	-7.7	-3.7	-11.6	-7.0	-2.7
LSU	0.0	-0.1	1.0	-0.6	0.0	-2.4	-2.1	-0.1	-0.5	0.4
Added value	-2.1	-5.3	-3.6	-5.9	-5.0	-6.7	-5.5	-4.6	-5.9	-6.0
Family labour	-2.8	-6.7	-7.3	-8.0	-7.9	-5.2	-4.8	-7.6	-7.0	-5.2
External labour	-12.9	-26.2	-23.6	-32.6	-28.8	-24.4	-21.2	-24.0	-27.7	-29.9
Feeds	4.1	5.9	6.6	4.8	3.9	8.7	5.2	6.7	3.4	5.8
Water use	-8.6	-14.8	-12.1	-15.1	-17.7	-16.4	-17.6	-15.9	-14.4	-8.4
Water pumping	-7.8	-15.6	-16.3	-8.9	-12.4	-18.1	-20.2	-15.1	-16.6	-16.8
Mineral fertilizers	-20.0	-25.0	-23.9	-27.0	-22.7	-25.5	-24.9	-24.9	-24.7	-27.1
Manure	-6.3	-13.0	-15.9	-16.0	-7.8	-5.5	-11.0	-13.9	-11.0	-14.0
Pesticides classified	-9.5	-28.4	-26.5	-32.0	-27.2	-27.8	-25.0	-29.0	-25.1	-36.1
Pesticides unclassified	-12.2	-13.1	-16.2	-9.3	-6.7	-8.9	-14.4	-14.6	-9.2	-4.6

The impact also transfers to the use of other resources and farming productive factors. The UAA decreases -4.7% in Sim1 and -7.6% in Sim2, and the impact is greater in areas where intensive agriculture is conducted, such as Northeast (-9.3%), Northwest (-8.7%), and plain (-11.6%). Appreciable reductions also affect the use of family and external labour. Generally, the model simulations reduce external labour more than family labour since it determines an explicit cost for the maximization process. Thus, the hours of family work employed decrease from -2.8% for Sim1 to 6.7% for Sim2 and, yet, the hours of external work collapse to -26.2% in Sim2. The reduction in labour hours is observed in all territories, reaching -8.0% for family labour and -42.2% for external labour in the Northeast.

Overall, the irrigation water use is reduced. In the less restrictive scenario, Sim1, the use of total water and groundwater is reduced by similar percentages, -8.6% vs. -7.8%. With the most restrictive simulations groundwater suffers the higher percentage reductions, -15.6% vs -14.8% for the total water use. In particular, in Sim2 the reductions in the use of irrigation water in the lowland areas, as well as in the geographic areas, are around 16%; only in the North West, the use of water decreases by 16.5%. Considering the absolute values, the reductions in groundwater use are observed in Southern areas (-20.2%) and in the lowland areas (-15.1%).

Finally, it should be noted that the LUS remains almost constant: this requires increasing feed purchases which grow by 4.1% in Sim1 and 5.9% in Sim2. In the last simulation, the increase is essential in all territories to maintain the number of LSUs especially in northern Italy (6.6% and 4.8%) where most of the breeding is concentrated.

The impact on added value is determined by the compression of production activities, although partly balanced by the reduction in costs due to the lower use of the various production inputs. The result is a progressive decrease in the added value, from 2.1% to 5.3% proceeding from Sim1 to Sim2. The impact on added value is more intense in areas where there are fewer choices among crop and livestock production options (hill 5.9% and mountain 6.0%).

3.4.2. Impacts on agricultural production and income

The decrease in sold crops affects all geographic areas (Table 5b). The greatest reductions occur in the plain areas (all with percentages lower than -12.8%) and then in the hills (lower than -9.4%); in the mountains the impacts are more contained apart from fresh fruit (-20.4%) and grapes (-19.8%) that especially involve the production of apples in Trentino-Alto Adige and grapes in Toscana.

Also reused crops suffer major decreases for silage and grain, varying from -7.0% to -16.2% in the various scenarios: silage is reduced by 21.5% in the Islands, by 14.5% in the South and by 10.6% in the Center. Grain decreases by about 17.0% in Northern Italy and 14.9% in the South. Hay and pasture especially grow in Northern Italy and in the Centre, and all these increases occur mainly in the lowlands: 1.7% and 3.7% respectively.

Table 5b. Impacts on vegetable and animal production for total area (Sim1 and Sim2 scenarios) and at geographical areas and altimetric levels (Sim2 scenario). Percentage variations with respect to baseline.

	Sim1	Sim2	Northwest	Northeast	Central	South	Islands	Plain	Hill	Mountain
Grain	-10.8	-15.1	-15.3	-16.0	-15.2	-12.1	-13.8	-16.0	-13.4	-13.3
Fresh fruit	-7.1	-16.0	-11.9	-15.2	-18.7	-18.2	-19.4	-14.7	-16.6	-20.4
Grapes	-5.8	-15.4	-16.9	-16.9	-9.7	-17.3	-11.6	-14.4	-15.8	-19.8
Tubers and roots	-4.9	-12.5	-14.4	-12.5	-28.1	-10.4	-14.2	-13.1	-15.4	-9.5
Leafy vegetables	-3.6	-11.1	-8.2	-12.6	-13.2	-10.7	-11.2	-12.8	-9.8	-10.8
Olives	-4.0	-10.7	-15.0	13.2	-7.4	-11.7	-8.3	-16.1	-9.4	-3.1
Dried fruit	-3.9	-17.0	-24.4	-26.9	-22.0	-6.1	-2.5	-14.8	-19.5	-4.0
Silage	-7.0	-11.8	-9.4	-9.8	-10.6	-14.5	-21.5	-12.1	-10.7	-10.7
Hay	-1.0	-0.4	0.8	0.9	0.8	-3.2	-3.4	1.7	-1.3	-1.4
Pasture	0.9	1.2	0.4	7.3	1.3	0.4	1.5	3.7	2.0	0.4
Grain	-10.8	-16.2	-17.6	-16.0	-10.9	-14.9	-11.1	-17.3	-13.6	-11.5
Bovine	-0.6	-1.2	-0.4	-0.6	-1.7	0.2	-10.1	-1.9	-0.9	0.0
Buffalo	-4.4	-6.3	0.0	-16.1	0.0	-7.0	0.0	-6.9	-5.7	0.1
Sheep	-0.3	-0.1	14.3	0.7	0.2	0.1	-0.6	-0.8	-0.1	0.8
Goat	0.6	2.9	2.9	13.1	0.6	-0.3	-0.3	14.1	-0.3	1.5
Poultry	0.3	0.4	2.6	0.4	0.6	-0.1	0.0	0.2	0.6	0.0
Swine	1.2	1.2	1.4	0.6	0.3	0.4	0.3	1.4	0.1	0.7
Bovine	-0.6	-0.9	0.2	-2.3	-0.3	0.2	-2.3	-1.9	-0.3	0.7
Sheep	-0.1	0.3	2.3	-0.7	0.2	0.7	-0.5	-0.9	0.3	0.5

The production of buffalo milk decreases considerably (-4.4%, -6.3%) mainly due to a reduction in the geographical area of greatest production: -7.0% in southern Italy, -6.9% in the plains. The production of sheep's milk remains constant, while the production of goat's milk increases (+ 0.6%, 2.9%) especially in northern Italy (2.9% in the north-west and 13, 1% in the north-east) and in the plains (14.1%). There are also differences in the variations of the different meat products: in fact, while bovine production undergoes a slight decline (-0.6%, -0.9%), the other categories of animals remain almost stable, as for sheep, or increase, as for pigs (1.2%). Moreover, poultry increases especially in North West (2.6%), as well as swine (1.4%); beef cattle decrease in North East (-2.3%) and sheep further slightly increase in Southern Italy (0.7%).

Table 5c shows the impact on operating income in the various simulations, both in total terms and by size classes of farms. Overall, the reduction of income is equal to -2.2% and -6.1% in the two scenarios, which determine a reduction per hectare respectively equal to 31 and 86 €/ha (not shown in the table). For some types of farming, the impact is more negative. In the Sim2 scenario, for specialist horticulture and permanent crops, it is greater than 10%. Moreover, the most impacted farms are small ones both in terms of UAA (-12.4%) and Economic Size (-11.1%).

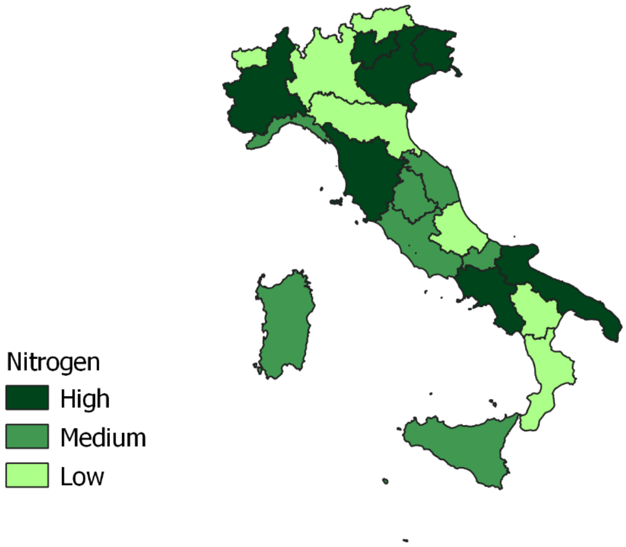
Table 5c. Impacts on operating income for total sample, types of farming and size classes (Utilised Agricultural Area and Economic Size). Baseline values are expressed in € million; simulated scenarios (Sim1 and Sim2) are percentage variations with respect to the Baseline.

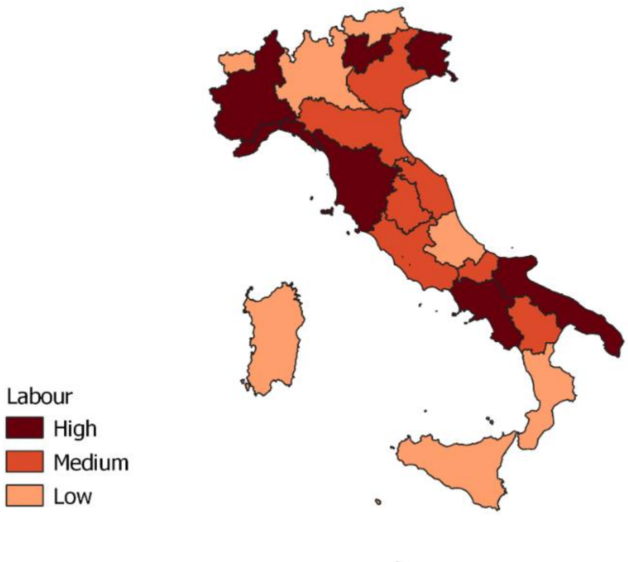
	Baseline	Sim1	Sim2
Total sample	2,189	-2.2	-6.1
Types of farming:			
Specialist field crops	407	-2.4	-5.8
Specialist horticulture	131	-2.1	-11.2
Specialist permanent crops	551	-5.7	-14.1
Specialist grazing livestock	580	-0.8	-2.1
Specialist granivores	352	-0.5	-1.1
Mixed cropping	83	-1.7	-7.2
Mixed livestock	20	-1.0	-1.8
Mixed crops-livestock	66	-1.2	-3.3
Size class – Utilised Agricultural Area:			
<5 ha	185	-3.2	-12.4
5-15 ha	401	-3.3	-8.8
15-40 ha	501	-2.1	-5.5
>40 ha	1,102	-1.7	-4.3
Size class – Economic Size:			
Small	68	-3.4	-11.1
Medium	441	-3.5	-9.1
Large	1,680	-1.8	-5.2

3.4.3. Impacts in the Italian regions.

In this paragraph, some simulation results are shown on maps, using the QGIS software. In general, a Geographic Information System is used to study of space-time phenomena and allows to analyze and represent data by associating them with their geographical position on the Earth's surface.

The variables used are the percentage changes observed in the Sim2 scenario regarding the use of nitrogen, income and total labour hours. These variables were associated with the 21 Italian regions (Coordinate Reference System: WGS84 / UTM zone 33N) in order to obtain thematic maps. For each variable analyzed, the values were divided into 3 quantiles (or tertiles) within each of which there are 7 regions. A low intensity of the phenomenon is represented with a lighter colour, and vice versa (a higher intensity with a darker colour). In other words, the lighter colour means a lower percentage change, while the darker colour a greater percentage change. In other words, the percentage change (of nitrogen use, income level and hours of labour) observed in the Sim2 scenario was considered for each region, and three groups of seven regions were obtained based on the percentage change values. Therefore, in the first group (darker colour) there are the seven regions that have higher percentage variations, while in the third group (lighter colour) there are the regions that have lower percentage variations, passing through the group of seven regions that have intermediate percentage changes.
Comparing these results with the maps in Figure 1, note that the greatest reductions in nitrogen use tend to occur in regions where the average use per hectare of chemical inputs is higher. As regards the three maps in Figure 2, a relationship between the use of nitrogen, income and labour is observed. In fact, in general, larger reductions in nitrogen use also determine larger reductions in income and labour. In summary, also analysing the individual regions emerges that the Farm to Fork strategy could have positive impacts from an environmental point of view, but at the same time have a negative impact on income and labour.


Nitrogen
High
Medium
Low


Labour
High
Medium
Low

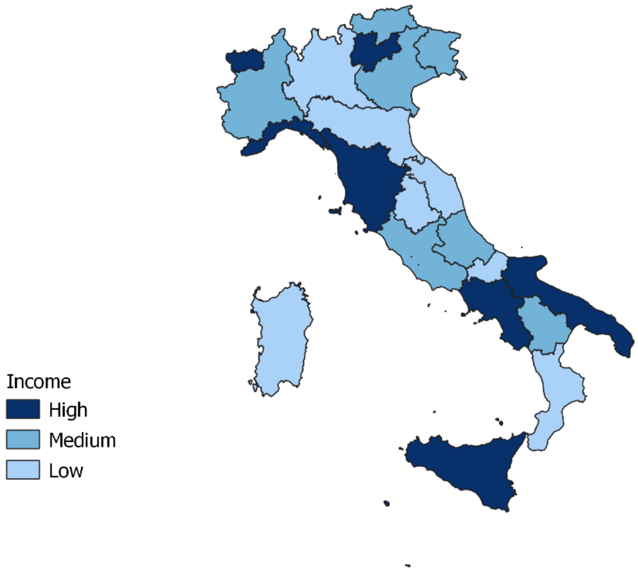


Figure 2: Impacts in Italian Regions in terms of nitrogen, income and labour.

3.5. Discussions

The obtained results offer many insights for discussions on agricultural production, input use and environment, and economic aspects. However, some characteristics and limitations of economic modelling must be highlighted.

3.5.1. Agricultural production

In line with our results, recent studies show that the targets set by the Farm to Fork strategy could lead to a reduction in agricultural production in the short and medium term (Beckman et al., 2020; Noleppa and Cartsburg, 2021; Barreiro-Hurle et al., 2021). The downsizing in the local product availability could greatly reduce the operations of key Italian agro-food chains, reducing economies of scale and agglomeration and increasing the risks of supply chain management. There is a wide literature on these aspects and among the main risks of managing commercial chains are the inadequacy of production or processing capacity, the variability of production levels, and the lack of certain inputs (Manuj and Mentzer, 2008). All these risks increase if supply is reduced and the ability to control the quality and quantitative availability decreases. Moreover, the reductions in agricultural production could generate major problems for Protected Designations of Origin (PDOs), whose specifications being stringent in linking the brand to local production prevent the replacement of the latter with sources from other areas.

Coming to livestock production, milk and beef do not suffer significant reductions, thanks to the increase in the purchase of feed. Yet, problems with the feed supply and a possible increase in their prices could lead to different results. Furthermore, feed purchases would increase in all areas of the national territory, therefore, imports and transport by ship and road would be necessary to reach the various areas. This will have costs that could increase feed prices or make it more difficult to supply, especially in some areas. Encouraging local production of protein forage crops could be of primary interest to help farmers depend less on purchased feed, provide agronomic benefits to farming systems and increase EU protein self-sufficiency (Carof et al., 2019). The mentioned impacts of our analysis can lead to different geographies of the various types of animal husbandry.

Especially in mixed livestock farms, the reduction in the use of chemical inputs for crops leads to a contraction of the forage area. This determines a reduction of livestock needing greater forage surface (e.g. bovine), and in part, there is an increase in the animals needing less surface (e.g. poultry and swine). Even in some mixed farms, vegetal activity is reduced and is partially replaced by small-sized animals (especially poultry). As for sheep farms, overall changes are very minimal, while the pasture area decreases. This is because, in order to maintain the same number of sheep animals, a greater pasture area is needed which, especially in some areas and in some periods, has a lower productivity than other forage crops.

The use of pesticides, in particular fungicides and insecticides, is essential for the cultivation of tree crops. Some tree crops are more demanding (e.g. fresh and dried fruits, and grapes) and others less (e.g. olive trees). However, even in the case of the olive, especially for the more intensive plants, treatment interventions for diseases are important, and a reduction in the use of pesticides could cause a relevant decrease in production.

3.5.2. Input use and environment

Our results show a link between restrictions on the use of various fertilizers and pesticides, and other factors of production, that reveal cross impacts of reduction and substitution between the various factors. In general, in agreement with Suh and Moss (2021), it can be concluded that the agricultural sector has little flexibility in adjusting the demand for inputs in response to changes in input availability. Yet, substitutable relationships among labor, capital, and intermediate inputs exist, which may reduce the pressures on production levels. For high restrictions use, technical and technological development seems essential to determine an efficient substitution between production factors and, in general, to limit the negative effects in terms of output quantities.

Reductions in the use of chemical inputs occur mainly in plain areas. However, other effects connected with these transformations should not be overlooked. On the one hand, as shown by Beckman et al. (2020), a transfer of environmental impacts to other areas is determined by the increase in the use of their feed production. On the other hand, mainly in areas already with a high production intensity such as the North West plains, the production of poultry and pigs is growing this increases the problems of sewage disposal, even in the face of a reduction in the cultivated area. The intensification of pig production could determine the worsened environmental indicators, in particular, potential losses of nitrogen (Jouan et al, 2020).

Our results on the Italian geographic areas and their altimetric levels suggest that, although attractive, the idea of a system based on simple and uniform mechanisms for the whole territory, which offers appreciable environmental benefits, could be inadequate. Due to the vast diversity of agronomic, environmental and economic conditions across the UE areas, it is impossible to design a set of simple rules that are universally applicable to the whole territory. Efficient environmental management requires place-specific adjustment, or spatial targeting, which is the diametric opposite of universal rules (Brady et al., 2017).

3.6. Socio-economic and political issues

The economic results show that any monetary support of the agricultural policies, defined on the basis of lost income, as a whole would involve an acceptable expenditure compared with the available financial resources. Yet, it should be emphasized that this does not apply to some farm types which could be very expensive, in terms of lost income, to comply with environmental standards (e.g. horticultural, permanent). Furthermore, to compensate for these farms, mechanisms should be put in place that include them in EU I pillar policies, where in many cases they are not currently involved in those measures. The policy support should consider the different costs of application (in terms of lost income) in the various territories (as shown in the results) in order to incentivize and adequately support the compliance of environmental policies and achieve the set objectives. This aspect is partly considered in the II pillar measures that differentiate the monetary support per hectare and head by different groups of crops and livestock. Still, additional premiums could be added to the achievement of environmental objectives, based on the different initial conditions. Measures to support eco-efficiency would also be more easily acceptable by policymakers than the imposition of radical measures that reduce farm profitability (Coderoni and Esposti, 2018). Furthermore, considering that the most impacted farms could be the smallest ones, both in terms of surface area and economics, these farms could be exempted from compliance with any environmental rules, as is also the case with greening practices.

From the social point of view, notice that the reduction of labour in agriculture could affect some social categories, and certainly among these immigrants. In fact, agricultural activity, especially in some territories (e.g. south and north-east) is an important source of employment, and therefore of social and economic integration.

3.6.1. Economic modelling

Some characteristics and limitations of the economic model must be listed and discussed to provide insights and improvements to be achieved in the next analyses. First of all, no economic model can be a perfect description of reality, but the very process of constructing, testing, and revising models forces economists and policymakers to tighten their views about how an economy works (Ouliaris, 2011). Additional limitations due to not capturing the full scope of the transition to sustainable food systems promoted by the strategies (e.g. change in the functioning of the value chain, impacts of soil degradation, etc.) also prevent providing a comprehensive assessment of their impacts (Barreiro-Hurle et al, 2021).

The model is based on income maximisation, and it is well known that many other factors also affect choices, including but not only behavioural ones (Dessart et al., 2019). In the analysis presented, the farm choices are based on economic objectives, not on specific recommendations on maximising social and environmental benefits.

As for the simulated scenarios, to consider is the distance from baseline values to aspirational targets. The model is based on the EU mid-term outlook and responds reasonably well to marginal changes in parameters. However, it becomes problematic when these changes are unprecedented. In particular, when the changes have not been observed in the past, the shocks can potentially lead to an over- or under-reaction of the system and frequently require additional judgment. When dealing with systemic changes, other research tools such as foresight and perspective can be used in a complementary manner to inform some of the parameters that could reflect novel practices and business models that could be developed by farmers to adapt to the new sustainable food systems paradigm (Barreiro-Hurle et al, 2021).

3.7. Conclusions

This analysis highlighted different aspects of Italian agriculture which should act on the European strategy called Farm to Fork and, in particular, focused on the influence of chemical inputs on agricultural production. The estimated impacts show possible trends and changes in the use of production factors, in agricultural production, in economic results, and can provide useful information to decision-makers in terms of political choices regarding environmental targets and economic measures. In fact, the achievement of an environmental target could impact differently on the various farms considering the different structural, economic, technical-productive and managerial characteristics. Consider also that the various territories have different relationships between production activities and the use of resources. Our analysis does not consider aspects regarding innovation that could improve productivity in agriculture, and therefore, obtain the same quantity of output but with a lower use of production inputs, including chemical ones. Specifically, in the case of technological innovation, waste can be reduced, and the efficiency of production inputs can be improved. The genetic improvement over the past 20 years has allowed to use of natural resources (e.g. soil) in a more sustainable way and not depend totally on imports from other countries (Noleppa and Cartsburg, 2021). Therefore, in general, innovation seems fundamental to achieving the environmental targets of the Green Deal and Farm to Fork strategy and to producing satisfactorily within the European Union.

The reduction of domestic production (in Italy and in Europe in general) could relocate more intensive and polluting agricultural production to other parts of the world (Fuchs et al., 2020).

To avoid this, in the coming years, European agriculture is challenged to achieve environmental objectives without affecting agro-food production. Agricultural sustainable intensification is needed to tackle food insecurity and global change. Local environmental conditions determine the needs and potential for increasing the sustainability of farming practices. Yet, the implementation potentials also depend on socio-economic factors, as farmers need to adopt novel practices, and consumer demand affects the economic feasibility (Scherer et al., 2018).

Common Agricultural Policy is prospecting eco-schemes as new instruments to be implemented by Member States to support this transition towards the Green Deal targets. These schemes refer to practices for organic farming, integrated pest management, agroecology, husbandry and animal welfare plans, carbon farming, precision farming, improved management of nutrients, water resources protection, and GHG emissions-related practices. Combining payments and practices should incentivize farms to implement the latter and reduce the use of inputs while preserving farms' income and agro-food production. Still, this challenge is very ambitious and requires modifying the payment calculation system, defining commitments, aid applications, timing for payments and financing, and the management of unused funds.

Some limitations of the analysis should be highlighted. The analysis put forward does not fully capture the underlying drivers of the policy initiatives assessed. The Farm to Fork strategy includes many more targets than those we have selected for analysis, such as the reduction of food waste, the move towards different diets or the demand side promotion of organic and sustainably produced food. In addition, the assumptions about the impacts on farm management and yields of the reduction in chemical inputs use do not capture potential beneficial side-effects on agricultural production and beyond (e.g. health benefits).

The model is not comprehensive in the representation of technologies and farm practices. There are many more technologies and farm practices that could be included, which could contribute to achieving the objectives while minimising the impacts on production. In any case, there are certain methodological limitations that need to be considered when introducing explicit technologies and management practices within an economic model: without data on the current adoption of these technologies and practices, the calibration of the model becomes challenging (and zero adoption has to be assumed in the baseline).

The impact on the livestock sector is underestimated as the reduction of antimicrobials is not considered, and no limits are imposed on the purchase of feeds on the market, which already currently sees a large deficit between internal production and needs. Moreover, the representation of the livestock sector should also be improved if we want to capture the impacts of enhanced animal welfare levels and different production systems and the potential changes towards organic or more extensive livestock production methods. These production methods could accelerate the transition towards sustainable food systems.

Lastly, the changes in the levels of European agro-food production can have notable impacts on the international market and on product prices (Beckman et al., 2020).

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3.8. References

Angenendt E., Poganietz WR., Bos U., Wagner S., Schippl J. (2018) Modelling and Tools Supporting the Transition to a Bioeconomy. In: Lewandowski I. (eds) Bioeconomy. Springer, Cham. https://doi.org/10.1007/978-3-319-68152-8_9

Arfini, F. and Paris, Q. (1995). A positive mathematical programming model for regional analysis of agricultural policies, In The Regional Dimension in Agricultural Economics and Policies, EAAE, Proceedings of the 40th Seminar, Ancona (Italy), June 26–28 1995.

Alexander P., Reddy A., Brown C., Henry R.C., Rounsevell M.D.A. (2019). Transforming agricultural land use through marginal gains in the food system, Global Environmental Change 57 (2019) 101932, https://doi.org/10.1016/j.gloenvcha.2019.101932

Balezentis T., Chen X., Galnaityte A., Namiotko V. (2020). Optimizing crop mix with respect to economic and environmental constraints: An integrated MCDM approach, Science of the Total Environment 705 (2020) 135896

Barreiro-Hurle, J., Bogonos, M., Himics, M., Hristov, J., Pérez- Domínguez, I., Sahoo, A., Salputra, G., Weiss, F., Baldoni, E., Elleby, C. 2021. Modelling environmental and climate ambition in the agricultural sector with the CAPRI model. Technical report by the Joint Research Centre (JRC), Publications Office of the European Union, 2021.

Beckman J., Ivanic M., Jelliffe J.L., Baquedano F.G., Scott S.G. (2020). Economic and Food Security Impacts of Agricultural Input Reduction Under the European Union Green Deal's Farm to Fork and Biodiversity Strategies, Economic Research Service - Economic Brief - Number 30, November 2020

Brady, M., Hristov, J., Höjgård, S., Jansson, T., Johansson, H., Larsson, C., Nordin, I., Rabinowicz, E., 2017. Impacts of direct payments – lessons for CAP post-2020 from a quantitative analysis. AgriFood Economics Centre, Report. 2017:2.

Carof, M., Godinot, O., Ridier, A., 2019. Diversity of protein-crop management in western France. Agronomy for Sustainable Development (2019). 39, p. 15. https://doi.org/ 10.1007/s13593-019-0561-7.

Coderoni, S., Esposti, R., 2018. CAP payments and agricultural GHG emissions in Italy. A farm-level assessment. Sci. Total Environ. 627, 427–437.

Cortignani R., Severini S. (2012) "A constrained optimization model based on generalized maximum entropy to assess the impact of reforming agricultural policy on the sustainability of irrigated areas". Agricultural Economics, 43(6) 621-633, November 2012, ISSN: 0169-5150, online ISSN: 1574-0862

de Frahan, B.H., Buysse, J., Polomé, P., Fernagut, B., Harmignie, O., Lauwers, L., Van Huylenbroeck, G., Van Meensel, J. (2016). Positive mathematical programming for agricultural and environmental policy analysis: review and practice, International Series in Operations Research and Management Science, Vol. 99, pp. 129-154.

Dessart, F., Barreiro-Hurle, J., van Bavel, R. 2019. Behavioural factors affecting the adoption of sustainable farming practices: a policy-oriented review. European Review of Agricultural Economics 46(3): 417-471.

European Commission, 2019. The European Green Deal. Brussels, COM/2019/640 final, https://ec.europa.eu/info/strategy/priorities-2019-2024/european-green-deal_en

European Commission, 2020. Farm to Fork Strategy—For a Fair, Healthy and Environmentally-Friendly Food System, COM/2020/381 final, https://ec.europa.eu/food/farm2fork_en

European Commission, 2022, Regulation of the European Parliament and of the Council on the sustainable use of plant protection products and amending Regulation (EU) 2021/2115. Brussels, 22.6.2022 COM (2022) 305 final 2022/0196 (COD)

Fitton N., Alexander P., Arnell N., Bajzelj B., Calvin K., Doelman J., Gerber J.S., Havlik P., Hasegawa T., Herrero M., Krisztin T., van Meijl H., Powell T., Sands R., Stehfest E., West P.C., Smith P. (2019). The vulnerabilities of agricultural land and food production to future water scarcity, Global Environmental Change 58 (2019) 101944, https://doi.org/10.1016/j.gloenvcha.2019.101944

Fuchs R., Brown C., Rounsevell M. (2020). Europe’s Green Deal offshores environmental damage to other nations, Nature Vol 586, 29 October 2020.

Godard, C., Roger-Estrade, J., Jayet, P. A., Brisson, N., & Le Bas, C. (2008). Use of available information at a European level to construct crop nitrogen response curves for the regions of the EU. Agricultural Systems, 97(1), 68-82.

Heckelei, T., Wolff, H. (2003). Estimation of constrained optimisation models for agricultural supply analysis based on generalised maximum entropy, European Review of Agricultural Economics, Vol. 30(1), pp. 27–50.

Heckelei, T., Britz, W. and Zhang, Y. (2012). Positive mathematical programming approaches – Recent developments in literature and applied modelling, Bio-based and Applied Economics, Vol. 1(1), pp. 109–124.

Howitt, R.E. (1995). Positive Mathematical Programming, American Journal of Agricultural Economics, Vol. 77(2), pp. 329–342.

Jouan J., Ridier A., Carof M. (2020). SYNERGY: A regional bio-economic model analyzing farm-to-farm exchanges and legume production to enhance agricultural sustainability, Ecological Economics 175 (2020) 106688, https://doi.org/10.1016/j.ecolecon.2020.106688

Malek Ž.,Verburg P.H. (2020). Mapping global patterns of land use decision-making, Global Environmental Change 65 (2020) 102170, https://doi.org/10.1016/j.gloenvcha.2020.102170

Manuj, I. and Mentzer, J.T. (2008), Global supply chain risk management strategies, Journal of Business Logistics, Vol. 29, No. 1, https://doi.org/10.1002/j.2158-1592.2008.tb00072.x

Montanarella L., Panagos P. (2021). The relevance of sustainable soil management within the European Green Deal, Land Use Policy 100 (2021) 104950, https://doi.org/10.1016/j.landusepol.2020.104950

Noleppa, S., Cartsburg M. (2021). The socio-economic and environmental values of plant breeding in the EU and for selected EU member states, HFFA Research GmbH.

Ouliaris, S. 2011. What are economic models? How economists try to simulate reality. Finance and Development 48(2): 46-47.

Paris, Q. and Howitt, R. (1998). An analysis of Ill-Posed Production Problems Using Maximum Entropy, American Journal of Agricultural Economics, Vol. 80(1), pp. 124-138.

Prudhomme R., Brunelle T., Dumas P., Le Moing A., Zhang X. (2020). Assessing the impact of increased legume production in Europe on global agricultural emissions, Regional Environmental Change (IF 3.481), DOI: 10.1007/s10113-020-01651-4

Scherer L.A., Verburg P.H., Schulp C.J.E. (2018). Opportunities for sustainable intensification in European agriculture, Global Environmental Change 48 (2018) 43–55, https://doi.org/10.1016/j.gloenvcha.2017.11.009

Suh D.H., Moss, C. B., 2021. Examining the Input and Output Linkages in Agricultural Production Systems. Agriculture 11(1):54. DOI: 10.3390/agriculture11010054

3.9. Appendix: Mathematical representation of the AGRITALIM model

A.1. Objective function

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

Operating income = $\boldsymbol{Z}$

Gross Saleable Production = $\mathbf{GPS} = \boldsymbol{pc} * \boldsymbol{yc} * \boldsymbol{XC} + \boldsymbol{pm} * \boldsymbol{ym} * \boldsymbol{XA} + \boldsymbol{revnm} * \boldsymbol{XA}$

CAP payments = $\mathbf{CAP} = \boldsymbol{dp} + \boldsymbol{cpc} * \boldsymbol{XC} + \boldsymbol{cpa} * \boldsymbol{XA}$

Revenues from Complementary Activities = $\mathbf{RCA}$

Variable Costs = $\mathbf{VC} = \boldsymbol{pfp} * \boldsymbol{qfp} * \boldsymbol{XC} + \boldsymbol{acc} * \boldsymbol{XC} + \boldsymbol{aca} * \boldsymbol{XA}$

Quadratic Costs = $\mathbf{QC} = \frac{\mathbf{1}}{\mathbf{2}} \boldsymbol{XC}' \boldsymbol{Q} \boldsymbol{XC} + \frac{\mathbf{1}}{\mathbf{2}} \boldsymbol{XA}' \boldsymbol{Q} \boldsymbol{XA}$

External Labour = $= \mathbf{EXL} = \boldsymbol{ph} * \boldsymbol{XH}$

Feed Purchased = $\mathbf{FP} = \boldsymbol{pf} * \boldsymbol{XF}$

Pumped Water = $\mathbf{PW} = \boldsymbol{pw} * \boldsymbol{XW}$

Depreciation Rates Observed = $\mathbf{DRO}$

Depreciation Rates New Investments = $\mathbf{DRNI} = \boldsymbol{drtc} * \boldsymbol{ADTC} + \boldsymbol{drsf} * \boldsymbol{ADSF}$

Variables

XC = hectares of crops

XA = number of animals

XH = hours of labour

XF = quantity of feed

XW = quantity of water pumping

ADTC = additional area of tree crops

ADSF = additional area of stables and facilities

Market

pc = prices of crops

pm = prices of milk

pfp = prices of factors of production (fertilizers, pesticides)

ph = prices of external labour

pf = prices of feed purchased

pw = prices of water pumped

drtc = depreciation rates of new investments (tree crops)

drsf = depreciation rates of new investments (animals)

Production function

yc = yields of crops

ym = yields of milk

qfp = quantities of factors of production (fertilizers, pesticides)

Common Agricultural Policy payments

dp = decoupled payments

cpc = coupled payments for crops

cpa = coupled payments for animals

Revenues and average costs

revnm = revenues from other animal products no milk (meat, eggs, honey,…)

acc = average costs for crops (per hectare)

aca = average costs for animals (per number)

A.2. General constraints

$$\sum_{j} \boldsymbol{XC_{j,n}} \leq \boldsymbol{ald_n} \quad \forall\, \boldsymbol{n}$$

$$\sum_{j} \boldsymbol{ml_{j,n}} * \boldsymbol{XC_{j,n}} + \sum_{ja} \boldsymbol{ml_{ja,n}} * \boldsymbol{XA_{ja,n}} \leq \boldsymbol{alb_n} \quad \forall\, \boldsymbol{n}$$

$$\sum_{j} \boldsymbol{mw_{j,n}} * \boldsymbol{XC_{j,n}} \leq \boldsymbol{awt_n} \quad \forall\, \boldsymbol{n}$$

$$\sum_{jt} \boldsymbol{XC_{jt,n}} \leq \boldsymbol{atc_n} + \boldsymbol{ADTC_n} \quad \forall\, \boldsymbol{n}$$

$$\sum_{ja} \boldsymbol{msf_n} * \boldsymbol{XA_{ja,n}} \leq \boldsymbol{asf_n} + \boldsymbol{ADSF_n} \quad \forall\, \boldsymbol{n}$$

$$\sum_{ja} \boldsymbol{mf_n} * \boldsymbol{XA_{ja,n}} \leq \boldsymbol{afp_n} + \boldsymbol{XF_n} \quad \forall\, \boldsymbol{n}$$

$$\sum_{jan} \boldsymbol{rc_n} * \boldsymbol{XA_{jan,n}} \geq \sum_{jap} \boldsymbol{XC_{jap,n}} \quad \forall\, \boldsymbol{n}$$

Sets shown in the mathematical representation

j = types of crops

n = farms

ja = types of animals

jt = tree crops

jan = types of animals non-productive

jap = types of animals productive

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, animal production, time

Matrix coefficients

ml = labour (manual and mechanical) needs per each crop and animal

mw = water needs per each irrigated crop

msf = square meter of stables and facilities per animal

mf = feed needs for each animal

rc = ratio between productive and non-productive animals

Availabilities

ald = land availability per farm

alb = labour availability per farm

awt = water availability per each source (e.g. water unit association, well,…) and farm

atc = tree crops area per farm

asf = total square meter of stables and facilities

afp = quantity of feeds produced in the farm

A.3. Constraints on use of chemical inputs

$$\sum_{j,tf} qfp_{j,tf,n} * XC_{j,n} \leq QF_n^0 * 0.8 \quad \forall n$$

$$\sum_{j,tp,tc} qfp_{j,tp,tc,n} * XC_{j,n} \leq QP_n^0 * 0.5 \quad \forall n$$

$$QF_n^0 = \sum_{j,tf} qfp_{j,tf,n} * XC_{j,n}^0 \quad \forall n$$

$$QP_n^0 = \sum_{j,tp,tc} qfp_{j,tp,tc,n} * XC_{j,n}^0 \quad \forall n$$

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

4. Irrigation water economic value and productivity: an econometric estimation for maize grain production in Italy

Following the comprehensive reconstruction of the entire Italian agricultural production system conducted in Chapter 3, the focus has then shifted to specific crops. These crops were selected based on AGRITALIM results, which identified the most vulnerable sectors. Specifically, the previous study highlighted that cereal production appeared to be among the most vulnerable ones. Given that Italy is the fourth-largest European producer and considering its strategic and economic significance for various supply chains, along with its high requirements for inputs such as water and chemicals, maize grain has been selected as the focal crop for this investigation.

Specifically, since AGRITALIM has identified a relationship and influence on other inputs due to the reduction of fertilizers and pesticides, attention has shifted to another critical production factor: irrigation water. In fact, the previous analysis highlighted that a reduction in chemicals leads to a significant decrease in the use of irrigation water, ranging from 8.6% to 14.8%, respectively for a 20% reduction in fertilizers alone and in the case of a 20% reduction in fertilizers and a 50% reduction in pesticides. These impacts undoubtedly stem from a contraction of agricultural land, but also from existing interdependencies among various inputs. Furthermore, considering that the agricultural production process is highly influenced by exogenous factors such as climate, water scarcity may exacerbate this impact, especially in certain regions and during particularly unfavourable years. In other words, despite the increasing demand for irrigation due to rising temperatures and limited precipitation, the climate conditions themselves can reduce the quantity of available water, creating a significant challenge for agriculture (Hristov et al., 2020; Lionello and Scarascia, 2018). This risk is particularly marked in the Mediterranean region, where water deficits have resulted in significant production losses and quality issues in recent years (Mereu et al., 2021).

Considering these challenges, this study embarks on a comprehensive exploration of the role of irrigation water in maize production, assessing its economic relevance and its impact on the productivity of Italian maize grain production, carefully considering its link with other agricultural inputs and consequently exploring the complex dynamics that characterize the agricultural sector. However, understanding how water resources contribute to the production of a single crop involves determining the shadow price of irrigation water, which, under certain assumptions, reflects its marginal productivity. Several methods have been proposed to estimate the shadow price of water, including deductive approaches like the Residual Value Method (RVM) and optimization models, as well as inductive methods primarily based on econometrics (Young, 2005). Deductive methods require strong assumptions, which risk oversimplifying complex economic relationships. In contrast, inductive methods rely heavily on data (both primary and secondary) and offer reliable estimations, particularly through the estimation of production functions. This body of literature largely focuses on estimating the shadow price of irrigation water for river basins (García Suárez et al., 2019; Koundouri et al., 2014; Mesa-Jurado et al., 2010; Williams et al., 2017) or at the national level (Kiani and Abbasi, 2012; Takatsuka et al., 2018; Veninga, 2017) with limited use of detailed microeconomic data to estimate shadow prices for irrigation water at the farm level (Mesa-Jurado et al., 2010). Therefore, while previous studies have estimated irrigation water shadow prices for various crops at the country or river basin level, this study advances the literature by focusing on maize grain production in Italy using detailed microeconomic data at the farm level. The research presented in this study aims to fill this gap and enhance the understanding of the economic importance of irrigation water in agriculture. The methodological approach involves estimating several econometric specifications, including both rigid and flexible production functions, and incorporating climate variables to account for spatial heterogeneity. By providing accurate and up-to-date estimates of the water shadow price and its variability, this study can inform evidence-based water management strategies and identify vulnerable areas or clusters of farms that may be particularly susceptible to water-related challenges. This research is especially relevant in the current context, where there is a significant demand for data-driven water management strategies to identify regions and farms at risk.

Within the broader context of the research agenda, this study effectively addresses two specific research questions:

- **Identify and analyze the relationships among agricultural inputs**: This study is aligned with the first research objective by undertaking a comprehensive reconstruction of the Italian agricultural maize grain production process within the selected sample of farms. To fulfil this objective, an econometric approach is utilized, employing specifications that consider both rigid and flexible production functions. This methodology leverages the panel structure of the FADN data. The empirical specification of these models allows us to not only identify the relevance of the inputs of interest but, in the case of flexible production functions, i.e. translog functional form, to detect substitution effects and interactions among various production factors. This analytical framework provides a nuanced understanding of the intricate dynamics shaping Italian maize grain production, thereby directly addressing the first research objective.
- **Evaluate the relevance and quantify the contribution of irrigation water to crop production:** This work also provides a thorough examination of the economic relevance of irrigation water in the context of Italian maize grain production, a high-water-demanding crop. The core of this

assessment revolves around the estimation of the marginal productivity of this input relying on the production functions' econometric estimation. Under certain assumptions, in the case of water, this value corresponds to its shadow price (Bierkens et al., 2019). By rigorously exploring irrigation water productivity variations across a variety of farm characteristics and areas through quantile regressions, the research identifies clusters of farms and areas where the role of irrigation water in economic viability is most pronounced. This thorough comprehension establishes a strong foundation for assessing vulnerabilities under specific conditions, directly addressing the second research objective.

This research has clarified the intricate dynamics between irrigation water and other inputs, such as fertilizers and labor, in maize grain production. The estimation of the water shadow price has highlighted its economic relevance and heterogeneity, revealing variations based on regional disparities, farm sizes, and irrigation water sources. These findings underscore the importance of tailoring strategies for sustainable water usage practices in agriculture, acknowledging the diverse contexts and characteristics of farms across different areas. The approach proposed in this analysis serves as a preliminary step in evaluating the productivity of this increasingly scarce natural resource and provides a valuable tool for identifying vulnerable areas and those with potential for improvement. This is particularly relevant in the context of policies and strategies aimed at preserving water resources and allocating them efficiently, especially considering that the latest regulation in this regard is the Water Framework Directive (WFD) 2000/60. Moreover, it is important to note that only in some cases have Member States been able to apply it rigorously. For instance, Italy has faced several challenges, especially related to defining access rights to groundwater withdrawals. Given the growing emphasis on water resources, as demonstrated by the European Commission's initiative to transform the FADN into the Farm Sustainability Data Network (FSDN), with a specific focus on water resources in Italy, such analyses are increasingly important. When based on reliable models and data, such as research can make a significant difference in proposing strategies to manage scarce resources efficiently. Furthermore, they can serve as the foundation for further analyses and scenarios characterized by CC, i.e. higher temperatures and lower water availability, or extreme events that threaten agricultural production. Identifying the relevance and productivity of water resources with attention to territorial heterogeneity and the specific characteristics of farms can be an essential and highly precise tool for predicting the impacts of future scenarios and developing policies to address these critical issues. The scientific paper resulting from this study, titled “Irrigation water economic value and productivity: an econometric estimation for maize grain production in Italy,” has been submitted to the journal "Agricultural Water Management.”

Irrigation water economic value and productivity: an econometric estimation for maize grain production in Italy

Rebecca Buttinelli[a], Raffaele Cortignani[b*], Francesco Caracciolo[c]

[a] University of Tuscia, Department of Economics, Engineering, Society and Business Organization (DEIM), 01100 Viterbo, Italy

b University of Tuscia, Department of Agriculture and Forest Sciences (DAFNE) Via San Camillo del Lellis, 01100 Viterbo (VT), Italy. E-mail addresses: buttinelli@unitus.it, cortignani@unitus.it

[c] University of Naples "Federico II", Dept. Agricultural Sciences - Economics and Policy Group, Via Università 96 - 80055 Portici (NA), Italy. E-mail address: francesco.caracciolo@unina.it

[*]Corresponding author at University of Tuscia, Department of Agriculture and Forest Sciences (DAFNE), Via San Camillo de Lellis, 01100 Viterbo, Italy. E-mail address: cortignani@unitus.it (R. Cortignani).

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4.1. Abstract

Climate change, characterized by rising temperatures and limited precipitation, has intensified the demand for irrigation water while simultaneously restricting its availability. This challenge poses significant risks to agricultural and food production, particularly in the Mediterranean regions where, recently, water deficits have led to substantial production losses and quality issues. Water is a critical determinant of crops' economic viability, especially for water-intensive crops, making it essential to estimate its economic relevance, especially in the absence of reliable water market prices. This study has two primary objectives: first, to evaluate the shadow price of irrigation water for maize grain at the farm level, which is defined as the value generated by the marginal unit of water consumed; and second, to analyse its heterogeneity. Leveraging a Farm Accountancy Data Network (FADN) panel of 1,625 Italian farms over a decade (2010-2020), an econometric production function approach is employed. Moreover, quantile regressions reveal variations in the shadow price linked to geographical, managerial, and structural farm characteristics. Our findings underscore water's key role in economically viable maize grain production, significantly enhancing the productivity of other inputs like fertilizers and pesticides. The average shadow price is 0.29 €/m³, with a median of 0.20 €/m³ and water total productivity accounts for one-third of maize's average gross output. Quantile regressions uncover how factors like geographic location, altitude, farm management, irrigation water source, and farm size influence the distribution of water productivity, reflecting either efficient use or scarcity of this resource. Our estimation provides valuable insights for policymakers by offering accurate shadow price estimates for irrigation water in Italian maize grain production. Furthermore, it enhances our understanding of irrigation water's role in the economic viability of this crop, while contributing to support evidence-based water management strategies, identifying vulnerable areas and farms and allowing for future methodological developments.

Keywords: Irrigation water, FADN data, Maize, Production Function, Shadow Price

JEL codes: C23 Q12 Q15

4.2. Introduction

Water is necessary for human existence and a key input for several economic activities, including agriculture, which is crucial for the global food supply (Damania et al., 2020). Population growth, urbanization, and the growing demand for food make water an increasingly scarce resource in several areas of the world. In addition, climate change makes adverse weather events more violent, frequent, and less predictable. This is also true for drought, a threat now spreading to areas that do not usually face precipitation constraints or extremely high temperatures (FAO, 2022). Moreover, water is primarily allocated to industrial and civilian uses in the case of water shortages, leading to losses in irrigated crop yields and revenues. However, the rising temperatures and increasing scarcity of precipitation have led to a greater demand for irrigation water, often making groundwater recharge insufficient to counterbalance extractions (Wada et al., 2010). In this scenario, agriculture accounts for 72% of global water extractions and represents 70% of extractions in Mediterranean areas (Berbel et al., 2019; FAO, 2022).

Policies and institutions have failed to face these human and economic implications in the past, and even today, water management policies are struggling to address this complex scenario[3]. In recent decades, the European Union has attempted to promote the rational use of water resources among its Member Countries. One of the fundamental approaches used in this regard has been the adoption of the Water Framework Directive (WFD), which aims to encourage efficient water use through economic incentives such as Full Cost Recovery (FCR)[4] and the "polluter pays" principle. In 2015, Italy took a step further by introducing mandatory measurements and estimations for irrigation volumes and environmental and resource-related costs associated with such activities. However, the number of countries in which water pricing meets the requirements set out by the WFD remains relatively low, with most countries, including Italy, failing to fully comply with these principles (Zucaro, 2014).

[3] Indeed, water has commonly been considered a renewable resource. However, at the International Conference of Water Environment in 1992, it was admitted that the failure to acknowledge the economic value of water has led to waste and inefficient use of this resource (ICWE, 1992).

[4] WFD makes of FCR principle one of its pillars: in Article 9 it is stated that Member States must take account of the principle of recovery of the costs of water services, including environmental and resource costs in accordance with the "polluter pays" principle. This, with the aim to provide an adequate incentive for users to use water resources efficiently. This incentive had to be given through the adoption of effective economic instruments of pricing, and, as underlined by Gallego-Ayalal et al. (2011), volumetric pricing has primarily been seen as the most suitable tool, since accurate water-metering is considered a necessary condition to estimate appropriate costs for water usage in agriculture. See Berbel and Expósito (2020) for an overview on WFD water pricing and cost recovery.

In fact, in certain areas, especially where volumetric tariffs are not applied and where metering is not adopted, the quantification of irrigation volumes poses the most significant challenge when analysing water consumption in agriculture. Giannoccaro et al. (2020) highlighted that in Italy, defining access rights to groundwater withdrawals and managing asymmetric information and free riding is a complex matter. Introducing pricing mechanisms and FCR measures, as highlighted by Berbel et al. (2019) and Galioto et al. (2017), is also an ambitious objective that requires the knowledge of water's economic value as well as environmental and related service costs (Gómez-limón and Martin-Ortega, 2013). In addition, recently, the European Green Deal and Farm to Fork Strategy have further emphasized the need for natural resource preservation, leading to the new Common Agricultural Policy (CAP) design which, among many other goals, aims to help the WFD reach its objectives[5].

Considering the urgent need for sustainable water resource management, driven by policies aimed at preserving natural resources and by climate change threats, such as rising temperatures and reduced water availability, the estimation of water economic value and productivity arises as a powerful tool to thoroughly understand the key economic aspects of water use. However, the estimation of water's economic value is particularly difficult when market prices are absent or distorted and, in such circumstances, it is primarily feasible using simulated market or "shadow prices" (Young, 2005). Several definitions of water shadow prices exist in the literature (He et al., 2007): For irrigation water, they can be either based on the value of water alternative use (e.g., different users or different times) or farmer's behaviour. In this study, we consider the latter circumstance, in which the economic mechanism behind water consumption is based on two main assumptions: farmers are price takers (for outputs and inputs) and profit maximizers. Thus, they will use water up to the point where its price will be equal to the added value derived from using a marginal unit of this input (Williams et al., 2017). Bierkens et al. (2019), following this approach, stated that water shadow price denotes the value of crops produced per marginal unit of water consumed, given the quantity of other inputs. Therefore, estimating the shadow price is crucial for the optimal allocation of scarce water resources and the efficient functioning of water markets.

Under these assumptions, this study aims to assess the relevance of irrigation water in agricultural production. Specifically, it seeks to estimate the irrigation water shadow price for maize grain production at the farm level leveraging data from a sample of 1,625 farms over Italy spanning from 2010 to 2020. Maize grain was selected as the focal crop due to its economic importance among

[5] In fact, the European Court of Auditors in 2021 published a special report stating that past CAP policies have failed to promote sustainable water use in agriculture (ECA Special Report 20/2021, Sustainable water use in agriculture: CAP funds more likely to promote greater rather than more efficient water use).

irrigated crops and its vulnerability to market volatility and climate change threats. Italy, ranking as the fourth-largest maize producer in the European Union (Erenstein et al., 2022), relies heavily on maize in various supply chains, including Parmigiano Reggiano production, where silage fodder as feed is prohibited (Mantovi et al., 2015). Nonetheless, water deficits have forced many parts of Italy to rationalize or suspend irrigation water, resulting in yield losses and concerns related to crop quality (CREA, 2021). Moreover, this situation could worsen due to the increasing occurrence of extreme weather events, e.g., water scarcity (IPCC, 2019; Rosenzweig et al., 2014), especially in Mediterranean countries (Hristov et al., 2020; Lionello and Scarascia, 2018), including Italy (Mereu et al., 2021).

Several methods have been proposed to estimate water shadow price, most of which rely on production functions (Johansson et al., 2002). This strand of literature mainly focuses on estimating the irrigation water shadow price for river basins (Garciá Suárez et al., 2019; Koundouri et al., 2014; Mesa-Jurado et al., 2010; Williams et al., 2017) or at the national scale (Kiani and Abbasi, 2012; Takatsuka et al., 2018; Veninga, 2017), and it rarely uses detailed microeconomic data to estimate shadow prices for irrigation water at the farm scale (Mesa-Jurado et al., 2010; Koundouri et al., 2014). While previous studies have already estimated irrigation water shadow prices for various crops at the Country or River Basin level, this study contributes to the existing literature by focusing on maize grain production in Italy at the farm level. An econometric production function approach coupled with detailed microeconomic data spanning a decade was adopted to derive reliable estimates. Furthermore, quantile regression was implemented to better understand the factors influencing water irrigation shadow prices among farms. By providing accurate and up-to-date estimates of water shadow price and its variability, this study can help suggest evidence-based water management strategies and identify vulnerable areas or clusters of farms that may be particularly vulnerable to water-related challenges.

The paper is structured as follows: Section 2 briefly overviews water shadow price definitions and estimation methods. Section 3 describes data and methodology specifying the econometric models, production function form, and shadow price estimation procedure. Section 4 presents econometric estimates and the obtained results. Section 5 discusses the implications of these results. Finally, conclusions are provided in Section 6.

4.3. Shadow Prices of Irrigation Water: a brief overview

The variety of theoretical frameworks in approaching the estimation of shadow prices of irrigation water is associated to multiple definitions, each contingent on different underlying economic mechanisms such as the value of alternative use or farmer behaviour (He et al., 2007) and relying on different methodologies. While this section does not intend to be an exhaustive overview, it does offer a brief overview that addresses some theoretical and methodological issues in the analysis of irrigation water shadow prices.

4.3.1. Definitions and assumptions

Among the various definitions, Bierkens et al. (2019) use the following definition: "*The shadow price of water reflects the value of crops that can be produced by the marginal unit of water consumed, given the quantity of the other inputs*." This definition is based on the assumption that farmers are price takers (for outputs and inputs) and profit maximisers; as rational agents, farmers use water up to the point where its price equals the added value derived from using a marginal unit of this input (Williams et al., 2017). While this definition provides a snapshot of the actual irrigation water economic value at the farm level, it has several advantages as well as limitations. One of its main advantages is that it allows one to precisely pinpoint the maximum price a farmer would be willing to pay for the last unit of irrigation water used, thus making it particularly relevant for short-term policy considerations. It provides a practical framework for assessing irrigation water productivity, which is essential for farmers who operate under stringent budget constraints and face immediate production decisions. On the flip side, this definition intentionally sidesteps some complexities. Unlike more comprehensive approaches like those by Young and Loomis (2014), it does not incorporate broader environmental or opportunity costs, nor does it explicitly consider the temporal aspect of irrigation water allocation (Young and Loomis, 2014; Elnaboulsi, 2002). Indeed, this study follows the aforementioned definition, without delving into long-term environmental externalities, the value of water in alternative uses, or the intertemporal efficiency or opportunity costs that may emerge in longer-term scenarios. In this specific context and under these assumptions, the shadow price aligns with the marginal value (He et al., 2007; Wang and Lall, 2002). Limitations can be seen as calculated, as a narrower perspective is common because farmers often prioritize maximizing their current profits and may not account for the availability of water in the future when making decisions. We assume, then, that farmers aim to maximize their current net returns and that the shadow price is determined through free competition among them.

4.3.2. Methodologies and limitations

Several methods exist to estimate the shadow price of irrigation water. According to Young (2005), there are two main methods: deductive and inductive. Deductive methods use logical processes and rely on economic postulates, such as profit and utility maximization, whereas inductive methods rely mainly on econometrics and statistics. Among deductive methods, the most popular are the Residual Value Method (RVM) (Berbel et al., 2011; Hellegers and Davidson, 2010; Ziolkowska, 2015), General Equilibrium Models (GEM) (Jiang et al., 2014; Smith et al., 2015) and Mathematical Programming (MP) (Liu and Chen, 2008; Rosegrant et al., 2000). Under RVM, it is assumed that all inputs except for water are priced at market rate. The price of irrigation water is then calculated as the ratio between the net returns from crop production and the total quantity of water used for irrigation. As for MP, this method derives the optimal allocation of resources, including water, based on objective functions such as profit maximization or cost minimization[6]. For analyzing the broader, economy-wide implications of changes in water use and availability, General Equilibrium Models are often preferred (Jiang et al., 2014; Smith et al., 2015).

However, the aforementioned methods have several limitations. RVM, upon which most deductive methods are based, estimates water value by deducting costs from predicted revenues. It requires the assumption that all markets are perfectly competitive, with the exception of the water market. Additionally, this method requires a thorough estimation of input costs, which can be challenging when dealing with inputs that are not priced on markets—for example, assets owned by the firm like land and machinery. Under these circumstances, a certain degree of uncertainty is inevitable, and omitting or misrepresenting some input costs will inevitably lead to an overestimation of water value. Similarly, both MP and GEM, rely heavily on theoretical assumptions and may oversimplify complex economic relationships.

Inductive procedures include econometric estimations of the production function or water demand (Bruno and Jessoe, 2021; de Bonviller et al., 2020; Scheierling et al., 2006), Hedonic Pricing, Contingent Valuation (Calatrava and Garrido, 2005; Li et al., 2021), Choice Experiments (Rigby et al., 2010), Stochastic Frontier Analysis (SFA) (Coelli and Orion, 2013; P. Koundouri et al., 2014a) and Data Envelopment Analysis (DEA), or a combination of both (Shen and Lin, 2017). Inductive methods are more reliable when data are available. Given an accurate specification of the production

[6] Distinct approaches are employed such as linear programming (Dayananda et al., 2023; Esmaeili and Shahsavari, 2015; Liu et al., 2009; Schmitz et al., 2013; Shi et al., 2014; Weerahewa and Dayananda, 2023), revealed preference models (Pérez-Blanco and Gutiérrez-Martín, 2017) and positive mathematical programming (Lionboui et al., 2018; Rodríguez-Flores et al., 2019).

function that captures the relationship between water and production, these estimates can provide a reliable assessment of shadow prices using experimental (field experiments) or observational (primary or secondary) data (Mesa-Jurado et al., 2010)[7].

Among its various applications, Njuki and Bravo-Ureta (2019) employed a Cobb-Douglas stochastic production function to determine the shadow price of irrigation water in the US. In a similar vein, Bopp et al. (2022) applied this method to Chilean wine grape production, Conradie et al. (2006) to South African vineyards, and Coelli and Orion (2013) to wine grape production in Eastern Australia. More recently, Nouri-Khajebelagh et al. (2021) estimated the average water shadow price for various crops in Iran. In different contexts, Bellver-Domingo et al. (2019) derived the irrigation water shadow price by analyzing the avoided environmental cost through water desalination using distance function estimation. Irrigation water shadow price estimates based on distance functions were also used by Riera and Brümmer (2022) in Argentina, by Koundouri et al. (2014b) and Koundouri et al. (2014a) in Greece and by Li et al. (2019) in the Beijing- Tianjin-Hebei city region in China.

Bierkens et al. (2019) utilized macro data and a Cobb-Douglas production function to estimate the irrigation water shadow price for various crops in 11 countries, including Italy. Similar studies have been conducted to estimate green water economic value in the Czech Republic (Grammatikopoulou et al., 2020) and South Florida (Takatsuka et al., 2018). Veninga (2017) applied a translog production function to calculate irrigation water shadow prices for maize, sugarcane, and citrus in twelve countries, among them, Italy, where groundwater extraction is the primary water source. Garciá Suárez et al. (2019) assessed the impact of increased irrigation volumes on the total biomass yield in the High Plains River Basin, US. A table concisely summarizing key features of some relevant studies using the production function approach is available in Appendix (Table A1)[8].

While previous studies have mainly focused on estimating the economic value of irrigation water for crops at the country or river basin scale using secondary or primary macro data, our study estimates the water irrigation shadow prices for Italy using detailed microeconomic data, which offers two significant advantages. Firstly, using farm-level accurate and reliable data over 10 years enhances the accuracy of the shadow price estimates. Secondly, by estimating the shadow prices at the farm level,

[7] Among others, Baniasadi et al. (2020) and Jana (2018) use several methods, including production function, to obtain water shadow price to monetize environmental impacts of excessive groundwater extraction in Iran and the use of wastewater in aquaculture.

[8] Although not exhaustive, Table A1 in the appendix illustrates the diversity of functional forms, variables, and contexts used in recent irrigation water valuation research. This highlights the complexity and context-specific nature of the studies considered.

we can identify the circumstances or areas in which irrigation water productivity is most affected by water scarcity or efficiency. This approach aids in better resource allocation and identification of vulnerable farms or territories. Furthermore, a better understanding of the factors affecting shadow prices at the farm level could aid in the development of more effective strategies and interventions for water management.

4.4. Materials and methods

4.4.1. Data

This study focuses on Italian maize grain farms, leveraging a Farm Accountancy Data Network (FADN) sample that provides detailed information at both farm and crop levels. FADN is the only source of microeconomic data based on harmonized bookkeeping principles. Based on national surveys, it aggregates data on 68,000 farms, representing almost 5 million EU farms, 90% of the European UAA and Standard Output. The Italian sample comprises 11,000 farms, whose data are stratified by region, size, and type of farming (TF). The data include Gross Output, land, crop-specific variable costs, work-related costs for families and employed workers, and irrigation water volumes.

To ensure the homogeneity of the sample and enable accurate attribution of measured costs at the farm level to the specific crop (particularly work-related expenses), we selected an unbalanced panel of 1,625 farms growing irrigated maize grain, and excluded those with livestock, for the period 2010–2020; a total of 5,224 observations were analysed. Northern Italy regions (predominantly Lombardy, Piedmont, Friuli-Venezia Giulia, Emilia-Romagna, and Veneto) accounted for 87.3% of the sample, Central Italy for 11%, and the South for 1.7%. The majority of farms were family-run (67.5%), and corporate entities comprised only 18% of the sample. In terms of economic size, 48% of the observations' Standard Production ranges from 50,000 to 100,000 €, while 35.7% ranges from 8,000 to 50,000 € and only 16.3% exceeds 100,000 €. Concerning water sources, a significant part of the sample relied on Water User Associations (WUA) infrastructures (78.1%), while the rest relied on self-supply irrigation.

In fact, in Italy, WUA are the primary administrators of irrigation water and play an essential role in planning the responsible use of this resource.[9] These associations typically consist of organized groups of water users, such as farmers and agricultural communities who collectively manage and allocate water for irrigation purposes. The infrastructure associated with WUAs often includes a

[9] The National Association of Management and Protection Consortia for Land and Irrigation Waters (ANBI) estimates that approximately 59.47% of the national territorial surface is covered and managed by WUAs.

network of canals, ditches and water distribution systems that serve as conduits for irrigation water. These structures are designed to facilitate the distribution of water, involving the scheduling and coordination of water deliveries to ensure that each member receives their allocated share during the irrigation season, which typically goes from spring (March-April) to the end of the summer (September-October). The characteristics of irrigation across various regions of the country are shaped by a combination of hydrogeological, topographical, environmental, and historical factors and these influence both the infrastructure and the management of water provision. [10]

Table 1 presents sample descriptive statistics for key variables that are utilized in the estimation of shadow prices. These variables include the total agricultural area measured in hectares, family and employed labor quantified in work units, and a range of cost factors—namely, land value, work costs, machinery, pesticides, and fertilizers—all expressed per hectare for the cultivation of maize grain. The table also includes data on the volumes of irrigation water, also denominated per hectare.

[10] see Dono et al. (2019) and INEA (2011) for a comprehensive overview of irrigation sector in Italy.

Table 1: Descriptive statistics of the farm sample – unit of measure, description, mean, and standard deviation.

Variable	UM	Description	Mean	Sd
Total Agricultural Area	Ha	Agricultural Land (Owned and Rented)	44.47	62.09
Family Labor	2,300 hours/ unit	Total Family Work Units	1.15	0.68
Employed Labor	2,300 hours/ unit	Total Employed Work Units	1.27	0.94
Area	Ha	Hectares of Land under Maize Grain	19.48	34.70
Gross Output	€/ha	Maize Grain Gross Output per hectare	1867.17	610.97
Land Value	€/ha	Return on Land under Maize Grain (2% of owned land value + rents) per hectare	479.99	435.79
Work	€/ha	Maize Grain Total Work Cost per hectare (both Family and Employed Work)	399.80	414.69
Machinery	€/ha	Maize Grain Machinery Costs (only owned machinery) per hectare	484.96	635.55
Pesticides	€/ha	Maize Grain Pesticides Costs per hectare	120.46	70.70
Fertilizers	€/ha	Maize grain Fertilizers Costs per hectare	252.74	138.05
Variable Costs	€/ha	Maize grain Variable Costs per hectare (certifications. energy. subcontracting. marketing. seeds)	329.23	173.93
Water Volumes	m^3/ha	Irrigation Water volume per hectare	1003.61	985.84

4.4.2. Econometric Model

Following the definition provided by Bierkens et al. (2019), the water shadow price has been estimated by calculating the value of maize that can be produced using a unit of irrigation water.

From an empirical standpoint, the shadow price can be obtained by estimating the production function and taking its partial derivative of the production function concerning irrigation water. The production function (Eq. 1) describes the relationship between crop production and various marketable inputs (such as seeds, fertilizers, and pesticides), labor, land, and water.

$$Y = f(L, W, F, P, VC, WR, M, T, R) + e \quad (1)$$

Here, Y represents the Maize Grain Gross Output; L, land; W, water; F, use of fertilizers; P, use of pesticides; VC, other variable costs; WR, labor, and M, use of machinery. All the aforementioned quantities are expressed as monetary values, except for water, which is expressed in volume (m^3). In addition, T represents average annual temperatures (°C), and R is the average annual precipitation (in 100 mm) at the provincial level. These variables are included to capture the effect of climate variability.[11]

For each observation, the expenditure on each input utilized for maize grain production was assessed in Euros (€). Land (L) is constructed by identifying the annual expenditure of rented land and attributing a return of 2% on the land value for owned land. F, P, and VC represent annual expenditures on maize production, with VC encompassing costs such as quality certifications, energy consumption, subcontracting, marketing, seed procurement, and machinery renting. The costs related to water supply are included in the variable VC and concern the fees charged by WUAs, as for the costs related to self-supply, this amount depends mainly on the energy cost required for pumping or transportation, which, in turn, is influenced by the well's depth and pumping or distribution system adopted.

Labor (WR) comprises both employed labor, whose cost is obtained from FADN Balance Sheets, and family labor, whose compensation includes an hourly wage reflecting the opportunity cost and a reward for the managerial work of the entrepreneur. M represents the owned machinery work expenditure and encompasses fuel, insurance, maintenance, and machine operator payments. W

[11] The source used for climate data is the ISTAT database (Italian National Institute of Statistics) for the years 2010-2020.

indicates the water irrigation volumes for maize grain production, covering both the farms' self-supplied water services and those served by WUAs.

The choice to use economic variables rather than quantities derives from the characteristics of the Italian FADN data. While this dataset provides extensive and detailed information on both individual farms and specific crops, it includes data on both the type of fertilizers and pesticide use. This results in significant heterogeneity in both the formulations and types of products used. While it might be possible to differentiate between organic and inorganic fertilizers distinguishing among various types of pesticides, and more importantly, various units of measurements are not always feasible. This could have introduced a bias in the creation of variables and, subsequently, in the estimation process. For this reason, in alignment with common practices in the literature (see, among others Latruffe et al., 2023; Zhu et al., 2012; Zhu and Lansink, 2010), we have chosen to use monetary values. However, we have chosen to differentiate between inputs rather than aggregating them into a single variable. This approach allows us to maintain a finer level of detail and provides more specific insights for each of the inputs under consideration.

Table 2 lists all variables used in the econometric model.

Table 2: Description 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	m³	Water Volume per year
VC	Variable Costs	€	Crop-specific variable costs per year (certifications. energy. subcontracting. marketing. seeds)
F	Fertilizers	€	Expenditure per year
P	Pesticides	€	Expenditure per year
WR	Labour	€	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

Empirically, the production function is estimated following the Cobb-Douglas specification (Cobb, C.W. and Douglas, 1928):

$$Y = \alpha \prod_{i=1}^{N} X_i^{\beta_i} + e \tag{2}$$

Where X represents the vector of inputs including water (W), and $\boldsymbol{\beta}$ are the estimated parameters vector reflecting input elasticities on production, α is the intercept while e is the error component. This equation can be rewritten as Equation 3 for estimation purposes:

$$lnY = ln\alpha + \sum_{i=1}^{n} \beta_i lnX_i + e \tag{3}$$

Vector $\boldsymbol{\beta}$ includes a specific parameter related to water elasticity, β_w (Equation 4):

$$\beta_w = \frac{\partial ln\, Y}{\partial ln\, W} \cdot \frac{W}{Y} \tag{4}$$

Equation 2 can be rearranged to derive the partial derivative of equation 1 with respect to the water input (W), as illustrated in Equation 5:

$$\frac{\partial ln\, Y}{\partial ln\, W} = \beta_w \cdot \frac{Y}{W} \tag{5}$$

The Cobb-Douglas specification assumes that all inputs are substitutes, and the elasticity of substitution between inputs is constant. This limitation can be overcome through a translog specification of the production function. The latter provides a more flexible range of substitution options than those limited by the constant elasticity of substitution assumed in the Cobb-Douglas function. The translog production function is expressed as follows:

$$lnY = \alpha + \sum_{i=1}^{n} \beta_i lnX_i + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \beta_{ij}\, ln\, X_i lnX_j + e \qquad (6)$$

Where X represents the vector of inputs including water (W); $\boldsymbol{\beta}$, estimated parameters vector; α, intercept; and *e,* error component. As before, $\boldsymbol{\beta}$ includes a specific parameter related to water elasticity, β_w (Equation 6). The marginal productivity of irrigation water is expressed as the partial derivative of equation 5 with respect to the water input (w), as in Equation 7:

$$\frac{\partial ln\, Y}{\partial ln\, W} \cdot \frac{Y}{W} = \left(\beta_w + \sum_{j=1}^{n} \beta_{wj}\, ln\, X_j\right) \cdot \frac{Y}{W} \qquad (7)$$

Where all the variables are the same as in Equation 6.

In both Cobb-Douglas and translog specifications, in order to account for environmental factors characterizing the varying context of each farm over time, we included average temperature and precipitation at the provincial level per year. By following Coelli et al., (1999) and Rahman et al., (2009) we assume that the environmental factors, enter in the production function linearly[12]. The constant term α was augmented to:

$$\alpha_{i,t} = a + \gamma_1 T_{i,t} + \gamma_2 R_{i,t} \qquad (8)$$

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.

[12] We assume the separability of precipitation and temperature variables from the other production inputs in our model. This assumption is based on the spatial and temporal scales at which these environmental factors are measured. Specifically, they are calculated as annual averages at the provincial level, and as such, do not represent moment-to-moment variations in weather that might directly interact with other production inputs. Instead, these variables serve to characterize the broader climatic landscape or ecosystem within which the farms operate. In this context, they are conceptually distinct from the production inputs, thus justifying their separable treatment.

From an empirical perspective, a weighted fixed-effects specification was estimated. Several methodological issues emerge when elasticities and Total Factor Productivity (TFP) are estimated using traditional methods such as OLS. This is because productivity and input choices are correlated, which causes simultaneity or endogeneity problems (Beveren, 2012; Wooldridge, 2009). In addition, if market entry and exit are not allowed, selection bias will emerge. Several estimators have been proposed to address these biases, including those developed by Olley and Pakes (1996) and Levinsohn and Petrin (2004). However, by assuming that firm-specific productivity is time-invariant[13], it is possible to estimate production functions using a fixed-effects estimator (Pavcnik, 2002), as done by several studies focusing on the marginal productivity of irrigation water (Bierkens et al., 2017; Grammatikopoulou et al., 2020; Veninga, 2017). Moreover, the fixed-effects estimator addresses potential sources of endogeneity that may arise from the exclusion of time-invariant variables in the estimates (Baltagi, 2008). In addition, using an unbalanced panel, we overcome the self-selection bias.

Upon calculating shadow prices according to Equation 7, a quantile regression (Koenker and Bassett, 2013) was estimated, which enabled us to identify farm characteristics associated with various levels or quantiles of shadow prices.

$$\mathrm{Q}p(\tau \mid \mathbf{z}) = \theta(\tau) + \mathbf{z}'\boldsymbol{\gamma}(\tau) + u(\tau) \tag{9}$$

Table 3 reports all the variables used in the quantile regression. In particular, we rely on the first and the third quartiles, $\tau = 25$ and $\tau = 75$, and on the difference between them, $\Delta = \mathrm{Q}p(25) – \mathrm{Q}p(75)$, to immediately note which characteristics of the farm are associated with relatively low and high levels of shadow price, while $\gamma(\tau)$ parameters can be estimated by using the estimator described by Hunter and Lange (2000). The independent variables represent territorial, structural, and managerial farm characteristics. Among territorial attributes, we consider geographic and altimetric location while we examine farm size for structural factors. Lastly, regarding organizational aspects, we consider labor organization, specifically the proportion of family or employed labor and irrigation water sources.

[13] The marginal productivity of water is unlikely to be affected by productivity or "innovation" shocks that could affect the efficiency of this input in maize production over-time.

Table 3: Description of the quantile regression independent variables and share of total sample (%)

Types of variables	Variables	Share (%)
Geographic Area	North	87.3
	Central	11
	South	1.7
Altimetric Area	Plain	76.8
	Hill	21.5
	Mountain	1.7
Irrigation Water Source	WUA	77.8
	Surface Water	10.3
	Groundwater	11.9
Farm Management	Family-run	67.5
	Mainly Family labor	24.9
	Mainly Employed Labor	4.1
	Other (Subcontracting, only employed labor)	3.5
Farm Size (ha)	<5	3.3
	1-15	30.9
	15 - 40	33.6
	> 40	32.2

4.5. Results

As costs (Gómez-limón and Martin-Ortega, 2013). In addition, recently, the European Green Deal and Farm to Fork Strategy have, as the Hausman test suggests, a fixed-effects model was employed rather than a random-effects specification. To the latter, year-fixed effects have been included to control for systematic temporal variability. Table 4 presents the estimated parameters of the translog production function and their significance levels. The estimated parameters for the Cobb-Douglas model are presented in the Appendix (see Table A2), alongside the parameters for the translog model without fixed effects over years (see Table A3).

Table 4: 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 (100mm)	-0.007	0.006	
Constant	-0.054	0.734	

*Note: *p < 0.1; **p < 0.05; ***p < 0.01. Obs.: 5,224. Adjusted R-Sq: within = 0.50, between = 0.78, overall = 0.73. All the variables are expressed in logarithms, except for Temperatures and Precipitations.*

Only the linear parameter of irrigation water was significant, revealing its role in maize production. The coefficients further revealed the significant complementarity of water with fertilizers (0.027) and work (0.011). However, a negative relationship was observed between water and pesticides (-0.026). The coefficients associated with climatic variables are not statistically significant, neither for Temperatures nor Rainfall. This is likely because these variables, representing annual means at the provincial level, have their effects absorbed by the annual fixed effects.

After estimating the parameters, we calculated the value of water elasticity for gross maize output, which showed an inelastic response to irrigation water, with an average water elasticity of 0.08. Half of the farms in the sample showed an elasticity value ranging from 0.06 to 0.10. Additionally, the average water shadow price, calculated using equation 6, was found to be 0.29 €/m³, with a median of 0.20 €/m³ (Table 5). The water shadow price for half of the farms within the sample ranged from 0.10 €/m³ to 0.39 €/m³.

Table 5: Summary statistics of estimated water elasticity and water shadow price (€/m³): mean, standard deviation (St. Dev.), 25th percentile (p25), 50th percentile (p50), and 75th percentile (p75)

	Mean	St. Dev.	p25	p50	p75
Water Elasticity	0.08	0.03	0.06	0.08	0.10
Water Shadow Price (€/ m³)	0.29	0.26	0.10	0.20	0.39

Figure 1 shows the predicted marginal and total water productivity for irrigation volumes that align with the requirements for Italy (4000-6000 m³/ha). We observed that the marginal productivity of irrigation water for maize (i.e., the shadow price) exhibits diminishing marginal returns with decreasing productivity for higher volumes, as indicated by the blue line. On the contrary, the total water productivity (in red) showed an increasing trend, although at a decreasing rate. It starts higher in the initial section and decreases as marginal productivity decreases. The estimated water shadow price for the aforementioned irrigation volumes ranges from 0.02 to 0.04 €/m³. Total water productivity ranges between 620 and 670 €/ha, accounting for approximately one-third of the maize grain total gross output.

The insights provided by Figure 1 are crucial for pricing mechanisms. Assuming no adjustment of other production inputs, if prices exceed 0.05 €/m³, they will surpass the value of the marginal productivity of water. In the short term, farmers may choose to reduce irrigation water use, resulting in a decrease in overall production of approximately one-third, with potentially important consequences within the overall supply chain.

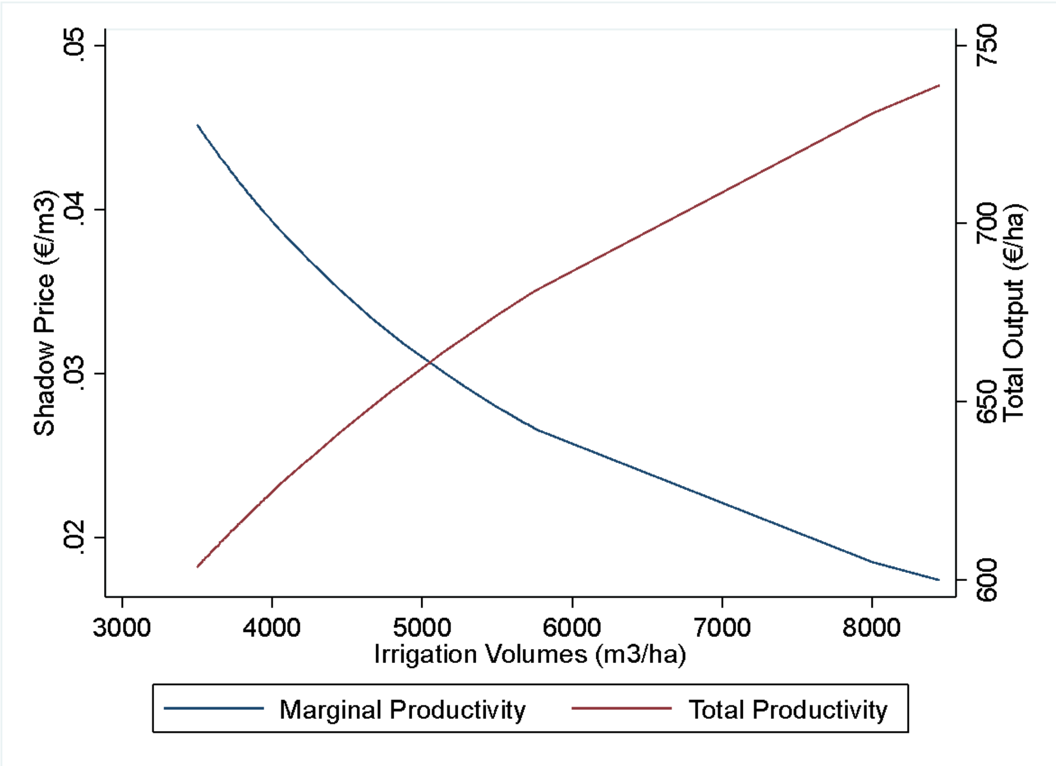

Figure 1: Estimated Marginal Productivity (in blue) and Total Water Productivity (in red) for maize grain.

While the above-mentioned results provide an average estimation of shadow prices and productivity, it is essential to note that different farms may have different shadow prices or productivity levels for water use. This underscores the significance of farm-level analysis in identifying the variability of water productivity and its association with farm characteristics: estimated shadow price distribution has been analyzed using quantile regressions to detect the influence of several farms' characteristics on water irrigation economic value. The first (Q1, τ = 25) and third quartiles (Q3, τ = 75) were considered to highlight the differences between low and high-water marginal productivity levels (Table 6). The model also highlights a negative trend, with shadow prices decreasing over time. The estimated parameters show significant differences between geographical areas at the Q3 level, with the *Central* Regions showing lower marginal productivity than the *Northern* Regions (-0.150). The altitudinal area shows significant differences in Q1, where the shadow price is inversely proportional to the altitude. The Irrigation Water Source highlights a significant positive difference between

Groundwater and *WUA* in Q3 (+0.060). Concerning farm management, *Family-Run* farms show lower shadow prices than farms with *Mainly Employed Labor* (+0.028) or *Mainly Family Labor* in Q1 (+0.033), while farms relying on subcontracting solely on employed labour show lower shadow prices in Q3 (-0.143). Farm Size, instead, shows significant differences with increasing acreage: *Medium Farms* (15-40 ha), especially, show a gap with *Small Farms* (< 5 ha) equal to -0.046 and -0.153, respectively, in Q1 and Q3. Table 7 presents the estimated shadow prices for Q1 and Q3 deriving from the quantile regressions.

Table 6: Quantile regressions estimate, standard errors (in parentheses), and significance levels for structural, managerial and geographical variables considered.

		Parameters			
		Q1		Q3	
Geographic Area	**North**	-		-	
Central		-0.001		-0.150	***
		(0.007)		(0.057)	
South		-0.007		0.045	
		(0.045)		(0.092)	
Altimetric Area	**Plain**	-		-	
Hill		-0.037	***	0.045	
		(0.007)		(0.055)	
Mountain		-0.086	***	0.030	
		(0.022)		(0.141)	
Irrigation Water Source	**WUA**	-		-	
Surface Water		0.014		0.015	
		(0.010)		(0.023)	
Groundwater		0.014	**	0.060	**
		(0.008)		(0.030)	
Farm Management	**Family-run**	-			
Mainly Family labor		0.033	***	-0.026	**
		(0.007)		(0.012)	
Mainly Employed Labor		0.028	**	-0.041	
		(0.013)		(0.031)	
Other		-0.011		-0.143	***
		(0.007)		(0.031)	
Farm Size	**<5 ha**	-		-	
5-15 ha		-0.042	*	-0.122	***
		(0.023)		(0.029)	
15 - 40 ha		-0.046	**	-0.153	***
		(0.023)		(0.035)	
> 40		-0.042	*	-0.129	***
		(0.022)		(0.034)	
Time		-0.059	***	-0.138	***
		(0.008)		(0.029)	
Intercept		0.149	***	0.523	***
		(0.024)		(0.030)	

*Note: *p < 0.1; **p < 0.05; ***p < 0.01, Std. Err. are in parentheses.*

Significance (*) shows the difference from the baseline (in bold).

Table 7: Estimated shadow prices (quantile margins both in Q1 and Q3) with significance levels relative to the baseline (in bold) for structural, managerial and geographical variables considered.

		Shadow Price			
		Q1		Q3	
Geographic Area	***North***	**0.111**		**0.400**	
		(0.002)		(0.013)	
	Central	0.110		0.251	***
		(0.009)		(0.055)	
	South	0.104		0.445	
		(0.036)		(0.079)	
Altimetric Area	**Plain**	**0.117**		**0.380**	
		(0.003)		(0.007)	
	Hill	0.080	***	0.426	
		(0.007)		(0.039)	
	Mountain	0.031	***	0.410	
		(0.027)		(0.158)	
Irrigation Water Source	**WUA**	**0.111**		**0.379**	
		(0.003)		(0.008)	
	Surface Water	0.125		0.395	
		(0.006)		(0.025)	
	Groundwater	0.094	*	0.439	**
		(0.010)		(0.043)	
Farm Management	**Family-run**	**0.101**		**0.400**	
		(0.003)		(0.010)	
	Mainly Family labor	0.134	***	0.374	
		(0.007)		(0.013)	
	Mainly Employed Labor	0.130	*	0.359	
		(0.015)		(0.041)	
	Other	0.090		0.257	***
		(0.005)		(0.022)	
Farm Size (ha)	**<5 ha**	**0.153**		**0.519**	
		(0.015)		(0.053)	
	5-15 ha	0.111	**	0.397	**
		(0.003)		(0.013)	
	15 - 40 ha	0.107	***	0.365	***
		(0.005)		(0.014)	
	> 40	0.110	**	0.390	***
		(0.005)		(0.014)	

*Note: *p < 0.1; **p < 0.05; ***p < 0.01, Std. Err. are in parentheses.*

Significance (*) shows the difference from the baseline (in bold).

4.6. Discussion

Our analysis underscores the relevance of water irrigation for maize grain in Italy and shows that water is an essential input for maize production, especially because of its contribution to other inputs' productivity. Both Cobb-Douglas and translog-derived elasticities showed low values, implying that maize grain production response to water was rigid on average. However, translog estimation allowed the detection of synergies between water and other inputs, highlighting the mutual dependence between water and fertilizers, which can enhance the contribution of both inputs to maize grain production (Hernández et al., 2015; Sadras, 2005; Zhou and Turvey, 2014). The same phenomenon occurs for water and work, suggesting the importance of water in more intensive production systems. Conversely, the negative relationship between water and pesticides suggests a positive contribution of water to maize grain quality and a reduction in sanitary risks (Medina et al., 2015; Wu et al., 2010). Lastly, the climate variables demonstrate no significant contribution. This finding aligns with Di Paolo and Rinaldi's (2008) observation that in Mediterranean regions, rainfall alone may not substantially impact maize grain production without supplemental irrigation water[14].

The estimation of the water shadow price indicates water's contribution to crop productivity and assesses its economic value. The derived estimated average value stands at 0.29 €/m³ and the median at 0.20 €/m³. This analysis is based on a national sample of detailed microeconomic data; therefore, this variability could influence the average shadow price. Italy is characterized by strong territorial, climatic, and pedologic heterogeneity. Therefore, the median value is a more robust indicator. Our results are in line with the water shadow price obtained by Veninga (2017), whose value ranges between 0.19 and 0.53 $/m³ (0.18 and 0.50 €/m³) and D'Odorico et al. (2020), who estimate water value as the farmers' willingness to pay (WTP) for a marginal unit of irrigation water and show a global average price of 0.16 $/m³ (approximately 0.15 €/ m³). Finally, Bierkens et al. (2019) also estimated the same average price for maize grain in Italy. All these works analyzed less recent data and estimated irrigation water shadow prices at the country scale; hence, a comparison must be made carefully. The same is true for studies that rely on different approaches and focus on the same crop. Berbel et al. (2011) estimated a shadow price of 0.07 €/m³ while Ziolkowska (2015) and El-Gafy and El-Ganzori (2012) estimated a value ranging between 0.004 and 0.12 €/m³ for Texas and Kansas, respectively. Finally, de Brito and de Azevedo (2022) showed a higher value (0.14 $/m³) in Brazil, and Kiprop et al. (2015) estimated a price of 0.13 €/m³ in Kenya.

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[14] Rainfed maize production is not widely observed in Italy, and this can be attributed to the predominance of intensive production methods and specific climatic and soil conditions.

The estimated water shadow price is also consistent with the current pricing imposed by WUAs[15], the primary organization responsible for the distribution of irrigation water in Italy. However, it should be noted that WUA tariffs mainly aim to recover water delivery and distribution costs. Considering the estimated shadow price as an indication of water pricing would be inaccurate, our price could be viewed as an estimate of water resource value, not accounting for water-related costs, externalities, or opportunity costs as WFD requires. However, any pricing imposed above the marginal productivity level would present a potential constraint for the producer, considering that according to our estimation, total water productivity accounts for one-third of the maize average gross output. In such a scenario, farmers would have to choose between reducing water usage, which could lead to a loss of production, and optimizing the overall production process by reducing water usage and adopting novel technologies in the long term[16]. The results of these strategies depend on local and regional characteristics as well (Hatfield et al., 2011).

Shadow price heterogeneity could reflect multiple scenarios and even water availability or efficient usage; a higher price reveals a water shortage or lower efficiency in water allocation, while a lower price reveals the opposite. Considering the first quartile (Q1), that is, farms not constrained by water availability, the Geographic Area does not show a significant difference. In contrast, the altimetric area shows that the water shadow price decreases with increasing altitude levels, reflecting greater water availability for *Hill* and *Mountain*. This result could also highlight the greater productivity of water in traditional maize-growing areas, such as Po Valley. In contrast, where water is scarce, this constraint mainly affects the most productive areas (*Northern Italy*). At the Q1 level, Farm Management shows a higher price for *Mainly Employed Labor* and *Mainly Family Labor* farms, revealing greater efficiency in *Family-Run* farms and *Subcontracting* or *Only Employed Labor* farms, which is in line with the findings of Speelman et al. (2008). Instead, at the Q3 level, management plays a role especially in *Subcontracting* or *Only Employed Labor* farms, that show a significantly lower price, likely reflecting higher efficiency in irrigation water management. *Small farms* (<5 ha)

[15] Tariffs for irrigation vary widely and are influenced by individual WUAs and regional regulations. In Northern Regions, they are based on irrigated or irrigable areas, while in Central and Southern regions, they depend on water volume or irrigated crops in compliance with the Water Framework Directive. In addition, tariffs can take various forms, including flat rates, volumetric rates, or tiered structures and some WUAs also impose fixed annual fees to cover service access and administrative costs. On average, volumetric rates typically range from 0.10 to 0.40 €/m³ while the cost per m3 of well water is highly variable due to factors like the well's depth and operational expenses, making precise estimation challenging.

[16] Among these, precision farming, digitalization, and more efficient management of water productivity are promising strategies (Hatfield and Dold, 2019), coupled with the adoption of soil conservation measures, such as the introduction of legume crops in modern cropping systems (Stagnari et al., 2017; Wreford and Topp, 2020). The most common crop management practices include crop cultivar diversification, scheduling of planting dates, early maturing crops, drought-tolerant cultivars, and crop rotation (Dono et al., 2016; Pais et al., 2020; Yang et al., 2019, 2021)

were the most vulnerable in both Q1 and Q3, possibly because of the greater incidence of water-related costs, making them more susceptible to water shortages. These results are consistent with those of Speelman et al. (2008) and Gadanakis et al. (2015), who found that farmers need to develop economies of scale to be more efficient and achieve input cost savings.

Concerning irrigation water sources, when farmers rely on groundwater, the marginal productivity is lower in Q1, indicating a lower shadow price compared to that obtained for farms relying on WUAs infrastructure. Considering that WUAs impose seasonal programming and farmers must schedule irrigation volumes and shifts before the sowing season, this result could depend on greater flexibility in irrigation schemes for farms relying on groundwater. WUAs usually carefully plan the irrigation season and the planning process typically takes into account factors such as anticipated water availability, crop water requirements and historical usage patterns. These schedules aim to strike a balance between providing a consistent water supply for irrigation needs and managing water resources. However, water availability can be highly variable, especially in regions prone to seasonal fluctuations or drought conditions. When water availability becomes limited WUAs may need to implement restrictions on water delivery. For example, they might prioritize supplying water for high-value crops or essential agricultural activities. As a result, there may be occasions when water delivery is curtailed or restricted to ensure equitable distribution during periods of scarcity. However, this can also reveal lower efficiency and suboptimal use of water resources. The main costs incurred by self-supplied farms concern infrastructure, delivery, and water extraction, which translates to fewer constraints on resource usage (Gómez and Pérez Blanco, 2012). Where farms are constrained by water availability or are less efficient in this input allocation (Q3) the most affected farms are self-supplied farms (groundwater). The use of a support decision tool (smart irrigation), recycling water at the farm level, has been proven to have a positive effect on water efficiency at the farm scale (Gadanakis et al., 2015) and collective action in irrigation management (Chaudhry (2018), seems to improve on-farm water use efficiency. However, Wang (2010) found that farmers adopting well, or mixed irrigation exhibited higher water efficiency than those using river irrigation, probably because of greater flexibility and less water wastage during transportation. However, these results often depend on social and territorial characteristics, making comparisons inappropriate.

In summary, small and family-run farms are the most affected by water shortages, especially where water is already scarce. Where water is not very scarce, improving the efficiency of irrigation water use in farms located on the *Plain* can contribute the most to maize productivity. Concerning water irrigation sources, it must be highlighted that if water is scarce, thanks to seasonal planning, WUAs can probably guarantee farmers a more efficient water distribution and lower risks or production losses. Concomitantly, groundwater allows greater flexibility when water is not scarce, potentially leading to the suboptimal use of this resource. However, it has to be reminded that Italian WUAs can follow different pricing approaches: Northern Regions often apply a fixed cost per year or crop, while Southern Regions mainly use a volumetric approach. In the latter, farmers could be pushed to search for alternative water sources (groundwater) to reduce water-related costs and compensate for water scarcity (Cortignani et al., 2018). Hence, farmers' responses to water shortages should be further examined when they rely on both irrigation sources, to establish whether a substitution or additional effect exists between them. For this reason, it is crucial to analyze the economic value of water in detail, highlighting variations and differences across territories, areas, and types of farms, to develop strategies to balance the economic value of water with its environmental significance and to ensure sustainable water usage practices in agriculture (Bozzola and Swanson, 2014).

4.7. Conclusions

The results of our analysis have several potential applications, including establishing the relevance, productivity, and economic value of irrigation water and allowing for further methodological development. We found that water is a crucial input for making maize grain economically viable, emphasizing the significant dependence of this crop on water, and the contribution of this resource to other inputs' productivity. This is particularly significant because Italy is the fourth-largest maize grain producer in the EU, and Northern Regions account for 85% of the Italian maize agricultural area. Maize plays a strategic role in several supply chains, particularly in Parmigiano Reggiano production, which does not allow the use of silage fodder (Mantovi et al., 2015). Moreover, if imposed prices surpass the value of the marginal productivity of water, farmers may choose to reduce irrigation water use resulting in losses in overall production of approximately one-third, or to replace maize with rainfed crops (Aldaya et al., 2023; Sapino et al., 2022). Consequently, a shortage in maize production could result in greater dependence on imports and economic losses in several Italian agricultural sectors.

Moreover, our water shadow price estimation can assist policymakers in partially fulfilling the requirements of the WFD by estimating the resource value, which assesses water relevance and scarcity, and by identifying vulnerable areas and clusters of farms, taking into account Italy's territorial and productive heterogeneity. Additionally, our estimation facilitates the assessment of each input's impact on output, allowing the distinction between fertilizers and pesticides. Combining these results with a Mathematical Programming approach could lead to the estimation of flexible models, establishing economic, social, and environmental impacts on farms resulting from a reduction in chemical input use, as required by the F2F targets (Cortignani et al., 2022). Importantly, it should be noted that our estimation of the water shadow price for irrigation neglects any other economic returns derived from the overall supply chain; namely, it does not include the contribution of maize to downstream or upstream supply chains. As such, the provided estimation only indicates the direct economic value of water for maize production and does not reflect the full value of water's contribution to the supply chain and economy. Further, our analysis presumes that unobserved firm-specific water productivity does not vary over time and does not consider external productivity shocks that could influence the level of inputs used by the farmer. Moreover, our analysis does not account for intertemporal efficiency and opportunity costs associated with water use. In specific circumstances where extraction costs are notably high or where externalities have a significant impact, the estimated shadow price in our study may be lower than in an assessment that includes these considerations. These limitations should be kept in mind when interpreting the estimated shadow price of water.

In conclusion, our estimation serves as a starting point for further research and analysis that incorporates these additional factors to establish a more accurate assessment of water's value and its impact on agricultural production and supply chains. Integrating social, environmental, and economic factors is crucial for achieving sustainable water use practices that account for the total value of water as a vital resource for agriculture and the economy.

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4.8. References

Aldaya, M.M., Gutiérrez-Martín, C., Espinosa-Tasón, J., Ederra, I., Sánchez, M., 2023. The impact of the territorial gradient and the irrigation water price on agricultural production along the first phase of the Navarra Canal in Spain. Agric. Water Manag. 281, 108245. https://doi.org/10.1016/J.AGWAT.2023.108245

Baltagi, B.H. (2008) Econometric Analysis of Panel Data. John Wiley & Sons Ltd., Chichester.

Baniasadi, M., Zare’ Mehrjordi, M.R., Mehrabi Boshrabadi, H., Mirzaei Khalilabad, H.R., Rezaei Estakhrooye, A., 2020. Evaluation of Negative Economic-Environmental Externalities of Overextraction of Groundwater. Groundwater 58, 560–570. https://doi.org/10.1111/gwat.12933

Bellver-Domingo, A., Fuentes, R., Hernández-Sancho, F., 2019. Reclaimed water and irrigation: A cost-benefit analysis for desalination of WWTPs effluents. Desalin. Water Treat. 166, 193–201. https://doi.org/10.5004/dwt.2019.24556

Berbel, J., Borrego-Marin, M.M., Exposito, A., Giannoccaro, G., Montilla-Lopez, N.M., Roseta-Palma, C., 2019. Analysis of irrigation water tariffs and taxes in Europe. Water Policy 21, 806–825. https://doi.org/10.2166/wp.2019.197

Berbel, J., Expósito, A., 2020. The theory and practice of water pricing and cost recovery in the water framework directive. Water Altern. 13, 659–673.

Berbel, J., Mesa-Jurado, A., Pistón, J.M., 2011. Value of Irrigation Water in Guadalquivir Basin (Spain) by Residual Value Method. Water Resour. Manag. 25, 1565–1579. https://doi.org/10.1007/s11269-010-9761-2

Beveren, I. Van, 2012. TOTAL FACTOR PRODUCTIVITY ESTIMATION : 26, 98–128. https://doi.org/10.1111/j.1467-6419.2010.00631.x

Bierkens, M.F.P., Reinhard, S., de Bruijn, J.A., Veninga, W., Wada, Y., 2019. The Shadow Price of Irrigation Water in Major Groundwater-Depleting Countries. Water Resour. Res. 55, 4266–4287. https://doi.org/10.1029/2018WR023086

Bopp, C., Jara-Rojas, R., Bravo-Ureta, B., Engler, A., 2022. Irrigation water use, shadow values and productivity: Evidence from stochastic production frontiers in vineyards. Agric. Water Manag. 271, 107766. https://doi.org/10.1016/j.agwat.2022.107766

Bozzola, M., Swanson, T., 2014. Policy implications of climate variability on agriculture: Water management in the Po River basin, Italy. Environ. Sci. Policy 43, 26–38. https://doi.org/10.1016/j.envsci.2013.12.002

Bruno, E.M., Jessoe, K., 2021. Using price elasticities of water demand to inform policy. Annu. Rev. Resour. Econ. 13, 427–441. https://doi.org/10.1146/annurev-resource-110220-104549

Calatrava, J., Garrido, A., 2005. Modelling water markets under uncertain water supply. Eur. Rev. Agric. Econ. 32, 119–142. https://doi.org/10.1093/eurrag/jbi006

Chaudhry, A.M., 2018. Improving on-farm water use efficiency: Role of collective action in irrigation management. Water Resour. Econ. 22, 4–18. https://doi.org/10.1016/j.wre.2017.06.001

Cobb, C.W. and Douglas, P.H., 1928. Theory of production. Am. Econ. Rev. https://doi.org/10.1007/978-4-431-54433-3_9

Coelli, T., Orion, S., 2013. The Technical Efficiency of Wine Grape Growers in the Murray–Darling Basin in Australia. Wine Econ.

Coelli, T., Perelman, S., & Romano, E. 1999. Accounting for environmental influences in stochastic frontier models: with application to international airlines. *Journal of productivity analysis*, 11, 251-273.

Conradie, B., Cookson, G., Thirthle, C., 2006. EFFICIENCY AND FARM SIZE IN WESTERN CAPE GRAPE PRODUCTION: POOLING SMALL DATASETS 74, 334–343.

Cortignani, R., Buttinelli, R., Dono, G., 2022. Farm to Fork strategy and restrictions on the use of chemical inputs: Impacts on the various types of farming and territories of Italy. Sci. Total Environ. 810, 152259. https://doi.org/10.1016/j.scitotenv.2021.152259

Cortignani, R., Dell'Unto, D., Dono, G., 2018. Recovering the costs of irrigation water with different pricing methods: Insights from a Mediterranean case study. Agric. Water Manag. 199, 148–156. https://doi.org/10.1016/j.agwat.2017.12.016

CREA PB, 2020. Annuario dell'Agricoltura Italiana 2018, Vol. LXXII, Consiglio per la Ricerca in Agricoltura e l'Analisi dell'Economia Agraria, Centro di ricerca in Politiche e Bio-economia, Roma, 2021.

CREA PB, 2021. Annuario dell'Agricoltura Italiana 2018, Vol. LXXII, Consiglio per la Ricerca in Agricoltura e l'Analisi dell'Economia Agraria, Centro di ricerca in Politiche e Bio-economia, Roma, 2022.

D'Odorico, P., Chiarelli, D.D., Rosa, L., Bini, A., Zilberman, D., Rulli, M.C., 2020. The global value of water in agriculture. Proc. Natl. Acad. Sci. U. S. A. 117, 21985–21993. https://doi.org/10.1073/pnas.2005835117

Damania, R., Desbureaux, S., Hyland, M., Islam, A., Moore, S., Rodella, A.-S., Russ, J., Zaveri, E., 2020. The economics of water scarcity and variability, Oxford Review of Economic Policy. https://doi.org/10.1093/oxrep/grz027

Dayananda, D., Weerahewa, J., Weerasooriya, S.A., 2023. Resource-use efficiency and environmental sustainability in the village tank cascade systems in the dry zone of Sri Lanka: An assessment using a bio-economic model. Front. Sustain. Food Syst. 7. https://doi.org/10.3389/fsufs.2023.1084973

de Bonviller, S., Wheeler, S.A., Zuo, A., 2020. The dynamics of groundwater water markets: Price leadership and groundwater demand elasticity in the Murrumbidgee, Australia. Agric. Water Manag. 239. https://doi.org/10.1016/j.agwat.2020.106204

de Brito, P.L.C., de Azevedo, J.P.S., 2022. Economic value of water for irrigation in São Francisco River Basin, Brazil. Appl. Water Sci. 12. https://doi.org/10.1007/s13201-022-01678-4

Decreto 31 luglio 2015 Ministero delle Politiche agricole alimentari e forestali: Approvazione delle linee guida per la regolamentazione da parte delle Regioni delle modalità di quantificazione dei volumi idrici ad uso irriguo

Di Paolo, E., Rinaldi, M., 2008. Yield response of corn to irrigation and nitrogen fertilization in a Mediterranean environment. F. Crop. Res. 105, 202–210. https://doi.org/10.1016/j.fcr.2007.10.004

Dono, G., Cortignani, R., Dell'Unto, D., Deligios, P., Doro, L., Lacetera, N., Mula, L., Pasqui, M., Quaresima, S., Vitali, A., Roggero, P.P., 2016. Winners and losers from climate change in agriculture: Insights from a case study in the Mediterranean basin. Agric. Syst. 147, 65–75. https://doi.org/10.1016/j.agsy.2016.05.013

Dono, G., Severini, S., Dell'Unto, D., Cortignani, R. (2019). Italy. In: Molle, F., Sanchis-Ibor, C., Avellà-Reus, L. (eds) Irrigation in the Mediterranean. Global Issues in Water Policy, vol 22. Springer, Cham. https://doi.org/10.1007/978-3-030-03698-0_6

El-Gafy, I., El-Ganzori, A., 2012. Decision support system for economic value of irrigation water. Appl. Water Sci. 2, 63–76. https://doi.org/10.1007/s13201-012-0029-2

Elnaboulsi, J. C. (2001). Nonlinear pricing and capacity planning for water and wastewater services. Water Resources Management, 15(1), 55–69. https://doi.org/10.1023/A:1012228611303

Erenstein, O., Jaleta, M., Sonder, K., Mottaleb, K., Prasanna, B.M., 2022. Global maize production, consumption and trade: trends and R&D implications. Food Secur. 14, 1295–1319. https://doi.org/10.1007/s12571-022-01288-7

Esmaeili, A., Shahsavari, Z., 2015. Water allocation for agriculture in southwestern Iran using a programming model. Appl. Water Sci. 5, 305–310. https://doi.org/10.1007/s13201-014-0192-8

European Commission, 2019. The European Green Deal. Brussels, com/2019/640 final. -- https://ec.europa.eu/info/strategy/priorities-2019-2024/european-greendeal_en.

FAO, 2022. 3 Cereals. Oecd-Fao Agric. Outlook 2021-2030 124–137.

FAO, 2022. The State of the World's Land and Water Resources for Food and Agriculture 2021 – Systems at breaking point, The State of the World's Land and Water Resources for Food and Agriculture 2021 – Systems at breaking point. https://doi.org/10.4060/cb9910en

Gadanakis, Y., Bennett, R., Park, J., Areal, F.J., 2015. Improving productivity and water use efficiency: A case study of farms in England. Agric. Water Manag. 160, 22–32. https://doi.org/10.1016/j.agwat.2015.06.020

Galioto, F., Guerra, E., Raggi, M., Viaggi, D., 2017. The impact of new regulations on water pricing in the agricultural sector: A case study from Northern Italy. Agric. Econ. Rev. 18, 77–95.

Gallego-Ayalal, J., Gomez-Limon, J.A., Arriaza, M., 2011. Irrigation water pricing instruments: A sustainability assessment | Tarifación del agua de riego: Una evaluación de la sostenibilidad. Spanish J. Agric. Res. 9, 981–999. https://doi.org/10.5424/sjar/20110904-449-10

Garciá Suárez, F., Fulginiti, L.E., Perrin, R.K., 2019. What is the use value of irrigation water from the high plains aquifer? Am. J. Agric. Econ. 101, 455–466. https://doi.org/10.1093/ajae/aay062

Giannoccaro, G., Sardaro, R., de Vito, R., Roselli, L., de Gennaro, B.C., 2020. Policy instruments for irrigation groundwater management. An assessment of farmers’ stated preferences. Econ. Agro-Alimentare 22, 1–27. https://doi.org/10.3280/ecag2-2020oa10409

Gómez Gómez, C.M., Pérez Blanco, C.D., 2012. Do drought management plans reduce drought risk? A risk assessment model for a Mediterranean river basin. Ecol. Econ. 76, 42–48. https://doi.org/10.1016/j.ecolecon.2012.01.008

Gómez-limón, J.A., Martin-Ortega, J., 2013. The economic analysis in the implementation of the Water-Framework Directive in Spain. Int. J. River Basin Manag. 11, 301–310. https://doi.org/10.1080/15715124.2013.823977

Grammatikopoulou, I., Sylla, M., Zoumides, C., 2020. Economic evaluation of green water in cereal crop production: A production function approach. Water Resour. Econ. 29, 100148. https://doi.org/10.1016/j.wre.2019.100148

Greene, W. H., 2002. Econometric analysis (5th ed.). Upper Saddle River, NJ: Prentice Hall

Hatfield, J.L., Boote, K.J., Kimball, B.A., Ziska, L.H., Izaurralde, R.C., Ort, D., Thomson, A.M., Wolfe, D., 2011. Climate impacts on agriculture: Implications for crop production. Agron. J. 103, 351–370. https://doi.org/10.2134/agronj2010.0303

Hatfield, J.L., Dold, C., 2019. Water-use efficiency: Advances and challenges in a changing climate. Front. Plant Sci. 10, 1–14. https://doi.org/10.3389/fpls.2019.00103

He, J., Chen, X., Shi, Y., Li, A., 2007. Dynamic computable general equilibrium model and sensitivity analysis for shadow price of water resource in China. Water Resour. Manag. 21, 1517–1533. https://doi.org/10.1007/s11269-006-9102-7

Hellegers, P., Davidson, B., 2010. Determining the disaggregated economic value of irrigation water in the Musi sub-basin in India. Agric. Water Manag. 97, 933–938. https://doi.org/10.1016/j.agwat.2010.01.026

Hernández, M., Echarte, L., Della Maggiora, A., Cambareri, M., Barbieri, P., Cerrudo, D., 2015. Maize water use efficiency and evapotranspiration response to N supply under contrasting soil water availability. F. Crop. Res. 178, 8–15. https://doi.org/10.1016/j.fcr.2015.03.017

Hristov, J., Toreti, A., Pérez Domínguez, I., Dentener, F., Fellmann, T., Elleby, C., Ceglar, A., Fumagalli, D., Niemeyer, S., Cerrani, I., Panarello, L., Bratu, M., 2020. Analysis of climate change impacts on EU agriculture by 2050 JRC PESETA IV project-Task 3, JRC Technical Report . https://doi.org/10.2760/121115

Hunter, D.R., Lange, K., 2000. Quantile Regression via an MM Algorithm. J. Comput. Graph. Stat. 9, 60–77. https://doi.org/10.1080/10618600.2000.10474866

ICWE, 1992. The Dublin Statement and Report of the International Conference on Water and the Environment. Development issues for the 21st century, Dublin.

INEA (2011), Atlante nazionale dell'irrigazione, a cura di Zucaro R., Roma 2011

IPCC, 2019. Summary for Policymakers. In: Climate Change and Land: an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems [P.R., Shukla, J., Skea, E., Calvo Buendia, V., Masson-Delmotte, H.- O., P¨ortner, D. C. Roberts, P. Zhai, R. Slade, S. Connors, R. van Diemen, M. Ferrat, E. Haughey, S. Luz, S. Neogi, M. Pathak, J. Petzold, J. Portugal Pereira, P. Vyas, E. Huntley, K. Kissick, M. Belkacemi, J. Malley, (eds.)].

Jana, S., 2018. Socioeconomic impacts and cost-benefit analysis of wastewater-fed aquaculture, in: Wastewater Management Through Aquaculture. pp. 269–284. https://doi.org/10.1007/978-981-10-7248-2_14

Jiang, L., Wu, F., Liu, Y., Deng, X., 2014. Modeling the impacts of urbanization and industrial transformation on water resources in China: An integrated hydro-economic cge analysis. Sustain. 6, 7586–7600. https://doi.org/10.3390/su6117586

Johansson, R.C., Tsur, Y., Roe, T.L., Doukkali, R., Dinar, A., 2002. Pricing irrigation water: A review of theory and practice. Water Policy 4, 173–199. https://doi.org/10.1016/S1366-7017(02)00026-0

Kiani, R.A., Abbasi, F., 2012. Optimizing Water Consumption Using Crop Water Production Functions. Crop Prod. Technol. https://doi.org/10.5772/29543

Kiprop, J.K., Lagat, J.K., Mshenga, P., Macharia, A.M., 2015. Determining the Economic Value of Irrigation Water in Kerio Valley Basin (Kenya) by Residual Value Method. J. Econ. Sustain. Dev. 6, 102–108.

Koenker, R., Bassett, G., 2013. No Title Regression Quantiles. J. Chem. Inf. Model. 53, 1689–1699.

Koundouri, P., Babalos, V., Stithou, M., Anastasiou, I., 2014. A micro-econometric approach to deriving use and non-use values of in situ groundwater: The vosvozis case study, Greece. Handb. Econ. Ecosyst. Serv. Biodivers. 423–435. https://doi.org/10.4337/9781781951514.00032

Koundouri, P., Dávila, O.G., Anastasiou, Y., Antypas, A., Mavrogiorgis, T., Mousoulides, A., Mousoulidou, M., Vasiliou, K., 2014a. An Econometric Analysis of Agricultural Production, Focusing on the Shadow Price of Groundwater: Policies Towards Socio-Economic Sustainability, Global Issues in Water Policy. https://doi.org/10.1007/978-94-007-7636-4_5

Koundouri, Phoebe, Babalos, V., Stithou, M., Anastasiou, I., 2014b. A micro-econometric approach to deriving use and non-use values of in situ groundwater: The vosvozis case study, Greece. Handb. Econ. Ecosyst. Serv. Biodivers. 423–435. https://doi.org/10.4337/9781781951514.00032

Latruffe, L., Niedermayr, A., Desjeux, Y., Dakpo, K.H., Ayouba, K., Schaller, L., Kantelhardt, J., Jin, Y., Kilcline, K., Ryan, M., O'Donoghue, C., 2023. Identifying and assessing intensive and extensive technologies in European dairy farming. Eur. Rev. Agric. Econ. 50, 1482–1519. https://doi.org/10.1093/erae/jbad023

Levinsohn, J. and A. Petrin. 2003. Estimating production functions using inputs to control for unobservables. Review of Economic Studies 70(2): 317–342.

Levinsohn, J., Petrin, A., 2004. Production function estimation in Stata using inputs to control for unobservables 113–123.

Li, G., Shi, M., Zhou, D., 2021. How much will farmers be compensated for water reallocation from agricultural water to the local ecological sector on the edge of an oasis in the Heihe River Basin? Agric. Water Manag. 249. https://doi.org/10.1016/j.agwat.2021.106801

Li, Y., Li, Z., Cui, S., Chang, S.X., Jia, C., Zhang, Q., 2019. A global synthesis of the effect of water and nitrogen input on maize (Zea mays) yield, water productivity and nitrogen use efficiency. Agric. For. Meteorol. 268, 136–145. https://doi.org/10.1016/j.agrformet.2019.01.018

Lionboui, H., Benabdelouahab, T., Elame, F., Hasib, A., Boulli, A., 2018. Estimating the economic impact of climate change on agricultural water management indicators. Pertanika J. Sci. Technol. 26, 749–762.

Lionello, P., Scarascia, L., 2018. The relation between climate change in the Mediterranean region and global warming. Reg. Environ. Chang. 18, 1481–1493. https://doi.org/10.1007/s10113-018-1290-1

Liu, X., Chen, X., 2008. Methods for approximating the shadow price of water in China. Econ. Syst. Res. 20, 173–185. https://doi.org/10.1080/09535310802075349

Liu, X., Chen, X., Wang, S., 2009. Evaluating and predicting shadow prices of water resources in China and its nine major river basins. Water Resour. Manag. 23, 1467–1478. https://doi.org/10.1007/s11269-008-9336-7

Mantovi, P., Dal Prà, A., Pacchioli, M., & Ligabue, M., (2015). Forage production and use in the dairy farming systems of Northern Italy.

Medina, Á., Rodríguez, A., Magan, N., 2015. Climate change and mycotoxigenic fungi: Impacts on mycotoxin production. Curr. Opin. Food Sci. 5, 99–104. https://doi.org/10.1016/j.cofs.2015.11.002

Mereu, V., Gallo, A., Trabucco, A., Carboni, G., Spano, D., 2021. Modeling high-resolution climate change impacts on wheat and maize in Italy. Clim. Risk Manag. 33, 100339. https://doi.org/10.1016/j.crm.2021.100339

Mesa-Jurado, M.A., Berbel, J., Orgaz, F., 2010. Estimating marginal value of water for irrigated olive grove with the production function method. Spanish J. Agric. Res. 8. https://doi.org/10.5424/sjar/201008s2-1362

Njuki, E., Bravo-Ureta, B.E., 2019. Examining irrigation productivity in U.S. agriculture using a single-factor approach. J. Product. Anal. 51, 125–136. https://doi.org/10.1007/s11123-019-00552-x

Nouri-Khajebelagh, R., Khaledian, M., Kavoosi-Kalashami, M., 2021. Economic value of irrigation water for major crops in the Ardabil plain, Iran*. Irrig. Drain. 70, 1359–1367. https://doi.org/10.1002/ird.2619

Olley, B.Y.G.S., Pakes, A., 1996. The Dynamics of Productivity in the Telecommunications Equipment Industry Author (s): G . Steven Olley and Ariel Pakes Published by : The Econometric Society Stable URL : https://www.jstor.org/stable/2171831 64, 1263–1297.

Pais, I.P., Reboredo, F.H., Ramalho, J.C., Pessoa, M.F., Lidon, F.C., Silva, M.M., 2020. Potential impacts of climate change on agriculture-A review. Emirates J. Food Agric. 32, 397–407. https://doi.org/10.9755/ejfa.2020.v32.i6.2111

Pavcnik, N., 2002. Trade Liberalization , Exit , and Productivity Improvements : Evidence from Chilean Plants 69, 245–276.

Pérez-Blanco, C.D., Gutiérrez-Martín, C., 2017. Buy me a river: Use of multi-attribute non-linear utility functions to address overcompensation in agricultural water buyback. Agric. Water Manag. 190, 6–20. https://doi.org/10.1016/j.agwat.2017.05.006

Rahman, S., Wiboonpongse, A., Sriboonchitta, S., & Chaovanapoonphol, Y. 2009. Production efficiency of Jasmine rice producers in Northern and North-Eastern Thailand. *Journal of Agricultural Economics*, 60(2), 419-435.

Riera, F.S., Brümmer, B., 2022. Environmental efficiency of wine grape production in Mendoza, Argentina. Agric. Water Manag. 262. https://doi.org/10.1016/j.agwat.2021.107376

Rigby, D., Alcon, F., Burton, M., 2010. Supply uncertainty and the economic value of irrigation water. Eur. Rev. Agric. Econ. 37, 97–117. https://doi.org/10.1093/erae/jbq001

Rodríguez-Flores, J.M., Medellín-Azuara, J., Valdivia-Alcalá, R., Arana-Coronado, O.A., García-Sánchez, R.C., 2019. Insights from a calibrated optimization model for irrigated agriculture under drought in an irrigation district on the central Mexican high plains. Water (Switzerland) 11, 1–23. https://doi.org/10.3390/w11040858

Rosegrant, M.W., Ringler, C., McKinney, D.C., Cai, X., Keller, A., Donoso, G., 2000. Integrated economic-hydrologic water modeling at the basin scale: The Maipo river basin. Agric. Econ. 24, 33–46. https://doi.org/10.1016/S0169-5150(00)00113-4

Rosenzweig, C., Elliott, J., Deryng, D., Ruane, A.C., Müller, C., Arneth, A., Boote, K.J., Folberth, C., Glotter, M., Khabarov, N., Neumann, K., Piontek, F., Pugh, T.A.M., Schmid, E., Stehfest, E., Yang, H., Jones, J.W., 2014. Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. Proc. Natl. Acad. Sci. U. S. A. 111, 3268–3273. https://doi.org/10.1073/pnas.1222463110

Sadras, V.O., 2005. A quantitative top-down view of interactions between stresses: Theory and analysis of nitrogen-water co-limitation in Mediterranean agro-ecosystems. Aust. J. Agric. Res. 56, 1151–1157. https://doi.org/10.1071/AR05073

Sapino, F., Dionisio, C.P., Guti, C., García-prats, A., Pulido-velazquez, M., 2022. Influence of crop-water production functions on the expected performance of water pricing policies in irrigated agriculture 259. https://doi.org/10.1016/j.agwat.2021.107248

Scheierling, S.M., Loomis, J.B., Young, R.A., 2006. Irrigation water demand: A meta-analysis of price elasticities. Water Resour. Res. 42, 1–9. https://doi.org/10.1029/2005WR004009

Schmitz, C., Lotze-Campen, H., Gerten, D., Dietrich, J.P., Bodirsky, B., Biewald, A., Popp, A., 2013. Blue water scarcity and the economic impacts of future agricultural trade and demand. Water Resour. Res. 49, 3601–3617. https://doi.org/10.1002/wrcr.20188

Shen, X., Lin, B., 2017. The shadow prices and demand elasticities of agricultural water in China: A StoNED-based analysis. Resour. Conserv. Recycl. 127, 21–28. https://doi.org/10.1016/j.resconrec.2017.08.010

Shi, M., Wang, X., Yang, H., Wang, T., 2014. Pricing or quota? A solution to water scarcity in oasis regions in China: A case study in the Heihe River Basin. Sustain. 6, 7601–7620. https://doi.org/10.3390/su6117601

Smith, R.B.W., Nelson, H., Roe, T.L., 2015. Groundwater and Economic Dynamics, Shadow Rents and Shadow Prices: The Punjab. Water Econ. Policy 1. https://doi.org/10.1142/S2382624X15500149

Speelman, S., D'Haese, M., Buysse, J., D'Haese, L., 2008. A measure for the efficiency of water use and its determinants, a case study of small-scale irrigation schemes in North-West Province, South Africa. Agric. Syst. 98, 31–39. https://doi.org/10.1016/j.agsy.2008.03.006

Stagnari, F., Maggio, A., Galieni, A., Pisante, M., 2017. Multiple benefits of legumes for agriculture sustainability : an overview 1–13. https://doi.org/10.1186/s40538-016-0085-1

Takatsuka, Y., Niekus, M.R., Harrington, J., Feng, S., Watkins, D., Mirchi, A., Nguyen, H., Sukop, M.C., 2018. Value of irrigation water usage in South Florida agriculture. Sci. Total Environ. 626, 486–496. https://doi.org/10.1016/j.scitotenv.2017.12.240

Veninga, W. (2017). The shadow price of fossil groundwater. MSc thesis Wageningen University. Thesis online collection, WTO/2223572 (http://edepot.wur.nl/425744), 50 p.

Wada, Y., Van Beek, L.P.H., Van Kempen, C.M., Reckman, J.W.T.M., Vasak, S., Bierkens, M.F.P., 2010. Global depletion of groundwater resources. Geophys. Res. Lett. 37, 1–5. https://doi.org/10.1029/2010GL044571

Wang, H., Lall, S., 2002. Valuing water for Chinese industries: a marginal productivity analysis Valuing water for Chinese industries : a marginal productivity analysis. Appl. Econ. 34, 759–765. https://doi.org/10.1080/00036840110054044

Wang, X.Y., 2010. Irrigation water use efficiency of farmers and its determinants: Evidence from a survey in northwestern China. Agric. Sci. China 9, 1326–1337. https://doi.org/10.1016/S1671-2927(09)60223-6

Water Framework Directive (WFD) 2000/60/EC: Directive 2000/60/EC of the European Parliament and of the Council of 23 October 2000 establishing a framework for Community action in the field of water policy.

Weerahewa, J., Dayananda, D., 2023. Land use changes and economic effects of alternative fertilizer policies: A simulation analysis with a bio-economic model for a Tank Village of Sri Lanka. Agric. Syst. 205. https://doi.org/10.1016/j.agsy.2022.103563

Williams, R.B., Al-Hmoud, R., Segarra, E., Mitchell, D., 2017. An Estimate of the Shadow Price of Water in the Southern Ogallala Aquifer. J. Water Resour. Prot. 09, 289–304. https://doi.org/10.4236/jwarp.2017.93019

Wooldridge, J.M., 2009. On estimating fi rm-level production functions using proxy variables to control for unobservables 104, 112–114. https://doi.org/10.1016/j.econlet.2009.04.026

Wreford, A., Topp, C.F.E., 2020. Impacts of climate change on livestock and possible adaptations: A case study of the United Kingdom. Agric. Syst. 178, 102737. https://doi.org/10.1016/j.agsy.2019.102737

Wu, F., Bhatnagar, D., Bui-Klimke, T., Carbone, I., Hellmich, R., Munkvold, G., Paul, P., Payne, G., Takle, E., 2010. Climate change impacts on mycotoxin risks in US maize. World Mycotoxin J. 4, 79–93. https://doi.org/10.3920/WMJ2010.1246

Yang, C., Fraga, H., van Ieperen, W., Trindade, H., Santos, J.A., 2019. Effects of climate change and adaptation options on winter wheat yield under rainfed Mediterranean conditions in southern Portugal. Clim. Change 154, 159–178. https://doi.org/10.1007/s10584-019-02419-4

Yang, X., Menefee, D., Cui, S., Rajan, N., 2021. Assessing the impacts of projected climate changes on maize (Zea mays) productivity using crop models and climate scenario simulation. Crop Pasture Sci. 72, 969–984. https://doi.org/10.1071/CP21279

Young, R. A., & Loomis, J. B. (2014). Determining the economic value ofwater: Concepts and methods. Washington, DC: Routledge.

Young, R., 2005. Nonmarket Economic Valuation for Irrigation Water Policy Decisions: Some Methodological Issues. Water.

Zhou, L., Turvey, C.G., 2014. Climate change, adaptation and China's grain production. China Econ. Rev. 28, 72–89. https://doi.org/10.1016/j.chieco.2014.01.001

Zhu, X., Demeter, R.M., Lansink, A.O., 2012. Technical efficiency and productivity differentials of dairy farms in three EU countries: the role of CAP subsidies 13, 66–92.

Zhu, X., Lansink, A.O., 2010. Impact of CAP Subsidies on Technical Efficiency of Crop Farms in Germany, the Netherlands and Sweden 61, 545–564. https://doi.org/10.1111/j.1477-9552.2010.00254.x

Ziolkowska, J.R., 2015. Shadow price of water for irrigation-A case of the High Plains. Agric. Water Manag. 153, 20–31. https://doi.org/10.1016/j.agwat.2015.01.024

Zucaro, R., 2014. Condizionalita ' Ex-Ante Per Le Risorse Idriche: Opportunita ' E Vincoli per il mondo agricolo. Inea.

4.9. Appendix

Table A1: Functional forms, dependent and independent variables, case studies and concerned crops in the recent literature estimating irrigation water shadow price using production function approach.

Functional Form	Dependent Variable	Independent Variables	Case Study	Crop	References
Translog	Crop Production (t)	Area (ha) Employment in agriculture (1000 person) Agricultural Value Added per Worker ($) Green water use (km³) Blue water + non-renewable groundwater (km³) Fertilizers (kg/ha)	China, Egypt, India, Iran, Italy, Mexico, Pakistan, Saudi Arabia, South Africa, Turkey, USA	Sugarcane, Maize, Citrus	*Veninga, 2017*
	Biomass output per acre (t/acre)	Fertilizers (quantity index) Chemicals (quantity index) Precipitation (inches) Irrigation water (ratio of irrigated area to total cropland) Degree Days	High Plains Aquifer, USA	All crops produced in a county	*Garcia Suarez et al., 2019*
Cobb Douglas	Value of crop products sold ($)	Employment in cropland (number of FTEs) Amount of surface water usage in cropland (acre-ft/yr) Amount of groundwater usage in cropland (acre-ft/yr) Ratio of surface water on total water Rate of land share of irrigated lands out of the total cultivated croplands Rate of fertilized lands out of the total cultivated lands	South Florida, USA	Croplands products (mainly sugarcane and citrus)	*Takatsuka et al., 2018*
	Crop Production (kg/year/AA)	Agricultural Land (ha) Energy (kg di oil equivalent per year/AA) Water (green water e irrigation water in mc/year/AA	China, Egypt, India, Iran, Italy, Mexico, Pakistan, South Africa, Spain, Turkey, USA	Wheat, Potato, Maize, Rice, Citrus	*Bierkens et al., 2019*
	Production output (t)	Labour (1000 persons) Fertilizers (kg)	Czech Republic	Cereals (Wheat,	*Grammatikopoulou et al., 2020*

		Pesticides (kg) Harvesting equipment (n. of harvesters) Transport fuel (terajoule) Green water use (m^3) Harvested crop area (ha)		Barley, Maize, Oats, Triticale)	
Several Forms	Yield (kg/ha)	Seed (kg/ha) Fertilizers (kg/ha) Pesticides (kg/ha) Machinery Costs ($) Manpower (man days) Irrigation water (m^3/ha)	Ardabil Plain, Iran	Wheat, Potato, Alfalfa, Barley, Canola	*Nouri-Khajebelagh et al., 2021*

* *Green water (evapotranspiration), blue water (withdrawal from rivers, surface water and renewable groundwater) and non-renewable groundwater (Oki et Kanae, 2006)*

Table A2: Estimates of the Fixed-Effects Cobb Douglas Production Function and their Significance Levels

Variable	Parameter	Std. Err.	
Land	0.131	0.025	***
Water	0.011	0.003	***
Variable Costs	0.188	0.028	***
Fertilizers	0.241	0.024	***
Pesticides	0.207	0.042	***
Work	0.096	0.035	***
Machinery	0.000	0.006	
Temperatures	- 0.074	0.021	***
Rainfall (100 mm)	-0.003	0.003	
Intercept	4.286	0.362	***

*Note: *p < 0.1; **p < 0.05; ***p < 0.01, Std. Err. Are in parentheses. Obs.: 5,224. Adjusted R-Sq: within = 0.41, between = 0.79, overall = 0.74.*

Table A3: Weighted fixed effects model estimates for the translog production function and their Standard Errors (St. Err.) and significance levels.

Variable	Parameter	Std. Err.	
Land	0.139	0.112	
Water	-0.070	0.025	***
Variable Costs	0.059	0.169	
Fertilizers	0.848	0.144	***
Pesticides	0.331	0.132	***
Work	0.390	0.092	***
Machinery	-0.053	0.034	
Land×Water	-0.004	0.004	
Land×Variable Costs	-0.044	0.027	*
Land×Fertilizers	-0.021	0.027	
Land×Pesticides	-0.079	0.026	***
Land×Work	-0.019	0.016	
Land×Machinery	-0.007	0.006	
Water×Variable Costs	0.004	0.009	
Water×Fertilizers	0.028	0.008	***
Water×Pesticides	-0.029	0.008	***
Water×Work	0.012	0.005	**
Water×Machinery	0.001	0.002	
Variable Costs×Fertilizers	-0.088	0.049	*
Variable Costs×Pesticides	-0.153	0.046	***
Variable Costs×Work	-0.098	0.030	***
Variable Costs×Machinery	0.010	0.012	
Fertilizers×Pesticides	-0.050	0.044	
Fertilizers×Work	-0.067	0.029	**
Fertilizers×Machinery	-0.005	0.011	
Pesticides×Work	0.083	0.024	***
Pesticides×Machinery	0.015	0.010	
Work×Machinery	-0.001	0.009	
Land^2	0.096	0.014	***
Water^2	0.004	0.003	
Variable Costs ^2	0.200	0.031	***
Fertilizers ^ 2	0.021	0.033	
Pesticides ^2	0.090	0.028	***
Work ^2	0.008	0.011	
Machinery^2	0.003	0.003	
Temperatures	-0.079	0.017	***
Rainfall (100mm)	-0.006	0.003	*
Constant	0.802	0.669	

*Note: *p < 0.1; **p < 0.05; ***p < 0.01. Obs.: 5,224. Adjusted R-Sq: within = 0.48, between = 0.78, overall = 0.72. All the variables are expressed in logarithm, except for Temperatures and Precipitations.*

5. Reducing Chemical Inputs under the European Union's Farm to Fork Strategy: Implications for Italian Processing Tomato based on a Stochastic Frontier Analysis

Building upon the in-depth analysis of Italian agriculture in Chapter 3 and the conceptual framework outlined in Chapter 4, this study shifts its focus to another vulnerable sector and a specific crop. The initial analysis presented in this thesis identified "Fresh Fruits" as one of the sectors most affected by the reduction in chemicals instructed by the Farm to Fork (F2F) targets. Being Italy the leading European producer, accounting for 13% of the global market, processing tomato has been chosen as a case study. This crop, primarily destined for industrial processing to produce peeled tomatoes, sauces, and concentrated tomato products, represents a significant component of the national agri-food sector, covering vast territories across Italy. Processing tomatoes has been chosen not only for its economic relevance but also because of its intensive production, making it vulnerable to variations in the relationships among inputs (Ronga et al., 2019). Moreover, the tomato supply chain involves numerous actors, from the agricultural phase to the industrial one, contributing to national employment and local economies.

Following the examination of the cereal sector, specifically focusing on maize grain in Chapter 4, this analysis investigates the potential repercussions of reducing chemical inputs, especially fertilizers, on the industrial tomato sector. Furthermore, this study incorporates additional elements into the analysis, by assessing the level of Technical Efficiency (TE) among the examined farms and identifying the factors that influence it. Indeed, in accordance with the literature, the research goes further in understanding production dynamics, analyzing how exogenous factors such as risk aversion, subsidies, and other farm characteristics might influence farmers' decision-making process, potentially leading to inputs' overuse. Estimating production functions reliably assesses agricultural inputs' contributions to production (Bierkens et al., 2017; Onofri et al., 2019; Zhang et al., 2015). However, econometric estimation alone does not account for farm efficiency variations or factors like input overuse and managerial behavior. To address these limitations, methods like Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) are employed. DEA is a non-parametric approach that evaluates farm efficiency without specifying a functional form, as seen in studies by Shen and Lin (2017) and Singbo et al. (2015). In contrast, SFA assesses efficiency and its influencing factors through the estimation of specific production functions' functional forms as shown by Moutinho et al. (2018) and Zhu and Lansink (2010) to study the impact of CAP subsidies and climate conditions on farm efficiency.

Despite valuable insights from these studies, there's a gap in understanding the impact of the F2F strategy on specific crops and regions and linking “vulnerability” with TE. This further step could contribute to the application of such ambitious targets, for example by identifying which farms are most efficient in input use and whether these farms could therefore be negatively affected by additional constraints. In other words, this analysis can help offset the impacts of these reductions in chemical inputs by pinpointing farms where inputs are already used in the most efficient way possible. This study uses SFA combined with an inefficiency effects model to analyze inputs like fertilizers and pesticides in Italian tomato production, identifying susceptible farms and regions. It also considers exogenous factors influencing farmers’ production decisions, as highlighted in the literature. For instance, farmers' risk aversion significantly impacts production choices and pesticide use (Bakker et al., 2021; Bontemps et al., 2021; Menapace et al., 2013). Uncertainty also affects input use: Paulson and Babcock (2010) highlighted that input-related uncertainty (e.g., soil quality) can lead to fertilizer overuse, while output-related uncertainty may result in underuse. Henke et al. (2007) and Singbo et al. (2015) discussed how specialized production can influence input levels. Additionally, socioeconomic factors, such as age, income, and education, certainly play a role in input efficiency, especially irrigation water (Karagiannis et al., 2003; Wang, 2010). Finally, subsidies impact production decisions and input use, as shown by Hennessy (1998) and Latruffe (2010). In this scenario, comprehensive approach adopted in this Chapter aim to integrate economic variables, exogenous factors to the production process, and sociodemographic characteristics to analyze agricultural decision-making. Specifically, it addresses the following research objectives:

- **Identify and analyze the relationships among agricultural inputs**: This research aims to address the first research objective by examining the production process of processing tomatoes in Italy. Using a Stochastic Frontier Analysis (SFA), this analysis identifies the relevance of the considered inputs using a translog Output Distance Function and provides indications on farms’ TE. Moreover, an inefficiency effects model identifies exogenous factors serving as proxies for factors that could influence farmers’ decision-making process concerning the use of agricultural inputs, potentially leading to their excessive use and influencing TE.
- **Quantify the economic impact of the European F2F Strategy goals on Italian agriculture**: thanks to the identification of existing links among various agricultural inputs, this analysis allows for the assessment of the responsiveness of the analyzed farms to reductions in the level of production factors, focusing especially on chemical fertilizers. This enables the identification of the potential impact of a reduction aligned with the F2F targets. Additionally, the analysis, through the estimation of TE and its influencing factors, allows the identification of the most

vulnerable farms and areas. This detailed and stratified view provides a deep comprehension not only of this sector but also of the vulnerabilities to external variations, thus addressing the specific research objectives and maintaining consistency with the previous chapters.

The study reveals the crucial role of Family Labor, Pesticides, and Chemical Fertilizers in processing tomato production, highlighting the limited potential for substitution. When applied to the Farm to Fork context, a reduction in chemical fertilizers and decreased pesticide usage emerges as a significant threat to Italian processing tomato production. Emphasizing the importance of avoiding short-term losses, the analysis highlights the need for tailored support to farmers during the transition to low-input agricultural practices outlined in the F2F strategy. This research enhances the thesis's agenda by employing econometric estimation of production functions, evaluating Technical Efficiency, and exploring factors influencing it. This work provides a detailed understanding of this sector's vulnerabilities, contributing valuable insights to comprehend the challenges and opportunities associated with EU policies. This research was conducted in collaboration with Professor Xueqin Zhu during the visiting PhD period at Wageningen University and Research (WUR) in the Netherlands. The resulting scientific paper, titled "Reducing Chemical Inputs under the European Union’s Farm to Fork Strategy: Implications for Italian Processing Tomato based on a Stochastic Frontier Analysis," is a product of this collaboration.

Reducing Chemical Inputs under the European Union's Farm to Fork Strategy: Implications for Italian Processing Tomato based on a Stochastic Frontier Analysis

Rebecca Buttinelli[a*], Raffaele Cortignani[b], Gabriele Dono[b], Xueqin Zhu[c]

[a] University of Tuscia, Department of Economics, Engineering, Society and Business Organization (DEIM), 01100 Viterbo, Italy

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

[c] Environmental Economics & Natural Resources Group, Wageningen University, Wageningen, the Netherlands

[*] Corresponding Author at University of Tuscia, Department of Economics, Engineering, Society and Business Organization (DEIM), 01100 Viterbo, Italy

5.1. Abstract

In the pursuit of a climate-neutral Europe by 2050, the European Union (EU)'s Farm to Fork Strategy aims to contribute to this goal by promoting sustainable food production, specifically by reducing the use of chemical pesticides by 50% and fertilizers by 20% by 2030. This study explores the impacts of these reductions on processing tomato farms in Italy, employing a Stochastic Frontier Analysis (SFA) method to estimate a translog Output Distance Function and an Inefficiency Effect Model. Based on 2,147 observations from 843 farms from 2010 to 2021, our findings highlight the significant reliance of Italian processing tomato farms on chemicals, especially fertilizers. A reduction in chemical fertilizers could result in significant losses in Output, mainly impacting larger and more intensive farms. Moreover, exogenous factors influencing technical efficiency (TE) are identified. Variables such as degree of specialization, location, altitude, CAP subsidies and farm characteristics emerge as key determinants of TE. This finding not only identifies the contexts where efficiency enhancements are possible but also provides valuable insights for tailored support and interventions. This research emphasizes the need for caution in reducing chemicals in agricultural production, as transitioning towards less chemical-dependent agriculture, while essential to preserve the environment and natural resources, may entail serious consequences on production. Addressing this trade-off requires additional efforts in improving efficiency, embracing technological advancements, adapting agronomic techniques and providing tailored support to ensure the welfare of farmers. In conclusion, achieving synergy between environmental sustainability and food production emerges as a central challenge, providing perspectives necessary to tackle various challenges associated with EU goals.

Keywords: Farm to Fork Strategy, Stochastic Frontier Analysis (SFA), Processing Tomato, Fertilizers

5.2. Introduction

Climate change (CC) is the main global challenge of this century since it has impacted several economic activities, including agriculture (IPCC, 2022). Acknowledging this concern, the EU Commission formulated the European Green Deal (GD) aiming to make Europe the world's first climate-neutral continent by 2050 while promoting a sustainable, circular economy, advancing the transition to clean energy, and preserving biodiversity and natural resources (European Commission, 2019). As part of its broader objectives, the GD places a strong emphasis on agriculture, in pursuit of the creation of a fair, healthy, and environmentally friendly food system. This vision is actively pursued through the Farm to Fork Strategy (F2F), which is specifically designed to promote sustainable food production through ambitious targets, such as reducing chemical pesticide use by 50% and decreasing nutrient losses by 50% by 2030, ultimately leading to a 20% reduction in fertilizer use (European Commission, 2020). These goals have influenced the new Common Agricultural Policy (CAP) 2023-2027 design which aims to contribute to CC mitigation and adaptation and pursue environmental objectives. To this end, each Member State has outlined plans to achieve climate and environmental goals. Italy's Strategic Plan allocates over 10 billion euros for environmental and climatic targets consisting of mandatory ecological standards, five eco-schemes, and agroclimatic-environmental measures[17].

In this case, Italian farmers will have to face several challenges, i.e., coping with CC and phytosanitary risks using fewer chemical inputs and preserving natural resources while meeting market standards and consumers' needs. These challenges will likely affect the socioeconomic aspects of farms and rural areas, including farmers' decision-making processes, work organizations, and farm profitability. Wesseler (2022) provided a literature review on the impact of the F2F strategy, remarking that all reviewed studies predicted a decrease in EU agricultural production. Among others, Bremmer et al. (2021) assess a reduction in production value of around 92 billion euros by 2030 and predict an increase of 2 or 3 million hectares in land use needed to balance this economic loss, while Beckman et al. (2020), Noleppa et al. (2021) and Barreiro-Hurle et al. (2021), estimate a 7-12% decrease in agricultural output volumes. This could lead to either an expansion of agricultural land or inadequate food production in the EU with a consequent greater dependence on importing food.

[17] These components configuration depends on a common and national approach and on a regional declination for Rural Development interventions. Conditionality maintains its role as the primary tool for achieving the objectives of agronomic and environmental management of farmland, animal welfare, and food safety. Still, it's "strengthened", including new standards and part of the old "greening".

Therefore, it is crucial to examine the impacts of these policies on the farming sector (Alexander et al., 2019; Balezentis et al., 2020; Fitton et al., 2019; Malek and Verburg, 2018), especially in light of the European Commission’s reconsideration of chemical reductions targets, leading to the withdrawal of the Sustainable Use Regulation (SUR). SUR aimed to establish legally binding targets at the EU level to reduce the use of chemical pesticides by 50% (COM 2022/0196), and its revocation underscores the necessity to propose a new target. While pesticides have been the primary focus of recent regulatory discussions, it is crucial to recognize that reductions in fertilizers, also play a significant role in achieving sustainable agriculture practices. Establishing the impacts of reductions in chemical inputs in this context, especially considering territorial and productive specificities, can provide valuable insights to facilitate the transition to low-input agriculture. Assessing the effects of a reduction in chemical inputs, e.g. pesticides and fertilizers, on crop production in different regions and clusters of farms can help identify the most vulnerable ones. While the F2F impact analyses mentioned above often consider the EU as one unit, regional patterns in pesticide use across the EU have been identified (Robu et al., 2023). For example, according to Cortignani et al. (2022), the impacts of F2F objectives on nitrogen use, labour, crop, and livestock production in Italy vary across regions and farm types. Furthermore, considering the productive characteristics and vulnerabilities associated with individual crops, especially in Italy, whose territory is characterized by significant regional, agronomic, and climatic heterogeneity, could provide additional insights to determine the path forward in formulating new policy proposals aiming to find a balance between environmental and productive objectives Given its strong economic relevance and significant amount of required agronomic inputs (Ronga et al., 2019), processing tomatoes have been chosen as an example for the impact analysis in this study. According to the World Processing Tomato Council (WPTC), Italy is the first EU producer of processing tomatoes and represents 13% of the supply in the global market. This study aims to achieve two main objectives: (i) to assess the economic impact of the F2F objectives on conventional processing tomato farms in Italy, focusing specifically on the impact of a 20% reduction in fertilizer use; (ii) to identify the most vulnerable farms and areas to fertilizers reduction across Italy, considering not only farm-specific and regional characteristics but also evaluating their efficiency levels and exogenous factors influencing them. By employing a Stochastic Frontier Analysis (SFA) approach this study aims to provide insights into the economic implications of the EU environmental policies for the farming sector of processing tomatoes. Previous research suggests that farmers' risk perception and various farm characteristics can influence input use efficiency and potentially lead to input overuse (Bontemps et al., 2021; Nave et al., 2013; Paulson and Babcock, 2010; Singbo et al., 2015), an inefficiency effects model is also employed to account for these factors. The findings will contribute to the ongoing discussion on sustainable agricultural practices and inform policymakers about a resilient and environmentally conscious food system. The empirical analysis is based on a national Farm Accountancy Data Network (FADN) panel data, covering the period 2010-2021 consisting of 2,147 observations and 843 conventional processing tomato farms in Italy. The paper is structured as follows: Section 2 presents the theoretical background on efficiency and input productivity as well as the factors that influence it. Section 3 is on methodology for empirical analysis and Section 4 is on interpretation of the empirical results. Section 5 provides discussions and qualifies our results by comparing our results with other studies in the literature. Section 6 concludes.

5.3. Theoretical Background

5.3.1. Input Productivity and Efficiency

Assessing agricultural inputs' contribution to crop production, particularly in the context of lower-input production practices that aim to be environmentally beneficial, is crucial. Estimating production functions, i.e. the mathematical relationships linking inputs to outputs, provide insights into the overall input-output relationship and provides reliable estimates of agricultural inputs' contribution to agricultural production (Bierkens et al., 2019; Onofri et al., 2019; Zhang et al., 2015). However, the econometric estimation of production functions does not account for variations in farm efficiency or factors related to inputs overuse and farmers' managerial behaviour. To address these limitations, various econometric methods have been employed, with Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) being the most commonly used. DEA is a non-parametric approach that compares the performance of farms based on their efficiency without explicitly estimating a production function, e.g. does not require the specification of a functional form. In the context of analysis of agricultural input use, among others, Singbo et al. (2015) used DEA to analyse technical efficiency and marginal product value of agricultural inputs, especially focusing on pesticides, while Cao et al. (2020) and Shen and Lin (2017) employed DEA to estimate efficiency in water usage and various water-saving irrigation methods. However, one limitation of DEA is that it does not explicitly separate statistical noise from productive inefficiency, which can have a significant impact on the agricultural analysis for identifying components for improving efficiency. Statistical noise refers to random variations or measurement errors in the data that may distort the efficiency estimates while productive inefficiency represents the inability of a farm to achieve the maximum possible output level given its inputs.

In contrast, SFA is a parametric approach that explicitly models production functions and measures technical efficiency based on the distance of observed outputs from the estimated frontier. This approach allows for the separation of inefficiency from random error and enables the identification of the sources of this inefficiency by including an efficiency effects model. Several studies have used SFA to assess agricultural efficiency and its influencing factors. Among others, Zhu and Oude Lansink (2010) and Zhu et al (2012) investigated the impact of the CAP subsidies on the technical efficiency of crop and dairy farms in the Netherlands, Sweden and Germany respectively, while Moutinho et al. (2018) used SFA coupled with a generalized cross-entropy approach (GCE) to obtain efficiency scores of European Countries. Đoki (2022) employed SFA to calculate the technical efficiency of agriculture in the Western Balkans accounting for policy and climatic conditions, and Auci and Vignani (2021) estimated the impacts of climate variability on Italian regional agriculture technical efficiency. Furthermore, Lambarra and Zein, (2009) found that factors such as Less Favorite Area (LFA) payments, age of manager, workforce composition and farm size affect efficiency levels in Spanish olive farms. Several works conducted in China, including those by Ma et al. (2014) and Quemada and Gabriel (2016) focused on the factors influencing fertilizer use efficiency, highlighting the strong impact of household and farm characteristics on farmers' choices.

While existing literature provides valuable insights into input efficiency and resource allocation in agricultural production, there is still a gap in estimating the impact of specific targets outlined in the F2F strategy on specific crops and areas. To contribute to the existing knowledge, this study employs the SFA approach combined with an inefficiency effects model to estimate the relevance of various inputs, such as fertilizers and pesticides in conventional processing tomato production in Italy. This allows us to assess the economic impact of a reduction in these inputs, in line with the F2F strategy's target and especially a 20% reduction in fertilizer use. Furthermore, the included inefficiency effects model allows us to identify factors influencing input use efficiency. As such, we are able to identify vulnerable clusters of farms and regions in Italy and various factors to influence efficiency.

5.3.2. Exogenous factors influencing farmers' choices and input use

Economic theory suggests that farmers, as profit maximizers and rational agents, should use an optimal amount of inputs up to the point where marginal cost equals marginal benefit in production. However, the decision-making process of farmers is influenced by factors such as high uncertainty and risk aversion, which can impact their behaviour and choices. Existing literature demonstrates that farmers are generally risk averse (Menapace et al., 2013) and this risk aversion varies based on factors such as gender, age, education, size of the household and degree of specialization of the farms (Jin et al., 2017; Spicka, 2020). Risk preferences can significantly impact farmers' production decisions (Chavas, 2019) and Bontemps et al. (2021) found that risk aversion can increase pesticide use by 2-3% for moderate risk aversion levels and up to 7.4% for extreme risk aversion. Moreover, Bakker et al. (2020) explored the drivers that could lead farmers to decrease pesticide use and found that their willingness to transition to low-input practices is partly influenced by the belief that it may reduce crop yield or quality.

Optimal input use is also correlated with uncertainty, as indicated by Paulson and Babcock (2010): input-related uncertainty (e.g., soil quality or rainfall) may result in the overuse of fertilizers, while output-related uncertainty may lead to the underuse of fertilizers to control costs. These concepts incorporate climatic, pedologic and agronomic conditions which can determine the varying degrees of vulnerability. Additionally, Henke et al. (2007) suggest that the optimal amount of Nitrogen (N) may be influenced by the production of high-quality crops, while Singbo et al., (2015) show that specialized vegetable producers tend to overuse pesticides, potentially reflecting the characteristics of the vegetable production system or farmers' risk aversion.

Expanding on the complexities of farmers' decision-making, the literature also examines the drivers behind the adoption of low-input agronomic methods. Nave et al. (2013) demonstrate that economic factors alone cannot fully explain farmers' choice to reduce input use, suggesting that, instead, motivations and social environment play a significant role. In addition, sociodemographic factors, such as ownership of land and the availability of family labour force positively influence the choice of reducing input use. Water use efficiency is also influenced by sociodemographic factors, as highlighted by Wang (2010) who found that age, income, education level and farm size affect irrigation water efficiency in China. Karagiannis et al. (2003), similarly, show that technologies, education, farm extension, production intensity, and chemical use are associated with the intensity of water use in Greece.

In summary, the use of chemicals in agricultural production is influenced by various factors, reflecting farmer characteristics and production uncertainty. Risk aversion is related to farmer gender, age, education, household size, and farm's degree of specialization, while uncertainty related to production outcomes is influenced by soil quality and climatic variables such as rainfall. Additionally, factors like product quality, land ownership, family labor, income, water use intensity, and the specific characteristics of different crops or sectors play a significant role in shaping farmers' decisions regarding input reduction or the adoption of low-input techniques. A brief summary of the cited literature and the variables used to account for the influence of exogenous factors on pesticide use and efficiency is shown in Table 1, while the covariates used in this work are shown in Table 3. It is important to note that mentioned studies employ a variety of methods to identify the drivers and factors influencing farmers' behavior, including variables representing beliefs, tendencies or propension. Consequently, when possible, some of these variables have been included in this work through proxies. To comprehensively address the influence of these exogenous factors in our analysis, we have selected several variables, considering both their relevance according to the existing literature and their availability within our dataset. The variables considered include the share of owned land in the total farm area, the degree of specialization expressed as the share of tomato output in the total output, the irrigation water source, the share of family labor employed on the farm, the gender and age of the household head, farm size, and Economic Size expressed as levels of Standard Output. These variables not only provide detailed insights into farm structure, sociodemographic, managerial, and productive characteristics but also serve as proxies for farmers' risk perception and production uncertainty (see Table 3). Furthermore, the inclusion of regional characteristics (3 macro-regions and 3 altimetric dummies) allows for an assessment of the impact of pedologic, climatic, and agronomic factors. Additionally, we recognize the potential influence of subsidies on farmer production decisions, as outlined by Latruffe et al. (2017) and Zhu et al. (2012), through wealth and insurance effects. Moreover, subsidies may also impact input use, as suggested by Hennessy (1998). Hence, this analysis considers first and second-pillar payments within the CAP framework. This comprehensive approach allows us to consider the intricate relationship between economic variables, exogenous factors, and sociodemographic characteristics in shaping agricultural practices and decision-making.

Table 1: Variables Identified in the Literature Influencing Farmers' Decisions Regarding Agricultural Production and the Use of Chemicals such as Fertilizers and Pesticides.

Variables	**Reference**
Age, Crop Value, OP Member, OP representative, Past Crop Damage, Size, Risk Aversion	Menapace et al., 2013
Education, Household Size, Income, Water Flow, Water Fee, Income Source	Wang 2010
Technologies, Education, Farm Extension, Production Intensity, Water intensity	Karagiannis et al, 2003
Risk Aversion	Bontemps et al., 2021
Perceptions of behavior of others, Neighbouring effects, Limited alternatives, Moral considerations	Bakker et al., 2020

Risk aversion, Input Uncertainty (soil quality, rainfall), Output Uncertainty (yields)	Paulson and Babcock, 2010
Premium price related to High-quality Crops	Henke et al., 2007
Specialization in Vegetable Crops	Singbo et al, 2015
Family Work Availability, Land Ownership, Water Catchment Areas, Investments, Childs, Civic Engagement, Being affiliated to an agricultural extension group, Participation in professional meetings, Diversity of information sources, Type of Advisors, Awareness of Pesticide Harmful Effects, Innovation, Price Expectations, Capital	Nave et al., 2013
Rented land, Land ownership, Hired labor, Subsidies	Latruffe et al., 2017
Subsidies, Farm Size, Degree of Specialization, Family Labor, Rented Land, Debts	Zhu et al., 2012

5.4. Methodology

5.4.1. Output Distance Function and Inefficiency Effects Model

Assuming that producers use a vector of inputs $x = (x_1, \dots, x_N) \in R_+^N$ to produce a vector of outputs denoted $y = (y_1, \dots, y_M) \in R_+^M$, a boundary representing the maximum output achievable from any given input vector (or the minimum input usage required to produce any output vector) exists. This boundary serves as a benchmark to assess the structure of production technology and technical efficiency of production, e.g. an output frontier $f(x) = min\{y: x \in Y(x)\}$ where $Y(x)$ is $Y = \{(y, x): x\ can\ produce\ y\}$. An output-distance function gives the minimum amount that an output vector can be reduced and remain producible with a given input vector. It takes an output-expanding approach to the measurement of the distance from a producer to the boundary of production possibilities and it can be defined as $D(y, x) = min\{\lambda: x/\lambda \in Y(x)\}$.

Therefore, the technical efficiency (TE)[18] of input use is measured against the set of outputs that have a distance function value of one. Any other feasible output vectors have output distance function values less than one. Hence, considering that producers use multiple inputs to produce multiple outputs, the output-oriented measure of TE is $TE_i(y,x) = \max\{\theta: D(y,\theta x) \leq 1\}$ (Battese and Coelli, 1995; Kumbhakar and Lovell, 2000). Introducing a random error term (v_{it}) to account for statistical noise and incorporating a non-negative random error term (u_{it}) representing the time-varying technical inefficiency, taking the logarithms on both sides and dividing all outputs (y) by one of the outputs (y_m) a normalized stochastic distance function can be obtained (Greene, 1980):

$$lny_{im}^t = lnD_0^t(x_i^t, y_i^t/y_{mi}^t; \beta) + v_{it} - u_{it}, \tag{1}$$

where β is a vector of parameters to be estimated and u_{it} is independently distributed $N^+(z_{it}\delta, \sigma_u^2)$. The input-oriented TE for firm i at the time t is defined as:

$$TE_{it} = \exp(-u_{it}) = D_0^t(x_i^t, y_i^t; \beta). \tag{2}$$

Several factors can explain the TE differences amongst farms. These factors are exogenous variables, and this approach assumes that these factors can influence TE and are modelled in the inefficiency term. In fact, u_{it} is represented by non-negative random variables reflecting firm-specific and time-specific deviations from the frontier. It could be expressed as:

$$u_{it} = z_{it}\delta + \omega_{it}, \tag{3}$$

where z_{it} is a vector of J firm-specific time-varying variables (exogenous factors to the production process), δ is an unknown vector of J parameters to be estimated and ω_{it} is the error term and it is $\omega_{it} \sim N(0, \sigma_w^2)$ truncated from below by the variable truncation point $-z_{it}\delta$ (Kumbhakar and Lovell, 2000). The frontier model and the inefficiency effects model allow for simultaneous estimation of the impact of several factors that influence TE. Therefore, TE is defined as:

$$TE_{it} = \exp(-u_{it}) = \exp(-z_{it}\delta - \omega_{it}) \tag{4}$$

[18] Technical efficiency (TE) is defined as the ability to minimize input use in the production of a given output vector (or the ability to obtain maximum output from a given input vector). The output-oriented TE is a function $TE_I(y,x) = \max\{\theta: \theta x \in Y(x)\}$.

5.4.2. Empirical Model

The study employs a Translog specification of the output distance function since this functional form allows for more flexibility than a Cobb- Douglas (Christensen et al., 1975; Greene, 1980). For the vector of outputs $y \in R_+^M$, each output is indexed by m or n where m and n = 1,2, …, M. For the vector of inputs $x \in R_+^N$ each input is indexed by j of k where j or k= 1,2, …, N. The vector of exogenous variables is $z \in R^J$ and each variable is indexed by p, p=1, 2,…, J.

Following Zhu and Oude Lansink (2010), the specification for the i-th firm at time t is:

$$ln\, y_{1i}^t = \beta_0 + \sum_{k=1}^N \beta_k\, ln\, x_{ki}^t + \frac{1}{2}\sum_{k=1}^N \sum_{j=1}^N \beta_{kj}\, ln\, x_{ki}^t ln\, x_{ji}^t + \sum_{m=2}^M \beta_m\, ln\, \frac{y_{mi}^t}{y_{1i}^t} + \frac{1}{2}\sum_{m=2}^M \sum_{n=2}^M \beta_{mn}\, ln\, \frac{y_{mi}^t}{y_{1i}^t} ln\, \frac{y_{ni}^t}{y_{1i}^t} + \sum_{k=1}^N \sum_{m=2}^M \beta_{km}\, ln\, x_{ki}^t ln\, \frac{y_{mi}^t}{y_{1i}^t} + \beta_t t + \frac{1}{2}\beta_{tt} t^{\,2} + \sum_{k=1}^N \beta_{kt}\, ln\, x_{ki}^t t + \sum_{k=1}^N \beta_{mt}\, ln\, \frac{y_{mi}^t}{y_{1i}^t} t + v_{it} - u_{it}, \quad (5)$$

Where all the inputs x (Table 2) are considered at the farm level to account for the nature of the selected sample, which consists of multi-output farms. Tomato production, i.e. the dependent variable y, instead, is treated separately and is also used to derive a normalized stochastic distance function, as explained in Equation 1. Moreover, u_{it} is defined by:

$$u_{it} = z_{it}\delta + \omega_{it} = \delta_0 + \sum_{p=1}^J \delta_p z_{pit} + \omega_{it}\,. \quad (6)$$

The distribution of the error terms in (5) and (6) have the assumptions: $v_{it} \sim iid\, N(0, \sigma_v^2)$, $u_{it} \sim N^+(z_{it}\delta, \sigma_{it}^2)$ and $\omega_{it} \sim N(0, \sigma_w^2)$. For a specific input indexed by k and for the i-th firm at time t, the elasticity ε_{ki}^t can be calculated as follows:

$$\varepsilon_{ki}^t = \frac{\partial ln y_{1i}^t}{\partial ln x_{ki}^t} = \beta_{kj} + \sum_{j=1}^N \beta_{kj} ln\, x_{ji}^t + \sum_{m=2}^M \beta_{km} ln\, \frac{y_{mi}^t}{y_{1i}^t} + \beta_{kt} t\ . \quad (7)$$

Using $\varepsilon_{it} = v_{it} - u_{it}$, TE is, instead, estimated as:

$$TE_{it} = E[exp(-u_{it}) | \varepsilon_{it}]. \quad (8)$$

The marginal effect of each exogenous variable (z_p) on TE can be obtained from Wang and Schmidt (2002):

$$\frac{\partial \mathrm{TE_{it}}}{\partial \mathrm{z_{it}}} = \exp[-\mathrm{E}\,(u_{it})] \cdot \left(\frac{\partial \mathrm{E}\,(u_{it})}{\partial \mathrm{z_{it}}}\right) = -TE_{it} \frac{\partial \mathrm{E}\,(u_{it})}{\partial \mathrm{z_{it}}} \quad (9)$$

The output distance function (5) and inefficiency effects model (6) are estimated for all the farms included in the selected sample. Given that elasticity is a measure of the sensitivity of one variable to changes in another, its estimation could offer insights into the expected alterations in agricultural output resulting from a reduction in considered inputs. Therefore, the economic impact of a 20% reduction in chemical fertilizers in line with F2F objectives is estimated using (7). The hypothesized reduction is implemented as a linear cut of 20% at the farm level. Although it is not clear whether these targets will be applied, i.e. if at the regional, national, or farm level, this factor could influence the results. Assuming the target is applied at the farm level, the impact could be exacerbated or mitigated depending on the efficiency level of the farms. Indeed, vulnerability is not solely linked to a high reliance (i.e. higher elasticity) on specific inputs but could also be influenced by TE. Farms operating below their maximum potential output could be more susceptible to the impacts of reduced production inputs. Conversely, highly efficient farms may already have reached an optimum and variations in input availability could lead to economic losses. Under these assumptions, empirical estimations of TE using (8) serve as an additional indicator. This approach allows for discussing the link between empirical efficiency estimations and the anticipated impacts of the F2F on farm economic results. Furthermore, the analysis controls for factors potentially reflecting farmers' behaviour regarding input overuse, estimating the effect of these exogenous variables on TE (9) and enhancing our understanding of the dynamics at play.

5.4.3. Data

Data on farms producing processing tomatoes, were obtained from the Italian Farm Accountancy Data Network (FADN) database. FADN is the only source of microeconomic data based on harmonized bookkeeping principles. Based on national surveys, it aggregates data on 68,000 farms, representing almost 5 million UE farms, 90% of the European Utilized Agricultural Area (UAA) and Standard Output. The Italian sample includes 11,000 farms, whose data are stratified by region, size, and Type of Farming (TF). The data include Gross Output, land, crop-specific variable costs, work-related costs for family and employed workers, and irrigation water volumes.

The FADN database provides information on farm outputs, which consist of three categories: crops and crop products, livestock and livestock products and other outputs. Since our analysis focuses specifically on processing tomatoes, our analysis does not include livestock or livestock products due to the selected Types of Farm (TF)[19] and Tomato Output has been separated from the rest (Other Outputs). To ensure the focus on conventional farming practices and to avoid bias in our analysis, organic farms or farms declaring to follow integrated pest management or other techniques requiring lower input usage were excluded from the analysis. Likewise, observations related to farms with greenhouse tomato production were excluded. Finally, an unbalanced panel of 843 farms with 2,147 observations for 2010–2021 was selected.

Table 2: Descriptive Statistics for Output Distance Variables

Variables	Mean	Std. Dev.
Capital (€/ha)	2408	4655
Tomato Output (€/ha)	7930	6226
Other Outputs (€/ha)	3764	5275
Variable Costs (€/ha)	1630	1477
Land (ha)	61	92
Irrigation Water (m^3/ha)	1246	1265
Organic Fertilizers (100 kg/ha)	5.1	4.7
Chemical Fertilizers (100kg/ha)	5.3	38.1
Pesticides (€/ha)	292	347
Hired Work (Working Units)	3.1	4.9
Family Work (Working Units)	1.3	0.7

[19] TFs 1630, 1660, 2210, 6120, 6130, 6140 and 6150 have been selected. These TFs include farms specialized in vegetable crops and mixed farms that, among other products, produce processing tomato. Livestock and mixed farms with livestock are excluded.

In terms of inputs been categorized into Capital such as owned machinery, buildings, facilities, irrigation systems etc., Land, Variable Costs (seeds, insurance, fuel, energy, rents and other expenditures), Family Work, and Hired Work. Other Outputs include the farm Gross Saleable Production excluded Tomato Production. Pesticides were also included, using the annual expenditure, considering the challenges associated with aggregating quantities due to the various formulations and types of used pesticides, which could have led to distorted indications. In the case of Fertilizers, instead, a further distinction allows us to differentiate between Chemical Fertilizers and Organic Fertilizers. Finally, Irrigation Water volumes have been also considered. Table 2 shows the variables of the Output Distance Function and their summary statistics, while Table 3 provides the mean values and their distributions for the variables included in the inefficiency effects model.

Table 3: Explanatory variables (z variables) in the inefficiency effects model: definitions and descriptive statistics

Variables	Description	Mean	Std. Dev.
Owned Land	Share of Owned Land on UAA	0.42	0.4
Degree of Specialization	Share of Tomato Output on Total Output	0.39	0.23
CAP I	Share of Pillar 1 payments on Total Output	0.17	0.16
CAP II	Share of Pillar 2 payments on Total Output	0.02	0.1
Water Source	Share of land served by WUAs irrigation water on UAA	0.43	0.48
Family Work	Share of Family Workers on Total Workers	0.38	0.13
		Freq.	Share on Total (%)
Region	Northern	784	36.52
	Central	282	13.13
	Southern	1,081	50.35
Altitude	Plain	1,229	57.24
	Hill	768	35.77
	Mountain	150	6.99
Gender	F	325	15.14
	M	1,822	84.86
Age	> 40	1,819	84.72
	<40	328	15.28
Farm Size (ha)	<5	154	7.17
	5-15	413	19.24
	15-40	641	29.86
	>40	939	43.74
Economic Dimension (€)	8,000-25,000	165	7.69
	25,000-50,000	195	9.08
	50,000-100,000	243	11.32
	100,000-500,000	1,029	47.93
	500,000 – 1,000,000	515	23.99

5.5. Empirical Results

5.5.1. Output Distance Function Estimates and Elasticities

As a standard empirical application of Battese and Coelli's (1995) model, the maximum likelihood method was employed to obtain parameter estimates of the output distance function and inefficiency effects model (Table A1 in Appendix). As the Cobb-Douglas function is a restricted form of a Translog function, we conducted a comparison between these functions using an F-test, testing the restricted Cobb-Douglas model against the full Translog model. The obtained results confirmed that the Translog production function significantly better fits the data.

The estimated coefficients of the output distance function (see Table A1) show the high significance for several inputs and their interactions, thereby revealing various relations among them, both positive and negative. Focusing on this study's objective, Chemical Fertilizers show a positive interaction with Variable Costs (0.059) indicating a complementarity between the use of fertilizers and expenditures on other costs (plants, energy, fuel, etc.) and a negative interaction with Organic Fertilizers (-0.012), indicating that chemical fertilizers and organic fertilisers are substitutes. In contrast, the other interactions are not statistically significant, suggesting that the use of Chemical Fertilizers is not influenced by variations in other inputs at the farm level, including Land and Pesticides. Concerning Pesticides, on the other hand, this input shows a positive interaction with Other Products (0.105), Variable Costs (0.101) and Land (0.070) suggesting a correlation between pesticide use and increased production diversity, additional variable costs, and expanded cultivated area, may be indicative of greater intensification. Conversely, a negative relation is observed with Water (-0.029), suggesting a substitution effect between pesticides and water.

The estimation of the output distance function enables us to obtain output elasticity for each input, initiating its contribution to output production and assessing the output's sensitivity to the variations in that input while keeping others constant. The higher the elasticity, the greater the sensitivity of output to the variations of a certain input. This information allows us to evaluate the percentage changes in output associated with the F2F strategy targets, such as the 20% reduction in the input of chemical fertilizers.

Table 4 shows the output elasticity of each input in processing tomato production in Italy. The elasticity of tomato production concerning each input (i.e., the elasticity of the distance function) is positive except for Irrigation Water and Land. The average elasticity for Chemical Fertilizers is 0.48, while for Pesticides is 0.79. A smaller than one value of the elasticity for a specific input indicates that increasing the amount of this input by 1% does not increase the output by the same percentage, keeping other inputs fixed. However, the contribution of Organic Fertilizers is not significant. Among the other inputs, one of the variables with the major impact is Family Work, with an average elasticity of 1.25 indicating more output can be obtained by each unit of family work, while Hired Work, is statistically not significant. Concerning Variable Costs, the average elasticity shows a value of 0.43, while Other Products show a null and hence non-significant value. Capital shows a positive average value of 0.16. Finally, Irrigation Water exhibits a value of -0.35 which is highly significant. This negative relationship could be attributed to challenges posed by the limited availability of water in certain regions, especially in Southern Italy. The competition among different crops for irrigation resources, coupled with the substantial water requirements of tomato production, may contribute to the observed impact on the dependent variable. This is especially true for non-specialized farms, which may prioritize more profitable or less water-intensive crops.

Table 4: Average and St. Dev. for Estimated Elasticities

	Mean		St. Dev.
Chemical Fertilizers	0.48	**	0.08
Pesticides	0.79	**	0.15
Organic Fertilizers	-0.04		0.05
Land	-0.58	*	0.2
Hired Work	-0.54		0.22
Family Work	1.25	***	0.34
Variable Costs	0.43	***	0.26
Other Products	0.00		0.24
Capital	0.16	***	0.04
Irrigation Water	-0.35	***	0.08

*Note: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Source: Authors' elaboration*

Considering the estimated elasticity, which reflects the responsiveness of Tomato Output to Chemical Fertilizers (0.48), indicates a 0.48% increase in tomato output for every 1% increase in Chemical Fertilizers expenditure, a 20% reduction of this input under the Farm to Fork strategy would lead to an average reduction of 9.5% in Italian Processing Tomato Production. For an average Production of approximately 8.000 € per hectare, this would translate to a loss of 743 € per hectare.

To identify the most vulnerable areas and farms across the country, we also provide results for various clusters of farms, taking into account territorial characteristics such as Region and Altitude and farm characteristics such as Farm Size and Economic Size. Table 5 shows how the reduction of chemical fertilizers could affect the output of different clusters of farms in terms of region, altitude, farm size etc. This not only helps identify the most affected clusters but also offers insights into the chemical intensity within each group. This assessment helps determine whether groups with highly intensive tomato production are more affected or, conversely, if those already utilizing lower levels of fertilizers show greater vulnerability. The results reveal a higher vulnerability of Northern Italian regions (- 10.3), Plain areas (- 10.0) and especially larger farms, both in economic terms (- 11.1) and acreage (- 10.7)., notably the most productive ones.

However, these results do not always correspond to a higher level of fertilizer intensity. For instance, Northern regions show a lower value, as farms above 40 hectares and those whose Standard Output is between 50,000 and 100,000 euros. It is also interesting to note that the impact on Tomato Output proportionately increases with Farm Size and with Economic Size, with small farms showing a reduction of approximately -7%. Conversely, from Northern to Southern Italy, the impact decreases, as does the impact with increasing altitude, towards areas less suitable for processing tomato cultivation. However, these impacts do not consistently align with clear trends in the quantity of chemical fertilizers. Therefore, additional insights can be obtained by estimating Technical Efficiency

Table 5: Chemical Fertilizers average utilization and distribution of estimated tomato output reduction by farm characteristics (Mean, St. Deviation, Q1 and Q3)

		Chemical Fertilizers (100 kg/ha)	Tomato Output Reduction (%)			
		Mean	Mean	St. Dev.	Q1	Q3
Region	Northern	4.3	-10.3	1.2	-9.7	-11.1
	Central	5.6	-9.8	1.2	-9.1	-10.5
	Southern	5.9	-8.9	1.5	-7.7	-10.1
Altitude	Plain	5.2	-10.0	1.3	-9.4	-10.8
	Hill	4.9	-9.0	1.7	-7.7	-10.3
	Mountain	4.8	-8.5	1.3	-7.7	-9.5
Farm Size (ha)	< 5	7.8	-7.2	0.9	-6.6	-7.9
	5 15	5.0	-8.0	1.0	-7.3	-8.7
	15 – 40	4.5	-9.4	0.9	-8.9	-10.0
	> 40	5.0	-10.7	0.9	-10.1	-11.3
Economic Dimension (€)	8,000 - 25,000	5.2	-7.0	0.8	-6.4	-7.4
	25,000-50,000	4.7	-7.5	0.8	-7.0	-8.1
	50,000-100,000	5.1	-8.4	0.7	-7.9	-9.0
	100,000-500,000	4.8	-9.8	0.8	-9.4	-10.3
	500,000-1,000,000	5.7	-11.1	0.8	-10.6	-11.6
Average		5.1	-9.5	1.5	-8.5	-10.6

5.5.2. Technical Efficiency

The estimation results of technical efficiency for different clusters of farms are shown in Table 6. The estimated average TE is 64% based on our sample, but variations have been highlighted when examining territorial and farm characteristics (Table 6). The average TE shows lower values in the Hill areas (55%) and Southern Italy (62%). Additionally, TE increases proportionally to Economic Size, reaching a maximum of 77% in bigger farms while smaller farms show the lowest TE (41%) of the group. The same happens when acreage is concerned, with bigger farms showing an average TE of 68% and smaller farms of 54%. Figure 1 shows the estimated TE over the years, revealing a marked efficiency improvement in this sector. The decrease in TE from 2014 to 2017, is probably influenced by the tomato low market prices in those years, followed by a subsequent increase, with the average TE reaching its peak in 2021 (72%).

Full comprehension requires considering the influence of the exogenous variables included in the inefficiency effects model (Table A1), whose estimates indicate the direction of the effects of the considered variables on the inefficiency level: a positive sign implies a negative impact on TE and vice versa. It is important to note that the average TE values should not necessarily align with the marginal effects derived from the inefficiency effects model. The average TE provides an overall perspective, while the marginal effects highlight the specific impact of each variable on efficiency, allowing for specific dynamics and giving indications of factors affecting positive (or negative) changes in TE.

Results show that farms located in the Northern Regions show lower TE than farms located in the Central Regions but do not highlight any difference from Southern Regions. Concerning Altitude, a Plain location has a positive effect on TE than being in a Hilly region. Regarding CAP subsidies both first and second pillar payments show a highly significant negative effect on TE. The same can be said for the share of Owned Land, while the Degree of Specialization shows a negative sign, implying a positive effect on TE. The demographic characteristics of the farmers are not significant, indicating that Gender and Age do not have any effect on TE. The same is true for Farm Size, while the Economic Size show a positive impact on TE as the Standard Output produced increases. Finally, Family Work employed in the farms has a positive impact on TE, as it happens when the share of land served by WUAs water increases.

To facilitate an assessment of these effects, Table 7 shows the marginal effect on the estimated TE of the statistically significant variable considered in the inefficiency effects model. Specifically, the Northern regions exhibit a lower TE (-4.3%) compared to the Central Italy regions, while Mountain show a higher TE (+1.3%) compared to Hill. The share of first-pillar CAP subsidies on total Output results in a decrease of 19% in TE, while the impact is lower for second-pillar CAP subsidies (-5.3%). In contrast, specialization has a positive impact, standing at 77%, while the share of Owned Land on the total UAA results in a reduction in TE of 4.7%. Concerning the Economic Size, a positive impact relative to smaller farms (5,000 – 25,000) is observed in the 25,000-50,000 class, where TE is greater by 7.4%. However, as the Economic Size increases, the impact increases, with TE greater than 11% for the 50,000-100,000 class and 20% for the 100,000-500,000 class. The greatest difference from smaller farms occurs in the larger Economic Size class (500,000-1,000,000), with a difference of 28%. Lastly, the percentage of family workers increases TE by 24%, while water supply from WUAs improves by 1.1%.

Table 6: Estimated TE by Farm Characteristics (Mean, St. Deviation, Q1 and Q3)

		Mean	St. Dev.	Q1	Q3
Region	Northern	0.653	0.162	0.531	0.780
	Central	0.653	0.193	0.513	0.829
	Southern	0.621	0.216	0.452	0.808
Altitude	Plain	0.696	0.168	0.567	0.842
	Hill	0.551	0.198	0.399	0.698
	Mountain	0.598	0.220	0.413	0.766
Farm Size (ha)	< 5	0.535	0.174	0.409	0.642
	5 15	0.584	0.220	0.399	0.766
	15 - 40	0.641	0.201	0.506	0.802
	> 40	0.675	0.171	0.546	0.816
Economic Dimension (€)	8,000 - 25,000	0.407	0.159	0.287	0.510
	25,000-50,000	0.467	0.182	0.315	0.594
	50,000-100,000	0.558	0.185	0.422	0.685
	100,000-500,000	0.658	0.167	0.529	0.791
	500,000-1,000,000	0.770	0.133	0.692	0.878
Average		0.637	0.196	0.497	0.798

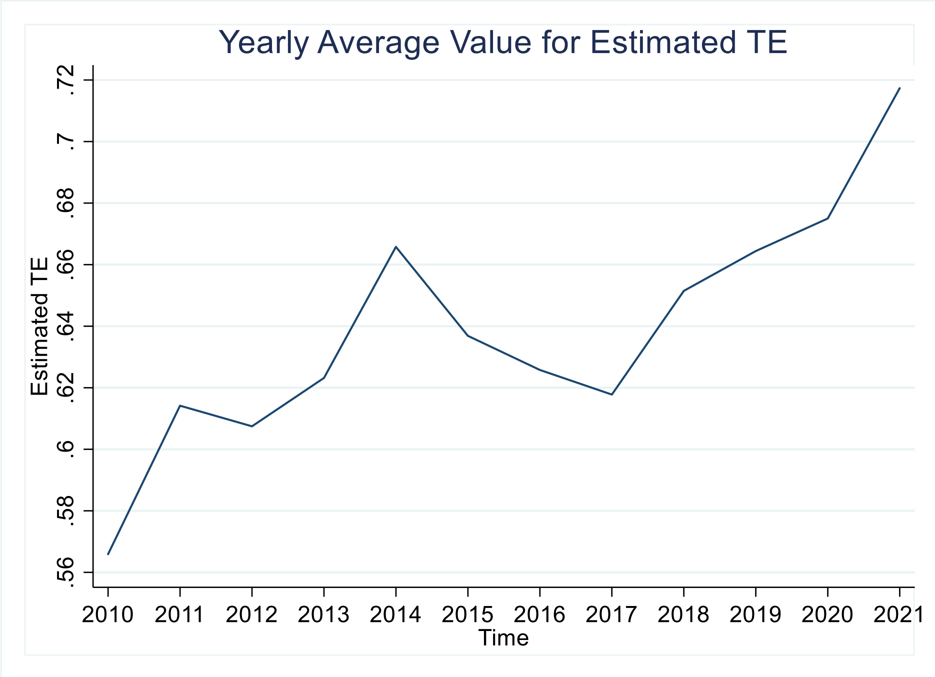

Figure 1: Average Estimated TE over the years (2010-2021)

Table 7: Marginal Effects on TE of Statistically Significant Variables Identified by the Inefficiency Effects Model

Variable	Marginal effect on TE
Region – Central	
Northern	-0.043
Altitude – Hill	
Mountain	0.013
CAP I	-0.192
CAP II	- 0.053
Specialization	0.771
Owned Land	-0.047
Economic Dimension (€) – 5,000 – 25,000	
25,000-50,000	0.074
50,000-100,000	0.105
100,000-500,000	0.197
500,000-1,000,000	0.284
Family work	0.241
WUA	0.011

Note: Region, Altitude and Economic Dimension marginal effects are expressed as the difference from the baseline (in bold).

5.6. Discussion

This analysis, based on the estimation of an Output Distance Function, allowed us to identify the key agricultural inputs that significantly contribute to processing tomato production in Italy. Among the multi-output farms in our sample, Family Labor, Pesticides, and Chemical Fertilizers emerge as the inputs with the most substantial impact on production confirming that tomato is a high-input-demanding crop (Cammarano et al., 2020; Ronga et al., 2019). In contrast, Variable Costs and Capital have a less pronounced influence. Conversely, Water and Land show negative elasticity values, which may be attributed to various factors. The negative sign for water may reflect competition among various crops for limited resources. Specifically in Southern Italy, a significant tomato-producing area prone to drought, the competition for water resources causes strategic decisions by farmers regarding crop allocation. Non-specialized farms may opt for more profitable or less water-intensive crops, given the critical role of water availability during key stages of cultivation. The allocation to other crops could also occur because tomatoes appear to react positively to controlled water deficit conditions in response to high temperatures and CC effects (Giuliani et al., 2019). This flexibility in water usage probably allows for allocation to other crops, especially during the dry season. Similarly, expanding cultivated land may divert investment to other crops, consequently reducing tomato production. Our findings align with those of Auci and Vignani (2020) who observed the negative effects of increased irrigated and cultivated areas on crop cultivation in Italy, especially for vegetables. These outcomes may also be linked to the efficiency of chosen irrigation methods, which can vary depending on soil and crops.

Focusing on the role of chemicals in processing tomato production, Chemical Fertilizers and Pesticides reveal a complex relationship with other inputs. More specifically, positive associations between Pesticides and Other Costs (including seeds, energy, etc.) as well as with Land and Other Products were uncovered. This reveals that larger scale and diversification enhance the role of pesticides in ensuring income stability, safeguarding production, and reducing uncertainty, especially in the case of vegetables where product quality and appearance are crucial for consumers (Bix et al., 2012). On the other hand, an adequate water supply mitigates the need for intensive pesticide use. Instead, Chemical Fertilizers show a positive interaction with Other Costs, and a substitution effect is observed with Organic Fertilizers. However, our analysis does not reveal any other significant interaction, suggesting that chemical fertilizers play a crucial role in market-oriented farms known for high productivity and intensity, a point also supported by Heeb et al. (2006).

An additional worth mentioning finding arising from the analysis concerns one of the objectives outlined in the Farm to Fork (F2F) Strategy, i.e., the pursuit of a 20% reduction of chemical fertilizers. Under this scenario, given a national average production of approximately 8,000 € per hectare, these farms would experience an average economic loss of approximately 9.6%, equivalent to a total of 743 € per hectare. Estimates of F2F and Green Deal impact on European agriculture, as per Barreiro-Hurle et al. (2021), suggest a 12% supply loss for vegetables (including tomatoes), albeit offset by a 15% increase in prices, resulting in a 5% income reduction due to concurrent cost increases, in line with findings by Beckman et al. (2020). Henning et al. (2021), instead, estimate a 13% loss of production. It's essential to note that these analyses cover the entire EU area, whereas our work specifically focuses on Italy and aims to assess the economic effects of only reducing chemical fertilizers. Comparing our results with those of Cortignani et al. (2022) for Italy, in a scenario that only includes a reduction in chemical fertilizers, the fresh fruit sector (including tomatoes) would experience a 7.1% yield loss. This impact varies significantly across the country, depending on geographic and farm characteristics: the most productive areas in the North and plains appear to be the most affected by this reduction. However, it's crucial to highlight that our analysis estimates the impact on total output, which may vary, as demonstrated by Beckman et al.(2020), depending on adjustments in prices and production costs.

The estimated average TE stands at 64%, but it shows a positive trend over the years, indicating growth and increased attention to input utilization by these farms. The results, in fact, show a TE value of 72% in the post-COVID-19 period. Obtained TE is consistent with previous studies on crop farms in Germany, the Netherlands, and Sweden by Zhu and Lansink (2010), in Poland (Latruffe et al. 2004), and by Čechura et al. (2021) for tomato production in Italy from 2004 to 2017. Nevertheless, the results obtained in this study are comparatively lower than those reported by Galluzzo (2022) for horticultural crops, whose analysis includes greenhouse cultivation, which tends to exhibit higher efficiency. Additionally, the findings for tomatoes in our study contrast with those of Iráizoz et al. (2003) in Spain and Benedetti et al. (2019) in Italy but it's important to note that the mentioned analyses focus on specialized and intensive areas based on a single year of observation. In contrast, this analysis uses a large sample covering ten years of data and does not focus on specialized farms.

In addition, the analysis has identified the most vulnerable farms to input reduction by considering both elasticities and TE. Interestingly, it reveals that more efficient farms are also the ones where a reduction in chemical fertilizers would lead to more substantial output losses. This could depend on the fact that these farms are close to an optimum of efficiency in input usage, and therefore, a reduction would have a greater impact on them. The inefficiency effects model, coupled with the

Output Distance Function, illustrates how exogenous variables influence TE. This is essential because, as discussed in the literature, input use decisions also depend on external factors that can potentially lead to input overuse (Singbo et al., 2015). Among the various factors, is risk aversion level (Bontemps et al., 2021) with proxies in this analysis being gender, age and farm specialization. Notably, our analysis did not reveal a significant effect of demographic factors on TE. However, specialization demonstrated a substantial effect, indicating that more specialized farms tend to operate with greater efficiency (Karagiannis and Sarris, 2005; Zhu et al., 2012; Zhu and Lansink, 2010) making diversified farms more vulnerable. Moreover, we found that Northern regions appear to be less efficient than those in Central Italy, while mountainous areas are more efficient than plain areas, contrasting with the results of Brümmer (2001). The disparity in efficiency levels could be attributed to the composition of our sample, where farms in mountainous regions are a minority and usually tend to adopt less intensive agricultural practices. In addition, the lower TE found in Plains regions could also suggest a potentially higher vulnerability in more intensive areas highlighting the nuanced influence of geographic and topographic factors on agricultural efficiency.

The analysis also underscores the positive impact associated with the use of family labour, implying potentially higher vulnerability to constraint in input use for farms heavily reliant on hired labour. It must be reminded, that Italian farms, irrespective of their size, are usually family-run or mainly family-run. The effect of family labour on these farms is probably advantageous due to familiarity with the land and crops and due to the direct engagement of family members, which also results in significant labour cost savings, contributing to overall economic efficiency. These results are in line with the findings of Rezitis et al. (2003) in Greece and Latruffe et al (2004) in Poland. However, the relationship between efficiency and family labour is ambiguous, as demonstrated by Kostov et al (2018) who found various effects depending on the efficiency level of the considered farms. Similarly, Bojnec and Latruffe (2009) found a non-significant effect for hired labour in Slovenian farms, making it difficult to assert that family labour necessarily leads to lower efficiency. On the other hand, Karagiannis and Sarris (2005) found that family labour has a negative impact on TE but a positive impact on scale efficiency suggesting that hired labour is more productive in reaching the maximum output for given inputs, but the opposite is true for achieving optimal scale.

In terms of irrigation source, WUAs exhibit a positive influence, consistent with the results obtained by Chaudhry (2018) and Gadanakis et al. (2015) reflecting a positive effect of scheduling irrigation season in advance and programming water volumes reserved for each crop. WUAs usually carefully plan the irrigation season and the planning process typically considers factors such as anticipated water availability, crop water requirements and historical usage patterns leading to greater efficiency in water use. In contrast, farms relying on alternative water sources, such as groundwater, might experience higher flexibility in irrigation water volumes and schedules, potentially resulting in less efficient allocation. In addition, the main costs incurred in this case concern infrastructure, delivery, and water extraction, which translates to fewer constraints on resource usage (Gómez and Pérez Blanco, 2012).

In terms of farm size, economic size positively affects TE, consistent with the findings of Mendes et al. (2013) and, concerning Italy, the results obtained by Forleo et al. (2021) for diversified farms. Economic size in agriculture can enhance TE due to economies of scale that enable a reduction in average costs, while the opportunity for specialization or diversification can optimize resource use. Larger farms often have access to advanced resources and technologies, allowing for substantial investments. Lastly, professional management, coupled with broader market access, contributes to an overall improvement in efficiency. However, the impact of economic size on efficiency can vary depending on the specific context as highlighted by the review of Latruffe (2010).

The same is true for land ownership: in our work owned land negatively influences TE, in line with the findings of Karagiannis et al. (2003), Rezitis et al. (2003) and also with Zhu et al. (2012) whose results indicate that an increase in rented land improves TE. The decision to rent land in agriculture offers financial flexibility, allowing farmers to direct more capital towards efficient investments without the burden of property ownership. With reduced operational complexity and maintenance costs, land renting emerges as a reasonable choice for enhancing efficiency in agriculture. Nevertheless, some studies diverge in this regard, as Bojnec and Latruffe (2009) suggest that the result for these variables changes depending on the estimation method used,i.e. DEA or SFA.

On the contrary, subsidies negatively impact TE, in line with previous studies (Zhu et al., 2012; Zhu and Lansink, 2010). For instance, Quiroga et al. (2017) demonstrated that in Italy, the percentage of first-pillar aids on total output reduces TE, as do decoupled payments. However, the effects of subsidies on farm efficiency could be ambiguous and context-dependent, as highlighted by Latruffe and Desjeux (2016), with local environmental and institutional framework playing a significant role as demonstrated by the various effects found by Latruffe et al. (2017) within a sample of European dairy farms.

5.7. Conclusions

This analysis, leveraging a FADN sample of 843 Italian farms for the period … and the estimation of an Output Distance Function, explores the dynamics influencing processing tomato production in Italy. The findings highlight the significant role of Family Labor, Pesticides, and Chemical Fertilizers for this crop, also shedding light on several aspects, i.e., the competition between tomatoes and other crops for crucial resources like water and land at the farm level. The study also reveals the high dependence of tomato production on chemical fertilizers, implying limited substitution possibilities. Applying these results to the Farm to Fork context, one can identify that a reduction in chemical fertilizers, coupled with a decrease in pesticides, could pose a genuine threat to Italian processing tomato production leading to an Output reduction of 9.6% on average. In addition, a substitution effect found between organic and chemical fertilizers, but organic fertilizers elasticity has no significant effect on tomato production, suggesting that despite the found substitutivity, transitioning to organic production may not be an effective solution, especially for larger and more intensive farms. Indeed, tomato production shows a null reaction to variations in organic fertilizers while chemical fertilizers reductions, especially in nitrogen, are found to significantly reduce productivity, except for certain low-input-tolerant tomato cultivars in organic farms (Rosa-Martínez et al., 2021; Tripodi et al., 2022).

Particularly modifications in chemical usage will affect the most productive and efficient farms, posing challenges for the production and export of processing tomatoes, an economically strategic crop for Italy if the environmental consequence related to the crop production is not a priority in the Country. In addition, several farms' characteristics influencing efficiency level are identified, contributing to the comprehension of the Italian processing tomato overall production system, such as degree of specialization, family labour and economic size. Moreover, our analysis suggests that despite increased support that may be necessary to offset productivity loss, careful consideration is essential to avoid long-term impacts on efficiency. Mitigating the adverse effects of reduced chemical fertilizers could benefit from adopting advanced technologies, low-input genotypes, precision agriculture and agronomic management strategies, especially considering the impact that CC will have on Mediterranean agriculture (Cammarano et al., 2020).

However, this study exhibits some limitations, mostly related to the sample composition, which mainly consists of unspecialized farms. Therefore, the findings might not directly apply to specialized ones. In addition, this analysis does not consider the potential price adjustments in response to variations in tomato supply, which could potentially offset yield reductions deriving from a reduction in chemicals. Moreover, considering the potential impacts of the CAP 2024-2027, especially voluntary measures such as Eco-Schemes could introduce additional uncertainties that could significantly influence outcomes, an aspect worth exploring further. In conclusion, our work describes a context where reducing chemicals may cause a short-term reduction in tomato production given the current technology. However, for agricultural sustainable production, the practices proposed by the Farm to Fork strategy might pay off in the long term. New CAP should pay more attention to the short-term losses of farmers. Anticipating the impacts of policy changes and the transition to a greener economy, as outlined in the EU Green Deal, demands technological advancements, strategic adaptation, and tailored support for farmers. In this context, the EU Commission's decision to withdraw the Sustainable Use Regulation (SUR) and reconsider chemical reduction targets introduces new challenges, requiring support to find a suitable alternative that reaches the necessary balance between production and the environment. This underscores the importance of such analyses, as they provide insights into this ongoing process, emphasizing the critical need for solutions that acknowledge the specific vulnerabilities of various sectors, areas, and contexts.

5.8. References

Alexander, P., Reddy, A., Brown, C., Henry, R.C., Rounsevell, M.D.A., 2019. Transforming agricultural land use through marginal gains in the food system. Glob. Environ. Chang. 57, 101932. https://doi.org/10.1016/j.gloenvcha.2019.101932

Auci, S., Vignani, D., 2020. Climate variability and agriculture in Italy: a stochastic frontier analysis at the regional level. Econ. Polit. 37, 381–409. https://doi.org/10.1007/s40888-020-00172-x

Bakker, L., Sok, J., van der Werf, W., Bianchi, F.J.J.A., 2021. Kicking the Habit: What Makes and Breaks Farmers' Intentions to Reduce Pesticide Use? Ecol. Econ. 180. https://doi.org/10.1016/j.ecolecon.2020.106868

Balezentis, T., Chen, X., Galnaityte, A., Namiotko, V., 2020. Optimizing crop mix with respect to economic and environmental constraints: An integrated MCDM approach. Sci. Total Environ. 705, 135896. https://doi.org/10.1016/j.scitotenv.2019.135896

Barreiro-Hurle, J., Bogonos, M., Himics, M., Hristov, J., Pérez-Domiguez, I., Sahoo, A., Salputra, G., Weiss, F., Baldoni, E., Elleby, C., 2021. Modelling environmental and climate ambition in the agricultural sector with the CAPRI model, JRC Technical Report. https://doi.org/10.2760/98160

Battese, G.; Coelli, T., 1995. A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data. J. Econom. 325–332.

Beckman, J., Ivanic, M., Jelliffe, J., Baquedano, F., Scott, S., 2020. Economic and food security impacts of agricultural input reduction under the European Union Green Deal's farm-to-fork and biodiversity strategies. U.S. Dep. Agric. Econ. Res. Serv. EB-30, 1–59.

Benedetti, I., Branca, G., Zucaro, R., 2019. Evaluating input use efficiency in agriculture through a stochastic frontier production: An application on a case study in Apulia (Italy). J. Clean. Prod. 236, 117609. https://doi.org/10.1016/j.jclepro.2019.117609

Bierkens, M.F.P., Reinhard, S., de Bruijn, J.A., Veninga, W., Wada, Y., 2019. The Shadow Price of Irrigation Water in Major Groundwater-Depleting Countries. Water Resour. Res. 55, 4266–4287. https://doi.org/10.1029/2018WR023086

Bix, L., Seo, W., Sundar, R.P., 2012. The Effect of Colour Contrast on Consumers' Attentive Behaviours and Perception of Fresh Produce. Packag. Technol. Sci. 29, 399–412. https://doi.org/10.1002/pts

Bojnec, Š., Latruffe, L., 2009. Determinants of technical efficiency of Slovenian farms. Post-Communist Econ. 21, 117–124. https://doi.org/10.1080/14631370802663737

Bontemps, C., Bougherara, D., Nauges, C., 2021. Do Risk Preferences Really Matter? The Case of Pesticide Use in Agriculture. Environ. Model. Assess. 26, 609–630. https://doi.org/10.1007/s10666-021-09756-8

Bremmer, J., Gonzalez-martinez, A., Jongeneel, R., Huiting, H., Stokkers, R., n.d. Effects of Farm to Fork and Biodiversity Strategy 2030 at farm , national and EU level c, 1–4.

Brümmer, B., 2001. Estimating confidence intervals for technical efficiency: The case of private farms in Slovenia. Eur. Rev. Agric. Econ. 28, 285–306. https://doi.org/10.1093/erae/28.3.285

Cammarano, D., Ronga, D., Di Mola, I., Mori, M., Parisi, M., 2020. Impact of climate change on water and nitrogen use efficiencies of processing tomato cultivated in Italy. Agric. Water Manag. 241. https://doi.org/10.1016/j.agwat.2020.106336

Cao, Y., Zhang, W., Ren, J., 2020. Efficiency analysis of the input for water-saving agriculture in China. Water (Switzerland) 12, 1–16. https://doi.org/10.3390/w12010207

Čechura, L., Kroupová, Z.Ž., Samoggia, A., 2021. Drivers of productivity change in the italian tomato food value chain. Agric. 11. https://doi.org/10.3390/agriculture11100996

Chaudhry, A.M., 2018. Improving on-farm water use efficiency: Role of collective action in irrigation management. Water Resour. Econ. 22, 4–18. https://doi.org/10.1016/j.wre.2017.06.001

Chavas, Jean-Paul. "Role of risk and uncertainty in agriculture." The Routledge handbook of agricultural economics. Routledge, 2018. 603-615.

Christensen, L.R., Jorgenson, D.W., Lau, L.J., 1975. Transcendental Logarithmic Utility Functions. Am. Econ. Rev. 65, 367–383.

Christian Henning; Peter Witzke, 2021. Economic and Environmental impacts of the Green Deal on the Agricultural Economy: A Simulation Study of the Impact of the F2F-Strategy on Production, Trade, Welfare and the Environment based on the CAPRI-Model 1–10.

Cortignani, R., Buttinelli, R., Dono, G., 2022. Farm to Fork strategy and restrictions on the use of chemical inputs: Impacts on the various types of farming and territories of Italy. Sci. Total Environ. 810, 152259. https://doi.org/10.1016/j.scitotenv.2021.152259

Đoki, D., 2022. Technical Efficiency of Agriculture in the European Union and Western Balkans : SFA Method.

Dono, G., Severini, S., Dell'Unto, D., Cortignani, R. (2019). Italy. In: Molle, F., Sanchis-Ibor, C., Avellà-Reus, L. (eds) Irrigation in the Mediterranean. Global Issues in Water Policy, vol 22. Springer, Cham. https://doi.org/10.1007/978-3-030-03698-0_6

Fitton, N., Alexander, P., Arnell, N., Bajzelj, B., Calvin, K., Doelman, J., Gerber, J.S., Havlik, P., Hasegawa, T., Herrero, M., Krisztin, T., van Meijl, H., Powell, T., Sands, R., Stehfest, E., West, P.C., Smith, P., 2019. The vulnerabilities of agricultural land and food production to future water scarcity. Glob. Environ. Chang. 58, 101944. https://doi.org/10.1016/j.gloenvcha.2019.101944

Forleo, M.B., Giaccio, V., Mastronardi, L., Romagnoli, L., 2021. Analysing the efficiency of diversified farms: Evidences from Italian FADN data. J. Rural Stud. 82, 262–270. https://doi.org/10.1016/j.jrurstud.2021.01.009

Gadanakis, Y., Bennett, R., Park, J., Areal, F.J., 2015. Improving productivity and water use efficiency : A case study of farms in England. Agric. Water Manag. 160, 22–32. https://doi.org/10.1016/j.agwat.2015.06.020

Galluzzo, N., 2022. Farms specialization, economic size and technical efficiency in Italian farms using a non-parametric approach. Bulg. J. Agric. Sci. 28, 36–41.

Giuliani, M.M., Gatta, G., Cappelli, G., Gagliardi, A., Donatelli, M., Fanchini, D., De Nart, D., Mongiano, G., Bregaglio, S., 2019. Identifying the most promising agronomic adaptation strategies for the tomato growing systems in Southern Italy via simulation modelling. Eur. J. Agron. 111, 125937. https://doi.org/10.1016/j.eja.2019.125937

Gómez, C.M., Pérez Blanco, C.D., 2012. Do drought management plans reduce drought risk? A risk assessment model for a Mediterranean river basin. Ecol. Econ. 76, 42–48. https://doi.org/10.1016/j.ecolecon.2012.01.008

Greene, W., 1980. Maximum Likelihood Estimation of Econometric Frontier Functions 13, 27–56.

Heeb, A., Lundegårdh, B., Savage, G., Ericsson, T., 2006. Impact of organic and inorganic fertilizers on yield, taste, and nutritional quality of tomatoes. J. Plant Nutr. Soil Sci. 169, 535–541. https://doi.org/10.1002/jpln.200520553

Henke, J., Breustedt, G., Sieling, K., Kage, H., 2007. Impact of uncertainty on the optimum nitrogen fertilization rate and agronomic , ecological and economic factors in an oilseed rape based crop rotation. J. Agric. Sci. 145, 455–468. https://doi.org/10.1017/S0021859607007204

Iráizoz, B., Rapún, M., Zabaleta, I., 2003. Assessing the technical efficiency of horticultural production in Navarra, Spain. Agric. Syst. 78, 387–403. https://doi.org/10.1016/S0308-521X(03)00039-8

Jin, J., He, R., Gong, H., Xu, X., He, C., 2017. Farmers' risk preferences in rural china: Measurements and determinants. Int. J. Environ. Res. Public Health 14. https://doi.org/10.3390/ijerph14070713

Karagiannis, G., Sarris, A., 2005. Measuring and explaining scale efficiency with the parametric approach : the case of Greek tobacco growers 33.

Karagiannis, G., Tzouvelekas, V., Xepapadeas, A., 2003. Measuring Irrigation Water Efficiency with a Stochastic Production Frontier 57–72.

Kostov, P., Davidova, S., Bailey, A., 2018. Effect of family labour on output of farms in selected EU Member States: A nonparametric quantile regression approach. Eur. Rev. Agric. Econ. 45, 367–395. https://doi.org/10.1093/erae/jbx036

Kumbhakar, S.C., Lovell, C.A.K., 2000. Stochastic Frontier Analysis, Stochastic Frontier Analysis. https://doi.org/10.1017/cbo9781139174411

Lambarra, F., Zein, K., 2009. Subsidies and technical efficiency : An application of stochastic frontier and Random-effect Tobit models to LFA Spanish olive farms. A resilient Eur. food Ind. food Chain a challenging world.

Latruffe, L., 2010. Competitiveness, Productivity and Efficiency in the Agricultural and Agri-Food Sectors. OECD Food, Agric. Fish. Pap. 30, 1–63.

Latruffe, L., Balcombe, K., Davidova, S., Zawalinska, K., 2004. Determinants of technical efficiency of crop and livestock farms in Poland. Appl. Econ. 36, 1255–1263. https://doi.org/10.1080/0003684042000176793

Latruffe, L., Bravo-Ureta, B.E., Carpentier, A., Desjeux, Y., Moreira, V.H., 2017. Subsidies and technical efficiency in agriculture: Evidence from European dairy farms. Am. J. Agric. Econ. 99, 783–799. https://doi.org/10.1093/ajae/aaw077

Latruffe, L., Desjeux, Y., 2016. Common Agricultural Policy support, technical efficiency and productivity change in French agriculture. Rev. Agric. Food Environ. Stud. 97, 15–28. https://doi.org/10.1007/s41130-016-0007-4

Malek, Ž., Verburg, P.H., 2018. Adaptation of land management in the Mediterranean under scenarios of irrigation water use and availability. Mitig. Adapt. Strateg. Glob. Chang. 23, 821–837. https://doi.org/10.1007/s11027-017-9761-0

Menapace, L., Colson, G., Raffaelli, R., 2013. Risk aversion, subjective beliefs, and farmer risk management strategies. Am. J. Agric. Econ. 95, 384–389. https://doi.org/10.1093/ajae/aas107

Mendes, A.B., Santos, J.M.A., Da Silva, E.L.D.G.S., 2013. Efficiency measures in the agricultural sector: With applications, Efficiency Measures in the Agricultural Sector: With Applications. https://doi.org/10.1007/978-94-007-5739-4

Moutinho, V., Madaleno, M., Macedo, P., Robaina, M., Marques, C., 2018. Efficiency in the European agricultural sector: environment and resources. Environ. Sci. Pollut. Res. 25, 17927–17941. https://doi.org/10.1007/s11356-018-2041-z

Nave, S., Jacquet, F., Jeuffroy, M.H., 2013. Why wheat farmers could reduce chemical inputs: Evidence from social, economic, and agronomic analysis. Agron. Sustain. Dev. 33, 795–807. https://doi.org/10.1007/s13593-013-0144-y

Onofri, L., Bianchin, F., Boatto, V., 2019. How to assess future agricultural performance under climate change ? A case-study on the Veneto region. Agric. Food Econ. 16.

Paulson, N.D., Babcock, B.A., 2010. Readdressing the Fertilizer Problem. Source J. Agric. Resour. Econ. 35, 368–384.

Quiroga, S., Suárez, C., Fernández-Haddad, Z., Philippidis, G., 2017. Levelling the playing field for European Union agriculture: Does the Common Agricultural Policy impact homogeneously on farm productivity and efficiency? Land use policy 68, 179–188. https://doi.org/10.1016/j.landusepol.2017.07.057

Rezitis, A.N., Tsiboukas, K., Tsoukalas, S., 2003. Investigation of Factors Influencing the Technical Efficiency of Agricultural Producers Participating in Farm Credit Programs: The Case of Greece. J. Agric. Appl. Econ. 35, 529–541. https://doi.org/10.1017/s1074070800028261

Robu, R.G., Holobiuc, A.M., Alexoaei, A.P., Cojanu, V., Miron, D., 2023. Regional Patterns of Pesticide Consumption Determinants in the European Union. Sustain. 15. https://doi.org/10.3390/su15032070

Ronga, D., Parisi, M., Pentangelo, A., Mori, M., Mola, I. Di, 2019. Effects of nitrogen management on biomass production and dry matter distribution of processing tomato cropped in southern Italy. Agronomy 9, 1–16. https://doi.org/10.3390/agronomy9120855

Rosa-Martínez, E., Adalid, A.M., Alvarado, L.E., Burguet, R., García-Martínez, M.D., Pereira-Dias, L., Casanova, C., Soler, E., Figàs, M.R., Plazas, M., Prohens, J., Soler, S., 2021. Variation for Composition and Quality in a Collection of the Resilient Mediterranean ‘de penjar’ Long Shelf-Life Tomato Under High and Low N Fertilization Levels. Front. Plant Sci. 12, 1–19. https://doi.org/10.3389/fpls.2021.633957

Shen, X., Lin, B., 2017. The shadow prices and demand elasticities of agricultural water in China: A StoNED-based analysis. Resour. Conserv. Recycl. 127, 21–28. https://doi.org/10.1016/j.resconrec.2017.08.010

Singbo, A.G., Oude, A., Emvalomatis, G., 2015. Estimating shadow prices and efficiency analysis of productive inputs and pesticide use of vegetable production. Eur. J. Oper. Res. 245, 265–272. https://doi.org/10.1016/j.ejor.2015.02.042

Spicka, J., 2020. Socio-demographic drivers of the risk-taking propensity of micro farmers Evidence from the Czech Republic. J. Entrep. Emerg. 12, 569–590. https://doi.org/10.1108/JEEE-09-2019-0143

Tripodi, P., Figàs, M.R., Leteo, F., Soler, S., Díez, M.J., Campanelli, G., Cardi, T., Prohens, J., 2022. Genotypic and Environmental Effects on Morpho-Physiological and Agronomic Performances of a Tomato Diversity Panel in Relation to Nitrogen and Water Stress Under Organic Farming. Front. Plant Sci. 13. https://doi.org/10.3389/fpls.2022.936596

Wang, H.J., Schmidt, P., 2002. One-step and two-step estimation of the effects of exogenous variables on technical efficiency levels. J. Product. Anal. 18, 129–144. https://doi.org/10.1023/A:1016565719882

Wang, X.Y., 2010. Irrigation water use efficiency of farmers and its determinants: Evidence from a survey in northwestern China. Agric. Sci. China 9, 1326–1337. https://doi.org/10.1016/S1671-2927(09)60223-6

Wesseler, J., 2022. The EU’s farm-to-fork strategy: An assessment from the perspective of agricultural economics. Appl. Econ. Perspect. Policy 44, 1826–1843. https://doi.org/10.1002/aepp.13239

World Processing Tomato Council, 2023. Available online at https://www.wptc.to/production/

Zhang, C., Guanming, S., Shen, J., Hu, R.F., 2015. Productivity effect and overuse of pesticide in crop production in China. J. Integr. Agric. 14, 1903–1910. https://doi.org/10.1016/S2095-3119(15)61056-5

Zhu, X., Demeter, R.M., Lansink, A.O., 2012. Technical efficiency and productivity differentials of dairy farms in three EU countries : the role of CAP subsidies 13, 66–92.

Zhu, X., Lansink, A.O., 2010. Impact of CAP Subsidies on Technical Efficiency of Crop Farms in Germany, the Netherlands and Sweden. J. Agric. Econ. 61, 545–564. https://doi.org/10.1111/j.1477-9552.2010.00254.x

5.9. Appendix

Table A1: Estimation Results of Output Distance Function and Inefficiency Effects Model

	Coef.	Std. Err.	
Tomato Output			
Other Products	-0.353	0.132	***
Variable Costs	-0.413	0.300	
Water	0.247	0.060	***
Organic Fertilizers	-0.006	0.072	
Chemical Fertilizers	-0.146	0.081	*
Pesticides	-0.090	0.135	
Hired WU	1.338	0.216	***
Family WU	-0.033	0.256	
Land	0.732	0.210	***
Capital	-0.030	0.067	
Time	0.190	0.141	
Other Products × Variable Costs	-0.040	0.041	
Other Products × Water	0.024	0.010	**
Other products × Organic Fertilizers	0.026	0.011	**
Other Products × Chemical Fertilizers	0.009	0.013	
Other Products × Pesticides	0.105	0.023	***
Other Products × Hired WU	0.054	0.033	
Other Products × Family WU	-0.101	0.038	***
Other Products × Land	-0.153	0.028	***
Other Products × Capital	-0.001	0.011	
Other Products × Time	0.021	0.022	
Variable Costs × Water	-0.063	0.021	***
Variable Costs × Organic Fertilizers	0.006	0.023	
Variable Costs × Chemical Fertilizers	0.059	0.026	**
Variable Costs × Pesticides	0.101	0.046	**
Variable Costs × Hired WU	-0.155	0.062	***
Variable Costs × Family WU	-0.128	0.081	
Variable Costs × land	-0.258	0.061	***
Variable costs × Capital	-0.007	0.022	
Variable Costs × Time	-0.047	0.049	
Water × Organic Fertilizers	0.019	0.008	**
Water × Chemical Fertilizers	-0.006	0.007	
Water × Pesticides	-0.029	0.012	**
Water × Hired WU	0.020	0.015	
Water × Family WU	0.021	0.020	
Water × Land	0.059	0.015	***
Water × Capital	0.007	0.005	
Water × time	0.007	0.012	
Organic Fertilizers × Chemical Fertilizers	-0.012	0.006	**
Organic Fertilizers × Pesticides	0.001	0.015	
Organic fertilizers × Hired WU	0.004	0.015	
Organic fertilizers × Family WU	-0.007	0.025	

Organic Fertilizers × Land	-0.028	0.015	*
Organic Fertilizers × Capital	-0.013	0.007	**
Organic Fertilizers × Time	0.008	0.015	
Chemical Fertilizers × Pesticides	-0.007	0.016	
Chemical Fertilizers × Hired WU	-0.010	0.020	
Chemical Fertilizers × Family WU	-0.036	0.027	
Chemical Fertilizers × Land	-0.016	0.018	
Chemical Fertilizers × Capital	-0.005	0.008	
Chemical Fertilizers × Time	-0.022	0.017	
Pesticides × Hired WU	0.007	0.039	
Pesticides × Family WU	-0.042	0.053	
Pesticides × Land	0.070	0.031	**
Pesticides × Capital	-0.013	0.013	
Pesticides × Time	-0.020	0.029	
Hired WU × Family Wu	0.269	0.076	***
Hired WU × Land	-0.052	0.043	
Hired WU × Capital	-0.027	0.015	*
Hired WU × Time	-0.001	0.032	
Family WU × Land	0.190	0.051	***
Family WU × Capital	0.057	0.022	***
Family WU × Time	0.056	0.042	
Land × Capital	-0.008	0.016	
Land × Time	0.091	0.031	***
Capital × Time	-0.014	0.012	
Other Products ^2	-0.211	0.020	***
Variable Costs ^2	0.106	0.051	**
Water ^2	0.009	0.005	**
Organic Fertilizers ^2	-0.001	0.006	
Chemical Fertilizers ^2	-0.006	0.006	
Pesticides ^2	-0.043	0.017	***
Hired WU ^2	-0.018	0.036	
Family WU ^2	-0.143	0.059	**
Land ^2	0.120	0.030	***
Capital ^2	0.017	0.004	***
Time ^2	-0.012	0.024	
Constant	9.001	1.085	***
U			
Region - Central			
Northern	0.092	0.029	***
Southern	-0.025	0.025	
Altitude – Hill			
Mountain	-0.017	0.030	
Plain	-0.113	0.019	***
% CAP I	0.591	0.057	***
% CAP II	0.203	0.070	***
Specialization	-1.771	0.115	***
Owned Land	0.119	0.020	***
Gender _ Female			

Male	-0.014	0.020	
Age - > 40			
<40	-0.003	0.020	
Farm Size - <5 ha			
15 – 40	0.085	0.069	
5-15	-0.016	0.045	
> 40	0.118	0.081	
Standard Output (8,000 – 25,000)			
25,000-50,000	-0.230	0.037	***
50,000-100,000	-0.351	0.044	***
100,000-500,000	-0.579	0.050	***
500,000-1,000,000	-0.767	0.058	***
% family workers	-0.552	0.328	*
% WUA	-0.033	0.016	**
Constant	2.090	0.166	***
sigma2	0.084	0.003	
gamma	0.305	0.084	
sigma_v2	0.058	0.007	
sigma_u2	0.026	0.007	

*Note: * p<0.10, ** p<0.05, *** p<0.01. For the categorical variables (Region, Altitude, Gender, Age, Farm Size, Standard Output) parameters show the difference from the baseline (in bold).*

6. Assessing the Impacts of Chemicals Reduction on Arable Farms through an Integrated Agro-Economic Model.

This final chapter aims to introduce a methodological advancement stemming from the preceding analyses. The Leontief production function, which characterizes most PMP models, realistically represents the determinism of inputs (Howitt, 1995) and is the prevailing approach. Although these functions appropriately describe the relationship between inputs and outputs with fixed coefficients representing the quantity of inputs required per unit of output, in these models yields and quantity of inputs are considered exogenous, meaning that they are treated as external and predetermined factors. As previously mentioned in Chapter 3, AGRITALIM incorporates 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. Hence, in formulating the mathematical programming problem, a further step was taken with respect to Cortignani et al. (2022).

The integration of econometrics and Mathematical Programming (MP) offers a comprehensive approach to understanding and optimizing agricultural production. While many MP models are, in fact, based on the Leontief production function, which represents the deterministic relationship between productive inputs (Howitt, 1995a), several other studies include more flexible functions such as Constant Elasticity of Substitution (CES) (Edwards et al., 1996; Howitt, 1995b). Several researchers have employed flexible production function models, such as CES, to study agricultural water use and economic values, as evidenced by Howitt et al. (2012) and Graindorge et al. (2000). These methods are crucial for capturing the nuanced relationships within agricultural systems. Additionally, Britz (2010) utilized iso-elastic functions to model endogenous yields in response to price fluctuations in the CAPRI model. Similarly, Giraldo et al. (2014) integrated a translog cost function with PMP to evaluate the impact of implementing volumetric and cost-recovery pricing for irrigation water in Sardinia. Inspired by these methodologies, our research integrates MP with econometric techniques to address the complexities inherent in our specific case study. To assess the implications of the F2F Strategy, our simulations focus on reducing chemical inputs by 20% for fertilizers and 50% for pesticides. These reductions are applied as constraints at the individual farm level, targeting mineral fertilizers and pesticides classified as harmful, toxic, or very toxic. Our simulations aim to evaluate the significance of these inputs at both farm and crop levels, taking into account current market conditions, regulatory frameworks, and technological advancements. The scenario is tailored to analyze the impacts of fertilizers and pesticides while considering their interactions with other agricultural variables. This work represents a preliminary step concerning this methodological advancement, applied to a single case study and a small sample. This methodological development aligns effortlessly with the overall research framework of this thesis, particularly addressing the following specific objectives:

- **Identify and analyze the relationships among agricultural inputs:** The integration of flexible production functions for maize grain in AGRITALIM objective function enhances the model contribution and precision, allowing for the identification of substitution effects among inputs and their consideration in the obtained results and optimization process. This alignment closely reflects the realistic choices made by farmers. Leveraging the econometric function estimated using a panel of Italian maize farms over a 10-year period in Chapter 4, farmers' expectations are taken into account, facilitating ex-ante analyses. The inclusion of climatic variables and individual-specific characteristics in the econometric estimation allows for the consideration of farmers' expectations derived from their knowledge of past agricultural outcomes, market conditions, risk attitudes, and information concerning policies and subsidies.
- **Quantify the economic impact of the European Farm to Fork (F2F) Strategy goals on Italian agriculture**: In examining the strictest scenario, the consequences of a 50% reduction in chemical pesticides and a 20% reduction in fertilizers are analyzed, with a specific focus on one of the main vulnerable crops identified in previous analyses. This analysis goes further by allowing the identification of adjustments in terms of production, land use, income, and quantities of chemicals. Social indicators, including labor, are also analyzed for their influence on water. The impacts are assessed at both the farm level and the specific crop level, offering a more comprehensive understanding of these effects.

This last chapter provides a realistic illustration of the potential impacts of the F2F strategy on maize grain production in Italy. Despite allowing maximum flexibility to the model, our findings indicate that maize grain production does not adapt as flexibly, suggesting significant short and medium-term impacts. The study emphasizes the importance of region-specific strategies and careful considerations in transitioning to low-input agriculture, balancing environmental goals with the economic viability of farms. Protecting vulnerable farms, sectors, and areas, especially those reliant on agriculture for employment and income, is essential.

Assessing the Impacts of Chemicals Reduction on Arable Farms through an Integrated Agro-Economic Model

Rebecca Buttinelli[a*], Gabriele Dono[b], Raffaele Cortignani[b]

[a] University of Tuscia, Department of Economics, Engineering, Society and Business Organization (DEIM), 01100 Viterbo, Italy

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

[*] Corresponding Author at University of Tuscia, Department of Economics, Engineering, Society and Business Organization (DEIM), 01100 Viterbo, Italy

6.1. Abstract

The concurrent global demands of ensuring food production, preserving the environment and responsibly managing natural resources, shape the requirements and regulations that farmers must adhere to, thereby influencing their decision-making processes and agricultural production activities. In this context, recent EU initiatives, particularly the Farm to Fork Strategy (F2F), play a crucial role setting specific targets for agriculture, i.e. a 50% reduction in the use of chemical pesticides and a 20% reduction in fertilizers by 2030. Among the various objectives of the F2F, our analysis focuses on the reduction of chemical inputs in crop production, i.e. fertilizers and pesticides. The study analyzes a FADN sample of 395 arable farms producing maize grain and leverages an agro-economic supply model (AGRITALIM) integrated with an econometrically estimated translog function. This integration enhances the model's flexibility, enabling adjustments in coefficients related to chemical inputs (fertilizers and pesticides) and maize production or yield. The main findings reveal a significant reduction in maize grain output and land, leading to an extensification of production and to worsened economic outcomes for arable farms, particularly in terms of added value and income. Due to their economic relevance and the prevalence of maize cultivation in these areas, the most concerning impacts are observed in North-Western Italy and in the most intensive areas, such as plains. These effects are primarily driven by the reduction in pesticide use, especially in smaller farms. In the short term, achieving the F2F targets may lead to increased dependence on foreign productions and further deterioration of farm economic conditions. Given these circumstances, the European Commission's decision to withdraw the pesticide regulation (SUR) and the revision of established environmental targets appears appropriate and timely.

Keywords: Farm to Fork Strategy, Maize Grain, Agricultural sustainability, Positive Mathematical Programming, Production functions

6.2. 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 towards lower-impact agriculture, aimed at reconciling these three needs. Indeed, alongside market conditions, agronomic choices and personal attitudes, regulations and policies emerge as crucial factors influencing farmers' decision-making processes and agricultural production activities (Hebinck et al., 2021). Recent European Union initiatives such as the Green Deal (European Commission, 2019) and specifically the Farm to Fork Strategy (European Commission, 2020), emerge as crucial drivers of change. These plans not only align with the Commission's commitment to implement the United Nations' 2030 Agenda but also directly address the earlier highlighted challenges. The Farm to Fork Strategy (F2F), specifically designed for the agri-food sector, emphasizes a transition toward a fair, healthy and environmentally friendly food system (European Commission, 2020) 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 predicted 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.

An essential aspect of the analysis of agricultural production in this context is the management of inputs or production factors. Understanding how the production process responds to constraints on agricultural inputs, especially chemicals, is crucial to evaluate policies' effectiveness and risks. This comprehension is decisive in achieving the essential balance between the economic sustainability of the agricultural sector and environmental protection. Within this intricate web, the careful management of inputs aligns directly with the goals outlined in recent EU initiatives, i.e. Green Deal and F2F, establishing a key 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.

In this scenario, it is crucial to model this response 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). In fact, policy objectives that limit the use of chemical fertilizers or pesticides can significantly influence the dynamics underlying the decision-making process and the agricultural production affecting the response of other inputs. The integration of such elements into agricultural economics analysis provides a more comprehensive perspective on the management of agricultural resources and the adaptation of models to environmental and regulatory challenges (Godard et al., 2008).

Addressing these issues is crucial for developing strategies to preserve the environment while ensuring food production and safety, also identifying patterns in the reaction to modification in the relationship existent among agricultural inputs. The models to be used should indeed effectively capture all potential adaptation scenarios and accurately estimate the impacts of the imposed constraints. To this aim, the ultimate objectives of this analysis 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 pesticides 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.

From the empirical point of view, a FADN sample of 395 Italian maize grain farms for the year 2020 is used as a case study. The AGRIcultural TerritoriAL tIme economic (AGRITALIM) model, falling within the category of agro-economic supply model (such as FSSIM, EFEM, FARMIS), as in Cortignani et al. (2022) has been implemented with the inclusion of a flexible production function that enables gross saleable product, fertilizers and pesticides quantities as endogenous variables. The findings will enable an assessment of the repercussions of modifications both at the farm level and at the crop level. The impacts will be evaluated in terms of economic variables such as added value and income, land, inputs and resource use, production output and chemical intensity. Moreover, given the flexibility and sensitivity of these results, they can provide insights into the various nuances based on different farms and territorial characteristics. The paper is structured as follows: Section 2 presents the data used and the methodology, Section 3 provides the obtained results, and Sections 4 and 5 conclude with discussions and conclusions.

6.3. Material and Methods

6.3.1. Data

Cereal production is among the most impacted sectors by the F2F Strategy's targets for chemical reduction (Beckman et al., 2020; Cortignani et al., 2022). Therefore, the focus of this analysis is on maize grain, a strategic crop due to its economic relevance. Maize production is expected to play a central role in the future, with global cereal production expected to increase by 12% over the next decade. Almost half of this increase will come from maize, primarily used as feed (Erenstein et al., 2022). Within the European context, Italy currently ranks fourth[20] but, over the years, maize cultivation land has significantly decreased, leading to an increasing reliance on imported maize grain. This high dependence on foreign sources makes Italy vulnerable and subject to market volatility, especially during crises. Adding to the complexity of the situation is the rising frequency of extreme weather events, which could make grain prices more volatile (OECD, 2022). Recently, the combination of higher temperatures and water deficits has already forced the suspension of irrigation in various regions, leading to damages from pests, fungal attacks and 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). Within this context, Italy could find itself in a position of dependence. Additionally, being chemical inputs crucial for maize grain quality and safety, along with irrigation water, this crop could be highly impacted by restrictions in these production factors. Essentially, maize grain stands as one of the most significant crops within Italian agriculture, both in terms of cultivated area and for its role in several supply chains, i.e. Parmigiano Reggiano and Grana Padano (Mantovi, 2015).

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 Utilized Agricultural Area (UAA) 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) [21]. The collected data includes information on Gross Output, land, crop-specific

[20] 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).

[21] 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 basic TFs (Specialist field crops, Specialist horticulture, Specialist Permanent Crops, Specialist Grazing Livestock,

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 located in the Northwest regions, 42% in the Northeast regions, and 13% in the Central-South. Moreover, 78% of the observations are located in plain areas, while 22% are in hilly areas. In terms of farm size, the situation is homogeneous, with 31% of farms ranging from 1 to 15 hectares, 38% between 15 and 40 hectares, and 31% above 40 hectares. Finally, 27% of the farms belong to small economic size (< 25,000€), 55% to medium-sized (25,000-100,000 €), and 18% to large-sized (> 100,000 €)[22]. Descriptive statistics for the sample are shown in Table 1, including information both at the farm level and at the crop level.

Specialist granivores, mixed Cropping, mixed Livestock, mixed crops Livestock), and 21 branches of principal TFs, further divided into 61 specific TFs.

[22] Both farm size and economic dimension are defined according to FADN. Farm size is determined based on the hectares of UAA, while the economic dimension is assessed based on the standard output produced.

Table 1: Description and Descriptive Statistics (Mean and St. Dev.) for the analyzed sample.

Farm	**UM**	**Description**	**Mean**	**St. Dev.**
UAA	Hectares	Utilized Agricultural Area	41.95	48.80
Crops Output	€	Total Gross Output	69,089	85,607
Operative Income	€	Operative Income	29,379	59,813
Hired WU	1,800 hours/ unit	Hired Working Units per farm	1.24	0.82
Family WU	2,300 hours/ unit	Family Working Units per Farm	1.16	0.68
Maize Grain	**UM**	**Description**	**Mean**	**St. Dev.**
UAA	Hectares	Utilized Agricultural Area	16.92	20.49
Irrigated UAA	Hectares	Irrigated Land	12.93	19.91
Gross Margin	€	Maize Grain Gross Margin per farm	21,063	30,199
Net Margin	€	Maize Grain Net Margin per farm	8,650	28,661
Gross Output	€/ha	Maize Grain Gross Output	1,943	595
Variable Costs	€/ha	Expenditure per hectare (seeds, energy, insurance, subcontracting, fuel etc..)	320.23	170.21
Fertilizers	100kg/ha	Quantity of Fertilizers per hectare	5.44	33.32
Pesticides	q/ha	Quantity of Pesticides per hectare	2.79	20.36
Work	Hours/ha	Hours of Work per hectare	47.75	49.43
Machinery	Hours/ha	Hours of Machinery Work per hectare	26.04	33.24

6.3.2. AGRITALIM model

The AGRIcultural TerritoriAL tIme economic (AGRITALIM) model as in Cortignani et al. (2022), has been adapted to a FADN sample of 395 maize grain farms for the year 2020. Operating within the category of agro-economic supply models, the model is based on non-linear mathematical programming, 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) which automatically adjusts the model based on observed activity levels, avoiding arbitrary constraints. 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 change, and resource use.

The model incorporates dynamic elements, accounting for structural changes (e.g., modifications in tree crops and related areas) by annualizing investments through depreciation rates. The main components and fundamental characteristics of the objective function and constraints concerning land, labour and water availability are shown in Table 2 and Table 3, respectively. 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 (Table 2). Model variables include crop hectares, hours of labour and water pumped from wells, i.e. groundwater. Depreciation costs associated with additional depreciable capital are annualized in the objective function dividing the replacement value of those depreciable capitals by their technical duration, as indicated by the FADN database. In essence, the model aims to maximize operating income by selecting productive activities (such as the number of crop hectares) while considering the availability of resources like land, labor, and water. It accommodates additional variables related to labor and water, such as hours of labor and quantity of water pumping, and it also considers the possibility of additional fixed capital.

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 labour 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.

Table 2: Main components of the objective function: parameters (market, production function, policy) and variables.

Components	Market	Production function	Policy	Variables
Gross Saleable Production - crops	Prices	yields		hectares of crops
CAP coupled payments			payments	hectares of crops, number of animals
CAP decoupled payments			payments	
Complementary activities	total revenues			
Variables cost – crops	Prices	quantities		hectares of crops
External labour	Prices			hours of labour
Pumped water	Prices			quantity of water pumping
Depreciation rates observed	Costs			

Table 3: Structure of the constraints: left-hand and right-hand sides, involved variables.

Types	Matrix coefficients	Availabilities	Variables
Land		farmland	hectares of crops
Labour	manual and mechanical labour needs	family labour, permanent employment temporary employment, external labour	crops (hectares), external labour (hours)
Water	water needs	WUA, natural, artificial, pumped waters	crops (hectares), quantity of water pumping

6.3.3. The advantages of a mixed approach

As previously mentioned, AGRITALIM incorporates 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. Hence, in formulating the mathematical programming problem, a further step was taken with respect to Cortignani et al. (2022).

The integration of econometrics and Mathematical Programming (MP) offers a comprehensive approach to understanding and optimizing agricultural production. While many MP models are, in fact, based on the Leontief production function, which represents the deterministic relationship between productive inputs (Howitt, 1995a), several other 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 several calibration methods for models of agricultural production water use, including the estimation of CES regional production functions. Graindorge et al. (2000) uses a CES specification as Medellín-Azuara et al. (2010) do to obtain the agricultural water economic value. This use of flexible functions in various studies reflects a recognition of the need to capture nuanced relationships within agricultural systems. Moreover, Britz (2010) use iso-elastic functions to obtain endogenous yields responsive to variations in prices 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 implementing a volumetric and cost-recovery pricing method for irrigation water in Sardinia. Our research adopts a similar approach, combining MP with econometric estimation to comprehensively address the challenges and research questions in our case study.

By incorporating in the objective function the translog production function, specifically estimated econometrically for a ten-year panel of 5224 Italian maize grain farms (Buttinelli et al., 2024), we develop an integrated PMP model able to appropriately represent farm planning decisions and simulating realistic responses to policy limitations in the use of chemicals. Motivated by the need to model non-fixed and complex relationships among considered variables, the translog function provides a more nuanced representation, capturing interactions among agricultural inputs. This approach is particularly relevant given the dynamic nature of relationships within the agricultural system. In fact, farmers make their decisions upon expected outputs, which are determined by their own knowledge of past agricultural outcomes, market conditions, risk attitudes, and information concerning policies and subsidies.

Leveraging an econometrically estimated function based on a FADN panel covering ten years (2010-2020) this analysis ensures to obtain realistic outcomes (Buttinelli et al., 2024). In addition, the empirical specification, i.e., the weighted fixed effects panel model, allows to isolate individual-specific characteristics captured by the intercept coefficient [23].

Combined with the inclusion of climatic variables such as rainfall and temperature, the inclusion of the Translog function in the AGRITALIM model also allows to capture of climatic variability across the Country. The estimated Translog production function (Eq. 1) describes the relationship between

[23] 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).

maize grain production and various agricultural inputs. The empirical estimation of the production function is expressed as:

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

Where X represents the vector of inputs considered (detailed in Table 4); $\boldsymbol{\beta}$ is the estimated parameters vector; α is the intercept; and e is the error component. To incorporate environmental factors characterizing the varying context of each farm over time, average temperature and precipitation at the provincial level per year are included. For each observation, the expenditure on each input used for maize grain production was assessed in Euros (€) (Table 4).

Based on Equation 1, Maize Gross Saleable Production (MGSP) is defined in AGRITALIM objective function as follows (Eq. 2):

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

Where $XM, XFERTM$ and $XPESTM$ are variables representing hectares, quantity of fertilizers and quantity of pesticides for maize grain, respectively. On the other hand, l, w, vc, wr, m, t and r are parameters representing land, water quantity, variable costs (certifications, energy, subcontracting, marketing, seeds), work, owned machinery work[24], temperatures, and rainfall respectively, as in Table 4.

Considered variables and parameters have been obtained by decomposing each input value in terms of price and quantity and multiplying by the hectares considered[25]. This methodological development allows our model to dynamically adjust, enabling potential changes to coefficients regarding chemical inputs and maize yield for maize grain production.

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[24] Since smaller farms may not have enough capital to invest in their own machinery, they often use subcontracting services. This is reflected in the Variable Costs variable including, among others, the expenditure for Subcontracting. For owned machinery, the Machinery variable includes the operating hours of these assets.

[25] Specifically, MGSP enters the AGRITALIM objective function as follows: MGSP = $\alpha_i + \beta_{temperatures} \cdot t + \beta_{rainfall} \cdot r + \beta_{land} \cdot XM \cdot l + \beta_{water} \cdot XM \cdot w + \beta_{variable\ costs} \cdot XM \cdot vc + \beta_{fertilizers} \cdot XM \cdot XFERTM \cdot pfp + \beta_{pesticides} \cdot XM \cdot XPESTM \cdot pfp + \beta_{work} \cdot XM \cdot wr + \beta_{machinery} \cdot XM \cdot m + \frac{1}{2}\beta_{lw} \cdot XM \cdot l \cdot XM \cdot w + \cdots + \frac{1}{2}\beta_{wrm} \cdot XM \cdot wr \cdot XM \cdot m + \frac{1}{2}\beta_{l2} \cdot XM \cdot l \cdot XM \cdot l + \cdots + \frac{1}{2}\beta_{m2} \cdot XM \cdot m \cdot XM \cdot m$. Where l, w, vc, wr, m, t are defined as in Equation 3 and $\boldsymbol{\beta}$ are defined as in Equation 1, while pfp is the price of production factors.

Table 4: 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	Labour	€	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

The simulated scenario is designed in accordance with the F2F objectives, specifically addressing the strongest limitations on chemical inputs (reduction by 20% of fertilizers and 50% of pesticides). These targets were applied as maximum constraints at the individual farm level and consider mineral fertilizers and harmful, toxic, and very toxic pesticides. The simulations do not have the intention of proposing political actions and measures; instead, their purpose is to assess the relevance of chemical inputs for each farm, considering current market conditions, political frameworks, and technologies. The selected scenario was designed to obtain the impact of fertilizers and pesticides both at the farm level and at the crop level, while also considering the existing interactions linking these two inputs to other agricultural factors. The effects are evaluated through several indicators differentiating the impacts across the sample, considering territorial and farm characteristics.

6.4. Results

This section provides an overview of some of the obtained results, offering insights into the impacts of the analyzed scenario at the farm level (Table 5 and Table 6) and on maize grain production (Table 7 and Table 8). 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. Conversely, the results for maize grain production are expressed in terms of variations in Utilized Agricultural Area (UAA), Gross Saleable Output, and quantity of Fertilizers and Pesticides per hectare.

All the results are shown for the total sample and categorized by territorial (Table 5 for farm-level results and Table 7 for maize grain results) and farm characteristics (Table 6 for farm-level results and Table 8 for maize grain results). Concerning territorial characteristics Area (North-West, North-East and Centre-South) and Altitude (Plain and Hill) are considered. Instead, farm characteristics taken into account include Farm Size, Economic Size and Diversification. Farm Size is divided into two classes: under 15 hectares and above 15 hectares. Similarly, the Economic Dimension is classified into Small-Medium (under 100,000 €) and Large (above 100,000 €), categories based on economic production in terms of Standard Output.

The aggregation of farms based on Farm Size and Economic Dimension was influenced by the limited representativeness of certain groupings, resulting in the subdivision described above. However, the aggregation also considered similarities among the various groups, aiming to highlight the differences between small and medium-sized farms, mainly family-run, which are the most prevalent throughout the Italian territory, and large professionally managed farms, which are more market-oriented.

Additionally, the presence of complementary activities to agriculture (such as direct sales, agritourism, contract farming, etc.) is considered, as it may influence the flexibility and ability to offset losses resulting from restrictions in agricultural practices. Hence, two groups are analyzed: Specialized and Diversified farms. The results presented in the following sections represent just a subset of the outcomes achievable with AGRITALIM, which allows for detailed analysis at the regional level as well.

6.4.1. Impacts at the farm-level

The considered scenario, i.e. a 20% reduction in fertilizers and a 50% reduction in harmful, toxic and very toxic pesticides, affects productive activities, resulting in an overall reduction of Added Value by -4.7 %. Simultaneously, Variable Costs decrease by 13.4 % and Operative Income of 6.8 %. Moreover, there is an overall reduction in labor of 10.0%, while Water use undergoes a reduction of -13.3% and specifically, Groundwater decreases by -19.8%.

The analysis of different groups reveals significant variations, with some clusters more susceptible and others less affected by the simulation. As mentioned before, Table 5 presents the results categorized by territorial characteristics, whereas Table 6 categorizes them by farm characteristics.

Geographically, the Northwest and Centre-South appear more impacted in terms of Added Value (-5.4%), while the Northeast experiences a reduction of -4.0%. Looking at Altitude, there is a slightly greater reduction in the Plain (-4.9%) compared to the Hill (-4.4 %). Regarding Variable Costs, a similar pattern is observed, with the Northeast reducing by -12.1%, the Northwest by -14.1% and the Centre South by -14.9 %. Conversely, Variable Costs decrease more in the Hill (-16.1%) compared to the Plain (-12.7%). Concerning Operative Income, the Northwest shows a higher reduction (-8.5%), while the Northeast and Centre-South show a reduction of -5.4% and -7.2%, respectively. Instead, for Plain farms the impact is greater (-7.1%) than for Hill farms (-6.1%). Labor reduction is greater in the Centre South (-13.1%) and Northwest (-10.0%), while the Northeast shows a reduction of -9.1%. In terms of Altitude, the reduction is uniform, with values around -10% in both Plain and Hill. Water use also, similarly, experiences the most significant decrease in the Centre-South (-21.9%) as does Groundwater (-39.1%). In contrast, the reduction is considerably lower in Northern Italy, with impacts for Water slightly greater in the Northwest (-14.2%) and in the Northeast for Groundwater of 12.5%. These reductions are more pronounced in the Hill region, both for Water (-22.7%) and Groundwater (-39.1%), compared to the Plain where the reductions are respectively by -12.8 % and -12.5%.

Examining farms' characteristics, the greatest reduction in Added Value occurs in farms under 15 hectares (-5.9%), while farms above 15 hectares show a reduction of -4.7%. Economic Dimension, instead, shows a slightly greater impact in Large farms (-4.9%) but very similar to Small-Medium farms (-4.7 %). In addition, Specialized farms show a slightly higher reduction (-4.8%) than Diversified farms (-4.6%). Similarly for Variable Costs, a greater decline is found for smaller farms in terms of Farm Size (-14.5%) while the Economic Dimension shows a lower difference between the three groupings, with a slightly higher reduction in Small-Medium farms (-13.5%). Instead, Diversified farms are more impacted than Specialized ones (-17.3 % and -12.3 % respectively).

Concerning Operative Income, farms under 15 hectares suffer a reduction of - 10.1 %, while larger farms show a higher reduction (-6.6%). In terms of Economic Dimension, the situation is more homogeneous impacting both Small-Medium farms and Large farms with a reduction of around 7%. On the other hand, Specialized farms reduce Income by -7.1% while Diversified ones by -6.2%.

Regarding Farm Size, however, the reduction in Labor is more significant for farms under 15 hectares (-12.8%), while farms above 15 hectares show a decrease of -9.3%. In the Economic Dimension groupings, the reduction is homogeneous and around 10%, while Diversified farms suffer the greatest reduction of all the groupings (-13.4%). Water use is reduced by -20.6% and Groundwater by -26.3% in farms under 15 hectares. However, farms above 15 hectares reduce Water by 12.8% and Groundwater by -17.7%. Smaller farms in terms of Economic Dimension show a high reduction in both Water and Groundwater (-13.1 % and -20.0 % respectively) while larger farms show lower reductions by 14.3% for Water and by 18.8% for Groundwater. Looking at the Diversification degree, farms a greater reduction is observed in Diversified farms (-13.4% in Water and -13.8% in Groundwater).

6.4.2. Impacts on Maize Grain Production

Focusing on Maize Grain production, the results show differences among the considered groupings (Table 7 shows the results by territorial areas and Table 8 by farm characteristics). The average results indicate an overall decline of -18.2% in the Utilized Agricultural Area (UAA). This decline is more pronounced in the Centre-South (-28.0%), and Hill areas (-22.2%). Conversely, Northeastern farms appear less affected (-14.7%), as well as Plain regions (-17.3%). As a consequence, Maize Grain Gross Saleable Output also decreases by -17.4%. Once again, the Centre-South (-24.5%) and Hill regions (-20.0%) suffer the greatest impact.

However, concerning the chemical intensity, i.e. Fertilizers and Pesticides use, the situation is more heterogeneous. On average, in the sample, the quantity of fertilizers per hectare reduces by -2.8%, while the reduction in Pesticides is notably higher, at -13.0%. The distribution of this impact across geographical and farm groups reveals that Northwest farms show higher reductions, in terms of fertilizers (-4.7%) and pesticides (-13.8%) while the Centre-South regions are less affected, with reductions of -0.8% for fertilizers and -4.9% for pesticides respectively. Northeast stays in the middle, with a reduction of -2.6 % in Fertilizers and -12.5% in Pesticides. Similar patterns are observed in Altitude, where Plain areas show a reduction in fertilizers per hectare of -3.0 % and pesticides of -13.8%, while Hill areas reduce fertilizers by -2.5% and pesticides by -5.9%.

Concerning farm characteristics, maize UAA reduces the most in farms under 15 hectares (-22.1%). while farms above 15 hectares show a more contained impact (-17.8 %). Concerning the Economic

Dimension, Small-Medium farms reduce UAA by -18.0 %, while Large farms reduce slightly more (-18.4%). In terms of Diversification, Diversified farms reduce UAA the most (-22.2 %), while Specialized farms show a -17.2% reduction. Maize GSP shows a higher reduction in farms under 15 hectares (-20.8%) and lower for farms above 15 hectares (-16.9%) while reductions are slightly more homogeneous looking at Economic Dimension, with Small-Medium farms reducing slightly more (-17.5%) than Large farms (-17.2%). Once again, Diversified farms show a higher reduction (-19.0%) than Specialized ones (-17.0%)

Chemical intensity, in terms of Farm Size and Economic Dimension, shows different impacts for fertilizers and pesticides. The reduction in fertilizers is higher in farms above 15 hectares (-3.9 %), while farms under 15 hectares show a reduction of -0.3 %. Conversely in the same groups, the pesticide quantity per hectare shows a reduction of -12.2 % in farms above 15 hectares and by -16.8% in smaller ones. Similarly, regarding Economic Dimension, Small-Medium farms are the ones to reduce fertilizers the least (-1.5%) and pesticides the most (-16.9 %), while Large farms show a greater impact on fertilizers (-8.5%) and a lower reduction concerning pesticides (-6.0%). Looking at the presence of other activities, Diversified Farms show higher impacts in Fertilizers quantity (-5.0 %) than Specialized farms (-2.4%), while the latter shows a higher reduction in terms of Pesticides (-15.8% for Specialized farms and -6.1% for Diversified farms).

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 both the total sample and categorized by territorial characteristics (Area and Altitude).

		Area			Altitude		
		North West	North East	Centre-South	Plain	Hill	Total
	Farms (n°)	179	164	52	310	85	395
Baseline	Added Value (M)	8.7	9.4	2.5	16.5	4.0	20.6
	Variable Costs (€M)	4.3	4.3	0.8	8.0	1.4	9.5
	Operative Income (€M)	5.3	6.2	1.6	10.4	2.7	13.1
	Labor (1000 hours)	288	264	75	514	114	627
	Water (1000 m³)	1929	2836	238	4602	401	5003
	Groundwater (1000 m³)	30.4	68.9	38.3	99.3	38.3	137.6
%	Added Value	-5.4	-4.0	-5.4	-4.9	-4.4	-4.7
	Variable Costs	-14.1	-12.1	-14.9	-12.7	-16.1	-13.4
	Operative Income	-8.5	-5.4	-7.2	-7.1	-6.1	-6.8
	Labor	-10.0	-9.1	-13.1	-10.0	-9.8	-10.0
	Water	-14.2	-12.5	-21.9	-12.8	-22.7	-13.3
	Groundwater	-10.3	-13.4	-39.1	-12.5	-39.1	-19.8

Table 6: 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 farms characteristics (Farm Size, Economic Dimension and Diversification).

		Farm Size		Economic Dimension		Diversification		
		< 15 ha	> 15 ha	Small-Medium	Large	Specialized	Diversified	Total
	Farms (n°)	122	273	322	73	328	67	395
Baseline	Added Value (M)	1.9	18.7	9.9	10.6	15.4	5.1	20.6
	Variable Costs (€M)	0.8	8.7	4.4	5.1	7.7	1.7	9.5
	Operative Income (€M)	1.0	12.0	6.0	7.0	9.9	3.2	13.1
	Labor (1000 hours)	117	511	415	212	492	136	627
	Water (1000 m³)	562	4441	2695	2308	4306	697	5003
	Groundwater (1000 m³)	35.4	102.2	128.0	9.5	132.7	4.8	137.6
%	Added Value	-5.9	-4.7	-4.7	-4.9	-4.8	-4.6	-4.7
	Variable Costs	-14.5	-13.1	-13.5	-13.0	-12.3	-17.3	-13.4
	Operative Income	-10.1	-6.6	-6.8	-6.9	-7.1	-6.2	-6.8
	Labor	-12.8	-9.3	-10.0	-10.0	-9.0	-13.4	-10.0
	Water	-20.6	-12.8	-13.1	-14.3	-13.6	-13.8	-13.3
	Groundwater	-26.3	-17.7	-20.0	-18.8	-19.9	-19.0	-19.8

Table 7: 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 characteristics (Area and Altitude).

		Area			Altitude		
		North West	North East	Centre-South	Plain	Hill	Total
	Farms (n°)	179	164	52	310	85	395
Baseline	Maize UAA (1000 ha)	3.3	2.5	0.4	5.1	1.1	6.2
	Maize Gross Saleable Output (€M)	7.5	4.7	0.8	11	2.1	13
	Maize Fertilizers (quantity/ha)	5.6	6.8	15.3	6.1	12.2	7.4
	Maize Pesticides (quantity/ha)	4.9	1.3	1.3	3.3	1.4	2.9
%	Maize UAA	-19.5	-14.7	-28.0	-17.3	-22.2	-18.2
	Maize Gross Saleable Output	-18.5	-14.4	-24.5	-16.9	-20.0	-17.4
	Maize Fertilizers	-4.7	-2.6	-0.8	-3.0	-2.5	-2.8
	Maize Pesticides	-13.8	-12.5	-4.9	-13.8	-5.9	-13.0

Table 8: 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 farms characteristics (Farm Size, Economic Dimension and Diversification).

		Farm Size		Economic Dimension		Diversification		
		< 15 ha	> 15 ha	Small-Medium	Large	Specialized	Diversified	Total
	Farms number (n°)	122	273	322	73	328	67	395
Baseline	Maize UAA (1000 ha)	0.6	5.6	3.3	3.0	5.0	1.2	6.2
	Maize Gross Saleable Output (€M)	1.6	11.5	7.1	6.0	10.6	2.5	13.1
	Maize Fertilizers (quantity/ha)	7.0	7.5	7.3	7.7	7.5	6.6	7.4
	Maize Pesticides (quantity/ha)	6.1	3.5	2.3	5.6	2.5	5.0	2.9
%	Maize UAA	-22.1	-17.8	-18.0	-18.4	-17.2	-22.2	-18.2
	Maize Gross Saleable Output	-20.8	-16.9	-17.5	-17.2	-17.0	-19.0	-17.4
	Maize Fertilizers	-0.3	-3.9	-1.5	-8.5	-2.4	-5.0	-2.8
	Maize Pesticides	-16.8	-12.2	-16.9	-6.0	-15.8	-6.1	-13.0

6.5. Discussion

Our analysis underscores the impacts of the F2F objectives on Italian arable farms, with a focus on maize grain production. Specifically, the study assesses the economic repercussions of a 20% reduction in fertilizers and a 50% reduction in pesticides, both at the farm level and on the specific crop production. Leveraging a FADN sample, consisting of 395 farms engaged in maize grain production across Italy in 2020, the study provides in-depth insights into how changes in agricultural practices and inputs availability affect farms depending on their size and economic dimension, geographical locations and altitude.

The decrease in added value and operative income resulting from the implemented scenario suggests a significant economic impact on these farms. The contraction in production is inevitably linked to a decrease in variable costs and a substantial reduction in resource use. These changes could have significant social implications, with a pronounced decrease in employment affecting both family and hired labor, especially in the Central-South regions and smaller farms where family labor often represents the primary or sole labor resource. While the Northern regions exhibit a more contained impact in the same variables, their combined effect remains significant due to their substantial contribution to national maize grain production. Differences exist between the Northwest and Northeast areas, with the Northwest slightly more affected both economically and in terms of resource use, as well as employment. As noted by Beckman et al. (2020) the potential use of labor as a substitute for other agricultural inputs is largely crop and scale-dependent, i.e. some crops may readily transition, while others could face a substantial production decline. This variability in the ability to substitute labor for other inputs helps explain the observed decrease in both labor utilization and income among farms, coupled with the need to reduce costs in response to declining income.

Diversification also plays a role with diversified farms containing the impact on Operative Income, likely because the presence of alternative incomes allows offsetting the reduction in production due to the hypothesized scenario. However, the impact on Added Value and Variable Costs is similar to that of specialized farms, and the impacts on Labor are even higher. This is likely because the reduction in agricultural production inevitably affects the costs and workforce involved in other related activities.

Indeed, the reduction in chemicals, including both fertilizers and pesticides, inevitably affects other inputs, as noted by Cortignani et al. (2022). Among these inputs, water, and particularly groundwater emerges as the most affected. Our analysis underscores a stronger impact in the Southern areas, which are more prone to water scarcity. Specifically, the reduction is coupled with a significant decrease in agricultural production and maize grain production, given this crop's high-water requirements. Once again, smaller farms are the ones that reduce water use the most. 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. In terms of economic dimension, economically stronger farms are not immune to negative impacts, similar to diversified farms.

Interesting results also emerge from the reaction of maize grain crop production to the hypothesized scenario. The use of a flexible translog production function allows for obtaining detailed results, considering complementarity or substitution effects among inputs. This enables the model to simulate reality more accurately and allows for nuanced responses, mitigating the impact on land use and showing impacts on output and quantity of inputs. The analysis indicates an overall reduction of -18.2% in maize grain UAA. This reduction is closely linked to the decrease in UAA, but it could be exacerbated due to potential lower grain quality resulting from reduced fertilizers and pesticide usage. The observed trend reveals a decrease in less favorable and less productive areas, exemplified by significant declines in the Central-South and Hill regions, as well as in diversified farms. These farms experience substantial decreases in both UAA and Maize Gross Saleable Output and are more likely to transition to other crops or rely more on other agriculture-related activities. The impact on Maize Gross Saleable Output disproportionately affects the same areas, with the Central-Southern regions being the most affected, along with smaller farms. However, considering their economic significance and maize cultivation predominance in these areas, the Northern regions collectively exhibit significant losses that could translate into severe consequences for the supply chain.

Building upon the findings of Robu et al. (2023), it becomes evident that regional variations in pesticide use exist, not only across the EU but also within a single Country. Assessing the effects of a reduction in chemical inputs, i.e. pesticides and fertilizers, on crop production in different regions and clusters of farms can help identify the most vulnerable areas. Farms experiencing the most significant decrease in the quantity of fertilizers and pesticides per hectare are those characterized by more intensive production, i.e. in Northern Italy, specifically in the Northwest and Plains. The hypothesized 50% reduction in pesticide use at the farm level exerts a significant influence on maize grain, especially in smaller farms. Notably, the reduction in pesticides, with a decline approaching 13%, emphasizes the maize grain's substantial reliance on pesticide application under current agronomic practices. Conversely, while small and medium-sized farms undergo significant reductions in pesticides quantities, larger and economically robust farms exhibit a comparatively higher decrease concerning fertilizers. Nevertheless, larger farms undergo a lower decrease in maize grain production, likely mitigated by the option to extensify production and benefit from CAP subsidies for fallow land.

However, the situation differs in the economic dimension grouping, as larger farms demonstrate a reduction in UAA and output comparable to that of smaller farms, despite experiencing only a modest decrease in pesticide usage. In this case, the reduction in fertilizers plays a crucial role. Indeed, the impact on larger farms at the individual farm level underscores that despite their market influence, economically more robust farms cannot mitigate the effects through professional management and broader market access, experiencing impacts similar to those of smaller farms. This outcome may also be attributed to the farms' efficiency levels, considering that the effects of farm size on technical efficiency vary depending on the context (Latruffe, 2010). Additionally, the potential overuse of chemicals could be related to other specific factors such as soil conditions, regional variations, or farmers' characteristics such as risk aversion (Nave et al., 2013; Singbo et al., 2015). Guo et al. (2022) found that the farm scale effect reduces nitrogen levels in maize grain cultivation in China. This suggests that larger farms, which likely already operate with reduced fertilizer levels, may be more affected by further reductions in fertilizers.

The impacts on farms specialized in arable crops, may also be influenced by the presence of other crops. High specialization or greater production intensity may reduce flexibility in response to variations in inputs availability, affecting the feasibility of transitioning to crops with lower chemical demands or higher productivity and profitability. Mixed farms, particularly those combining crops and livestock, not considered in this analysis, could have an advantage in reducing fertilizer and pesticide use through diversification of agricultural activities, as noted by Czyżewski and Kryszak (2023), in Central and Eastern EU. However, according to Li et al. (2023), transitioning from chemical to organic fertilizers is not straightforward, as sociodemographic characteristics and maize cultivation can negatively impact the substitution effect between organic and chemical fertilizers, even in those types of farms. Additionally, transitioning to crops eligible for CAP coupled subsidies, such as durum wheat in southern Italy, could impact land use change and maize production to offset losses at the farm level. Furthermore, the presence of other associated activities contributes, with diversified farms able to compensate for income losses but sacrificing maize grain production, possibly opting to prioritize other income-generating activities or focusing on crops that require fewer inputs.

Overall, the analysis reveals several insights into the impacts of transitioning to low-input agriculture in specialized arable farms. Regional disparities are evident, underscoring the necessity for region-specific strategies. What appears to be happening is a significant extensification, primarily affecting areas less suited for maize grain, such as the Central-South and hilly regions as well as diversified farms. However, the more contained reduction in the Northern regions raises even more concerns as it jeopardizes various supply chains. The reduction in chemicals inevitably triggers effects on other productive factors such as labor, variable costs and water. Consequently, there could be a shift towards non-irrigated crops, potentially supported by CAP subsidies, impacting national maize production and confirming this crop's high vulnerability to F2F targets application (Barreiro-Hurle et al., 2021; Cortignani et al., 2022). Furthermore, this reduction could lead to water stress, rendering maize grain even more susceptible to pest and fungal attacks, exacerbated by CC. This could not only result in quality issues but also make pest control interventions ineffective, particularly where a reduction in pesticide quantity already results in lower coverage against these attacks (Leggieri et al., 2020; Medina et al., 2015; Wu et al., 2010).

Small-sized farms emerge as the most vulnerable, particularly to reductions in pesticide usage, facing not only production contractions but also occupational consequences. However, larger and economically more robust farms are not immune to impacts stemming from F2F objectives, experiencing significant reductions in maize grain production and economic outcomes, thus failing to mitigate the impact through professional management or greater financial availability. The observed reduction in chemical intensity, highlighting the context-specific vulnerability to fertilizers or pesticide reduction, suggests a need for deeper exploration, as Staniszewski et al. (2023) affirm observing that farms' structural features influence Sustainable Intensification (SI) in Europe. Considering unique agricultural characteristics, such as existing production practices, territorial features, and market and policy framework, contributes to a deeper understanding necessary to guide targeted interventions and support policies and further research.

6.6. Conclusions

Our analysis, which integrates an agro-supply model, i.e. AGRITALIM (Cortignani et al., 2022), and an econometrically estimated translog function based on a ten-year panel of 5,224 observations (Buttinelli et al., 2024), offers a realistic representation of production and decision-making processes within these farms. This approach allows us to consider reactions based on observed production choices over time, incorporating individual-specific effects and environmental variability through climatic variables. The results underscore the contribution of the translog function's flexibility in capturing complex relationships, thereby enhancing the accuracy and robustness of optimal solutions. This methodological advancement allows for adjustments not only in terms of land use but also in terms of gross output (or yield) and the quantity of chemical fertilizers and pesticides.

Our findings indicate that the targets set by the F2F strategy could lead to short to medium-term reductions in agricultural production in Italian arable farms, along with declines in income and added value. This decrease in production is associated with a reduction in variable costs, particularly linked to decreased utilization of resources such as irrigation water. The social implications of these impacts are significant, especially notable in smaller farms where family labor is often crucial and in diversified farms where the workforce is also employed in activities connected to agriculture.

What appears to be happening is a significant extensification, primarily affecting areas less suited for maize grain, such as the Central-South and hilly regions and more diversified farms. However, while the Central-South regions experience the greatest impact, intensive areas are not immune. Northern regions' reaction, given their substantial contribution to national maize production and their production intensity, reveals more threatening consequences. Of note is the combined effect of the reductions in gross output and land use in the Northeast and Northwest regions, which pose a significant threat to the supply chain.

In this context, despite regional differences, it is worth noting that smaller-sized farms are particularly affected by reductions in chemical usage, especially in pesticides, while larger farms are more affected by reductions in fertilizers. Maize grain demonstrates limited adaptability to restrictions on chemicals, particularly in the short term. Furthermore, this crop plays a critical role in several supply chains, such as Parmigiano Reggiano, where production specifications prohibit the use of silage forages (Mantovi et al., 2015). Italy is also the fourth-largest maize producer in the EU (Erenstein et al., 2022) and a simultaneous contraction in areas dedicated to forages, as estimated by Cortignani et al. (2022) poses a significant threat to the Italian livestock sector and overall economy, resulting in greater dependence on imports and economic losses in several Italian agricultural sectors, as Barreiro-

Hurle et al. (2021) estimate for the EU's net trade position. Moreover, the Mediterranean region is threatened by rising temperatures and water deficits (Hristov et al., 2020; Lionello and Scarascia, 2018; Rosenzweig et al., 2014), phenomena exacerbating agricultural risks and vulnerabilities, particularly for specific crops like maize (Mereu et al., 2021). Addressing these challenges necessitates robust economic support to mitigate the impact on production and income. It is crucial for policies to consider the farms incurred costs, including lost income, while also recognizing the territorial and contextual variability in which these changes occur. It is essential to protect the most vulnerable farms, sectors, and regions, especially in areas heavily dependent on agriculture for employment and economic livelihood.

However, it is essential to acknowledge some limitations. Our study considers current policy conditions but does not account for potential repercussions from enhanced conditionality under the 2023-2027 CAP or voluntary measures like eco-schemes. It is also important to recognize that the process of extensification highlighted by this analysis could also be driven by other policies promoting conservative agriculture, including practices such as no-tillage or minimum tillage, cover crops, and crop rotation and diversification. This is the direction in which the CAP reform for 2024-2027 is heading, strengthening conditionality and incorporating tools like eco-schemes aimed at introducing soil and resource conservation practices that could alter production pathways, albeit on a voluntary basis. While these practices are beneficial for the environment, they could have economic and productive consequences if not adequately compensated by financial support. Further analyses are needed to determine if this support, such as that provided by eco-schemes, can adequately offset the potential negative impacts.

Additionally, our model operates considering current agronomic techniques and technologies, and some results may also be influenced by external factors such as technical efficiency, outcome uncertainty, socio-demographic or behavioral features, which can affect the agricultural inputs quantity used by farmers (Bontemps et al., 2021; Nave et al., 2013). Furthermore, operating within the short to medium term, this model, while flexible in terms of responses, does not accommodate radical strategies for coping with input reductions. Therefore, new crops, cover cropping, or other agronomic techniques that could offset the impact of these targets are not considered in the short term analyzed by this work. However, the analysis remains robust in the short term under the assumption that farmers are not immediately adopting new strategies, as doing so requires time, education, information, and innovation. We also do not assume adjustments in prices and repercussions due to contractions in international production. Therefore, our estimate might overestimate the F2F effect on gross output, as a contraction in international production could lead to higher maize grain prices.

On the other hand, our analysis might underestimate these impacts, as increasing input prices pose a significant challenge. Even if farmers reduce chemical use to sustain production, additional costs and income losses could markedly affect maize grain production. Furthermore, increased risks due to CC, such as drought, fungal, or pests' attacks, could further jeopardize production, which would already be vulnerable due to the reduced pesticide coverage. This, in turn, would negatively impact the national budget and the quality of products derived from this commodity. Lastly, the estimated production function (Buttinelli et al., 2024) is based on Maize Gross Output and this means that, having maize grain several final market destinations, this variable could be influenced by this factor. However, the empirical specification accounts for individual-specific characteristics over time controlling for within variation and this allows to account for the differences existing between farms producing maize grain for food, feed or energy crop. However, potential further developments could consider this differentiation in a more explicit way.

In conclusion, our research sheds light on the potential impacts of the F2F strategy on arable farms engaged in maize grain production in Italy, emphasizing the need for careful consideration and region-specific strategies when transitioning to low-input agriculture. As we plan this transition, it's crucial to recognize the limitations of current policies, consider necessary adjustments, 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 goes in this direction and underscores the urgency of debating the future of EU agricultural policies, considering the importance of collaborative efforts to develop effective and balanced agricultural policies that address both environmental and economic challenges.

6.7. References

Alexander, P., Reddy, A., Brown, C., Henry, R.C., Rounsevell, M.D.A., 2019. Transforming agricultural land use through marginal gains in the food system. Global Environmental Change 57, 101932. https://doi.org/10.1016/j.gloenvcha.2019.101932

Balezentis, T., Chen, X., Galnaityte, A., Namiotko, V., 2020. Optimizing crop mix with respect to economic and environmental constraints: An integrated MCDM approach. Science of the Total Environment 705, 135896. https://doi.org/10.1016/j.scitotenv.2019.135896

Barreiro-Hurle, J., Bogonos, M., Himics, M., Hristov, J., Pérez-Domiguez, I., Sahoo, A., Salputra, G., Weiss, F., Baldoni, E., Elleby, C., 2021. Modelling environmental and climate ambition in the agricultural sector with the CAPRI model, JRC Technical Report. https://doi.org/10.2760/98160

Beckman, J., Ivanic, M., Jelliffe, J., Baquedano, F., Scott, S., 2020. Economic and food security impacts of agricultural input reduction under the European Union Green Deal's farm to fork and biodiversity strategies. U.S. Department of Agriculture, Economic Research Service EB-30, 1–59.

Bontemps, C., Bougherara, D., Nauges, C., 2021. Do Risk Preferences Really Matter? The Case of Pesticide Use in Agriculture. Environmental Modeling and Assessment 26, 609–630. https://doi.org/10.1007/s10666-021-09756-8

Bremmer, J., Gonzalez-Martinez, A., Jongeneel, R., Huiting, H., Stokkers, R., 2021. Effects of Farm to Fork and Biodiversity Strategy 2030 at farm, national and EU level c, 1–4.

Britz, W., 2010. Endogenous yields and decomposition of yield and activity related income indicators.

Britz, W., Pérez, I., Zimmermann, A., Heckelei, T., 2007. Definition of the CAPRI Core Modelling System and Interfaces with other Components of SEAMLESS-IF.

Buttinelli, R., Cortignani, R., Caracciolo, F., 2024. Irrigation water economic value and productivity: An econometric estimation for maize grain production in Italy. Agric Water Manag 295, 108757. https://doi.org/10.1016/j.agwat.2024.108757

Coelli, T., Perelman, S., & Romano, E. 1999. Accounting for environmental influences in stochastic frontier models: with application to international airlines. Journal of productivity analysis, 11, 251-273.

Cortignani, R., Buttinelli, R., Dono, G., 2022. Farm to Fork strategy and restrictions on the use of chemical inputs: Impacts on the various types of farming and territories of Italy. Science of the Total Environment 810, 152259. https://doi.org/10.1016/j.scitotenv.2021.152259

Cortignani, R., Severini, S., 2012. A constrained optimization model based on generalized maximum entropy to assess the impact of reforming agricultural policy on the sustainability of irrigated areas. Agricultural Economics (United Kingdom) 43, 621–633. https://doi.org/10.1111/j.1574-0862.2012.00608.x

Czyżewski, B., Kryszak, Ł., 2023. Can a pursuit of productivity be reconciled with sustainable practices in small-scale farming? Evidence from central and eastern Europe. J Clean Prod 414. https://doi.org/10.1016/j.jclepro.2023.137684

De Frahan, H.B., Buysse, J., Polomé, P., Fernagut, B., Harmignie, O., Lauwers, L., Van Huylenbroeck, G., Van Meense, J., 2016. Positive mathematical programming for agricultural and environmental policy analysis: Review and practice. International Series in Operations Research and Management Science 99, 129–154. https://doi.org/10.1007/978-0-387-71815-6_8

Edwards, B.K., Howitt, R.E., Flaim, S.J., 1996. Fuel, crop , and water substitution in irrigated agriculture 18.

Erenstein, O., Jaleta, M., Sonder, K., Mottaleb, K., Prasanna, B.M., 2022. Global maize production, consumption and trade: trends and R&D implications. Food Secur 14, 1295–1319. https://doi.org/10.1007/s12571-022-01288-7

European Commission, 2019. The European Green Deal. Brussels, COM/2019/640 final, https://ec.europa.eu/info/strategy/priorities-2019-2024/european-green-deal_en

European Commission, 2020. Farm to Fork Strategy—For a Fair, Healthy and Environmentally-Friendly Food System, COM/2020/381 final, https://ec.europa.eu/food/farm2fork_en

Fitton, N., Alexander, P., Arnell, N., Bajzelj, B., Calvin, K., Doelman, J., Gerber, J.S., Havlik, P., Hasegawa, T., Herrero, M., Krisztin, T., van Meijl, H., Powell, T., Sands, R., Stehfest, E., West, P.C., Smith, P., 2019. The vulnerabilities of agricultural land and food production to future water scarcity. Global Environmental Change 58, 101944. https://doi.org/10.1016/j.gloenvcha.2019.101944

Gadanakis, Y., Bennett, R., Park, J., Areal, F.J., 2015. Improving productivity and water use efficiency: A case study of farms in England. Agric Water Manag 160, 22–32. https://doi.org/10.1016/j.agwat.2015.06.020

Giraldo, L., Cortignani, R., Dono, G., 2014. Simulating volumetric pricing for irrigation water operational cost recovery under complete and perfect information. Water (Switzerland) 6, 1204–1220. https://doi.org/10.3390/w6051204

Godard, C., Roger-Estrade, J., Jayet, P.A., Brisson, N., Le Bas, C., 2008. Use of available information at a European level to construct crop nitrogen response curves for the regions of the EU. Agric Syst 97, 68–82. https://doi.org/10.1016/j.agsy.2007.12.002

Graindorge, C., de Frahan, B.H., Howitt, R.E., 2000. Analysing the Effects of Agenda 2000 Using a CES Calibrated Model of Belgian Agriculture. Agricultural Sector Modelling and Policy Information Systems. Proceedings of the 65th EAAE Seminar 177–186.

Guo, J., Li, C., Xu, X., Sun, M., Zhang, L., 2022. Farmland scale and chemical fertilizer use in rural China: New evidence from the perspective of nutrient elements. J Clean Prod 376, 134278. https://doi.org/10.1016/j.jclepro.2022.134278

Hebinck, A., Zurek, M., Achterbosch, T., Forkman, B., Kuijsten, A., Kuiper, M., Nørrung, B., Veer, P. van 't, Leip, A., 2021. A Sustainability Compass for policy navigation to sustainable food systems. Glob Food Sec 29. https://doi.org/10.1016/j.gfs.2021.100546

Heckelei, T., Britz, W., Zhang, Y., 2012. Positive Mathematical Programming Approaches – Recent Developments in Literature and Applied Modelling. Bio-based and Applied Economics 1, 109–124.

Heckelei, T., Wolff, H., 2003. Estimation of constrained optimisation models for agricultural supply analysis based on generalised maximum entropy. European Review of Agricultural Economics 30, 27–50. https://doi.org/10.1093/erae/30.1.27

Howitt, R.E., 1995a. Positive Mathematical Programming. Am J Agric Econ 77, 329–342. https://doi.org/10.2307/1243543

Howitt, R.E., 1995b. a Calibration Method for Agricultural Economic Production Models. J Agric Econ 46, 147–159. https://doi.org/10.1111/j.1477-9552.1995.tb00762.x

Howitt, R.E., Medellín-Azuara, J., MacEwan, D., Lund, J.R., 2012. Calibrating disaggregates economic models of agricultural production and water management. Environmental Modelling and Software 38, 244–258. https://doi.org/10.1016/j.envsoft.2012.06.013

Hristov, A.N., Degaetano, A.T., Rotz, C.A., Hoberg, E., Skinner, R.H., Felix, T., Li, H., Patterson, P.H., Roth, G., Hall, M., Ott, T.L., Baumgard, L.H., Staniar, W., Hulet, R.M., Dell, C.J., Brito, A.F., Hollinger, D.Y., 2018. Climate change effects on livestock in the Northeast US and strategies for adaptation. Clim Change 146, 33–45. https://doi.org/10.1007/s10584-017-2023-z

Hristov, J., Toreti, A., Pérez Domínguez, I., Dentener, F., Fellmann, T., Elleby, C., Ceglar, A., Fumagalli, D., Niemeyer, S., Cerrani, I., Panarello, L., Bratu, M., 2020. Analysis of climate change impacts on EU agriculture by 2050 JRC PESETA IV project-Task 3, JRC Technical Report. https://doi.org/10.2760/121115

IPCC, 2021. Synthesis Report of the Ipcc Sixth Assessment Report (Ar6). European University Institute 2–5.

Karagiannis, G., Sarris, A., 2005. Measuring and explaining scale efficiency with the parametric approach : the case of Greek tobacco growers 33.

Latruffe, L., 2010. Competitiveness, Productivity and Efficiency in the Agricultural and Agri-Food Sectors. OECD Food, Agriculture and Fisheries Papers 30, 1–63.

Leggieri, M.C., Lanubile, A., Dall'Asta, C., Pietri, A., Battilani, P., 2020. The impact of seasonal weather variation on mycotoxins: Maize crop in 2014 in northern Italy as a case study. World Mycotoxin J 13, 25–36. https://doi.org/10.3920/WMJ2019.2475

Li, C., Wan, D., Xu, X., Li, J., Gaffney, P.P.J., Ma, Y., Zhang, L., 2023. Anti-substitution effect of coupling crop and livestock production on fertilizer use: Evidence from Chinese smallholder farms. J Clean Prod 412, 137359. https://doi.org/10.1016/j.jclepro.2023.137359

Lionello, P., Scarascia, L., 2018. The relation between climate change in the Mediterranean region and global warming. Reg Environ Change 18, 1481–1493. https://doi.org/10.1007/s10113-018-1290-1

Malek, Ž., Verburg, P.H., 2018. Adaptation of land management in the Mediterranean under scenarios of irrigation water use and availability. Mitig Adapt Strateg Glob Chang 23, 821–837. https://doi.org/10.1007/s11027-017-9761-0

Mantovi, P., Dal Prà, A., Pacchioli, M., & Ligabue, M., (2015). Forage production and use in the dairy farming systems of Northern Italy.

Medellín-Azuara, J., Harou, J.J., Howitt, R.E., 2010. Estimating economic value of agricultural water under changing conditions and the effects of spatial aggregation. Science of the Total Environment 408, 5639–5648. https://doi.org/10.1016/j.scitotenv.2009.08.013

Medina, Á., Rodríguez, A., Magan, N., 2015. Climate change and mycotoxigenic fungi: Impacts on mycotoxin production. Curr Opin Food Sci 5, 99–104. https://doi.org/10.1016/j.cofs.2015.11.002

Mereu, V., Gallo, A., Trabucco, A., Carboni, G., Spano, D., 2021. Modeling high-resolution climate change impacts on wheat and maize in Italy. Clim Risk Manag 33, 100339. https://doi.org/10.1016/j.crm.2021.100339

Montanarella, L., Panagos, P., 2021. Land Use Policy The relevance of sustainable soil management within the European Green Deal. Land use policy 100, 104950. https://doi.org/10.1016/j.landusepol.2020.104950

Nave, S., Jacquet, F., Jeuffroy, M.H., 2013. Why wheat farmers could reduce chemical inputs: Evidence from social, economic, and agronomic analysis. Agron Sustain Dev 33, 795–807. https://doi.org/10.1007/s13593-013-0144-y

Noleppa, S., Cartsburg, M., 2021. The socio-economic and environmental values of plant breeding in the EU and selected EU member states an ex-post evaluation and ex-ante assessment considering the.

Paris, Q., Arfini, F., 1995. A positive mathematical programming model for regional analysis of agricultural policies Frontier Cost Functions, Self-Selection, Price Risk, PMP, and Agenda 2000 Quirino Paris and Filippo Arfini December 1998.

Paris, Q., Howitt, R.E., 1998. An Analysis of Ill-Posed Production Problems Using Maximum Entropy. Am J Agric Econ 80, 124–138. https://doi.org/10.2307/3180275

Rahman, S., Wiboonpongse, A., Sriboonchitta, S., & Chaovanapoonphol, Y. 2009. Production efficiency of Jasmine rice producers in Northern and North-Eastern Thailand. Journal of Agricultural Economics, 60(2), 419-435.

Robu, R.G., Holobiuc, A.M., Alexoaei, A.P., Cojanu, V., Miron, D., 2023. Regional Patterns of Pesticide Consumption Determinants in the European Union. Sustainability (Switzerland) 15. https://doi.org/10.3390/su15032070

Rosenzweig, C., Elliott, J., Deryng, D., Ruane, A.C., Müller, C., Arneth, A., Boote, K.J., Folberth, C., Glotter, M., Khabarov, N., Neumann, K., Piontek, F., Pugh, T.A.M., Schmid, E., Stehfest, E., Yang, H., Jones, J.W., 2014. Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. Proc Natl Acad Sci U S A 111, 3268–3273. https://doi.org/10.1073/pnas.1222463110

Singbo, A.G., Oude, A., Emvalomatis, G., 2015. Estimating shadow prices and efficiency analysis of productive inputs and pesticide use of vegetable production. Eur J Oper Res 245, 265–272. https://doi.org/10.1016/j.ejor.2015.02.042

Speelman, S., D'Haese, M., Buysse, J., D'Haese, L., 2008. A measure for the efficiency of water use and its determinants, a case study of small-scale irrigation schemes in North-West Province, South Africa. Agric Syst 98, 31–39. https://doi.org/10.1016/j.agsy.2008.03.006

Staniszewski, J., Guth, M., Smędzik-Ambroży, K., 2023. Structural conditions of the sustainable intensification of agriculture in the regions of the European Union. J Clean Prod 389, 136109. https://doi.org/10.1016/j.jclepro.2023.136109

Wesseler, J., 2022. The EU's farm-to-fork strategy: An assessment from the perspective of agricultural economics. Appl Econ Perspect Policy 44, 1826–1843. https://doi.org/10.1002/aepp.13239

Wu, F., Bhatnagar, D., Bui-Klimke, T., Carbone, I., Hellmich, R., Munkvold, G., Paul, P., Payne, G., Takle, E., 2010. Climate change impacts on mycotoxin risks in US maize. World Mycotoxin J 4, 79–93. https://doi.org/10.3920/WMJ2010.1246

Zhu, X., Demeter, R.M., Lansink, A.O., 2012. Technical efficiency and productivity differentials of dairy farms in three EU countries : the role of CAP subsidies 13, 66–92.

Zhu, X., Lansink, A.O., 2010. Impact of CAP Subsidies on Technical Efficiency of Crop Farms in Germany, the Netherlands and Sweden. J. Agric. Econ. 61, 545–564. https://doi.org/10.1111/j.1477-9552.2010.00254.x

7. Conclusions

This thesis undertakes a comprehensive evaluation of the economic impacts on Italian farms resulting from changes in the relationships among various agricultural inputs, with a particular focus on chemicals and irrigation water. It addresses two main themes: analyzing the intricate aspects of agricultural production and evaluating the economic implications of the European F2F Strategy objectives for Italian farms. To achieve these ambitious goals, the thesis employs several case studies that reveal underlying complexities in the relationships between agricultural inputs and production activities.

Specifically, the agro-supply model AGRITALIM played a crucial role in analyzing over 40,000 farms, identifying the most susceptible sectors to changes in agricultural inputs availability under the F2F strategy. This initial step revealed a correlation between the reduction in chemicals and other inputs, such as water and labor, resulting in repercussions not only for production but also for employment. Furthermore, by providing a realistic representation of the agricultural structure and insights into farmers' decision-making processes, this first step highlighted that variations upstream in the supply chain can pose risks for downstream actors, contributing to remarkable economic and social impacts. In addition, the findings facilitated the identification of the most vulnerable sectors, opening the way for more detailed analyses. Based on these insights, two economically significant crops in Italian agriculture, i.e. maize grain and processing tomato, were selected as case studies to contribute additional layers to the overall analysis.

Consistent with the second research objective, the examination of irrigation water's relevance for maize grain production went beyond quantitative analysis, growing into a deep understanding of its role in sustaining this crop production across Italy. This research is particularly relevant in the Mediterranean context, where water availability is at risk (Hristov et al., 2020) and where water suspension has recently caused quality issues and production losses in maize yield. By quantifying its economic contribution and marginal productivity, and identifying vulnerable farms and areas, the research provided indications of how variations in irrigation water availability could affect crop production, especially concerning high water-demanding crops such as maize grain, which have already been identified as vulnerable to chemical input reductions. Furthermore, the econometric methodologies employed allowed for a sophisticated understanding and assessment of the influence that water has on yields, adding a fundamental component to the overall investigation.

The analysis of the economic impact of the EU F2F Strategy targets on processing tomatoes, provided a detailed overview of how environmental goals interconnect with economic viability, introducing other elements. Indeed, we took into account the influence of exogenous factors shaping farmers' decision-making processes, such as risk aversion (Bontemps et al., 2021) or reliance on subsidies (Latruffe et al., 2017; Zhu and Lansink, 2010). Moreover, Technical Efficiency (TE) estimation allowed us to look at the agricultural production process from another perspective, providing insights into the effectiveness of resource utilization and identifying areas for potential improvement. However, in all the analyses, the contribution of production functions properties was crucial, especially reinforcing the first hypothesis that interventions on a single production factor do not just impact that individual component. Indeed, in all conducted analyses, the translog production function proved to be the most suitable functional form for fitting the data, revealing each time significant effects of substitution or synergy among the various inputs considered.

Finally, the latest conducted analysis fully leverages these properties allowing the maximum exploitation of both MP and Econometrics features. This final step underscores once again the significance of the flexibility offered flexible production functions in capturing intricate relationships, thus enhancing the accuracy and flexibility of the optimal solutions and enabling methodological advancements. This approach is particularly relevant given the dynamic nature of relationships within the agricultural system. Indeed, farmers base their decisions on expected outputs, influenced by their knowledge of past agricultural outcomes, market conditions, risk attitudes, and information regarding policies and subsidies. Thus, the integration of an econometrically estimated function that considers the farmers' production choices over the past ten years, integrated with a MP model, allows for the endogenization of outputs and chemical quantities considering farmers' past production choices. This step results in detailed and aligned responses with the chosen case study.

Methodologically, the thesis integrates econometrics and optimization models to obtain robust empirical results, addressing the complex challenge of assessing impacts from changes in input availability and external constraints on agricultural production deriving from the EU political framework. This approach acknowledges that farmers' decision-making processes are influenced by several factors such as agronomic practices, future expectations, policy frameworks, market dynamics, and socio-cultural characteristics. Moreover, the thesis underscores that sector-specific vulnerabilities are to be considered, highlighting susceptibility to input reductions based on supply chain characteristics and production systems characteristics. Indeed, economic impacts vary across sectors, with crops showing differing adaptabilities despite methodological flexibility allowing for nuanced responses. For instance, high-profit crops such as processing tomatoes are notably penalized by reductions in chemical inputs, particularly in intensive production regions, also depending on farms TE levels. Conversely, less profitable crops like maize grain are most affected in less intensive areas or in less specialized farms. Indeed, the analyses not only evaluate the contribution of various production factors to crop outputs but also differentiate impacts across different farm characteristics and specific regions, revealing existing disparities and offering insights for targeted interventions. For instance, according to the results obtained in this thesis, exemptions could be considered for more efficient farms to mitigate the impact of reducing chemicals in strategic productions such as processing tomatoes which might otherwise be penalized further despite already using inputs efficiently. This consideration is only an example of the potentiality of such analyses, underscoring the importance of specific and detailed modeling tailored to the examined context, as Country-level assessments may provide a general overview but often overlook the most vulnerable areas or specific farms within each Member State.

In other words, in this framework, MP models allow for ex-ante policy evaluations adapted to specific farms' characteristics, including crop choices, agronomic techniques, and resource availability constraints. Econometric models, by contrast, use farmers' past production choices to assess the productivity, relevance, and efficiency of inputs used, accounting for individual-specific characteristics and territorial variability through the several employed empirical specifications. Moreover, the pursuit of flexibility in both approaches through flexible production functions such as the Translog (Christensen et al., 1975) and through the relaxation of assumptions of fixed relationships between input and output in Leontief-based MP models (Britz et al., 2007), enables the identification of substitution effects among inputs, providing realistic representations of the agricultural production in Italy and identifying potential strategies to mitigate production constraints effects. Together, these methodological foundations facilitate a methodical understanding of the agricultural sector, supporting targeted interventions (Godard et al., 2018). Integrating econometrics and optimization models enhance the ability to obtain flexible and precise responses, contributing methodologically and practically to this line of research, offering relevant insights to stakeholders and policymakers.

In conclusion, this thesis addresses research objectives comprehensively, offering varied perspectives to clarify and fill gaps emerging chapter after chapter. By indagating interrelations, quantifying input impacts on crop production, and exploring economic complexities related to efficiency and land use changes, the thesis aims to offer a comprehensive understanding of Italian agriculture's dynamics. It highlights the delicate balance required between environmental goals and economic viability in reducing chemical inputs taking a first step towards a methodological approach useful as valuable guidance for policymakers. Indeed, all the conducted research emphasizes the need for further investigation and strategic planning to achieve the ambitious objectives set by the EU Commission, encouraging for territorial and sector-specific strategies. Such analyses can support policy assessments and impact evaluations, emphasizing the need for flexible, detailed models that take into account agricultural heterogeneity when designing policies to minimize economic impacts on farms while preserving the environment and promoting sustainability. Policies must consider these distinctions to avoid overlooking sector-specific and territorial dynamics potentially leading to social consequences. The various researches conducted in this thesis contribute methodologically and scientifically to this ambitious goal, providing a foundation for integrated and informed decision-making in agricultural policy aiming for scientific rigor and effectiveness in policymaking. Moreover, they highlight the complexity of reducing chemical inputs acknowledging the need for careful consideration of climate-related threats such as rising temperatures and severe weather events (Mereu et al., 2021), which could exacerbate phytosanitary risks, in a circumstance where chemical inputs use is already limited and in areas at risk such as the Mediterranean.

However, despite the in-depth analysis conducted in this thesis, it is necessary to acknowledge certain limitations and emphasize that further developments and analyses are necessary, especially considering the EU Commission decision to withdraw the Sustainable Use Regulation (SUR). Additionally, it should be considered, that the various F2F's objectives not only pertain to the use of chemical inputs but also to other issues such as biodiversity conservation, reducing antimicrobial use in livestock, and achieving 25% of agricultural land under organic farming in Europe. These interconnected goals could have significant impacts in various areas or mitigate the impacts of the policies considered in these analyses. For instance, the conversion to organic farming could allow some sectors to transition to low-input agriculture relatively easily but this could not be true for all sectors and regions, especially in intensive areas where such a change could lead to high profitability losses and potentially threatening national production and farms' viability. From our analyses, particularly the one conducted on the industrial tomato sector, such a transition is not at all effortless, as the allowed organic formulations in terms of fertilizers cannot be considered substitutes for conventional formulations. Therefore, the approach used in this thesis could help to understand how straightforward is for some sectors or farms to switch from conventional agricultural techniques to lower-intensity ones, allowing for targeted support and intervention.

As a future step, it would be interesting to simulate the impact of the F2F objectives simultaneously and differentiate by sectors and production intensity to obtain more realistic and reliable results (Noleppa et al., 2021). Moreover, the emphasis on reducing GHG and antimicrobial use introduces additional complexities and potential conflicts with other objectives. For instance, further analyses are necessary to investigate additional outcomes concerning the impact on livestock, which has been indirectly addressed primarily through crops used as feed (e.g., maize grain). Indeed, the livestock sector emerges as vulnerable due to its increased dependence on purchased feed in the event of production contractions in Italian feed crops. Additionally, the EU's concurrent demand for reduced antimicrobial use and its emphasis on decreasing greenhouse gas emissions (GHG) from these activities further underscores its exposure (Coderoni et al., 2024). Understanding these trade-offs necessitates robust models capable of simulating integrated impacts across various dimensions, thereby guiding policymakers in balancing environmental goals with economic realities. Other limitations concern our assumptions about the impacts of chemical reductions on yields, income, and gross output, that do not consider international market prices adjustments concerning inputs and outputs that could counterbalance these losses. The analyses also show limitations in accounting for technological development, as they assume constant technological levels in the short term and do not consider significant innovations. Given this limitation, it must be emphasized that these estimates are intended to assess short-term impacts or could represent worst-case scenarios. Innovation, education or the adoption of other agronomic techniques could partially mitigate these impacts on the farming sector.

Despite these limitations, the adopted approach not only addresses current challenges but also seeks to detect future uncertainties, contributing to the design of an adaptive sector capable of meeting diverse social, economic and environmental goals. In this context, flexible models that can identify specific vulnerabilities, detect input substitution effects, and consider intrinsic farm characteristics are essential to support a conscious formulation of policies and the potential identification of strategies to cope with imposed constraints. As next steps, enhancing models' capabilities to dynamically simulate technological advancements and adaptation strategies would improve accuracy in predicting long-term impacts on agricultural systems. Other improvements could also focus on incorporating socio-economic factors more robustly as farmers' decision-making processes are influenced not only by agronomic factors but also by socio-cultural contexts and personal beliefs. Integrating these elements would provide more realistic assessments of policy impacts and enhance the relevance of findings for policymakers and stakeholders.

In conclusion, advancing methodological frameworks to better capture the complexities of agricultural systems and the interplay among F2F objectives will be crucial for designing effective and sustainable agricultural policies. Methodological advancements are crucial in this regard, especially to establish whether the implementation of new voluntary actions such as eco-schemes introduced by the 2023-2027 CAP reform will facilitate the process towards low-input agriculture or, conversely, complicate it further. Such models can help identify the drivers of participation, assess the impact of these policies in terms of farm adaptation strategies, and predict the most likely reactions with high granularity.

In conclusion, while this thesis comprehensively addresses the research objectives outlined at the beginning of this journey, it is essential to recognize not only its potential contribution to policy evaluation and quantification of the economic impacts of constraints on agricultural input use but also its capability to represent a step towards methodological approaches that can model the agricultural sector as comprehensively and realistically as possible. The proposed variety of methodologies represent a robust foundation for policy assessment and possible insights for policies design, especially needed in light of recent farmers' protests and the European Commission's decision to reexamine F2F targets on pesticides (Finger, 2024). The EU's acknowledgement of farmers' concerns underscores the urgent need for the formulation of new alternatives, highlighting the ongoing relevance and importance of analytical research in shaping conscious future policies. Providing empirical evidence and influencing policy and the formulation of new proposals is crucial at a time when the green transition is more necessary than ever. The complexity of the scenario demands targeted interventions and a thoughtful approach to ensure a sustainable transition, especially in the short term. In this context, the insights of this thesis not only conclude the present research but also lay a foundation for future exploration into the complex interplay of environmental sustainability and economic viability underscoring the central role of agricultural economics in policy design.

8. References

Agovino, M., Casaccia, M., Ciommi, M., Ferrara, M., Marchesano, K., 2019. Agriculture, climate change and sustainability: The case of EU-28. Ecol. Indic. 105, 525–543. https://doi.org/10.1016/j.ecolind.2018.04.064

Alexander, P., Reddy, A., Brown, C., Henry, R.C., Rounsevell, M.D.A., 2019. Transforming agricultural land use through marginal gains in the food system. Glob. Environ. Chang. 57, 101932. https://doi.org/10.1016/j.gloenvcha.2019.101932

Auci, S., Vignani, D., 2020. Climate variability and agriculture in Italy: a stochastic frontier analysis at the regional level. Econ. Polit. 37, 381–409. https://doi.org/10.1007/s40888-020-00172-x

Bakker, L., Sok, J., van der Werf, W., Bianchi, F.J.J.A., 2021. Kicking the Habit: What Makes and Breaks Farmers' Intentions to Reduce Pesticide Use? Ecol. Econ. 180. https://doi.org/10.1016/j.ecolecon.2020.106868

Balezentis, T., Chen, X., Galnaityte, A., Namiotko, V., 2020. Optimizing crop mix with respect to economic and environmental constraints: An integrated MCDM approach. Sci. Total Environ. 705, 135896. https://doi.org/10.1016/j.scitotenv.2019.135896

Barreiro-Hurle, J., Bogonos, M., Himics, M., Hristov, J., Pérez-Domiguez, I., Sahoo, A., Salputra, G., Weiss, F., Baldoni, E., Elleby, C., 2021. Modelling environmental and climate ambition in the agricultural sector with the CAPRI model, JRC Technical Report. https://doi.org/10.2760/98160

Bartolini, F., Bazzani, G.M., Gallerani, V., Raggi, M., Viaggi, D., 2007. The impact of water and agriculture policy scenarios on irrigated farming systems in Italy: An analysis based on farm level multi-attribute linear programming models. Agric. Syst. 93, 90–114. https://doi.org/10.1016/j.agsy.2006.04.006

Battese, G.; Coelli, T., 1995. A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data. J. Econom. 325–332.

Baulcombe, D., Crute, I., Davies, B., Dunwell, J., Gale, M., Jones, J., Ptetty, J., Sutherland, W., Toulmin, C., 2009. Reaping the benefits: science and the sustainable intensification of global agriculture, The Royal Society, Policy Document.

Bazzani, G.M., Di Pasquale, S., Gallerani, V., Morganti, S., Raggi, M., Viaggi, D., 2005. The sustainability of irrigated agricultural systems under the Water Framework Directive: First results. Environ. Model. Softw. 20, 165–175. https://doi.org/10.1016/j.envsoft.2003.12.018

Beach, R.H., Cai, Y., Thomson, A., Zhang, X., Jones, R., McCarl, B.A., Crimmins, A., Martinich, J., Cole, J., Ohrel, S., Deangelo, B., McFarland, J., Strzepek, K., Boehlert, B., 2015. Climate change impacts on US agriculture and forestry: Benefits of global climate stabilization. Environ. Res. Lett. 10. https://doi.org/10.1088/1748-9326/10/9/095004

Beckman, J., Ivanic, M., Jelliffe, J., Baquedano, F., Scott, S., 2020. Economic and food security impacts of agricultural input reduction under the European Union Green Deal's farm to fork and biodiversity strategies. U.S. Dep. Agric. Econ. Res. Serv. EB-30, 1–59.

Beillouin, D., Schauberger, B., Bastos, A., Ciais, P., Makowski, D., 2020. Impact of extreme weather conditions on European crop production in 2018: Random forest - Yield anomalies. Philos. Trans. R. Soc. B Biol. Sci. 375. https://doi.org/10.1098/rstb.2019.0510

Bennett, Jeff W.; Pearce, D. W.; Turner, R.K., 1991. Economics of Natural Resources and the Environment. Econ. Nat. Resour. Environ. Am. J. Agric. Econ. 73, 227–228. https://doi.org/doi:10.2307/1242904

Bierkens, M.F.P., Reinhard, S., de Bruijn, J.A., Veninga, W., Wada, Y., 2019. The Shadow Price of Irrigation Water in Major Groundwater-Depleting Countries. Water Resour. Res. 55, 4266–4287. https://doi.org/10.1029/2018WR023086

Bontemps, C., Bougherara, D., Nauges, C., 2021. Do Risk Preferences Really Matter? The Case of Pesticide Use in Agriculture. Environ. Model. Assess. 26, 609–630. https://doi.org/10.1007/s10666-021-09756-8

Brás, T.A., Seixas, J., Carvalhais, N., Jagermeyr, J., 2021. Severity of drought and heatwave crop losses tripled over the last five decades in Europe. Environ. Res. Lett. 16. https://doi.org/10.1088/1748-9326/abf004

Bremmer, J., Gonzalez-Martinez, A., Jongeneel, R., Huiting, H., Stokkers, R., 2021. Effects of Farm to Fork and Biodiversity Strategy 2030 at farm, national and EU level c, 1–4.

Britz, W., 2010. Endogenous yields and decomposition of yield and activity related income indicators.

Cammalleri, C, Naumann, G, Mentaschi, L, Formetta, G, Forzieri, G, Gosling ,S, Bisselink, B, Roo, De A, Feyen, L., 2020. Global warming and drought impacts in the EU. Publ. Off. Eur. Union. https://doi.org/10.2760/597045

Cassman, K.G., Grassini, P., 2020. A global perspective on sustainable intensification research. Nat. Sustain. 3, 262–268. https://doi.org/10.1038/s41893-020-0507-8

Christensen, L.R., Jorgenson, D.W., Lau, L.J., 1975. Transcendental Logarithmic Utility Functions. Am. Econ. Rev. 65, 367–383.

Cobb, C.W. and Douglas, P.H., 1928. Theory of production. Am. Econ. Rev. https://doi.org/10.1007/978-4-431-54433-3_9

Coderoni, S., Dell'Unto, D., Cortignani, R., 2024. Curbing methane emissions from Italian cattle farms. An agroeconomic modelling simulation of alternative policy tools. J. Environ. Manage. 351, 119880. https://doi.org/10.1016/j.jenvman.2023.119880

Coderoni, S., Pagliacci, F., 2023. The impact of climate change on land productivity. A micro-level assessment for Italian farms. Agric. Syst. 205, 103565. https://doi.org/10.1016/j.agsy.2022.103565

Cortignani, R., Buttinelli, R., Dono, G., 2022. Farm to Fork strategy and restrictions on the use of chemical inputs: Impacts on the various types of farming and territories of Italy. Sci. Total Environ. 810, 152259. https://doi.org/10.1016/j.scitotenv.2021.152259

Cortignani, R., Unto, D.D., Dono, G., 2018. Recovering the costs of irrigation water with different pricing methods : Insights from a Mediterranean case study. Agric. Water Manag. 199, 148–156. https://doi.org/10.1016/j.agwat.2017.12.016

Edwards, B.K., Howitt, R.E., Flaim, S.J., 1996. Fuel , crop , and water substitution in irrigated agriculture 18.

Erenstein, O., Jaleta, M., Sonder, K., Mottaleb, K., Prasanna, B.M., 2022. Global maize production, consumption and trade: trends and R&D implications. Food Secur. 14, 1295–1319. https://doi.org/10.1007/s12571-022-01288-7

FAO, 2022. The State of the World's Land and Water Resources for Food and Agriculture 2021 – Systems at breaking point, The State of the World's Land and Water Resources for Food and Agriculture 2021 – Systems at breaking point. https://doi.org/10.4060/cb9910en

FAO, 2022. The State of the World's Land and Water Resources for Food and Agriculture 2021 – Systems at breaking point, The State of the World's Land and Water Resources for Food and Agriculture 2021 – Systems at breaking point. https://doi.org/10.4060/cb9910en

Finger, R., 2024. Europe's ambitious pesticide policy and its impact on agriculture and food systems. Agric. Econ. https://doi.org/10.1111/agec.12817

Fitton, N., Alexander, P., Arnell, N., Bajzelj, B., Calvin, K., Doelman, J., Gerber, J.S., Havlik, P., Hasegawa, T., Herrero, M., Krisztin, T., van Meijl, H., Powell, T., Sands, R., Stehfest, E., West, P.C., Smith, P., 2019. The vulnerabilities of agricultural land and food production to future water scarcity. Glob. Environ. Chang. 58, 101944. https://doi.org/10.1016/j.gloenvcha.2019.101944

García Suárez, F., Fulginiti, L.E. and Perrin, R.K., 2019. What is the use value of irrigation water from the high plains aquifer? Am. J. Agric. Econ. 101, 455–466. https://doi.org/10.1093/ajae/aay062

García-León, D., Standardi, G., Staccione, A., 2021. An integrated approach for the estimation of agricultural drought costs. Land use policy 100, 104923. https://doi.org/10.1016/j.landusepol.2020.104923

Giraldo, L., Cortignani, R., Dono, G., 2014. Simulating volumetric pricing for irrigation water operational cost recovery under complete and perfect information. Water (Switzerland) 6, 1204–1220. https://doi.org/10.3390/w6051204

Gómez-Limón, J.A., Arriaza, M., Berbel, J., 2002. Conflicting Implementation of Agricultural and Water Policies in Irrigated Areas in the EU. J. Agric. Econ. 53, 259–281. https://doi.org/10.1111/j.1477-9552.2002.tb00020.x

Gómez-Limón, J.A., Riesgo, L., 2004. Irrigation water pricing: Differential impacts on irrigated farms. Agric. Econ. 31, 47–66. https://doi.org/10.1016/j.agecon.2003.02.001

Gómez-Limón, J.A.A., Riesgob, L., 2012. Agriculture and economics in the Water Framework Directive: Progress and limitations. Water Policy 14, 31–44. https://doi.org/10.2166/wp.2011.091

Graindorge, C., de Frahan, B.H., Howitt, R.E., 2000. Analysing the Effects of Agenda 2000 Using a CES Calibrated Model of Belgian Agriculture. Agric. Sect. Model. Policy Inf. Syst. Proc. 65th EAAE Semin. 177–186.

Henke, J., Breustedt, G., Sieling, K., Kage, H., 2007. Impact of uncertainty on the optimum nitrogen fertilization rate and agronomic , ecological and economic factors in an oilseed rape based crop rotation. J. Agric. Sci. 145, 455–468. https://doi.org/10.1017/S0021859607007204

Hennessy, D.A., 1998. The Production Effects of Agricultural Income Support Policies under Uncertainty. Am. J. Agric. Econ. 80, 46–57. https://doi.org/10.2307/3180267

Howitt, R.E., 1995a. Positive Mathematical Programming. Am. J. Agric. Econ. 77, 329–342. https://doi.org/10.2307/1243543

Howitt, R.E., 1995b. a Calibration Method for Agricultural Economic Production Models. J. Agric. Econ. 46, 147–159. https://doi.org/10.1111/j.1477-9552.1995.tb00762.x

Howitt, R.E., Medellín-Azuara, J., MacEwan, D., Lund, J.R., 2012. Calibrating disaggregate economic models of agricultural production and water management. Environ. Model. Softw. 38, 244–258. https://doi.org/10.1016/j.envsoft.2012.06.013

Hristov, J., Toreti, A., Pérez Domínguez, I., Dentener, F., Fellmann, T., Elleby, C., Ceglar, A., Fumagalli, D., Niemeyer, S., Cerrani, I., Panarello, L., Bratu, M., 2020. Analysis of climate change impacts on EU agriculture by 2050 JRC PESETA IV project-Task 3, JRC Technical Report . https://doi.org/10.2760/121115

Karagiannis, G., Sarris, A., 2005. Measuring and explaining scale efficiency with the parametric approach : the case of Greek tobacco growers 33.

Karagiannis, G., Tzouvelekas, V., Xepapadeas, A., 2003. Measuring Irrigation Water Efficiency with a Stochastic Production Frontier 57–72.

Kiani, R.A., Abbasi, F., 2012. Optimizing Water Consumption Using Crop Water Production Functions. Crop Prod. Technol. https://doi.org/10.5772/29543

Koundouri, P., Babalos, V., Stithou, M., Anastasiou, I., 2014. A micro-econometric approach to deriving use and non-use values of in situ groundwater: The vosvozis case study, Greece. Handb. Econ. Ecosyst. Serv. Biodivers. 423–435. https://doi.org/10.4337/9781781951514.00032

Kumbhakar, S.C., Lovell, C.A.K., 2000. Stochastic Frontier Analysis, Stochastic Frontier Analysis. https://doi.org/10.1017/cbo9781139174411

Latinopoulos, D., 2008. Estimating the potential impacts of irrigation water pricing using multicriteria decision making modelling. An Application to Northern Greece. Water Resour. Manag. 22, 1761–1782. https://doi.org/10.1007/s11269-008-9252-x

Latruffe, L., 2010. Competitiveness, Productivity and Efficiency in the Agricultural and Agri-Food Sectors. OECD Food, Agric. Fish. Pap. 30, 1–63.

Latruffe, L., Bravo-Ureta, B.E., Carpentier, A., Desjeux, Y., Moreira, V.H., 2017. Subsidies and technical efficiency in agriculture: Evidence from European dairy farms. Am. J. Agric. Econ. 99, 783–799. https://doi.org/10.1093/ajae/aaw077

Lionello, P., Scarascia, L., 2018. The relation between climate change in the Mediterranean region and global warming. Reg. Environ. Chang. 18, 1481–1493. https://doi.org/10.1007/s10113-018-1290-1

Malek, Ž., Verburg, P.H., 2018. Adaptation of land management in the Mediterranean under scenarios of irrigation water use and availability. Mitig. Adapt. Strateg. Glob. Chang. 23, 821–837. https://doi.org/10.1007/s11027-017-9761-0

Malek, Ž., Verburg, P.H., R Geijzendorffer, I., Bondeau, A., Cramer, W., 2018. Global change effects on land management in the Mediterranean region. Glob. Environ. Chang. 50, 238–254. https://doi.org/10.1016/j.gloenvcha.2018.04.007

Medellín-Azuara, J., Harou, J.J., Howitt, R.E., 2010. Estimating economic value of agricultural water under changing conditions and the effects of spatial aggregation. Sci. Total Environ. 408, 5639–5648. https://doi.org/10.1016/j.scitotenv.2009.08.013

Medina, Á., Rodríguez, A., Magan, N., 2015. Climate change and mycotoxigenic fungi: Impacts on mycotoxin production. Curr. Opin. Food Sci. 5, 99–104. https://doi.org/10.1016/j.cofs.2015.11.002

Menapace, L., Colson, G., Raffaelli, R., 2013. Risk aversion, subjective beliefs, and farmer risk management strategies. Am. J. Agric. Econ. 95, 384–389. https://doi.org/10.1093/ajae/aas107

Mesa-Jurado, M.A., Berbel, J., Orgaz, F., 2010. Estimating marginal value of water for irrigated olive grove with the production function method. Spanish J. Agric. Res. 8. https://doi.org/10.5424/sjar/201008s2-1362

Mirra, L., D'Urso, G., Giannoccaro, G., Cicia, G., Del Giudice, T., 2021. Water Pricing in Agriculture following the Water Framework Directive: A Systematic Review of the Literature. Int. J. Food Syst. Dyn. 12, 327–340. https://doi.org/10.18461/ijfsd.v12i4.94

Moutinho, V., Madaleno, M., Macedo, P., Robaina, M., Marques, C., 2018. Efficiency in the European agricultural sector: environment and resources. Environ. Sci. Pollut. Res. 25, 17927–17941. https://doi.org/10.1007/s11356-018-2041-z

Nave, S., Jacquet, F., Jeuffroy, M.H., 2013. Why wheat farmers could reduce chemical inputs: Evidence from social, economic, and agronomic analysis. Agron. Sustain. Dev. 33, 795–807. https://doi.org/10.1007/s13593-013-0144-y

Nerantzaki, S.D., Efstathiou, D., Giannakis, G. V., Kritsotakis, M., Grillakis, M.G., Koutroulis, A.G., Tsanis, I.K., Nikolaidis, N.P., 2019. Climate change impact on the hydrological budget of a large Mediterranean island. Hydrol. Sci. J. 64, 1190–1203. https://doi.org/10.1080/02626667.2019.1630741

Noleppa, S., Cartsburg, M., 2021. The socio-economic and environmental values of plant breeding in the EU and selected EU member states An ex-post evaluation and ex-ante assessment considering the.

OECD Economic Outlook, Volume 2022 Issue 2

Onofri, L., Bianchin, F., Boatto, V., 2019. How to assess future agricultural performance under climate change ? A case-study on the Veneto region. Agric. Food Econ. 16.

Paris, Q., Arfini, F., 1995. A positive mathematical programming model for regional analysis of agricultural policies Frontier Cost Functions , Self-Selection , Price Risk , PMP , and Agenda 2000 Quirino Paris and Filippo Arfini December 1998.

Paris, Q., Howitt, R.E., 1998. An Analysis of Ill-Posed Production Problems Using Maximum Entropy. Am. J. Agric. Econ. 80, 124–138. https://doi.org/10.2307/3180275

Paris, Q., Howitt, R.E., 2000. Assessing the consequences of environmental policy scenarios in Flemish agriculture. Agric. Sect. Model. Policy Inf. Syst. 88–100.

Paulson, N.D., Babcock, B.A., 2010. Readdressing the Fertilizer Problem. Source J. Agric. Resour. Econ. 35, 368–384.

Pretty, J., 2008. Agricultural sustainability: Concepts, principles and evidence. Philos. Trans. R. Soc. B Biol. Sci. 363, 447–465. https://doi.org/10.1098/rstb.2007.2163

Pretty, J., Bharucha, Z.P., 2014. Sustainable intensification in agricultural systems. Ann. Bot. 114, 1571–1596. https://doi.org/10.1093/aob/mcu205

Pretty, J.N., 1997. The sustainable intensification of agriculture. Nat. Resour. Forum 21, 247–256. https://doi.org/10.1111/j.1477-8947.1997.tb00699.x

Robu, R.G., Holobiuc, A.M., Alexoaei, A.P., Cojanu, V., Miron, D., 2023. Regional Patterns of Pesticide Consumption Determinants in the European Union. Sustain. 15. https://doi.org/10.3390/su15032070

Ronga, D., Parisi, M., Pentangelo, A., Mori, M., Mola, I. Di, 2019. Effects of nitrogen management on biomass production and dry matter distribution of processing tomato cropped in southern Italy. Agronomy 9, 1–16. https://doi.org/10.3390/agronomy9120855

Shen, X., Lin, B., 2017. The shadow prices and demand elasticities of agricultural water in China: A StoNED-based analysis. Resour. Conserv. Recycl. 127, 21–28. https://doi.org/10.1016/j.resconrec.2017.08.010

Singbo, A.G., Oude, A., Emvalomatis, G., 2015. Estimating shadow prices and efficiency analysis of productive inputs and pesticide use of vegetable production. Eur. J. Oper. Res. 245, 265–272. https://doi.org/10.1016/j.ejor.2015.02.042

Tack, J., Barkley, A., Nalley, L.L., 2015. Effect of warming temperatures on US wheat yields. Proc. Natl. Acad. Sci. U. S. A. 112, 6931–6936. https://doi.org/10.1073/pnas.1415181112

Takatsuka, Y., Niekus, M.R., Harrington, J., Feng, S., Watkins, D., Mirchi, A., Nguyen, H., Sukop, M.C., 2018. Value of irrigation water usage in South Florida agriculture. Sci. Total Environ. 626, 486–496. https://doi.org/10.1016/j.scitotenv.2017.12.240

Veninga, W., 2017. The shadow price of fossil groundwater 1–50.

Viaggi, D., Raggi, M., Bartolini, F., Gallerani, V., 2010. Designing contracts for irrigation water under asymmetric information: Are simple pricing mechanisms enough? Agric. Water Manag. 97, 1326–1332. https://doi.org/10.1016/j.agwat.2010.03.014

Wada, Y., Van Beek, L.P.H., Van Kempen, C.M., Reckman, J.W.T.M., Vasak, S., Bierkens, M.F.P., 2010. Global depletion of groundwater resources. Geophys. Res. Lett. 37, 1–5. https://doi.org/10.1029/2010GL044571

Wang, X.Y., 2010. Irrigation water use efficiency of farmers and its determinants: Evidence from a survey in northwestern China. Agric. Sci. China 9, 1326–1337. https://doi.org/10.1016/S1671-2927(09)60223-6

Wesseler, J., 2022. The EU's farm-to-fork strategy: An assessment from the perspective of agricultural economics. Appl. Econ. Perspect. Policy 44, 1826–1843. https://doi.org/10.1002/aepp.13239

Williams, R.B., Al-Hmoud, R., Segarra, E., Mitchell, D., 2017. An Estimate of the Shadow Price of Water in the Southern Ogallala Aquifer. J. Water Resour. Prot. 09, 289–304. https://doi.org/10.4236/jwarp.2017.93019

Williges, K., Mechler, R., Bowyer, P., Balkovic, J., 2017. Towards an assessment of adaptive capacity of the European agricultural sector to droughts. Clim. Serv. 7, 47–63. https://doi.org/10.1016/j.cliser.2016.10.003

Young, R., 2005. Nonmarket Economic Valuation for Irrigation Water Policy Decisions: Some Methodological Issues. Water.

Zhang, X., Davidson, E.A., Mauzerall, D.L., Searchinger, T.D., Dumas, P., Shen, Y., 2015. Managing nitrogen for sustainable development. Nature 528, 51–59. https://doi.org/10.1038/nature15743

Zhu, X., Demeter, R.M., Lansink, A.O., 2012. Technical efficiency and productivity differentials of dairy farms in three EU countries : the role of CAP subsidies 13, 66–92.

Zhu, X., Lansink, A.O., 2010. Impact of CAP Subsidies on Technical Efficiency of Crop Farms in Germany, the Netherlands and Sweden. J. Agric. Econ. 61, 545–564. https://doi.org/10.1111/j.1477-9552.2010.00254.x