ISSN 2280-6180
www.fupress.net




BAE

VOL. 13, NO. 4, 2024

Bio-based and Applied Economics




FIRENZE UNIVERSITY PRESS

Bio-based and Applied Economics is the official journal of the Italian Association of Agricultural and Applied Economics – AIEAA (www.aieaa.org; E-mail: info@aieaa.org).

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Available online at: http://www.fupress.com/bae

Università degli Studi di Firenze
Firenze University Press
via Cittadella, 7 - 50144 Firenze, Italy
www.fupress.com
E-mail: journals@fupress.com

ISSN 2280-6180 (print)
ISSN 2280-6172 (online)
Direttore Responsabile: Corrado Giacomini
Registrata al n. 5873 in data 10 maggio 2012
del Tribunale di Firenze

BAE

Bio-based and Applied Economics

Volume 13, Issue 4 - 2024

Firenze University Press

Bio-based and Applied Economics
http://www.fupress.com/bae

Published by Firenze University Press

Firenze University Press
Università degli Studi di Firenze
via Cittadella, 7, 50144 Firenze, Italy
www.fupress.com

BAE
Bio-based and Applied Economics

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OPEN ACCESS

Citation: Ronzon, T., Gurria, P., Carus, M., Cingiz, K., El-Meligi, A., Hark, N., Iost, S., M'Barek, R., Philippidis, G., van Leeuwen, M., & Wesseler, J. (2024). Assessing the bioeconomy's contribution to evidence-based policy: A comparative analysis of value added measurements. *Bio-based and Applied Economics* 13(4): 317-331. doi: 10.36253/bae-14563

Received: March 30, 2023
Accepted: June 11, 2024
Published: December 31, 2024

Data Availability Statement: All relevant data are within the paper and its Supporting Information files.

Competing Interests: The Author(s) declare(s) no conflict of interest.

Editor: Silvia Coderoni

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Short Communications

Assessing the bioeconomy's contribution to evidence-based policy: A comparative analysis of value added measurements

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Abstract. This paper reviews the main approaches found in the literature to measure the size of the European bioeconomy. The various estimations published might be confusing at first sight, reporting a value added of the European bioeconomy within the large range of EUR 881 billion to EUR 2.3 trillion. However, each approach is best suited to measuring a different aspect of the bioeconomy. Using the different approaches, we estimate that markets of bio-based products and energy generate EUR 730-790 billion of value added, the use of biomass within the European economy generates EUR 670 billion of value added, and the sourcing of core bioeconomy industries with goods and services generates EUR 270 billion of value added. There is no evidence of an increased use of biomass inputs in EU industries in substitution of fossil resources, nor of a decreasing dependence of traditional bioeconomy industries towards fossil resources over the period 2005-2015.

Keywords: bioeconomy, value added, Europe, input-output tables, bio-based industries, methodologies.
JEL code: Q57.

1. INTRODUCTION

As defined in the European Commission's bioeconomy strategy, the bioeconomy covers all sectors and systems that rely on biological resources, their functions and principles (European Commission, 2012, 2018). The bioeconomy promotes the transition to a sustainable economic model derived from the use of biomass and the application of natural sciences, knowledge, and technologies. Its relevance is well acknowledged by international organi-

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zations such as the FAO (FAO, 2021; Gomez San Juan, Harnett, & Albinelli, 2022) and the OECD (OECD, 2018). The European Union (EU) has also stated its importance for the European economy in its bioeconomy strategy and action plan (European Commission, 2012, 2018), recently followed by Council conclusions on the opportunities of the bioeconomy in the light of current challenges with special emphasis on rural areas (Council of the European Union, 2023). Together with the development of bioeconomy strategies around the world, the need of tools for quantifying the bioeconomy and monitoring its development has become crucial. However, the bioeconomy is a complex concept, encompassing a broad range of economic activities and their associated workers and consumers, while being dependent on the planet's ecological boundaries and biomass availability. Understanding and analysing such a multidisciplinary phenomenon requires implementing several theoretical and conceptual approaches, using a broad range of methodologies.

From global (FAO, 2021), macro-regional (European Commission, 2022b), to national (Federal Ministry of Food and Agriculture (BMEL), 2014) and regional level (Junta de Andalucía, 2018), guidelines and monitoring systems are being developed and implemented. In the case of the EU, the indicators to measure the progress of the European bioeconomy are very broad and numerous (European Commission, 2022a; Mubareka et al., 2023). However, a smaller number of headline indicators is used by policymakers and stakeholders to analyse and report on the bioeconomy. Most prominently among those indicators features (gross) value added, which is the focus of the present study.

The European Union's statistical directorate general, EUROSTAT, does not (yet) provide statistics of a specific value-added indicator for the bioeconomy and all its sectors spanning a broad range from primary production (e.g., agriculture), via processing (e.g., wooden products) to services (e.g., restaurants). Here, a key scientific challenge relates to the separation of fossil and bio-based production to correctly delimit the bioeconomy (Ronzon, Piotrowski, M'Barek, & Carus, 2017). Over the last years different methodologies have been developed to fill this gap (for example on the EU: Cingiz, Gonzalez-Hermoso, Heijman, and Wesseler (2021); Iost et al. (2019); Iost and Weimar (2020); Kuosmanen et al. (2020); M'barek et al. (2014); Porc, Hark, Carus, and Carrez (2021); Ronzon, Iost, and Philippidis (2022a, 2022b); Wesseler and von Braun (2017)). However, these methodologies have not been consistently used in bioeconomy policy making for two reasons: (i) the calculation methods are difficult to understand by non-specialists, and (ii) the different methodologies yield very different estimates of the European bioeconomy's size, which may appear confusing at first sight.

The aim of this paper is to bring clarity on the estimates of the bioeconomy's value added size across different methodologies already published, in order to optimize their use by policy makers and consequently contribute to more evidence-based bioeconomy policies. To do so, the paper clarifies what are the concepts measured by each methodology (section 2) and puts their respective results into perspective (section 3). Emphasis is made on pointing to the different aspects of the bioeconomy measured by the different methodologies and on illustrating how each of them can be mobilised to inform on specific policy questions. Finally, conclusions are remarked in the final section.

2. PRESENTATION OF THE DIFFERENT METHODOLOGIES

2.1. Overview

Cingiz, Gonzalez-Hermoso, et al. (2021) give an overview of the different quantitative approaches for estimating the value added generated by bioeconomic activities from which four types of methodologies match monitoring requirements (i.e., methodologies based on statistical databases that are harmonized across EU Member States and updated over time). Each type is illustrated in this study by a particular publication that applies to all Member States of the EU (Cingiz, Gonzalez-Hermoso, et al., 2021; Cingiz, González Hermoso, Heijman, & Wesseler, 2021; Kuosmanen et al., 2020; Ronzon et al., 2022a, 2022b).

All four methodologies are based on industry-level statistics for quantifying the contribution of industry p to the bioeconomy in terms of value added (V_p). The bioeconomy being a cross-sectorial concept, the size of its value added is thus the sum of the contribution of all industries represented by NACE[1] codes in the European System of National Accounts that are indexed by $p = 1,\ldots,n$. They comprise the industries that fully fall within the scope of the bioeconomy indexed by $q = 1,\ldots,l$, the industries that partly fall within the scope of the bioeconomy indexed by $r = l+1,\ldots,m$, and the industries that do not fall at all within the scope of the bioeconomy indexed by $s = m+1,\ldots,n$.[2]

[1] NACE is the French acronym for Economic Activities in the European Community.

[2] We denote here the industries by letters p, q, r and s to differentiate with the original studies that use the same subscripts i, j, k with diverging definitions.

The families of methodologies differ on three main aspects:

(i) The set of industries q. All methodologies concur in considering the biomass producing industries fully part of the bioeconomy (i.e., agriculture, forestry and fishing). However, divergences occur on the additional industries that complete the set q within the full scope of industries considered (p), see Table 1.

(ii) The level of the contribution of industries r to the total bioeconomy's value added. Different quantification criteria are considered: the biomass content of products and energy produced or the bioeconomy relevance of the services delivered considering a given policy definition of bioeconomy (see section 2.2.1); the use of biomass; or the provision of inputs to industries q.

(iii) The inclusion or exclusion of the industries providing inputs to industries q into the bioeconomy aggregate (p).

The different approaches taken regarding points (ii) and (iii) provide distinct measures of the bioeconomy's value added and inform on a variety of aspects of the bioeconomy. Measurement principles are clarified in sections 2.2 to 2.5 while measured aspects are presented in section 3.

2.2. *The "output-based" approach*

2.2.1. Approach

The "output-based" approach quantifies the value added generated by an industry p in proportion to the biomass content of tangible (i.e., merchandise) outputs or to the bioeconomy relevance of intangible (i.e., services) outputs. The biomass content is calculated in dry matter content (Ronzon et al., 2022a). The 'bioeconomy relevance' criterion is derived from a policy definition of the bioeconomy. In the context of the EU Bioeconomy Strategy, it covers the services associated to a bio-based product (e.g., transport, trade, repair), the marketed ecosystem services (e.g., nature tourism), the generation of knowledge in bioeconomy fields (e.g., research and development in life sciences) or support to bio-based markets (e.g., market research, public administration) (Ronzon et al., 2022b).

The output-based approach quantifies the value added of the bioeconomy (V_{BE_O}) at a given point in time and space as:

$$V_{BE\_O} = \Sigma_q V_q + \Sigma_r \delta_r . V_r \qquad (1)$$

with δ_r = biomass content share or bioeconomy relevance share of industry r (Figure 1). V_q and V_r are the value added of individual industries q and r (see Annex 1).

In other terms, the total value added of the bioeconomy is the sum of the value added generated by those industries whose output is biomass (e.g., agriculture, forestry, fisheries, food and beverage manufacturing) or whose output is partially made of biomass (e.g. bio-based textile industry, biochemical industry) or whose output is fully or partially bioeconomy relevant (e.g., food services, veterinary activity, research).

Industries $q=1,\ldots,l$ comprise the biomass producing industries (A01, A02, A03), the manufacturing of food (C10) and beverage (C11), water supply, sewerage and management[3] (E36-E38) for their full biomass content, as well as food and beverage service activities (I56) and veterinary activities (M75) for their bioeconomy relevance.

Industries $s=m+1,\ldots,n$ comprise mining industries (B05-B09), the manufacturing of coke and petroleum products (C19), of mineral or metallic products (C23-C25), of electronic or electrical equipment (C26-C27), of machinery and motor vehicles (C28-C30, C33), the wholesale, retail trade and repair of motor vehicles (G45), the industries of information and communication (J59-J63), of financial, insurance and real estate activities (K64-K66, L68) and of management, employment, human health and social work activities (M70, N78, Q86-Q88).

Industries $r=l+1,\ldots,m$ comprise all other NACE industries.

2.2.2. Data sources

The output-based approach builds on a variety of data sources. Industry-level data on value added (V_q and V_r) are retrieved from the Eurostat Structural Business statistics (Eurostat, 2020a, 2020b, 2020c) and from Eurostat's national accounts (Eurostat, 2020d) for the industries not represented in the former databases. Other Eurostat databases are mobilised for the computation of the biomass content share or of the bioeconomy relevance share δ_r (Ronzon et al., 2022a, 2022b). In addition to official data, the output-based approach relies on literature, market reports and expert insights for the estimation of the biomass content of the 875 bio-based products listed in the Eurostat database on the production of manufactured goods (Eurostat, 2021). As δ_r cannot be quantified with precision with available Eurostat data and expert knowledge for all industries r, a minimum and maximum threshold value of δ_r is determined that consequently generates a minimum and a maximum value of bio-based amount of V_r.

[3] The dry matter content of water is considered 100% biomass (i.e., organic matter and micro-organisms).

Time series data of V_r are available from 2008 (the latest revision of the NACE classification), up to the most recent common year of data sources used, typically released with a time lag of two years.

2.2.3. Data interpretation

This approach has been coined "policy-driven" in the sense that the bioeconomy relevance of industries in set *p* follows the concept of bioeconomy as defined in the EU bioeconomy strategy. Indeed, by focusing on the bioeconomy nature of industries' outputs, the output-based approach provides lower and upper thresholds of domestic bio-based markets (min V_{BE_O} - max V_{BE_O}). Over time, market developments in the bioeconomy's valued added, or of an individual bio-based industry's value added, give insight on progress towards policy objectives of bio-based market uptake. Also, the difference between an industry's bio-based output share δ_r attained in one country compared with that of another country, or compared with a 100% δ_r share, gives an indication of the remaining potential for bio-based market development.

2.3. The "input-based" approach

2.3.1. Approach

The "input-based" approach quantifies the value added generated by an industry *p* in proportion to its bio-based input cost share. Among the different variants of input-based approaches published in the scientific literature (Efken, Dirksmeyer, Kreins, & Knecht, 2016; Heijman, 2016; Iost et al., 2019; Iost & Weimar, 2020; Kuosmanen et al., 2020; Meesters, van Dam, & Bos, 2013; Robert, Jonsson, Chudy, & Camia, 2020), only Kuosmanen et al. (2020) propose quantifications for the EU aggregate. Their methodology, also coined Fundamental Industry Level Model (FILM), is thus proposed here as a benchmark for the families of "input-based" approaches while variations from other input-based approaches are briefly discussed.

The FILM input-based approach relies on the use of monetary flows of input-output tables (IOTs) for quantifying the value added of the bioeconomy (V_{BE_I}) at a given point in time and space, such as:

$$V_{BE\_I} = \Sigma_q V_q + \Sigma_r \ \gamma_r . V_r \tag{2}$$

with *q* being the biomass producing industries (agriculture, forestry and fishing) and γ_r being the biomass input cost share of industry *r* (Figure 1 and equation 3).

$$\gamma_r = \frac{\Sigma_r \ I_{qr} + \Sigma_r \ \gamma_{r'} I_{r'r} + \gamma_{Mr} M_r}{\Sigma_r \ I_{pr} + M_r} \tag{3}$$

Thus, I_{qr} is the cost of inputs from the set of biomass producing industries *q* to industry *r*; $I_{r'r}$ is the cost of inputs from industry *r'* to industry *r* with *r'* = *l*+1,…,*m*; $\gamma_{r'}$ is the bio-based input cost share of industry *r'* (equation 4); M_r is the cost of imported inputs to industry *r*; γ_{Mr} is the bio-based input cost share of imported inputs to industry *r;* and I_{pr} is the cost of inputs from all industries to industry *r*. Note that intra-industry trade is captured when *r'* = *r*.

$$\gamma_{r'} = \frac{\Sigma_{r'} I_{qr'} + \gamma_{Mr'} M_{r'}}{\Sigma_{r'} I_{pr'} + M_{r'}} \tag{4}$$

That is, the total value added of the bioeconomy is the value added generated from biomass producing activities, and from the use of biomass in all other activity sectors, including from imported products and services.

2.3.2. Data sources

The FILM approach is systematic across all industries. The data source is the Eurostat IOTs (Eurostat, 2020e) released every five years with some Member States also providing annual estimates. This data does not offer a complete coverage of all EU Member States but does provide complete data for the EU28 aggregate.

2.3.3. Data interpretation

By focusing on biomass input cost shares, the FILM methodology reports on the value added (V_{BE_I}) generated from the use of biomass across all industries of an economy. The 5-year time step evolution of V_{BE_I} gives insight on the increasing (decreasing) mobilisation of biomass – measured in value terms - by the economic system considered. The bio-based input cost share γ_r gives an indication of the degree of dependence of industry *r* towards non-renewable biological resources: the smaller γ_r is, the higher the dependence. The development of γ_r over time indicates progress towards the objective of substituting non-renewable resources with bio-based equivalents.

2.3.4. Variation to the FILM approach

While the FILM approach is homogeneous across all NACE industries and employs data from a single source, Iost et al. (2019) and Iost and Weimar (2020) adapt the input-based approach to reflect the bioeconomy concept as defined in the previous German Bioeconomy Strategy (BMEL, 2014). First, the delineation of the bioeconomy's industrial scope is restricted to a selection of bio-based industries that includes only a few bio-based services (i.e., joinery installation and erection of frames and constructional timber works, food and beverage service activities and research and experimental development on biotechnology). Second, several sources of German statistics are employed for they offer more precise information than IOTs (AGEB, 2015; DESTATIS, 2018). Third, per policy definition, the bio-based share of research industries (M7219) is not determined according to its biomass input cost share but rather from the share of personnel cost incurred in bioeconomy-related research disciplines on total costs (DESTATIS, 2016). Data on value added are retrieved from EUROSTAT's structural business statistics.

2.4. The "Weighted Input-Output based" approach

The "weighted Input-Output based" approach provides a middle ground quantification of the bioeconomy's value added, taking into account the parameters δ_p and γ_p quantified by the output-based and the input-based approaches (Figure 1). It quantifies the value added of the bioeconomy (V_{BE_W}) at a given point in time and country as:

$$V_{BE\_W} = \Sigma_p\, \theta_p.V_p \tag{5}$$

where θ_p is the weighted average of the input-based and output-based coefficients. With that purpose, the output bio-based share δ_p is weighed with the ratio of value added on gross output, and the input bio-based share γ_p is weighed with the ratio of total cost of inputs on gross output:

$$\theta_p = (\delta_p.V_p + \gamma_p.I_p) \,/\, O_p \tag{6}$$

The total value added of the bioeconomy is the value generated from the utilization of biomass and bio-based inputs, as well as their conversion into bioeconomy outputs through further processing.

The data sources used are the same as those employed in the output-based and input-based approaches (see sections 2.2.2 and 2.3.2).

2.5. The "Upstream & Downstream" approach

2.5.1. Approach

The "upstream & downstream" approach quantifies two different aspects of the bioeconomy (Figure 1, Cingiz, Gonzalez-Hermoso, et al. (2021)):

– $\Sigma_r\, D_r$, the "downstream effect" of the bioeconomy which corresponds to the value added size of the industries *r* that use bio-based inputs in proportion to their respective bio-based input cost share β_r from industries *q*. *q* represents the biomass producing industries, the manufacture of food, beverage, tobacco, wood and paper products, and printing.
– $\Sigma_r\, U_r$, the "upstream effect" of the bioeconomy which corresponds to the value added size of the industries *r* that source industries *q* in proportion to their respective output cost share α_r.

In sum, the "upstream & downstream" approach quantifies the value added of the bioeconomy (V_{BE_UD}) at a given point in time and space as[4]:

$$V_{BE\_UD} = \Sigma_q\, V_q + \Sigma_r\, (D_r + U_r) \tag{7}$$

In other words, the total value added of the bioeconomy is the value generated by activities considered core to the bioeconomy (i.e., biomass producing, the manufacturing of food, beverage, tobacco products, wood products, paper and printed products) as well as the value generated by the use of the outputs of the former activities (downstream effect) and the use of inputs by them (upstream effect).

Similarly to equation (2), $D_r = \beta_r .V_r$ (8)

$$U_r = \alpha_r\, (1- \beta_r)\, V_r \tag{9}$$

where α_r is the output cost share of industry *r* to industries *q*. α_r is multiplied by $(1- \beta_r)$ to avoid double counting with the downstream effect.

$$\alpha_r = \frac{\Sigma_q\, I_{rq}}{\Sigma_p\, I_{rp} + F_r + E_r} \tag{10}$$

where F_r denotes the final demand for industry *r* and E_r denotes the exports of industry *r*.

2.5.2. Data sources

Similarly to the FILM approach, the "upstream & downstream" approach is systematic across all industries. The two effects are computed from the OECD's IOTs with annual data series from 2005 to 2015 for the 28 pre-Brexit EU Member States (OECD, 2021). EU28 data are calculated as the sum of IO matrix entries across the 28 countries.

[4] Notations have been changed compared to Cingiz, Gonzalez-Hermoso, et al. (2021) for the sake of harmonization across the various methodologies presented in the paper.

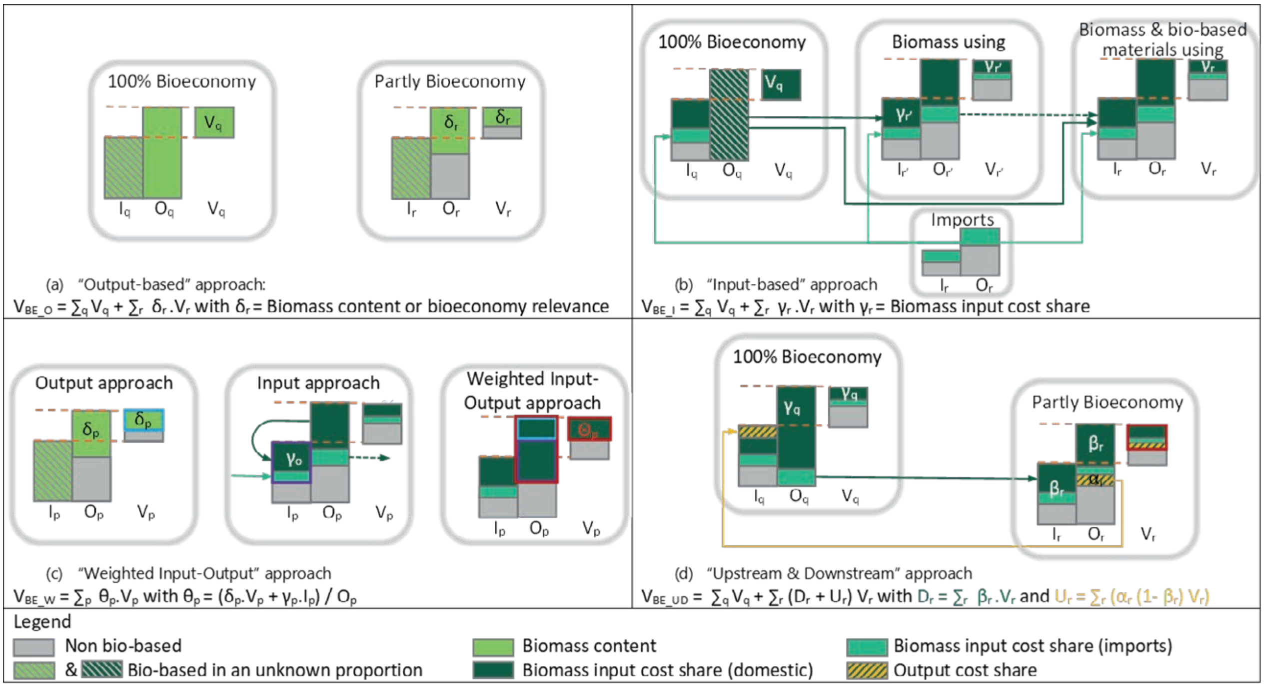

Figure 1. Four methodological approaches for determining the bio-based share of industry p. Note: I stands for Input, O for Output and V for Value added, all three are measured in monetary terms.

2.5.3. Data interpretation

Compared to the other three approaches, the "upstream & downstream" method adds information on how much the bioeconomy is integrated with the rest of the economy, in particular to non-bioeconomy sourcing industries.

The downstream component $\Sigma_r D_r$ provides similar information as the input-based approach (see section 2.3.3). Additionally, the output cost share α_r used for the quantification of the upstream component U_r illustrates the interconnection between industry *r* and the core bioeconomy industries *q*. The higher α_r is, the larger is the sourcing role of industry *r*. Moreover, the development of the total upstream and downstream effects over time ($\Sigma_r U_r$ and $\Sigma_r D_r$) informs whether an increasing (decreasing) value creation from the use of renewable biological resources ($\Sigma_r D_r$) is concomitant or not with a growth of the economic size of bioeconomy sourcing industries ($\Sigma_r U_r$). Finally, the ratio of bioeconomy value added on GDP (V_{BE_UD}/GDP) describes how much the bioeconomy is integrated into the whole economy.

As a summary, Figure 1 graphically illustrates the concepts or flows quantified in the four approaches and their related equations. Table 1 compares the main parameters of the four approaches.

3. RESULTS AND DISCUSSION

The four methodologies presented above yield very different estimates of the value added size of the EU bioeconomy in 2015, ranging from EUR 881 billion to EUR 2.3 trillion[5] (Figure 2). Such a large range may be puzzling at first sight or may even confuse policy makers. In fact, differences in numbers reflect the different aspects of the bioeconomy captured by each approach. This section summarises the main results and illustrates how the specific aspects of each methodology can be mobilised to answer relevant policy questions.

3.1. Aggregated results and complementary information on differences

In order to provide an overview of main results, we focus hereafter on the comparison of the aggregates of pri-

[5] The EU 2015 is the only common scope of the approaches commented at section 3. The output-based approach from Ronzon et al. (2022a and 2022b) provides data at country and EU level from 2008 to 2019, The input based approach published by Kuosmanen et al. (2020) provides data for the EU and the year 2015. The upstream and downstream approach published by Cingiz et al. (2021a) provides country and EU level data from 2005 to 2019.

Table 1. Summary comparison of the four approaches introduced at sections 2.2 to 2.5.

Approach	"output-based"	"input-based" (FILM)	"weighted Input-Output"	"upstream & downstream"
Quantification criteria	Biomass content of tangible outputs, bioeconomy relevance of intangible outputs	Biomass inputs (biomass input cost share)	See the two previous columns	Biomass inputs (biomass input cost share) and sourcing of industries *q* (output cost share)
Equations	$V_{BE\_O} = \Sigma_q V_q + \Sigma_r \delta_r V_r$ *Equation (1)*	$V_{BE\_I} = \Sigma_q V_q + \Sigma_r \gamma_r V_r$ *Equation (2)*	$V_{BE\_W} = \Sigma_p \theta_p V_p$ with $\theta_p = (\delta_p V_p + \gamma_p I_p) / O_p$ *Equations (5) and (6)*	$V_{BE\_UD} = \Sigma_q V_q + \Sigma_r (D_r + U_r)$ *Equation (7)*
Industries *q* (NACE codes)	A01-A03, C10-C12, E36, I56, M75	A01-A03	A01-A03	A01-A03, C10-C12, C16-C18
Industries *s* (NACE codes)	B05-B09, C19, C23-C30, C33, G45, K64-K66, L68, M70, N78, Q86-Q88.	None	None	None
Data sources	Expert knowledge and many Eurostat sources	Eurostat's IOTs	See the two previous columns	OECD's IOTs
Interpretation of the results	Bio-based market size	Use of biomass	Middle ground perspective between the previous two columns	Use of bio-based inputs and integration to the wider economy

mary, secondary and tertiary economic sectors[6] as illustrated by Figure 2. For each of these aggregates, we highlight the reasons leading to differences in value added estimates. The weighted input-output approach is not commented though, as it always provides an intermediate quantification between the input-based and the output-based approaches. All quantifications from the "upstream and downstream" approach are taken from the online database published by Cingiz, González Hermoso, et al. (2021)[7].

Estimations of value added for the bioeconomy industries of the **primary sector** are convergent (EUR 207 to 216 billion) in spite of methodological differences and slight variations from the different data sources employed by each approach. The output-based approach only considers those industries that produce biomass (EUR 216 billion) while the other three approaches also consider a proportion of the bioeconomy value added coming from the mining industries. From an input-based perspective, EUR 1 billion of value added is generated from the use of biological material in mining activities such as for bioleaching. Moreover, the upstream effect U_r calculated in the "upstream and downstream" approach reveals that EUR 1.2 billion of value added are generated from the sourcing of core bioeconomy industries *q* by mining industries.

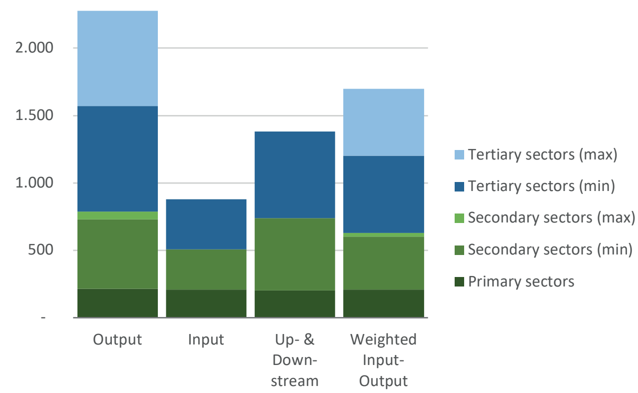

Figure 2. Estimation of the value added size of primary, secondary and tertiary activities of the EU28 bioeconomy according to the four quantitative approaches presented in the study

The value added of the bioeconomy industries operating in the **secondary sector** differs more from one approach to the other than in the case of primary sector industries: EUR 299 billion (input-based approach) to EUR 573 billion (output-based approach). The biomass input cost share γ_r (input-based approach) is systematically smaller than the biomass content δ_r of the outputs of the manufacturing industries (output-based approach), except for those industries *s* considered non bio-based in the output-based approach (γ_r ranging between 0.6% and 2.5%, Table 2). As a matter of example, only 55% of the inputs of the manufacturing of food, beverage and tobacco are bio-based inputs while that

[6] The primary sector refers to NACE sections A and B (biomass production and mining and carrying), the secondary sector to NACE C to F (manufacturing), and the tertiary sector to NACE G to T (services).
[7] Although the methodological comments exposed in section 2.5 were derived from Cingiz, Gonzalez-Hermoso, et al. (2021).

industry generates fully bio-based outputs (Table 2). The proportion (α_r (1- β_r)) of outputs that secondary sector's industries sell to bioeconomy industries *q* ranges from 0.3% to 5.3%.

The **tertiary sector** shows a high divergence in terms of value added size estimates from one approach to the other: EUR 370 billion (input-based approach) to EUR 1,488 billion (output-based approach). The four-fold difference is due to relatively small biomass input cost shares (γ_r = 1-5%, except for accommodation and food services where γ_r = 35%) compared with high biomass content or bioeconomy relevance of tertiary outputs (maximum δr = 12-100% in eight out of fourteen tertiary industries, Table 2). While the approaches based on IOTs (input and "up and downstream" approaches) are systematic and precise, the output-based approach suffers from both a lack of clarity about the definition of a bioeconomy service and a lack of informative data

Table 2. Output bio-based shares (a), biomass input cost shares (b), combined upstream and downstream shares (c) and weighted Input-Output shares (d) at the sectorial level and for the EU28 in 2015.

nace		(a) min	(a) max	(b)	(c)	(d) min	(d) max
A01_A03	Agriculture, forestry, fishing	100%	100%	100%	100.0%	100%	100%
B05_B09	Mining and quarrying	0.0%	0.0%	1.4%	3.0%	0.6%	0.6%
C10_C12	Food, beverages and tobacco products	100%	100%	54.8%	100.0%	66.4%	66.4%
C13_C15	Textiles, wearing apparel and leather products	35.6%	46.5%	40.9%	6.0%	38.4%	42.8%
C16	Products of wood and cork	99.7%	99.7%	45.7%	100.0%	61.7%	61.7%
C17_C18	Paper products and printing	60.8%	98.9%	30.7%	100.0%	37.3%	53.2%
C19	Coke and refined petroleum products	0.0%	0.0%	0.6%	3.7%	0.5%	0.5%
C20_C21	Chemicals and pharmaceuticals	25.6%	27.1%	4.3%	8.4%	12.1%	12.6%
C22	Rubber and plastics products	3.3%	3.9%	4.6%	9.1%	4.1%	4.4%
C23	Other non-metallic mineral products	0.0%	0.8%	2.5%	5.5%	1.6%	1.9%
C24	Basic metals	0.0%	0.0%	0.9%	1.5%	0.7%	0.7%
C25	Fabricated metal products	0.0%	0.0%	1.5%	4.4%	0.9%	0.9%
C26	Computer, electronic and optical equipment	0.0%	0.0%	1.4%	1.7%	0.9%	0.9%
C27	Electrical equipment	0.0%	0.0%	1.6%	2.1%	1.0%	1.0%
C28	Machinery and equipment, nec	0.0%	0.0%	1.1%	2.7%	0.7%	0.7%
C29	Motor vehicles, trailers and semi-trailers	0.0%	0.0%	1.5%	1.2%	1.1%	1.1%
C30	Other transport equipment	0.0%	0.0%	1.5%	1.4%	1.1%	1.1%
C31_C33	Manufacturing nec; repair and installation of machinery and equipment	8.8%	17.8%	8.3%	9.8%	8.4%	11.3%
D35_E39	Electricity, gas, water supply, sewerage, waste and remediation services	24.0%	25.4%	1.3%	5.6%	10.2%	10.6%
F	Construction	5.3%	5.6%	3.4%	4.4%	3.9%	4.0%
G45_G47	Wholesale and retail trade; repair of motor vehicles	24.8%	39.8%	3.7%	11.0%	15.0%	23.0%
H49_H53	Transportation and storage	20.1%	32.2%	0.9%	3.9%	8.9%	14.0%
I55_I56	Accommodation and food service activities	76.5%	76.5%	34.7%	34.3%	57.7%	56.4%
J58_J60	Publishing, audiovisual and broadcasting activities	0.0%	32.1%	4.6%	12.3%	2.4%	19.1%
J61	Telecommunications	0.0%	0.0%	0.9%	2.1%	0.5%	0.5%
J62_J63	IT and other information services	0.0%	0.0%	0.9%	2.7%	0.5%	0.5%
K64_K66	Financial and insurance activities	0.0%	0.0%	0.6%	3.3%	0.3%	0.3%
L68A	Real estate activities	0.0%	0.0%	0.9%	2.2%	0.2%	0.2%
M69_N82	Professional, scientific and technical activities, administrative and support services	4.0%	11.8%	2.1%	4.9%	2.0%	9.8%
O84	Public administration and defence; compulsory social security	10.5%	15.9%	2.6%	4.7%	0.9%	11.5%
P85	Education	2.2%	4.9%	4.3%	6.7%	0.9%	3.5%
Q86_Q88	Human health and social work activities	0.0%	0.0%	5.4%	5.6%	1.8%	1.8%
R90_S96	Arts, entertainment and recreation and other service activities	0.2%	47.1%	3.8%	6.9%	1.6%	27.1%
T97_T98	Activities of households as employers	0.0%	100.0%		0.0%	0.0%	0.0%

Sources: Cingiz, González Hermoso, et al. (2021); Kuosmanen et al. (2020); Ronzon et al. (2022a, 2022b).

for the quantification of their bioeconomy relevance. In two extreme cases, the bioeconomy relevance of the industries of sport, amusement and recreation activities and of household employers´ activities could not be quantified with available data, leading to the very broad assumption of minimum and maximum bioeconomy relevance shares of 0% and 100% (for a discussion of the output-based approach, see Ronzon et al. (2022b)). Finally, the industries of telecommunication and information technologies, finance, insurance, real estate, human health[8] and social work are excluded from the sectorial scope of the bioeconomy in the output-based approach (δ_r = 0%). Nevertheless, they use biomass (γ_r ranging between 0.6% and 5.4%) and source core bioeconomy industries q with their outputs (α_r (1- β_r) ranging between 0.4% and 2.0%). Consequently, they are worth EUR 75 billion according to the input-based approach and EUR 123 billion in the "upstream & downstream" approach.

3.2. Tailoring the right approach to specific policy requirements

The recent report from the International Advisory Council on Global Bioeconomy on "Bioeconomy globalization" (Dietz et al., 2024) stresses the monitoring of the bioeconomy as a central piece for the implementation of bioeconomy strategies in many countries around the world. The quantitative methodologies presented above all aim at supporting the monitoring and evaluation of public initiatives related to the bioeconomy, with a specific focus on their economic aspects.

Taken separately, the different approaches provide insight on fundamental policy questions:

(i) What is the size of bio-based markets? What is their potential for development?
(ii) What is the size of the economic activities that rely on the use of biomass?
(iii) How does the bioeconomy and the rest of the economy interlink?
(iv) Is the substitution of non-renewable resources by renewable biological resources happening?

Moreover, sectorial data can also be used to inform on more specific policy questions related with the bioeconomy such as the dependence of the EU economy to fossil resources, the size of the knowledge-based bioeconomy (KBBE) and many others.

[8] Human health is explicitly excluded from the bioeconomy in the European bioeconomy strategy (European Commission, 2018).

3.2.1. Size and development of bio-based markets

The development of bio-based markets is pivotal in the EU bioeconomy strategies, which have been conceived as engines of green growth.

The output-based approach precisely offers the means for monitoring the economic wealth created from the production and selling of bio-based products and bioenergy and from waste treatment (NACE sectors A to F). Taking the year 2015 as a reference for comparison with the other approaches, the value added size of the EU bio-based markets is estimated between EUR 730-790 billion. It has increased by 30-31% in the decade 2009-2019, which has permitted to maintain their contribution to the EU's total value added at approximately 5.5-5.9%. European bio-based markets are dominated by food and agricultural commodities (respectively EUR 189 billion and EUR 183 billion of value added, Table 3 (a)). If we follow a stricter definition of "bio-based products" that excludes agricultural, food and feed products, then the largest markets for bio-based products are the ones of paper products and of bio-based pharmaceuticals, with a value added size of EUR 45 billion each (Table 3 (a)). Interestingly, the four industries responsible for the biggest biomass-derived markets – agriculture, food, paper and bio-based pharmaceuticals – were also identified as the main motors of productivity growth in the EU over the last decade by Ronzon et al. (2022a), either because these industries have modernised their production processes (agriculture, the manufacture of paper), or because they have attracted workers from less intensive bio-based industries (manufacture of bio-based pharmaceuticals and food products) or both phenomena. Their market size has grown by 37-43% over the period 2009-2019, except for the food industry (30% growth).

The secondary sector of the EU28 (NACE C to F) is 19-21% bio-based in 2015 ($\delta_{NACE\ C\text{-}F}$). That proportion remains stable over the decade 2009-2019. It is certainly impossible to achieve a fully bio-based secondary sector as some metal, mineral and other non bio-based components of manufactured goods cannot be substituted with biomass. Notwithstanding, a 20% share seems low enough to expect some feasible progress. Output bio-based shares of 35-40% have been achieved by the secondary sectors of Latvia and Lithuania in 2015, thanks to an important manufacture of wood products and food and beverages (both countries), of wooden furniture (Lithuania) and bioenergy industry (Latvia). The Irish case illustrates a bioeconomy less oriented towards wooden biomass, where the manufacture of bio-based chemicals (δ_r=31%) together with a strong food and beverage industry drives a 32-33% bio-based secondary sector.

Table 3. Top 5 markets according to the different criteria discussed in the text (EU28, 2015).

(a) Top 5 markets of bio-based products and energy by value added size*

	Industry (nace sector)		Value added size (V_p in million euros)	Output bio-based share (δ_p in %)
1	Manuf. of food products	C10	189,000	100%
2	Agriculture	A01	183,441	100%
3	Manuf. of paper and paper products	C17	45,257 - 45,625	99% - 100%
4	Manuf. of bio-based pharmaceuticals	C21	44,827	49%
5	Manuf. of beverages	C11	40,890	100%

(b) Top 5 market industries by value added generated from biomass use

	Industry (nace sector)		Value added size (V_r in million euros)	Biomass input cost share (γ_r in %)
1	Manuf. of food products, beverage and tobacco products	C10_C12	152,458	55%
2	Accommodation and food service activ.	I55_I56	130,084	35%
3	Human health activities	Q86	29,762	4%
4	Education	P85	29,226	4%
5	Manuf. of textiles, wearing apparel and leather products	C13_C15	28,521	41%

(c) Top 5 industries relying on biomass and bio-based product resources in proportion to their inputs

	Industry (nace sector)		Value added size (V_r in million euros)	Biomass input cost share (γ_r in %)
1	Manuf. of food products, beverage and tobacco products	C10_C12	152,458	55%
2	Manuf. of products of wood and cork	C16	17,363	46%
3	Manuf. of textiles, wearing apparel and leather products	C13_C15	28,521	41%
4	Manuf. of paper and paper products	C17	17,484	37%
5	Accommodation and food service activ.	I55_I56	130,084	35%

(d) Top 5 sourcing industries to core bioeconomy industries ***q***, by value added size

	Industry (nace sector)		Value added size (V_r in million euros)	Output cost share (α_r.(1- β_r) in %)
1	Wholesale and retail trade; repair of motor vehicles	G45_G47	112,945	8%
2	Professional, scientific and technical activities, administrative and support services	M69_N82	34,750	2%
3	Transportation and storage	H49_H53	19,425	3%
4	Electricity, gas, water supply, sewerage, waste and remediation services	D35_E39	15,221	4%
5	Financial and insurance activities	K64_K66	14,152	2%

* sorted on the maximum estimation of value added size.
Note: the level of disaggregation varies from one methodology to the other (e.g., the aggregate C10-C12 in (b) is broken down into C10, C11 and C12 in (a)).

3.2.2. Use of biomass and value added creation

Side-by-side with market objectives, the two consecutive EU bioeconomy strategies promote the sustainable use of biomass – in particular for industrial purposes – to achieve a bioeconomy transition in Europe. A sustainability assessment is out of the scope of the present study. However, the input-based approach developed by Kuosmanen et al. (2020) and the downstream component quantified by Cingiz, González Hermoso, et al. (2021) do provide evidence on the extent to which biomass is used in the different economic sectors of the EU28, and on the ability of each industry to create value added from it.

According to Kuosmanen et al. (2020), the use of biomass and bio-based products generates EUR 670 billion of value added in the EU28 economy, excluding the biomass producing activities[9] (2015 data). The primary

[9] The industries that produce biomass are fully accounted part of the bioeconomy by Kuosmanen et al. (2020) (industries *q*). As a result, no biomass cost share γ_r is calculated for those industries and we cannot report on their use of biomass.

sector, mining and quarrying activities depend on the use of biomass for 1.4% of their input costs, from which they produce EUR 1 billion of value added. The secondary sector is more dependent on biomass inputs than the tertiary sector but less efficient at generating value added from it: with a 9% biomass input cost share, the secondary sector generates EUR 299 billion compared to a 4% share in the tertiary sector, generating EUR 370 billion.

The manufacturing of food, beverage and tobacco and accommodation and food services create the largest amounts of value added from biomass usage in the EU28 (EUR 152 and 130 billion each, Table 3 (b)). More surprisingly, they are followed by human health activities and education (EUR 29-30 billion each). Human health is excluded from the EU definition of the bioeconomy but it is preponderant in more process-based definitions (e.g., USA, Brazil). Education uses biomass in the form of paper, wooden desks and furniture and in the form of breakfasts served at school in some Member States.

The industries that depend more on biomass usages are traditional industrial activities (see the top four industries at Table 3 (c), again excluding biomass producing activities[8]). Their sourcing in biomass and bio-based products reaches 37% to 55% of total input costs (γ_r). Tertiary activities come only at the fifth position in the form of accommodation and food services (γ_r = 35%).

3.2.3. The degree of inclusivity of the Bioeconomy within the macroeconomy

The scope of the bioeconomy and its penetration into the rest of the economy is another topic of policy interest. The chronological evolution of bioeconomy-related policy initiatives indeed shows different perceptions of bioeconomy activities. The first policy concept of KBBE put the focus on those scientific and knowledge-productive activities in the domain of life sciences (Patermann & Aguilar, 2018). In contrast, the first bioeconomy strategy of the EU turned the spotlight onto primary and secondary bio-based production while the second strategy broadened the scope to all types of activities that use biomass, tertiary activities included.

The work from Cingiz, González Hermoso, et al. (2021) applies to all three perceptions and quantifies the interlinkages between the bioeconomy and the rest of the economy. At the EU28 level, the production of biomass contributes 1.6% of the total value added in 2015, which rises to 4.6% if we add the other fully bio-based industries *q* (food, beverage, tobacco, wood products and paper, see Table 1). The trickling down of industries *q*'s output to partly bio-based manufacturing and service activities permits the generation of an additional 3.9% of the EU28 total value added (EUR 511 billion).

In addition, Cingiz, González Hermoso, et al. (2021) claim that bioeconomy industries also depend on the rest of the economy for input provision. That economic link is quantified in the form of a so-called 'upstream effect' (equation 9) and is worth 2% of the EU28 total value added. The largest upstream effects are observed from tertiary activities (Table 3 (d)), nearly half of the upstream effect being the fact of trade activities (42%) and transportation and storage (7%). In sum, the authors estimate that fully bio-based industries *q* and the downstream and upstream effect of other industries account for a significant 10.4% of the EU28 value added.

Regarding the size of the KBBE, the results from Cingiz, González Hermoso, et al. (2021) are unfortunately not disaggregated enough to inform on the value added generated by the knowledge-productive activities used by the set of industries *q* (upstream effect of NACE M71-M75 and P85). The estimation could be computed with further research though. Another approximation could be provided from an output-based perspective, i.e., the value added created by the production of knowledge in bioeconomy fields. Unfortunately, available data sources cannot permit a more precise quantification than EUR 35-121 billion for the EU28 in 2015.

3.2.4. Substitution effect and dependence of the EU bioeconomy to fossil resources

The substitution of non-renewable resources in industrial and energy processes is central in the EU bioeconomy strategy for addressing the two objectives of lowering the EU dependence to non-renewable feedstocks and of contributing to climate change mitigation (European Commission, 2012 page 5; 2018 page 9). Such a substitution effect could be observable from the monitoring of sectorial biomass input cost shares (γ_r and β_r) over time in the form of increasing usage of biomass input in proportion to total inputs (in value terms). Time series are only offered for the biomass input cost shares β_r by Cingiz, González Hermoso, et al. (2021).

Contrary to the expected upward trend, Cingiz, González Hermoso, et al. (2021) indicate a reduction of biomass input cost shares from 2.7% to 2.5% in the secondary sector (excluding the set of sectors *q*) and from 5.1% to 4.4% in the tertiary sector between 2005 and 2015. The authors note, however, that the biomass input cost share of the secondary sector is stabilising since 2010. At the EU28 level, the reduction trend is particularly noticeable in the manufacture of furniture and repair and installation of machinery and equipment

(NACE C31-33) and in the industry of publishing, audiovisual and broadcasting (NACE J58-60) but trends differ across countries. A note of caution has to be introduced here on the monitoring of biomass inputs in value terms. Due to differentials in the relative value of biomass compared to other inputs, a decreasing proportion of biomass inputs in value does not always correlate with a decreasing proportion in quantity.

Beyond the capacity of a whole economy to use biologically renewable resources in industrial processes and services, some observers question the capacity of the bioeconomy to source itself with less fossil inputs. In that sense, the upstream component of mining and fossil-based industries provides evidence on the link between industries *q* and fossil resources. Cingiz, González Hermoso, et al. (2021) estimate that 1.1% of the output of the mining and carrying sector and 3.2% of the output of the manufacturing of coke and refined petroleum products source the core bioeconomy industries *q*. These proportions have remained fairly steady over the 2008-2015 time period but they vary across EU Member States: from 0.3% to 4.4% in the case of mining and carrying activities and from 0.5% to 8.1% regarding the manufacture of coke and petroleum products in 2015.

The same logic could apply to examine the use of plastics by industries *q* although the data source used for the quantification of the upstream component does not disentangle fossil-based from bio-based plastic inputs.

4. CONCLUSION

The bioeconomy is considered a strategic subsector of the economy. However, there is no single definition of the bioeconomy, and current policy and research questions address various aspects of the bioeconomy, for which different perspectives are required. This diversity of views makes quantification difficult, but the scientific community has responded well to the challenge of quantifying the economic performance of the EU bioeconomy. As this study demonstrates, a variety of sound methodologies are now implementable to inform on various aspects of value creation in bioeconomy sectors. The challenge lies in understanding, comparing and applying those different methods. This article gives an overview of four of these approaches, and discusses the different results obtained. We conclude that the communication of scientific outcomes to stakeholders could be improved, avoiding the general term "value added of the bioeconomy" without additional clarification of the methodology and sources of data used for its quantification.

The output method aligns with the definition of bioeconomy in the EU bioeconomy strategy and is therefore useful for monitoring progress from a policy perspective, both at the country and sectorial level. With this method, we can estimate EUR 730-790 billion of value added were created *from the aggregated domestic production of biomass, bio-based products and bioenergy* (i.e., 5.5-5.9% of the total EU value added) <u>and that it grew by 30-31% over the decade 2009-2019.</u> The agro-food industry is responsible for half of the EU bio-based market, followed by the paper and bio-based pharmaceuticals industries. Services are not yet well captured in the output-based approach. On the other hand, value creation from the use of biomass in the EU is best analysed with the input-based approach. EUR 670 billion of value added were created *from the use of biomass in all economic sectors,* that is, 5% of the total EU value added. This method indicates that the secondary sector is more dependent on biomass inputs than the tertiary sector but less efficient at generating value added from it (EUR 299 billion vs. EUR 371 billion). Finally, the upstream & downstream approach analyses the integration of the bioeconomy into the broader economy well beyond the production of biomass and the manufacturing of products. This approach shows that the bioeconomy contributes 10.5% of the total EU-28 value added: 4.6% from traditional bioeconomy industries, 3.9% from the processing of biomass into other products, and 2% from the use of products and services in the production of biomass and food, wood and paper products.

In addition, contrary to the EU bioeconomy strategy's expectations, there is no clear trend towards an increase of biomass input use in EU industries over the period 2009-2019 that could indicate a substitution of non-renewable resources by bio-based ones. However, such an effect could be masked by a reduction in the relative value of biomass compared to other inputs. The share of mining, coke and petroleum products bought by traditional bioeconomy industries has remained stable between 2009 and 2019. Within the bioeconomy, the size of services industries is at least comparable to the size of biomass producing and manufacturing industries. However, it is usually under-estimated because bioeconomy strategies tend to focus on biomass.

The approaches commented in this study can provide quantitative evidence to more sectorial questions, related to, among others, the size of paid recreational services, the Knowledge Bio-Based Economy or the circular economy. However, some limitations remain to be addressed through further research. Refining the estimation of bio-based shares of services and constructing time series with more sectorial breakdown and more recent data would enhance the methodologies based on IOTs.

Monitoring the use of biomass and the bio-based substitution of strategic sectors could also provide additional evidence to the debate on the classification of economic activities into green or brown sectors that has become topical in the context of the publication of a Green Taxonomy by the EU (Bohnenberger, 2022) or provide further tools to assess the degree of "greenness" of each specific activity and their development over time.

Further research could also address questions of efficient resource/biomass use and the needed transition from linear to circular resource use. Frameworks and indicators for measuring circularity are being developed and tested at micro- (Baratsas, Pistikopoulos, & Avraamidou, 2022; Chrispim, Mattsson, & Ulvenblad, 2023), regional (Bianchi, Cordella, & Menger, 2023), national or international level (Moraga et al., 2019). One of the main challenges is to determine the allocation of impacts to initial biomass use and their subsequent recycled cycles (Corona, Shen, Reike, Rosales Carreón, & Worrell, 2019). Sound knowledge of biomass material flows is a prerequisite for determining material bio-based in- and outputs.

Pursuing a growing value added from bio-based markets, bio-based feedstock, or bioeconomy inputs should not be the only objective of a functioning bioeconomy. Further research is also needed to complement the economic monitoring of the bioeconomy with environmental assessments. Only a truly sustainable bioeconomy can support the transformation of the economic system from fossil-based to green growth. The sustainability of production and consumption within the bioeconomy, the health of natural ecosystems and a fair distribution of bioeconomy's benefits are also central in the policy narrative. The methodologies presented here provide the basis for developing other indicators of the progress of the bioeconomy such as the number of persons it employs (Kuosmanen et al., 2020; M'barek et al., 2014; Ronzon et al., 2022b; Ronzon et al., 2017) or its impact on the greenhouse gas emissions (Kuosmanen et al., 2020). However, monitoring sustainability aspects of the bioeconomy requires a much more comprehensive set of indicators with its respective scientific methods.

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OPEN ACCESS

Citation: Baldi, L., Calzolai, S., Arfini, F., & Donati, M. (2024). Predicting the effect of the Common Agricultural Policy post-2020 using an agent-based model based on PMP methodology. *Bio-based and Applied Economics* 13(4): 333-351. doi: 10.36253/bae-14592

Received: April 6, 2023
Accepted: March 27, 2024
Published: December 31, 2024

Data Availability Statement: All relevant data are within the paper and its Supporting Information files.

Competing Interests: The Author(s) declare(s) no conflict of interest.

Editor: Simone Cerroni

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Predicting the effect of the Common Agricultural Policy post-2020 using an agent-based model based on PMP methodology

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Abstract. The objective of this study is to perform an ex-ante assessment of the potential impacts of agro-environmental measures included in the post-2020 Common Agricultural Policy (CAP), by estimating farmers' responsiveness in adopting organic agricultural practices and an eco-scheme that incentivises extensive forage systems. This research is conducted by means of an Agent-Based Model (ABM), based on Positive Mathematical Programming (PMP), implemented in GAMS. The ABM facilitates the simulation of interaction among farmers, allowing for an analysis of farm heterogeneity. The PMP methodology adds a non-rational dimention to the farmers' economic drivers. The model is calibrated using 2019 Farm Accountancy Data Network (FADN) data specific to the Emilia Romagna region in Italy. Our findings reveal significant impacts on land use, with a notable decrease in cereal cultivation in favour of protein and fodder crops. Moreover, structural shifts are observed, notably a decrease in the number of small-scale farms. We also assess environmental and economic implications, observing a modest reduction in CO_2 equivalent emissions per hectare, an increase in water demand, and an overall economic stability among farms, as indicated by changes in gross margin per hectare.

Keyword: CAP Reform, Agent Base Model, Land use, Structural change, CO2 Emission.
JEL Codes: C61, Q15, Q18, Q52.

1. INTRODUCTION

Since its first implementation in the early 1960s, the Common Agricultural Policy (CAP) has greatly impacted European Union agriculture, driving farm behavior through subsidies, direct and indirect payments, production constraints, and trade regulations. The CAP objectives have gradually moved from strengthening agricultural production to providing public goods through different reforms. However, despite the environmental principles embedded in the CAP regulations, as from the Fischler reform in 2003, the intensification of agricultural practices has progressively eroded several critical environmental components such as climate, water quality, pollination, biodiversity, physical and psychological well-being, as well as cultural heritage (European Environmental Agency 2019; Nègre, 2022). These developments have had significant repercussions on the provisioning of ecosystem services. The "greening" measures introduced in the 2014-2020 CAP reform proved inadequate to meet social demand for an EU agriculture more aware of its role in enhancing regulatory and cultural services (Cortignani & Dono, 2019; Alons, 2017). The CAP post-2020 reform aimed to redress past failures in meeting EU Green Deal objectives and following targets established by the Farm-to-Fork and Biodiversity strategies. The new green CAP architecture is based on eco-schemes, one of the most important innovations introduced by the CAP post-2020 reform, which obliges Member States to allocate at least 25% of first pillar payments to measures beneficial for the environment and the climate. Strategic Plan regulations limit eco-schemes to active farmers, which can apply voluntarily (European Commission 2020).

During the last decade, several economic models have been developed to help policymakers and stakeholders to evaluate CAP greening mechanisms from an ex-ante perspective. The main results provided by CAPRI, PASMA, and IFM-CAP models suggested that the CAP measures generating environmental benefits are not as effective as expected (Solazzo et al., 2016). A recent ex-post analysis confirmed these results (Bertoni et al., 2021). This empirical evidence supports the idea that economic modelling is a useful decision tool for designing more effective agricultural policies, increasing researcher and policymaker interest in in-depth impact assessment of agricultural policies at the farm scale (Kremmydas et. al 2018).

The aim of this paper is to present an ABM, based on Positive Mathematical Programming, for conducting an ex-ante impact evaluation of the agri-environmental measures incorporated into the post-2020 Common Agricultural Policy (CAP). This evaluation entails a comparative static exercise, whereas we equate the baseline scenario with two simulated scenarios wherein farmers receive the organic payments or the payment for extensive forage systems, if economically viable. The baseline scenario also represents the counterfactual scenario, enabling the evaluation of the impacts of a particular policy (where farmers receive basic coupled and decoupled payments) against alternative policies. The model employed is static in the sense that it evaluates the initial sample at a particular moment in time and compares it to the same sample where farmers have altered their behaviour to maximize their utility function due to different payment conditions. The quadratic functions, commonly used in dynamic models to capture temporal dynamics, are introduced, in this study, with the PMP to represent nonlinear relationships between variables at a specific point in time. Positive Mathematical Programming is widely used in agricultural policy assessment (Howitt, 1995; Britz et al., 2012; Solazzo et al., 2014; Reidsma et al., 2018; Matthews, 2022). A distinctive feature of PMP is its ability to recover important entrepreneurial decision variables, such as hidden costs related to past farming experience, risk attitude, and production expectations, useful for simulating more realistic behaviours, not solely driven by economic rationale. In this research, the PMP model is an agent-based model (ABM) which can capture interactions between farms in the use of scarce resources. ABMs are better suited to fulfilling important disaggregated specifications, to capturing farm heterogeneity at the regional level, and considering interaction between farmers in the use of scarce resources. They bring substantial innovations to mathematical programming models (Reidsma et al. 2018; Berger & Troost 2014).

Integrating positive mathematical programming (PMP) techniques within ABMs provides a rigorous framework for modelling agents' decision-making processes, particularly with respect to optimising their behavior subject to constraints and policy incentives. PMP helps in simulating how agents respond to policy changes based on economic principles represented by explicit and implicit variable cost. Moreover, the integrated methodology of ABMs and PMP enables the assessment of ex-ante agricultural policies by examining their potential effects on farmers' behaviour related to agricultural production choices, land use, structural adjustments, as well as their environmental and economic impacts, supporting policymakers in making informed decisions while considering farms heterogeneity.

That said, Implementing ABMs with PMP requires detailed data on agent characteristics, preferences, decision rules, and interactions, which can be challenging to obtain, especially at fine spatial scales. Limited or inaccurate data may lead to uncertainty and biases in model outcomes. ABMs can become highly complex, particularly when modelling large-scale agricultural systems with numerous interacting agents and processes. Calibrating such models to real-world data and ensuring their validity and reliability can be time-consuming and computationally intensive.

With over one million hectares of UAA (8.6% of national UAA), in 2016 Emilia Romagna accounts for respectively 10.9% (€3,221.91 million) and 15.17% (€2,292.83 million) of Italian crop production and animal value, making this region one of the most productive agricultural areas in Italy. Moreover, for the same reference year, 55% of agricultural land is under high intensity input agricultural practices, 37% under medium intensity and 8% under low intensity input practices.

Agricultural activities have a strong climate-change impact, accounting in Europe for 10% of total Greenhouse Gases emission (Eurostat 2022). Italy is the fifth largest contributor, after France, Germany, Spain and Poland, emitting 8% of total agricultural GHGs.

Not surprisingly, the high level of agricultural productivity and related impacts, as well as the consolidated presence of industrial and logistic infrastructures, heavy urbanization, and the peculiar geographical conformation of the Po Valley, make Emilia Romagna, together with the other three regions of the Valley – Lombardia, Piemonte and Veneto, the most polluted and impacted areas in Italy (Raffaelli et al. 2020).

This study is organised as follows. The materials and methods section presents the characteristics of the farm sample and discusses how PMP is particularly suitable for developing ABM models. The policy scenario section describes the main agricultural policy instruments used in the simulation, and the results are discussed in the last section.

2. METHODOLOGY AND DATA

2.1. Agent-based models and PMP

A key feature of ABMs is their capacity to evaluate the interactions between agents (farms) and to describe the impact on land use and structural change according to the structure, productivity, efficiency, and spatial heterogeneity of the agents in their territory (Reidsma et al., 2018). Agents can represent different individual farms, entrepreneurs, or aggregated entities, such as farm types.

The ability of ABMs to capture the interactions between farmers can be leveraged under the assumption of non-full rationality in production preferences. This can be done because farmers tend to maximize their utility function, rather than their profit function (Nolan et al., 2009; Kremmydas et. al 2018). This is plausible only if agents represent individual farm-households, in which family structure and other individual characteristics are particularly important in determining transaction costs affecting the economic objective to be maximized. Decisions are based on production factor endowment and level of technological knowledge, as well as the perception of economic and technical risks.The literature provides some attempts to measure the effect of CAP provisions through ABM-type models, such as AgriPoliS (Happe et. al 2004), MP-MAS (Schreinemachers and Berger, 2011), and RegMAS (Lobianco & Esposti, 2010), however none of them is associated with the PMP. Linking Agent-Based Models (ABMs) with Mathematical Programming (MP) models offers the advantage of creating micro-level models that can depict technological variations based on the structural characteristics of farms. For more insights into the different types of ABMs, Kremmydas et al. (2018) have conducted a systematic literature review on ABMs for evaluating agricultural policies. The integration between ABM and PMP models enables the optimization of the cost function for each farm within the sample. This optimization takes into consideration the unique characteristics and behaviors of individual farmers, starting from the observed optimal scenario. The cost function is hypothesized to be a quadratic functional form in output quantities: $C(x) = x'Qx/2$, where the Q matrix is symmetric and positive semidefinite. Additionally, this integration allows for the simulation of structural and technological changes, such as changes in farm size or the potential abandonment of farm activities. An ABM based on PMP can estimate these choices by simulating land exchange, the introduction of new activities and changes in agricultural management practices. Aggregating these results can provide a useful and solid insight into the general trend of the agricultural sector at regional, national, and international levels.

PMP is generally used as a straightforward calibration technique as seen in the CAPRI model, where specific technical coefficients are applied. In this study, the PMP methodology employed for calibration is based on farm marginal costs, which consider accounting costs c and the marginal implicit cost λ, intended as "transaction costs", or socio-economic costs (Anderson et al., 1985), perceived by the farmers. These costs are estimated under economic constraints using the dual property of a profit maximisation problem implicit in the model. This results in shadow prices linked to production activities that precisely equate to the combined total of the estimated accounting cost and the estimated differential marginal costs. The estimated accounting cost corresponds to the farm accounting values, whereas the estimated differential marginal costs can be viewed as the opportunity cost linked to each activity. The estimated differential marginal cost, usually referred as hidden cost, represents the portion of the estimated total marginal cost not documented in the farm accounting sheet but taken into account by farmers when formulating production plans (Cesaro and Marongiu, 2013). The hidden costs refer to the specific and individual opportunity costs that each farmer considers when deciding whether to introduce a given crop in the production plan. These hidden costs incorporate the specific and individual opportunity costs that each farmer weighs when determining whether to incorporate a particular crop into the production plan. These costs are important not only for the marginal cost calculation but also for the calibration. It is for this reason that the PMP guarantees that the cost estimates obtained can be used for reproducing the basic production situation, enabling the assessment of each farm's response within the sample to the policy measures implemented.

Although there is no theoretical rationale requiring a specific functional form for farmers' reactions, the quadratic form is employed in this study because it is widely used in Agricultural Economics and inherently represents the cost function. Additionally, the Cholesky decomposition ensures to obtain a symmetric and positive semidefinite matrix.

2.2. The model structure

AGRISP (Agricultural Regional Integrated Simulation Package), the model described in this paper, is a supply ABM, based on the PMP approach, which models farm-holders as agents and analyzes the impact of new CAP measures on agents' behaviours related to land use, gross margin, carbon emission, and water consumption. AGRISP is implemented in GAMS (GAMS 2023) and articulated in a calibration module and a simulation module, depicted in Figure 1.

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

Leveraging on the self-selection process, in AGRISP, agents belonging to a specific regional farm sample can exchange production techniques or adopt new agricultural practices, if experimental research makes technical information available.

This is accomplished through the use of a common frontier-cost function, shared at the regional level, estimated using the PMP and which incorporates the costs associated with all crops and cultivation techniques, and the deviation of each individual farm from this function (Arfini and Donati 2012). The common frontier-cost function serves as a link among the farms in the sample. The deviation from the common cost function is regarded as a basis for comparing costs and profitability among the farms included in the sample.

The introduction of a subsidy or a tax, which triggers changes in output prices of variable costs, leads farms to different cost-efficiency crop or techniques combination, as result of the optimization run in the simulation phase. This can be viewed as a form of "social learning process" or, more accurately, as an exchange of technical and economic information made available, because observed, in the sample. The interconnectedness stems from the fact that all farms are aware of the potential techniques available. The latent technologies or crops are those options that agents could potentially adopt but remain "unused" by a farm due to their lack of economic viability within a particular simulated scenario.. Supports coupled to a specific technique or tied to the acreage can alter the economic ratios among various production plans. As a result, farm holders may choose to adopt a new crop or technology from the array of agronomic techniques practiced by the farms in the sample, originally latent in their production plan, and their decision is influenced not only by the accounting cost but also by the utility cost unique to each farm.

Following calibration, the simulation module assesses the repercussions of alternative policy scenarios by leveraging the positive information embedded in the non-linear cost function and employing a set of hypothetical behavioural rules. These agent-based rules offer a more realistic representation of the interactions among farms, encompassing resource exchange, as well as the choices made by the farmers regarding different agricultural practices, taking into account the specific social and family characteristics. More specifically, as argued by Möhring et al., farm dynamism is correlated with the farm holder's age and successors' presence (Möhring et al. 2016).

The authors of this study make the assumption that once farmholders reach the age of 65, they are more inclined to reduce farm activity rather than expand it. Likewise, it is assumed that farms with holders aged 65 or older, without successors, are unlikely to lease additional hectares or opt for the conversion of farms from conventional to organic practices. Farmers over 65 are more likely to rent out their land, totally or partially. In the model, the complete rental of land is regarded as equivalent to abandoning the farming activity. On the other hand, if the holder is younger than 65 or the possibility of a generational renewal exists, they may consider expanding the farming activity by leasing additional land from neighboring farms or transitioning from conventional to organic practices.. It is important to highlight that all these decisions are contingent upon cost-effectiveness. Therefore, the economic cost function that needs to be optimized incorporates factors such as the cost of land rental and the supplementary expenses associated with converting and sustaining organic crops.

The equations associated with the key characteristics of the model are outlined below, and more details

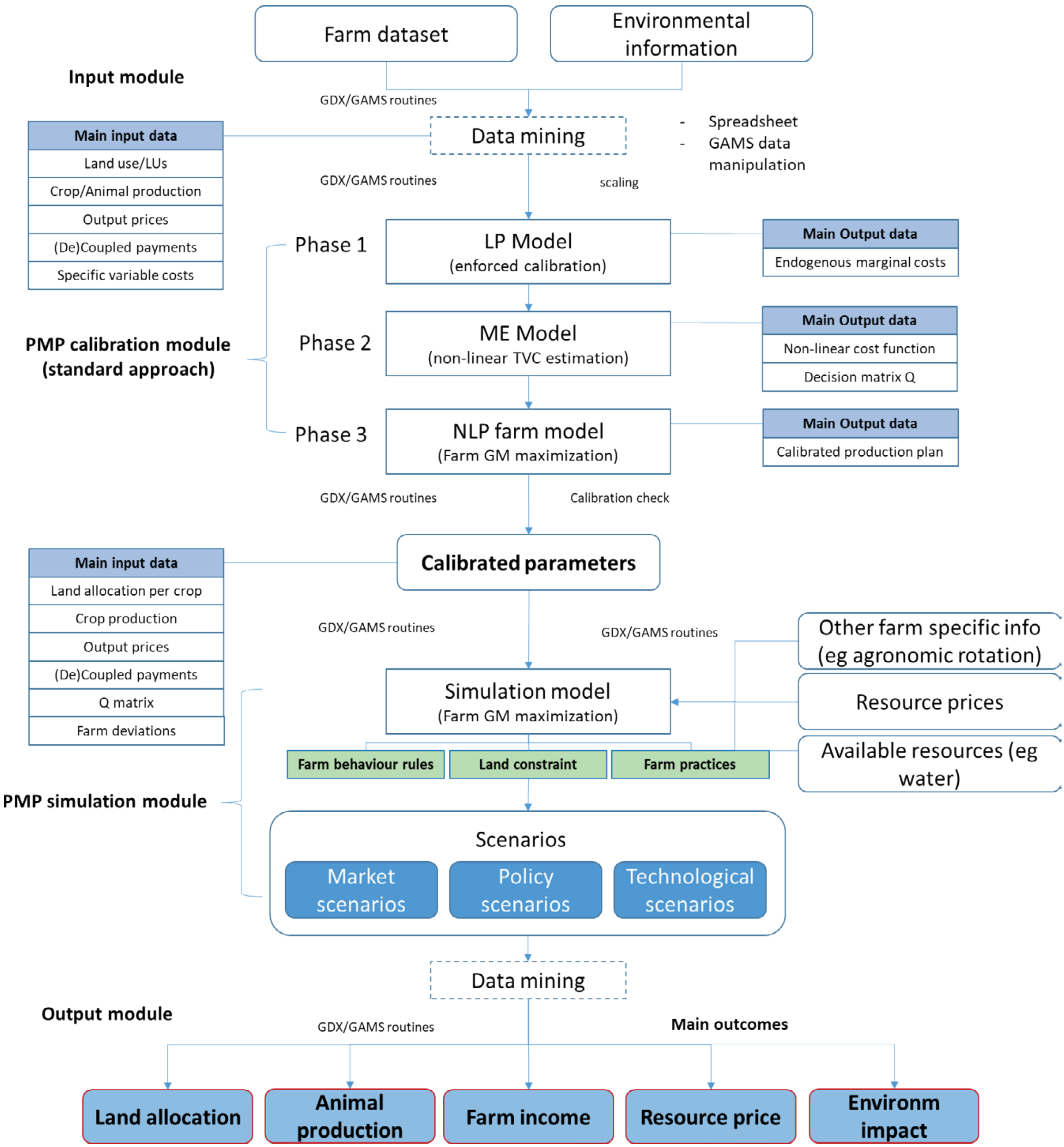

Figure 1. Model Structure. Source: authors' own elaboration.

on the implementation of the policy instruments can be found on the Appendix 1. The interactions between agents (1-3), related to the adoption of a specific production plan, are given by sharing the same frontier-cost function (Q) plus a deviation (u) and the adoption of the self-selection rule (4-5) by the n_{th} farm. The self-selection allows for the replication of the observed production plan through a comparison between the marginal cost of the current activity (or technology) and the average cost of a new activity or technology, which is defined within the Q matrix as latent activity or technology.

$$(p'_n x_n - {}^1/_2 x'_n \hat{Q}_n x_n - u_n x_n) \tag{1}$$

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

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

To simulate the fact that not all farms in the sample cultivate all the crops encountered in the region two sets of constraints are postulated.

The first set deals with the crops, which are produced, and, thus, the marginal cost relation is an equation:

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

where mc_{nk} is the marginal cost for the n^{-th} farm associated with the k^{-th} activity.

The second set of constraints deals with the activities which are not produced by the n^{-th} farm, in which case the marginal cost relation is a weak inequality with respect to the level of the frontier-cost function:

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

R is the level of production observed for activity **k** and the vector u_{nk} assumes the role of indexing the cost function with the farm n specific characteristics.
λ represents the implicit component of the marginal cost associated to the production of the activity k by the farm n.

Restrictions (4) and (5) enable farmers also to select possible production activities from all activities present in the region among the activities observed in the first phase of the PMP (Paris and Arfini, 2000).

In the case of conversion to organic farming, equations (1-3) are replaced by Equations (6-8).

$$p'_c x_c + p'_g x_g - {}^1/_2 \, [x_c \;\; x_g] \; Q_{cg} \, [x_c \; x_g] \tag{6}$$

$$S.t. \quad A_c x_c + A_g x_g \leq b \tag{7}$$

$$A_{nc} x_{nc} \cdot A_{ng} x_{ng} \leq 0 \tag{8}$$

Any farm using conventional technology (c) can convert to organic technology (g) if it is more profitable.

In the Italian FADN, information regarding the agronomic management practice (organic or conventional) is provided for each farm. From this information the average costs, yield and output prices of the organic production are extrapolated. When a farm converts to organic farming those values are applied for the crops included in its production plan. Appendix 1 explains the operational implementation of the conversion from conventional to organic agriculture in the simulation phase.

The objective function, with the non-linear cost component, takes advantage of the self-selection property, allowing the substitution of technology or crops based on the cost information provided in the Q_{cg} matrix.Consequently, farms that decide to convert to organic farming change their production plan and cost structure.

Equations (9-14) represent and rules related to the exchange of the land factor between agents. Setting j activities, n and m farm holdings exchange land between each other. Equation 9 indicates that the available utilised area is equal to the available area plus the rented-in land minus the rented land. Equations (9 - 14) indicate that a farmer can either rent or rent out land, and that the total amount of rented land must be equal to the total rented-out land at the agrarian region level.. More precisely constraint (9) requires that the total land allocated to the different crops **j** (j = 1, … ,J), must be less than or equal to the observed total available land at the j farm level, $\mathbf{b}_n$, plus the land rented ($\mathbf{Z}_n$) minus the land rented out ($\mathbf{V}_n$).

$$A_{nj} x_n \leq b_n + Z_n - V_n \tag{9}$$

The land rented is represented as:

$$Z_n = \sum_m ZZ_{nm} \tag{10}$$

and the land rented out is represented as:

$$V_m = \sum_n VV_{nm} \tag{11}$$

where $\mathbf{ZZ}_{nm}$ and $\mathbf{VV}_{nm}$ are the matrix tracing the transfer of land for each pair of farms for renting and renting out, respectively. Furthermore, for each pair of farms, the land rented by one farm must be equal to the land out by the other, as follows:

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

To avoid a given farm renting and renting out land at the same time, a specific constraint has been added:

$$Z_n \cdot V_n = 0 \tag{13}$$

Finally, to ensure that the exchange of land is consistent with the total available land at regional level, we establish that the total land rented must be equal to the total land rented out:

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

Therefore, we assume that the exchange of land is limited to the farms located in the same agrarian region. Each farm has a marginal cost level, estimated with the PMP, beyond which acquiring additional land provides no further advantage. Introducing a price shock or a policy incentive can lead to a change in the shadow price of land for a specific farm. However, the land rental price remains constant, as it is treated as exogenous to the model and is assumed to be uniform throughout the Emilia-Romagna region.

Agents' interactions are regulated by the behavioural rules already mentioned in the previous section and here summuarised: i) Conventional farmers older than 65 and without successors cannot move to organic practices; ii) Farms are only allowed to exchange land within the agrarian regions where they operate; iii) Farmers older than 65 and without successors cannot rent land.

The input level is calculated based on the spending on purchased inputs, both for crops and livestock, per hectare of UAA. The inputs are purchased fertilizers and soil improvers, plant protection products, other means for protection, bird scarers, anti-hail shells, frost protection and purchased feed.

To provide environmental impact assessment, we integrated the Italian FADN data with environmental information on greenhouse gas (GHG) emission factors and water consumption for the different crops. GHG emissions from agricultural activities were estimated by applying the ICAAI methodology (Impronta Carbonica dell'Azienda Agricola Italiana), developed by CREA-PB, following the guidelines provided by the IPCC for establishing a national inventory of greenhouse gas emissions (Coderoni and Vanino, 2022; IPCC, 2008). This procedure, already implemented by Solazzo et al. (2016) assumes that the amount of atmospheric emissions is linearly related to the level of economic activity, and the emission factors considered for the agricultural sector are carbon dioxide, methane and nitrous oxide, expressed in ton CO2eq per hectare or head of livestock. The conversion factors referred to the 100-year Global Warming Potential and are provided by the Fourth Assessment Report of the IPCC (2007), following Equation (15):

$$CO_2eq = CO_2 + 298 \cdot N_2O + 25 \cdot CH_4 \quad (15)$$

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

Table 1. Crop aggregation.

Macrocategory	Aggregated Crops
Cereals	wheat, barley, rice, sorghum, other cereals
Forages	alfalfa, forage maize, other forages
Proteic/Oilseeds	sunflower, soja, protein crops, other oilseeds
Maize	maize
Meadows Pastures	meadows and pastures
Indutrial tomato	industrial tomato
Other industrial crops	beetroot, potato

The water consumption measurement uses the Water Footprint Network, based on the extensive work of Mekkonnen and Hoekstra (Mekonnen and Hoekstra 2010) that estimates the water footprint of 147 crops and over 200 products, and which also calculates the water footprint at national and sub-national level of each crop worldwide. The concept of Water Footprint was previously introduced by Hoekstra in 2002 in order to assess the direct and indirect use of freshwater resources along a production chain (Hoekstra and Hung 2002), as a sum of i) Blue water, surface water or groundwater for irrigation; ii) Green water, the water naturally embedded in the rhizosphere and available for plant assimilation; iii) Grey water, the volume of water necessary to dilute ecotoxic compounds (mainly used in crop protection) to restore specific quality standards.

Results are analised using the aggregation depicted in Table 1.

2.3. Data

The economic agents in the model are the individual farms included in the "Rete di Informazione Contabile Agricola" (RICA or FADN) database, which has been operational in Italy since 1968. This database is managed by CREA and provides data for the year 2019. The initial sample is specific to the Emilia-Romagna (NUTS2) Region and comprises 739 farms out of the nearly 11,000 sampled farms across Italy. Since RICA assigns a sample weight to each farm to ensure it is representative of the entire population, the weighted sample corresponds to a total of 40,753 farms. Table 2 illustrates the distribution of farms based on their size class (measured in hectares) and their management practices, which can be either conventional or organic.

The set of farm data includes information on geographical location (region, province, altitude, agrar-

Table 2. Number of Farms according to size class (ha) and management practices.

Size (ha)	Conventional Farms		Organic Farms		Total	
	Initial Sample	Weighted Sample	Initial Sample	Weighted Sample	Initial Sample	Weighted Sample
< 10	246	17,312	23	1,397	269	18,710
10-20	120	7,714	17	1,950	137	9,664
20-50	152	5,975	34	1,610	186	7,585
50-100	68	2,197	25	964	93	3,160
100-300	47	1,249	3	92	50	1,342
> 300	1	51	3	61	4	112
total	634	34,499	105	6,074	739	40,573

Table 3. Farms per age and size class, based on management practices.

Holder's Age	Conventional Farms			Organic Farms			Total	% Organic Farms
	≤40	41–64	≥65	≤40	41–64	≥65	-	Size class
% Age class/Farm type	6.81	46.55	46.64	15.02	64.31	20.67	-	-
< 10	1,122	7,470	8,721	159	1,034	205	18,710	3.44%
10-20	230	3,350	4,134	283	1,293	375	9,664	4.81%
20-50	525	3,235	2,215	130	1,001	478	7,585	3.97%
50-100	439	1,112	645	340	481	142	3,160	2.37%
100-300	34	842	374	-	52	41	1,342	0.23%
> 300	-	51	-	-	46	15	112	0.15%
Total	2,350	16,059	16,089	913	3,906	1,255	40,573	14.97%

ian zone), agricultural practices (conventional, organic), household characteristics (age and gender of the farm holder, number of potential farm holder's successors), land use, specific production costs per crop (cost of seeds, fertilizers, pesticides, energy, water), gross total product, and CAP payments. Table 3 depicts the heterogeneity of the sample based on class of age, per farm size and percentage of organic farms, that represent almost 15% of the farms population in Emilia Romagna.

Within the sample, the average age of the landholders is 61 for conventional farms and 54 for organic farms. The "agrarian region" spatial definition is a peculiarity of the FADN and it further segments Italian provinces (NUTS3) based on geographical location and altitude range. Although similar to the European sampling, the Italian FADN is notably more comprehensive, considering over 2,500 variables for each sampled farm, in contrast to the European FADN, which only takes into account approximately 1,000 variables (CREA-PB 2021).

Table 4 detailed the observed land use in Emilia Romagna region in the year 2019.

The prevailing land use relates to cereals (33.26% of the total Utilized Agricultural Area (UAA)) followed by forage (33.17%); meadows and pastures count for 10.54% of the regional UAA.

2.4. Policy scenarios

To model how farmers respond to the adoption of organic agricultural practices and eco-scheme, two scenarios are implemented in AGRISP and evaluated through a comparative static analysis. More specifically, we compare the baseline scenario, represented by the calibrated FADN data for the year 2019, wherein farmers receive the basic coupled and decoupled payments, with the simulated scenario. Greening measures of the previous CAP reform: crop diversification, maintenance of permanent grassland, and the establishment of Ecological Focus Areas are simulated (European Commission 2017) are also included in the baseline.

The two CAP post-2020 scenarios implemented in the simulation module of AGRISP are:

1. the "Organic" scenario, where payments are made to encourage farm holders to adhere to organic agricultural practices in order to increase the area

Table 4. Land Use in thousands of hectars.

Land Use (1000 ha)	Cereals	Forages	Proteic/ Oilseeds	Maize	Meadows Pastures	Industrial Tomato	Other Industrial Crops	Total
Conventional	263	230	52	81	45	23	35	729
Organic	46	78	10	5	53	3	4	199
Total	309	308	62	87	98	26	39	928
%	33.26%	33.17%	6.64%	9.33%	10.54%	2.82%	4.24%	

under organic agriculture to 25%, according to the Farm to Fork strategy target (Appendix 1). Regional payments for organic crops are listed in the RDP of Emilia Romagna (DG AGRI 2021). In this scenario farmers will opt for organic farming if economically convenient, considering transition costs, organic yield and prices for organic products.

2. the "Eco-Scheme" scenario simulates the 4th eco-scheme in the Italian National Strategic Plan (MASAF 2022). It envisages incentives in the form of additional payment of 110 €/ha added to the basic payment, for an extensive forage system. In our model, we consider the crop category "Meadows and Pastures" as eligible for this payment. The "Eco-Scheme" scenario is added to the subsidy foreseen to support the conversion to the organic agronomic management practice.

The ABM rules and the PMP methodology integrated in the AGRISP model trigger farm owners' decisions on farm organisation, including factors such as land endowment and utilisation. This is achieved by optimising the individual utility functions of each farm, which subsequently influence the environmental impact and the overall regional gross margin.

Other models can be used to perform similar comparative analysis, such as partial equilibrium models based on farm types (e.g. CAPRI), providing a macroeconomic perspective by analysing the interactions between supply and demand in agriculture. However, these models can offer insights into how policies affect market equilibrium, prices and production but do not consider the farms heterogeneity.

As noted above (Equations 9 - 14), in both scenarios farmers can exchange land according to specific agent-based constraints that trace a one-to-one relationship between all the farms included in the sample, in the sense that each farm has the option to rent or rent out arable land with the other farms located in the same agrarian region. Farmers exchange land as a way of making optimal use of their resources. Farmers can adopt different structural strategies, such as leasing out their land and exiting the market entirely, or alternatively, they may choose to lease out only a portion of their land while continuing their farming activities.

The rental price for land is not resulting from a land market equilibrium but is assumed to remain fixed at 690€/ha. This price is derived from the "Survey on the Land Market" conducted by CREA-PB (2019) in Emilia Romagna.

3. DISCUSSION OF RESULTS

The "Organic" scenario and the "Eco-Scheme" scenario are executed using the calibrated 2019 Italian FADN data, and subsequently compared to the baseline, which does not incorporate any agent-based or policy constraints. The main emerging phenomena are: (i) The impact on land use, including technological changes for conversion to organic farming; (ii) The structural changes recorded in total number of farms per sized-class and in terms of farm holder age ; (iii) The environmental impact related to the carbon emissions and water consumption; (iv) The impacts on farmers' gross margin.

3.1. Impacts on land use

The impact of the two scenarios on land use has been analysed both in total hectares allocated and as a percentage (*Table* 5). Cereals, the less profitable crops, decrease overall by 13.74% in the Organic scenario and by 13.90% in the Eco-scheme one respectively. Meadows and pastures experience a modest decrease in the organic scenario, but the eco-scheme subsidy helps bring production back up slightly. All other crop categories show an increase. Among them, protein/oleaginous crops reveale the highest rise, with an increase of 8.58% for the Organic scenario and 8.59% for the Eco-scheme scenario. The greening requirement leads to land set-aside of 0.28% on "Organic" and 0.27% in "Eco-scheme" farms.

Additional elaboration is provided for each class of dimension concerning the four crops that exhibit higher

Table 5. Impact on land use, per crop in hectares and in %.

Crops	Land allocation in hectares per crop			Land allocation in % per crop		
	Baseline	Organic	Eco-scheme	Baseline	Organic	Eco-scheme
Cereals	308,691.60	181,205.60	179,665.30	33.27	19.53	19.36
Forages	307,796.00	331,914.00	333,666.00	33.17	35.77	35.96
Protein/oleaginous	61,604.60	141,340.40	141,267.40	6.64	15.23	15.22
Maize	86,561.00	90,632.00	88,917.00	9.33	9.77	9.58
Meadows Pastures	97,817.00	93,449.00	97,454.00	10.54	10.07	10.50
Industrial tomato	26,184.00	32,444.00	33,143.00	2.82	3.50	3.57
Other industrial crops	39,318.80	54,361.80	51,379.50	4.24	5.86	5.54
Greening	-	2,620.70	2,475.40	0.00	0.28	0.27
Total	927,973.00	927,967.50	927,967.60	-	-	-

variation: cereals, forage, protein/oleaginous crops, and industrial tomatoes (Figure 2). Delving into the results we notice that the decrease in cereal production is mostly accentuated in the small medium-sized farms (under 100 hectares), whereas the decrease is of lower intensity in farms between 100 and 300 ha and almost not relevant in farms over 300 ha. This could be explained with the fact that cereals are typically grown on large plots of land, and they tend to require less labor and inputs per unit of land compared to other crops. Large-scale cereal farms may have specialised equipment and processes optimised for extensive agriculture, making it less practical or economical to switch to different crops or practices and they may have more stable market contracts or subsidies that incentivise the continuation of existing cereal production methods. In smaller to medium-sized farms, the decrease in cereal production could be more pronounced when switching to organic or eco-schemes due to the relative increase in labor and management required for these practices. Smaller farms might not benefit from economies of scale in the same way larger operations do and may feel the shifts in practice more acutely.

For farms under 50 hectares there is no incentive to increase the production of forage. This is probably due to the relatively low amount of the subsidy for conversion to organic (only 120€/ha for alfalfa and other forage) that the Eco-scheme scenario is not able to counterbalance. However, for larger farms (50 hectares and above), the trend reverses, with the forage under Organic and Eco-scheme scenarios having more allocated land than in Baseline, with the largest increases seen in the 100-300 hectares size class. This could also be driven by the concentration of the dairy farms in class 3-5 (86.33%), which may have further interest in forage.

Strong positive shift towards protein/oleaginous crops production is reported in both the Organic and the Eco-scheme scenarios consistently across all farm sizes, suggesting that farmers find agroecological practices economically viable for these products, notably more profitable. This might be due to more favorable subsidies for these crops (351€/ha) or higher market price for organic products. The percentage increase in land allocation is higher in larger farms, especially in those over 300 hectares. This could be due to the greater financial resilience of larger farms, allowing them to take on the risk of transition and the associated costs more readily than smaller farms. Also for these crops, data suggests significant economies of scale for larger farms, more likely to distribute the costs and labor required for organic farming more efficiently. The total increase of around 129% for both Organic and Eco-scheme scenarios is particularly notable. It underscores a widespread and significant adoption of these practices across the sector.

A remarkable increase is depicted for smaller farms (<10 hectares) in the Organic and Eco-scheme scenarios for industrial tomatoes, which might be due to the high subsidy of 427€/ha. This makes it financially attractive for smaller operations to switch to these practices. Medium-sized farms (10-50 hectares) also show substantial increases for both scenarios. This could suggest that the subsidy is sufficient to cover the additional costs of transitioning and that the market for organic or eco-friendly tomatoes is strong. There's a notable decrease in land allocation for farms larger than 300 hectares, where there's no activity in the Organic and Eco-scheme scenarios. This stark contrast to other size classes might be influenced by several factors, including the possibility that farms producing industrial tomatos practice more intensive farming and consequently have relatively smaller size. Tomato cultivation typically involves higher costs for seeds, fertilizers, pesticides, and water. They also require careful management and more labor for tasks like pruning,

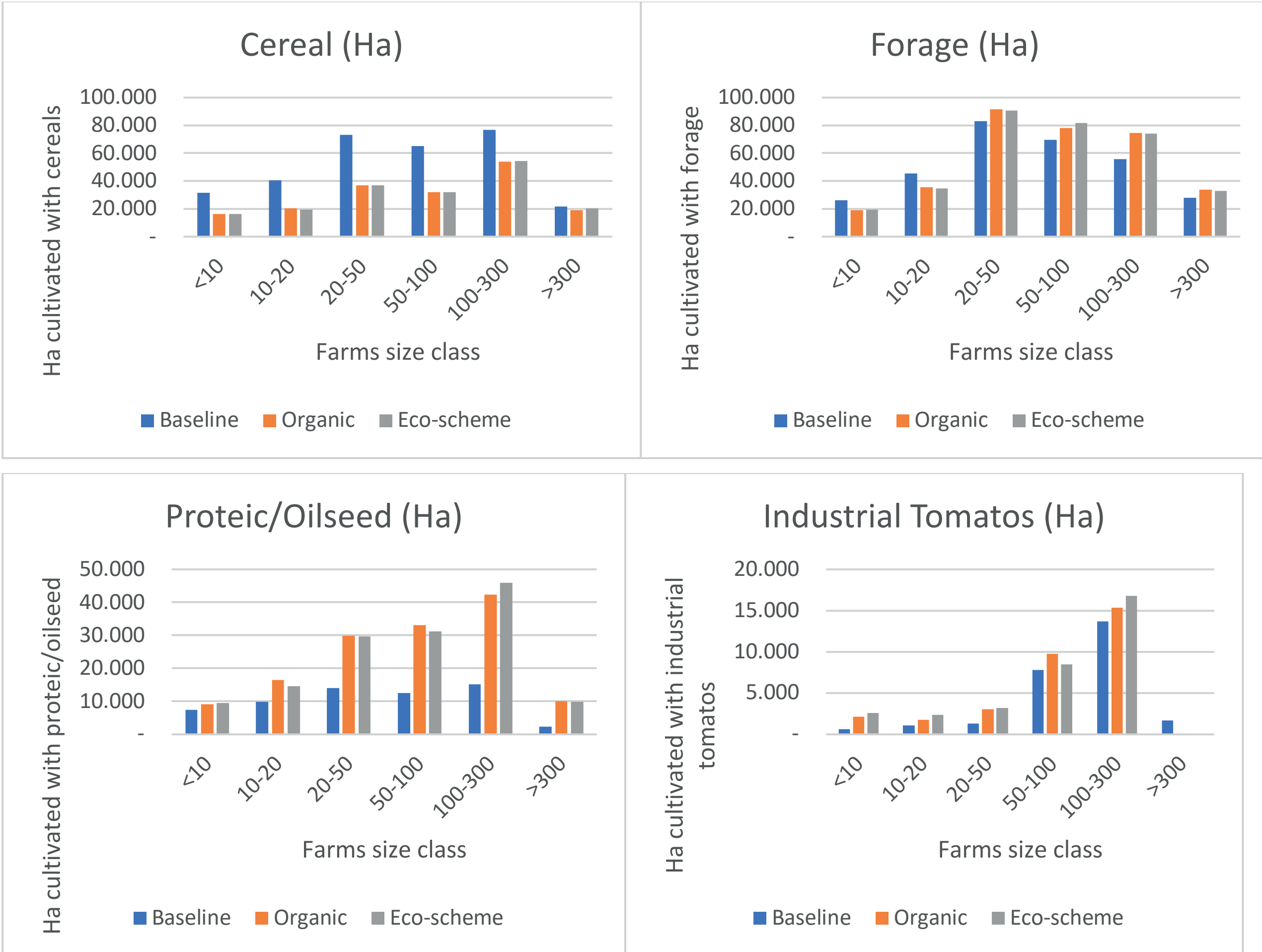

Figure 2. Land use per crop and per scenario.

trellising, and harvesting. Intensive crops like tomatoes are often grown in smaller areas with a higher yield per hectare and are more labor-intensive than extensive crops. The increase in Organic and Eco-scheme scenarios for the 50-100 and 100-300 hectares classes is lower compared to the smaller farms, and this could be because these larger operations might already be producing at scale, and the relative benefit of the subsidy is lower compared to their overall operations. Despite the differences in subsidies, the overall trend shows that there is a significant move towards Organic and Eco-scheme practices across most crop types and farm sizes. The data for the Industrial Tomato crop, especially the impressive increases in the smaller size classes, shows that when subsidies are perceived as significant and worthwhile, they can be a powerful motivator for changing farming practices. However, for larger farms, especially those over 300 hectares, the current subsidy rates and perhaps other factors related to scale, market dynamics, or the specifics of tomato cultivation may not provide enough incentive for a shift to Organic or Eco-scheme practices.

Overeall organic land increases significantly in the Organic scenario (+43% at aggregated level) but is lower at (+35% at aggregated level) for the Eco-scheme. Looking at the impact of the two payments schems per class of dimension (Figure 3) we notice that the more reactive are the medium size farms, particularly those in the class 100-300 ha. It's worth mentioning that the significant rise in organic surface area within this category might be attributed to the absence of a cap on the subsidies that farms can request.

3.2. Structural changes

The impact of the scenarios on the number of farms, in terms of farm size, is illustrated in Figure 4.

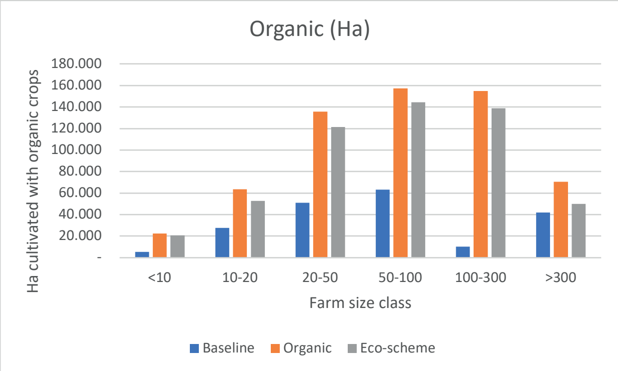

Figure 3. Changes in hectares cultivated under organic farming per scenario and size class.

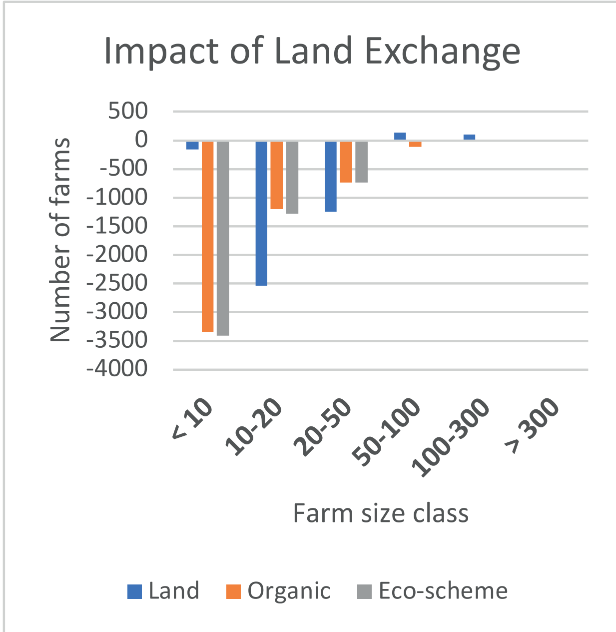

Figure 5. Effect of land exchange on number of farms per size class (in ha) compared to Baseline.

Table 6. Impact of scenarios on number of farms (weighted).

Farm size class	Baseline	Organic	Eco-scheme
< 10	18710	15368	15297
10-20	9664	8465	8387
20-50	7585	6852	6852
50-100	3160	3053	3159
100-300	1342	1342	1342
> 300	112	112	112

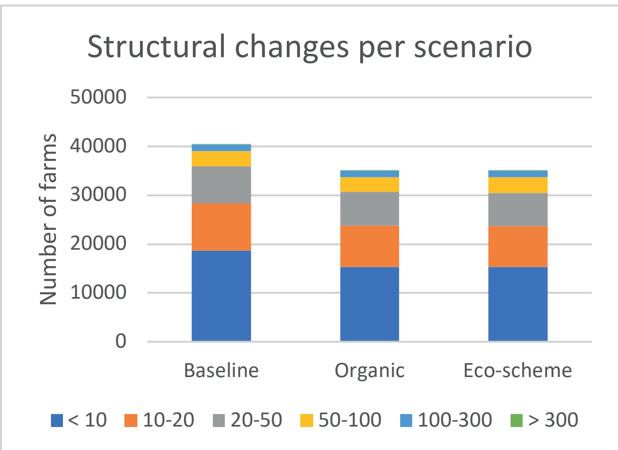

Figure 4. Structural changes according to farm size in ha.

Overall, there is a noticeable decline in the weighted figures, showing a drop of 5,381 units for the Organic scenario and a drop of 5,325 units for the Eco-scheme scenario. (Table 6).

The farms appearing to be the most affected are the smaller ones, with a decrease of 18% in farms smaller than 10 hectares, a 13% decrease in the class with a UAA of 10-20 hectares, and a 10% decrease for farms smaller than 50 hectares altogether (Figure 4).

The activation of the land exchange constraints, allowing for land rental, as highlighted in Figure 5, emerges as the primary trigger for this structural transformation in the scenarios. However, there is an exception with very small farms (less than 10 hectares), where the incentives for organic conversion and eco-scheme 4 do not seem adequate to support them.

These phenomena might be explained with the fact that small farm holders are more likely to leave the market, while big farms tend to consolidate. For small farms, with shadow prices lower than market prices, it becomes more economically efficient to lease out their land rather than continue farming. We can make the assumption that larger farms exhibit greater resilience, as they can capitalize on their economies of scale, as well as on the subsidies tied to their larger land holdings.

From an age-based analysis, and considering the initial agronomic practices of the sample, results reveal (Figure 6) that young farm holders (aged below 40), who represent only a small portion, experience a slight increase in the size class of less than 10 hectares, in conventional farming, due to the impact of the land exchange rules. However, their overall decrease remains relatively stable. Within the organic compart the decline is perceivable in the smaller size class

Figure 6. Variation in number of farms per size class and age range.

(less than 10 hectares) and in the 10-20 hectare range, primarily influenced by land exchange. In the 50-100 hectare class instead, incentives have a minor but still positive effect.

In the age range of 41-64, the land exchange rules contribute to a decrease in the number of very small farms, while subsidies help retain some of the 10-20 hectare farms in the market. For organic farms in this same age range, subsidies appear to be beneficial in the 20-50 hectare size class, although the impact of land exchange still remains a significant driver in reducing the number of small farms.

Farmers aged 65 or older, constituting 43% of the initial sample, appear to be the less responsive to change triggered by subsidies, with a slight exception for conventional farms in the 10-50 hectare range. The primary factor leading to the decrease in the number of very small conventional farms is the opportunity to exchange land.

If the total Utilized Agricultural Area (UAA) is assumed constant, the average farm size increases from the 31 hectares in the "Baseline" to the 41 and 40 hectares in "Organic" and "Eco-scheme" scenarios. This result is consistent with the ongoing trend according to the 7th General Census of Agriculture (ISTAT 2022).

Census results depict an overall decrease in the number of farms, while across all regions of Italy, farm sizes are increasing, which confirms that incentives to counter the disappearance of small farms need to be well-planned.

3.3. Environmental impacts

The environmental impact of the CAP post-2020 reform on climate change can be evaluated in terms of GHG emissions per agricultural activity. GHG emissions are measured in CO_2 equivalent. Implementing subsidies to support organic agriculture, in this research, leads to a total reduction of almost 6% of tons of CO_2 equivalent emitted at the regional level, resulting in a total reduction of 1,294 thousand and 1,297 thousand respectively for scenario Organic and Eco-scheme at the regional level (Table 7), confirming that organic practices impact less on the climate than conventional ones (Holka et. al 2022).

In line with these results is the average carbon emission per hectare (Figure 7). Carbon footprint aggregated per crop shows that the reduction in emissions is mainly due to the reduction of cereal cultivation (-11%), while there is a slight increase in emissions related to forage, protein crops and oilseeds.

The per farms-size analysis of the evolution of the GHG emissions across scenarios depicts (Figure 8) how the implemented policies generally lead to a significant reduction in CO_2 equivalent emissions across most farm sizes, with the exception of the largest farm size category (above 100 hectares), where emissions actually increase. This suggests that while subsidy-driven policies can effectively reduce GHG emissions in smaller to mid-sized farms, their impact on larger farms may require additional considerations or tailored approaches. The results underline the importance of carefully designing agricultural subsidies to ensure they achieve desired environmental outcomes across all farm sizes. It may also point towards the need for diversified strategies that cater specifically to the operational and environmental conditions of different farm sizes.

Table 7. Carbon Emission in 1,000 tCO2 equivalent aggregated per crop.

	Baseline	Organic	Eco-scheme
Cereals	493.22	290.93	290.67
Forages	184.15	196.02	198.88
Proteic/oilseeds	54.05	126.34	126.31
Maize	305.00	319.34	313.30
Meadows Pastures	219.08	209.29	218.26
Industrial tomato	55.34	68.57	70.04
Other industrial crops	62.90	83.81	79.58
Total	1,373.75	1,294.30	1,297.04

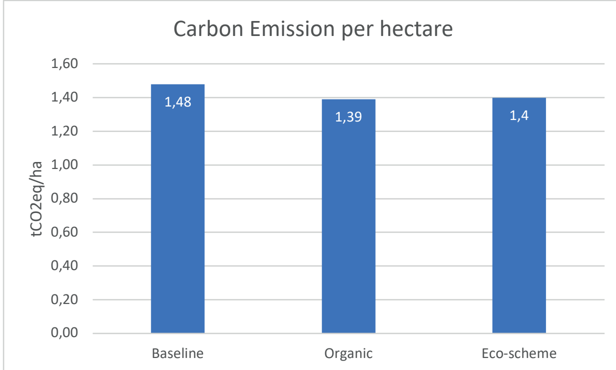

Figure 7. Average carbon emission (tCO2eq) per hectare.

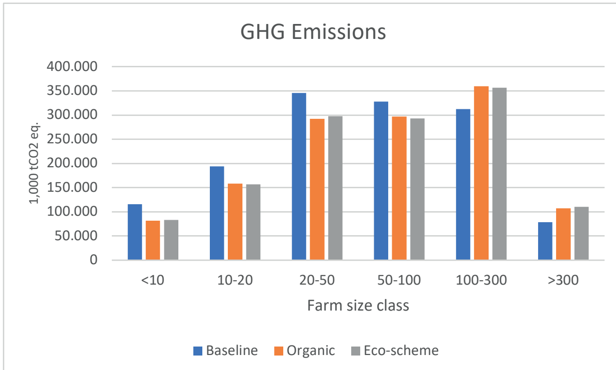

Figure 8. GHG Emissions (ton of CO2 equivalent) per class of farm size.

Unlike carbon emission, water resources are in general strongly affected by the transition to organic production. Water consumption in the Organic scenario increases by 9,4% (Figure 9), which is mainly due to the decrease in cereal production, offset by an increase in oilseeds and protein crops.

Forage cultivation consumes the most water of all crops, accounting for over 60% of the regional water footprint. The result is coherent with the fact that alfalfa is one of the most widespread crops in Emilia Romagna (Solazzo et al. 2016).

However, if we delve further in the results per farm size, we note that for farms smaller than 20 hectares, both subsidy scenarios lead to a reduction in water consumption, suggesting that the adoption of organic and eco-friendly practices can effectively decrease water usage in smaller scale operations. For farm sizes larger than 20 hectares, both subsidy scenarios result in an

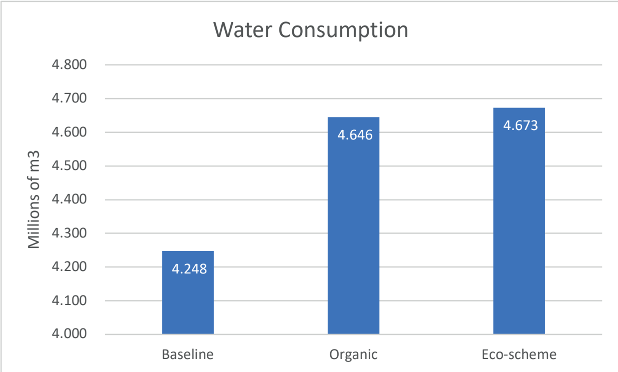

Figure 9. Water consumption (m3) per hectare.

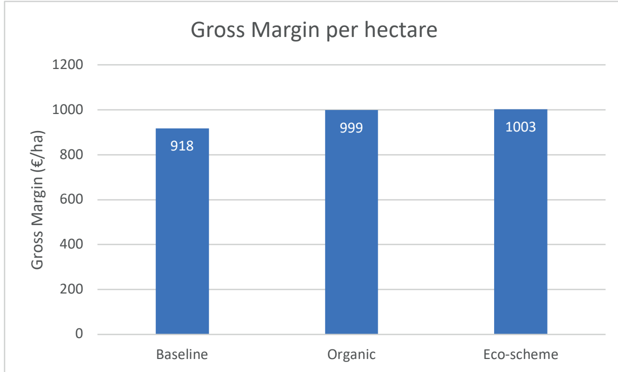

Figure 10. Gross margin variation.

increase in water consumption. This trend is especially pronounced in the largest farm size category (100-300 hectares), which could reflect the more water-intensive nature of some organic and eco-friendly practices, or possibly the increased water requirements for these practices to be effective at a larger scale.

The results indicate that while subsidy-driven policies can support water conservation in smaller farms, they may exacerbate water use in larger operations. This could have significant implications for water resources management, especially in regions facing water scarcity. These findings underscore the importance of designing agricultural subsidies and practices that are tailored to farm size and local water availability conditions. Policies should consider the varying impacts of organic and eco-friendly practices on water consumption across different farm sizes to ensure sustainable water use.

The increased water consumption under both scenarios for larger farms highlights the need for comprehensive environmental assessments of subsidy programs. Ensuring that efforts to reduce one form of environmental impact do not inadvertently increase another is crucial for the overall sustainability of agricultural practices.

3.4. Economic results

Gross margin per hectare increases in both "Organic" and "Eco-scheme" scenarios. The increase of 8.8% in the "Organic" scenario, corresponding to 81€/ha, can be attributed to the implementation of subsidies for organic farming conversion. Adding to these subsidies the payment for extensive forages leads to an overall increase in gross margin of 9.2% (85€/ha) (Figure 10).

Looking at gross margin relative variation according to size class (Figure 11), less economically efficient farms

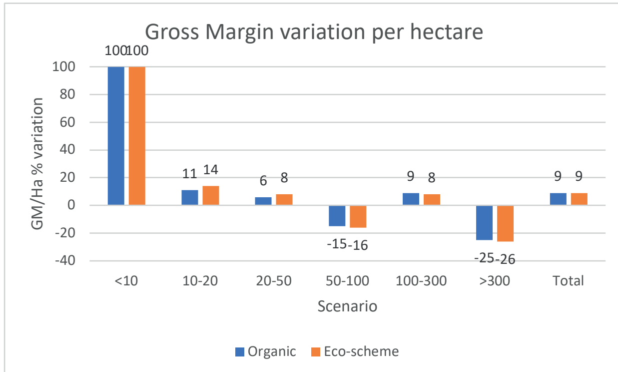

Figure 11. Gross margin variation per ha according to size class compared to baseline scenario.

are those with an UAA over 300 Ha, followed by those between 50 and 100 Ha. All the other classes show an increase in the gross margin per hectare.

4. DISCUSSION AND CONCLUSION

In this study, the application of the agent-based methodology within the AGRISP model has proven to be an effective tool for quantifying the supply-side impacts of CAP measures. Methodologically, AGRISP introduces unique features to capture the diverse characteristics of farms, their decisions, and interactions within their economic and social contexts. It facilitates predictions of the effects of CAP reform at a granular level, including individual farms, and enables analysis at both territorial and sectoral levels. The social variables, such as family structure and farmers' age, are taken in consideration in the model through the definition of specific rules, to characterise the behaviour of the entrepreneur. The choice of the social variables and the socio-structural rules in this paper was made to assess how the CAP strategies may benefit young farmers, however, other socio-structural rules linked to the characteristics of the agricultural family business can be included.

Another innovative feature is the capabilities of simulating the farmers' attitude to change their production plans or their production factors endowment. In order to model farmers' willingness to make changes, the PMP methodology was employed to calculate the marginal cost of individual agricultural productions and the constraining factor, represented by the availability of land. Comapring costs with alternative options acts as a benchmark for farmers when considering the adoption of new technologies and adjustments to their farm structure. Furthermore, the PMP methodology coupled with the self-selection process, enables agents to adapt their production plans by broadening their decision-making options, incorporating production methods and technologies employed by other farms in the sample, as well as considering new production technologies that may emerge due to policy interventions. Consequently, farmers can introduce new processes or modify production intensity, when these choices prove to be more advantageous. Using this approach, AGRISP enabled the simulation of the transition to organic farming in response to the introduction of additional payments and the Eco-scheme 4.

The analysis of the model results may highlight which farm categories are advantaged and which are penalised when policy measures are implemented, whether they are designed for specific production categories or are applicable to all farms across the agricultural region.

Micro-based farm models, capable of simulating farmers' behaviour and their aptitude to change production plans under economic, market, technological and environmental scenarios, are becoming increasingly important, however supply-side farm models, while accurately simulating the entrepreneur's strategies, have the limitation of assuming the farm as a "closed" production system whose decisions consider only the production resources available. Nontheless, the exchange of production factors between farmers, particularly land, in order to adjust to fluctuations in their marginal value, allows the sample's dynamics to be brought closer to reality.

The results illustrated in this paper showing how less efficient farmers rent out land to more productive ones, enabling the latter to expand their operations and leverage economies of scale and scope, well reproduce the decline in number of farms depicted in the most recent Italian agricultural census.

Furthemore, our preliminary results show that the ambitious objectives of the new CAP reform would have significant impacts on land use as well as non-negligible effects on climate change mitigation and water resource consumption.

The complexity of the new CAP, due to potential contradicting objectives such as competitiveness and environment sustainability, requires careful ex-ante evaluation of the possible outcome.

This study reveals that the subsidies allocated to organic farming conversion and the Italian Eco-scheme 4, applied to the Emilia-Romagna FADN sample (2019), may lead to:

1. a considerable decrease in the number of small farms,
2. a shift from cereal cultivation towards protein and feed crops,
3. a substantial economic stability among farms, measured by changes in gross margin per hectare,
4. a modest reduction in CO_2 equivalent emissions per hectare, and
5. an increased demand for water resources.

Overall, the effect appears to be positive in terms of CO_2 reduction. However, concerns are raised by the further increase of capital-intensive agriculture at detriment of small farms.

This work presents some results aggregated at the regional level, but further analysis could be done to highlight findings at the sub-regional level, to suggest more targeted actions able to consider the individual characteristics of different rural areas, allowing, for instance, different payment scheme better calibrated to the territorial conditions and specific regional policy objectives.

To conclude, it is noteworthy that like any modeling approach, ABMs with PMP involve simplifications and assumptions about agents' behavior, market dynamics, policy implementation, and other factors. These assumptions may not always hold true in practice, leading to potential limitations in the model's predictive accuracy and generalizability across different contexts. Integrating variuos modeling approaches could provide a comprehensive assessment of agricultural policies, taking into account farm heterogeneity, farmers' cost and risk perceptions, and the dynamic nature of production decisions and techniques. Collaboration between interdisciplinary teams of researchers and stakeholders is essential to develop and apply these models effectively in policy analysis and decision-making processes.

ACKOWLEDGMENTS

This research was funded by the European Union's Horizon 2020 research and innovation programme under grant agreement No 816078 for the AGRICORE Project

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APPENDIX 1 – CONVERSION TO ORGANIC PRACTICE SCENARIO

List of indexes, parameters, and variables:

Indexes

$n = (1,2,\ldots,N)$: index of farm

$j = (1,2,\ldots,J)$: index of crop

$k = (1,2,\ldots,K)$; $k = j$: index of crop

Parameters

pc_{nj}: output prices for conventional crops

pb_{nj}: output prices for organic crops

sh_{nj}: specific crop payment (€/ha)

shb_{nj}: specific payment for organic crops (€/ha)

SFP_n: single farm payment including basic and greening payments

r: rent price for land (€/ha)

Q_{jk}: matrix Q

u_{nj}: farm deviations

AB_{nj}: technical coefficients for organic crops

Ac_{nj}: technical coefficients for conventional crops

Variables

GM_n: gross margin

xh_{nj}: land use
xhc_{nj}: land use for convention crops
xhb_{nj}: land use for organic crops
xc_{nj}: production for conventional crops
xb_{nj}: production for organic crops
V_n: land rented
Z_n: land leased

List of relevant equations:

1) Constraint linking land allocation to conventional and organic practices
$xhc_{nj} + xhb_{nj} = xh_{nj}$
$\forall n$ [conventional AND ((with farm owner ≤ 65 years) OR (with farm owner > 65 years AND with successor))]: Δj

2) Constraint ensuring the total conversion by crop
$xhc_{nj} \cdot xhb_{nj} = 0$
$\forall n$ [conventional AND ((with farm owner ≤ 65 years) OR (with farm owner > 65 years AND with successor))]: Δj

3) Constraint linking organic land allocation and organic production
$Ab_{nj} \cdot xb_{nj} = xhb_{nj}$
$\forall n$ [conventional AND ((with farm owner ≤ 65 years) OR (with farm owner > 65 years AND with successor))]: Δj

4) Constraint linking conventional land allocation and conventional production
$Ac_{nj} \cdot xc_{nj} = xhc_{nj}$
$\forall n$ [conventional AND ((with farm owner ≤ 65 years) OR (with farm owner > 65 years AND with successor))]: Δj

5) Objective function at the farm level

$$\sum_j \left(pc_{nj} xc_{nj} \right) + \sum_j \left(pb_{nj} xb_{nj} \right) + \sum_j \left(shb_{nj} xhb_{nj} \right) + \sum_j \left(sh_{nj} xh_{nj} \right) + SFP_n +$$
$$+ \left(V_n - Z_n \right) r +$$
$$- \frac{1}{2} \sum_j \sum_k \left(xc_{nj} Q_{jk} xc_{nk} \right) - \sum_j \left(u_{nj} xc_{nj} \right) +$$
$$- \frac{1}{2} \sum_j \sum_k \left(xb_{nj} Q_{jk} xb_{nk} \right) - \sum_j \left(u_{nj} xb_{nj} \right) = GM_n$$

$\forall n$ [conventional AND ((with farm owner ≤ 65 years) OR (with farm owner > 65 years AND with successor))]: Δj

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OPEN ACCESS

Citation: Mantziaris, S., Rozakis, S., Karanikolas, P., Petsakos, A., & Tsiboukas, K. (2024). Simulating farm structural change dynamics in Thessaly (Greece) using a recursive programming model. *Bio-based and Applied Economics* 13(4): 353-386. doi: 10.36253/bae-14790

Received: June 3, 2023
Accepted: September 2, 2024
Published: December 31, 2024

Data Availability Statement: All relevant data are within the paper and its Supporting Information files.

Competing Interests: The Author(s) declare(s) no conflict of interest.

Editor: Matteo Zavalloni

Simulating farm structural change dynamics in Thessaly (Greece) using a recursive programming model

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Abstract. Although the policy impacts on farms accumulate year by year, most farm decision models focus on short-term decisions, evaluating policies based on snapshots. Structural changes are gradually built; therefore, farm decision models should consider the sequences within the period under study. Multiyear data from the arable sector in Thessaly, Greece, have fed a newly developed farm-level recursive linear programming model mainly to simulate farm structural change dynamics. The proposed model incorporates new evidence on the strategic decision of arable crop farms regarding their remaining in the production system and farm expansion. Results reveal an evident gradual farmland concentration in relatively large farms, accompanied by a gradual expansion of the most profitable cropping activities, verifying the real-world survival strategy of farms.

Keywords: farm structural change, land use change, recursive linear programming model, arable production system, Greece.
JEL Codes: C61, Q12, Q18.

1. INTRODUCTION

The declining number of surviving farms over time and the increase in average farm size generally signal the evolutionary process of structural change in the agricultural sector of developed economies (Plogmann *et al.*, 2022), implying changes in the farm size distributions (Zimmermann and Heckelei, 2012; Saint-Cyr *et al.*, 2019).

Agricultural economists have shown great interest in describing structural change dynamics and understanding its drivers (Plogmann *et al.,* 2022). Structural change is driven by various economic factors (Neuenfeldt *et al.,* 2019), environmental factors and social drivers (RIRDC, 2007). Neverthe-

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less, some authors (Wiborg, 1998; Plogmann *et al.,* 2022) consider farm economic performance the primary driver of structural change since it somehow encloses all the above factors.

Structural change is a normal evolutionary process in an economy (Goddard *et al.*, 1993). Over time, rising agricultural productivity enabled the transfer of productive factors required for the development of other sectors of the economy (Balmann and Valentinov, 2016). However, structural change in the agricultural sector is usually correlated with public concerns, which are mainly expressed through public debates in two terms, firstly as "dying peasants" and secondly as "factory farming" (Balmann and Valentinov, 2016).

Highlighting the first public concern, this may be because, generally, structural change hardly leads to Pareto Superior states (Balmann and Valentinov, 2016). From this perspective, Cochrane (1958) concludes that increased agriculture productivity positively affects only a limited number of innovative farms, while most farmers are affected negatively due to the following drop in agricultural commodity prices. Suppose we analyze this reasoning from the point of view of public policy; in that case, structural change may reduce the problem concerning the profitability of remaining farms but, on the other side, reduce the number of small farms and thus counters the equity goals of public society (Finger and Benni, 2021). Within this context, some authors consider the significant role of public policy in mitigating the consequences of structural change by pointing out that "much of the public policy agenda has clearly been established on a premise of optimality of a family farm structure" (Goddard *et al.*, 1993: 486). However, implementing appropriate policy interventions presupposes providing detailed information (by policy analysts) on structural change in agriculture through evidence-based policy-relevant research to support evidence-based agricultural policy decision-making.

The European Common Agricultural Policy (CAP) marks essential shifts in the context where farms operate, with significant reforms attempted every decade. Policy impacts on farms accumulate year after year, affecting the farm structures and, by extension, the well-being of rural communities, creating a ripple effect on the local economy. In this framework, modeling the dynamics of structural change adjustment (i.e., the change over time of farm numbers and farm size distribution) is highly desirable because it can provide policymakers and stakeholders with possible alternative scenarios of structural change adjustments, but it is still not widely used in policy analysis (Ciaian *et al.*, 2013; Espinosa *et al.*, 2016). Modeling exercises such as dynamic appraisals can support policy analysts in formulating public policies to obtain the "desired farm structure" considering the societal demands for equity (Finger and Benni, 2021).

Two main methodological approaches incorporate structural change in agriculture: econometrics and simulation models (which aim to analyze farm structural change endogenously) (Espinosa *et al.*, 2016; Zimmermann *et al.*, 2009). Econometric models include Markov chains (Zimmermann and Heckelei, 2012) and various other regression approaches (Zimmermann *et al.*, 2009). Simulation models include recursive programming models (e.g., Wiborg, 1998; Guinde *et al.*, 2005; Henningsen *et al.,* 2005; Offermann and Margarian, 2014; Djanibekov and Finger, 2018; Mittenzwei and Britz, 2018) and agent-based models (e.g., Balmann, 1997; Berger, 2001; Happe *et al.,* 2008; Freeman *et al.,* 2009; Bert *et al.,* 2011; Troost and Berger, 2016; Beckers *et al.,* 2018; Sun *et al.,* 2022; Donati *et al.,* 2024). As simulation models can endogenously capture farm structural change, they are considered suited to analyzing policy changes' allocative and distributive effects on an agricultural production system (Guinde *et al.*, 2005; Happe *et al.*, 2008; Espinosa *et al.*, 2016). Although agent-based models such as AgriPoliS (Balmann, 1997) are considered by various modelers the most comprehensive attempt at analyzing the impact of policies on structural change (e.g., Zimmermann *et al.*, 2009), are characterized by greater complexity (e.g., Zimmermann *et al.*, 2009), and they are very demanding in terms of parameterisation (e.g., Zimmermann *et al.*, 2009; Rowan *et al.*, 2011; Kremmydas *et al.,* 2023) and calibration (e.g., Zimmermann *et al.*, 2009). In addition, the preference for simpler process-based models[1] should not be ignored (Troost and Berger, 2020). Therefore, while capturing structural change endogenously and providing meaningful insights into the allocative and distributional effects of various exogenous factors, the farm-level recursive programming models can also be manageable regarding the degree of complexity and data requirements compared to other simulation models such as agent-based models.

Based on the above discussion, the main objective of this research is to investigate the impacts of policy experiments on farm structural change dynamics in Greece through an endogenous modeling approach based on a newly developed farm-level recursive linear programming model. While primarily aimed at simulating the impact of policy experiments on the evolutionary process of farm structural change, the proposed simulation model is also secondarily used to simulate the effect

[1] Process-based models include models such as simulation models and systems dynamics models.

on land use change while analyzing its relationship with structural change adjustment.

In the context of structural changes, the strategic decision of farms is summarized through the phrase "grow or go" (Plogmann *et al.*, 2022), implying the aspects of (i) farm viability and (ii) farm growth/expansion. Through the proposed modeling approach, we integrate the farm's economic performance as the main driver of this decision (e.g., Wiborg, 1998; Paroissien *et al.*, 2021; Plogmann *et al.*, 2022). In more detail, in addition to traditional monetary value criteria to determine a surviving/viable farm, we introduce a novel viability criterion, assuming that farmers may compare their economic performance to societal consumption benchmark, in the sense that the agent (in our case, real-world individual farm) must achieve a minimum level of profitability, allowing entry into the "rat race" according to "Keeping up with the Joneses" (KUJ) preferences (e.g., Barnett *et al.,* 2010; Lombardo, 2021; Paroissien *et al.*, 2021). Regarding farm expansion, the proposed modeling approach introduces a further novel element through the concept of relative optimal farm growth in equity to reallocate/allocate resources between neighboring surviving farms.

The proposed model can also be characterized as a One-Way Communication Model where the information flows from the econometric model to the recursive programming farm model (Huang *et al.,* 1980). In particular, the Autoregressive Integrated Moving Average (ARIMA) models are used to forecast the values of the exogenously determined parameters of interest to conduct out-of-sample simulations. Additionally, ARIMA stochastic process estimates express the agents' quasi-rational expectations regarding agricultural commodity prices and crop yields (Nerlove and Bessler, 2001; Siegle *et al.,* 2024).

For the empirical application of the proposed simulation model, a representative sample of arable crop farms (in terms of farm structure) of the region of Karditsa (NUTS-3 level), Thessaly, is chosen. The priority of empirical application given to the arable production system is justified by the fact that Greek arable farming is characterized by a comparatively higher rate of structural change concerning the other main types of farming (other permanent crops, other grazing livestock) (FADN Public Database).

From a general perspective, with this analysis, we attempt to contribute to the debate on dynamic assessments of the multidimensional effects in the context of policy reforms. Additionally, more specific contributions to literature are expressed through at least four ways:

First, we add knowledge by integrating evolutionary and social psychology elements to define a farm as viable based on KUJ preferences. Second, we simulate resource reallocation based on the criterion of relative optimal farm growth in equity as an alternative farm expansion/growth criterion to traditional criteria such as the shadow values of resources (e.g., Guinde *et al.,* 2005; Hennessy, 2007; Espinosa *et al.,* 2016). Third, the utilization of the ARIMA stochastic process for time series forecasting of the values of the exogenously determined parameters (such as agricultural commodities prices, input prices, and crop yields) is an addition to the existing literature since in similar simulation models; these values are mainly determined either from secondary data sources (e.g., Wiborg, 1998; Hennessy, 2007; Offermann and Margarian, 2014) or through assumptions/scenarios (e.g., Guinde *et al.,* 2005; Henningsen *et al.,* 2005; Troost and Berger, 2016; Mittenzwei and Britz, 2018) or simplified trend models (e.g., Happe *et al.,* 2008; Bert *et al.,* 2011; Beckers *et al.,* 2018). Fourth, despite the great importance of the arable production system for the Greek agricultural sector and the comparatively higher rate of structural change than the other main production systems, to our knowledge, farm-level recursive programming models have not been used to provide a "bottom-up" simulation of structural change of Greek arable production system.

The rest of the paper is organized as follows. Section 2 describes the applied methodology, the data used to apply the methodology, and the policy experiments. The empirical results are presented in Section 3, Section 4 discusses them, and concludes.

2. METHODOLOGY AND DATA

2.1. Recursive programming models for impact assessment in agriculture

Recursive programming models have already been introduced in the 1960s to represent dynamic adjustments of production capabilities at the farm level, and then with the study of Day and Cingo (1978) regional interdependence and structural elements were incorporated (Espinosa *et al*., 2016). Indicatively, recursive programming farm models have been utilized for the development of farm firm growth models (e.g., Chien and Bradford, 1976; Cittadini *et al*., 2008; Dowson *et al.,* 2019) to investigate the economic consequences due to farmers' adaptability to different water availability scenarios (e.g., Iglesias *et al*., 2003; Rowan *et al*., 2011; Robert *et al*., 2018; Dowson *et al.,* 2019), to assess the impacts of various policy reform and price scenarios on farm income and investment behavior (e.g., Viaggi *et al*., 2010; Viaggi *et al*., 2011; Davis *et al.,* 2013; Britz *et* *al.*, 2016) and to analyze the impact of policies on farm structural change (e.g., Wiborg, 1998; Guinde *et al.*, 2005; Henningsen *et al.*, 2005; Offermann and Margarian, 2014; Djanibekov and Finger, 2018; Mittenzwei and Britz, 2018).

The main structural elements of a recursive programming model correspond to a constrained optimization model and a data generator, where the data generator, given the optimal value or solution in period *t*, reinitializes the parameters of period *t+1,* including a set of constraints that relates the feasible values of current variables to past values of variables and exogenous events (McCarl and Spreen, 1997). Following Chien and Bradford (1976) and McCarl and Spreen (1997), the general formulation of the recursive programming farm model is as follows:

$$\text{Max} \quad E\{\Pi_t\} = \sum_j E\{C_{j,t}\}^T \; X_{j,t} \tag{1}$$

Subject to:

$$\sum_j A_{i,j,t} \; X_{j,t} \leq b_{i,t} \qquad \forall i \tag{2}$$

$$X_{j,t} \geq 0 \qquad \forall j \tag{3}$$

where $E\{\ \}$ denotes the expectation operator; $E\{\Pi_t\}$ is farm's expected gross profit in EUR which is maximized in year t ; $E\{C_{j,t}\}$ is the vector of expected gross profit in EUR/hectare (ha) of the j cropping activity in period t ; $X_{j,t}$ is the vector of the decisions variables that denotes the level of the j cropping activity (hectares for crops) in period t; $A_{i,j,t}$ are the resource I usages by the j cropping activity per ha in period t; $b_{i,t}$ is the vector of available resources i in period t, functionally dependent upon lagged phenomena (Kay, 1971; McCarl and Spreen, 1997).

The reinitialization of the vector of available resources ($b_{i,t}$) is conducted through farm firm growth rules such as the Endogenous Feedback Mechanism (EFM) (e.g., Kay, 1971; Chien and Bradford, 1976; McCarl and Spreen, 1997; Cittadini *et al.*, 2008; Davis *et al.*, 2013; Robert *et al.*, 2016). Although EFM has been applied with some variations, the general mathematical formulation is as follows:

$$b_{i,t} = f(b_{i,t-1}, X_{i,t-1}^*, V_{i,t})) \tag{4}$$

where the vector of available resources ($b_{i,t}$) in period t is determined by the vector of available resources in the previous period ($b_{i,t-1}$), the optimal decisions in the previous period ($X_{i,t-1}$) and by the vector $V_{i,t}$ that allows for external changes in the resource restrictions due to exogenous events that will occur in the period t which are rather determined by external economic and environmental factors (Kay, 1971; McCarl and Spreen, 1997; Davis *et al.,* 2013; Robert *et al.*, 2016).

Since the proposed model is used for structural change analysis, three more basic structural elements are included to determine (i) farm viability, (ii) farm growth/expansion, and (iii) capital stock evolution at the farm level. A detailed description of these structural elements of the model is carried out in subsequent sections.

2.2. ARIMA modeling for economic forecasting in agriculture

The usefulness of such a simulation model, which is optimized sequentially within a dynamic framework, lies in the ability to provide results outside the reference period (out-of-sample forecasts). Therefore, to conduct out-of-sample simulations, the forecasted values of the exogenously determined parameters of the farm are required.

Various modelers have used ARIMA models to forecast exogenously determined parameters such as agricultural commodity prices (e.g., Mao *et al.,* 2022), crop yields (e.g., Petsakos *et al.,* 2016), cost of production factors (e.g., Hloušková *et al.,* 2018) and supply of various resources (e.g., the total amount of agricultural land, total amount of pesticides) (Costache *et al.,* 2021).

ARIMA models are fitted utilizing the information in the series itself to predict future points in the series (Christodoulos *et al.,* 2010; Garnier, n.d.), and therefore the independent variables are lagged values of the series. More specifically, the future values of the dependent variable can only be described through their probability distribution rendering the series a stochastic process[2] (Pardoe, n.d.). In this vein, several modelers consider that the use of ARIMA models is appropriate for economic forecasting in agriculture, especially in cases of lack of well-developed theory or limited information (Petsakos *et al.,* 2016); as a result, the forecasting of exogenous variables often present problems for econometric model users (Oliveira et al., 1979).

Within this context, the ARIMA stochastic process is utilized for estimating the values of exogenously determined parameters of interest (in our case, agricultural commodity prices, crop yields, costs, interest rate, total arable land, and total circulating capital) to perform out-of-sample forecasts in the medium term. In

[2] Details on ARIMA modeling framework are provided in *Part A: Conceptual framework of ARIMA modeling* in the supplementary material.

addition, ARIMA models are utilized to estimate the values for random/stochastic parameters, such as agricultural commodity prices and crop yields, to express agents' quasi-rational expectations mechanism (Nerlove and Bessler, 2001; Siegle *et al.,* 2024).

2.3. Simulation model specification and assumptions

2.3.1. Model's basic structure

The initial endowments with production factors are specified before the sequential simulation starts (in our case, arable land, irrigated land, circulating capital, capital stock, and borrowed capital) (Happe *et al.*, 2008) (see Figure 1). To simulate farms' productive decisions through the proposed farm-level recursive linear programming model, we assume that farms optimize the expected gross profit (e.g., Rowan *et al.*, 2011) for each year *t* given the farm's resource, policy, and flexibility constraints. To elaborate more, resource constraints contain: (i) Arable land constraint; (ii) Irrigated land constraint; and (iii) Circulating capital constraint.

Policy constraints contain: (i) 2013 CAP reform constraints (greening obligations); (ii) CAP Post-2020 reform scenario constraints; (iii) Nitrate pollution reduction program constraints; and (iv) Organic farming program constraint. Flexibility constraint corresponds to the constraint of multiannual contract farming[3].

Each sub-model (based on representative individual real-world farm) optimized recursively[4] for a sequence of 15 years (from 2012 to 2026). Time progresses in discrete time intervals, symbolizing the commencement of a growing season at time *t* (see Figure 1). To perform out-of-sample simulations (i.e., outside the reference period, specifically after 2019), mainly ARIMA models are used to forecast the values of the exogenously determined parameters of interest (see Figure 1).

2.3.2. Farm agents' expectations specification and model validation

Various authors (e.g., Femenia *et al.*, 2017) consider naïve and quasi-rational expectations (ARIMA modeling), both based on past observations, to be the most frequent expectation mechanisms[5] in some types of farming. Influenced by this finding, we emphasize these two mechanisms of expectations regarding agricultural commodity prices and crop yields in the present study, considering that they will be representative of sample farms and the information available to them (mainly based on past observations).

More specifically, we have formulated two alternative models; one referred to as the Quasi-Rational expectations (QR) model and the other as the Naïve and Quasi-Rational expectations (NV&QR) model. In more detail, in the QR model case, the agent'' expectations are expressed through quasi-rational expectations (ARIMA modeling) for agricultural commodity prices and crop yields (e.g., Narayana and Parikh, 1981; Nerlove and Bessler, 2001; Siegle *et al.,* 2024). In the NV&QR model case, the agent'' expectations are expressed through naïve price expectations for agricultural commodity prices (e.g., Nerlove and Bessler, 2001; Robert *et al.,* 2018; Siegle *et al.,* 2024) and through quasi-rational expectations for crop yields.

Then the two proposed models are validated for their capability to reproduce activities allocation (Gómez-Limón *et al.,* 2016), the number of surviving farms (Beckers *et al.,* 2018), and the farm size distribution (Freeman *et al.,* 2009; Beckers *et al.,* 2018).

2.3.3. Determining farm viability

Usual approaches to defining farm viability are based on the opportunity cost of farming (e.g., Loughrey *et al.*, 2022) and the poverty line (e.g., Miller *et al.*, 1981; Loughrey *et al.*, 2022). Other approaches to defining farm viability focus on monetary returns, where the farm income should ensure long-term farm growth in equity, or at least the equity should remain stable into the future (e.g., Bright *et al.*, 2007; Barnes *et al.,* 2015).

Another interesting approach to defining farm viability from a socio-economic perspective is based on the "Keeping up with the Joneses" (KUJ) preferences (Miller *et al.*, 1981; Paroissien *et al.*, 2021). Farmers may compare their profits to the overall standard of living (average living expenditures/average consumption level) of socially close reference group (neighboring farms), which is considered the societal consumption benchmark or social reference point of consumption level (Paroissien *et al.*, 2021).

From this perspective, agents that stand below their societal reference point (in the sense of not being able to finance this level of consumption) are forced to stay out of the "rat race of keeping up with the Joneses" (Barnett *et al.*, 2010), may experience lower life satisfaction and professional well-being, a situation which may

[3] A detailed description of the objective function and constraints is provided in *Part B: Structure of the model's objective function and constraints* in the supplementary material.
[4] The model is written in GAMS language.
[5] A detailed description of farm agents' expectations mechanisms is provided in Nerlove and Bessler (2001), Haile *et al.* (2016), Femenia *et al.* (2017), and Siegle *et al.* (2024).

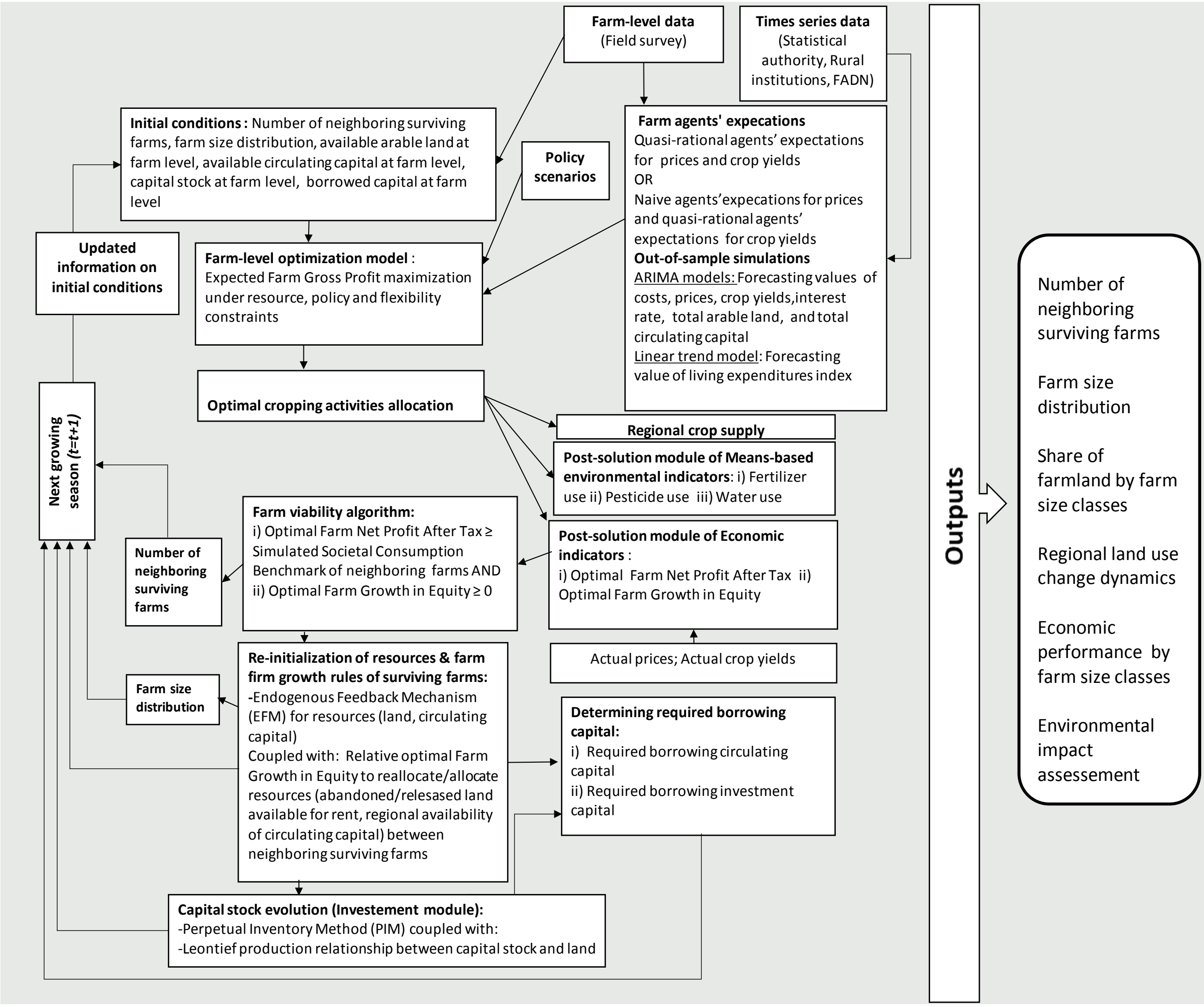


Figure 1. Conceptual diagram of the proposed modeling framework. *Notes*: A post-solution module of means-based environmental indicators enables the model to estimate the environmental performance of farms. However, to limit the size of this paper, the environmental impact assessment will not be presented here. *Source:* Authors

create incentives to exit the system (Paroissien *et al.*, 2021; Nguyen and Herron, 2021). Therefore, a farm must achieve a minimum level of profitability, allowing entry into the "rat race" (Lombardo, 2021) according to KUJ preferences (i.e., keeping up with a benchmark proportional to the average level of consumption of the socially close reference group (Barnett *et al.*, 2010) such as neighboring farms).

The influences for this hypothesis come from evolutionary and social psychology, where various researchers assume that the quest for status – frequently referred to in this context as "Keeping-up-with-the Joneses"– depends on the social norms related to a benchmark consumption level such as the average consumption level of the socially close reference group (Fisher and Heijdra, 2009; Lombardo, 2021; Mageli *et al.,* 2022). Based on the above reasoning, various researchers assume that the quest for social status can be linked to the striving to survive (Mageli *et al.,* 2022). Notably, since social groups can distribute resources among their members, an agent's chances to survive and reproduce are greatly enhanced if she/he belongs to a group and if she/he holds a relatively high social rank within the group, in the sense that an agent's relative position may give her/him a survival advantage through access to material and reproductive resources (Mageli *et al.,* 2022).

Alternatively, farm viability can be defined according to a combination of monetary value and socio-economic criteria (Bert *et al.*, 2011; Mittenzwei and Britz, 2018; Seidel and Britz, 2019).

In the present modeling approach, a sample farm is considered viable/surviving by satisfying two viability criteria: (i) the criterion of societal consumption benchmark of neighboring farms *(NBF)*[6] according to the KUJ preferences and, (ii) the criterion of non-negative optimal farm growth in equity. At this point, we would like to mention that, following similar simulation models (Bert *et al.,* 2011; Offermann and Margarian, 2014; Mittenzwei and Britz, 2018; Seidel and Britz, 2019) we simulate only farm exit according to the farm exit module considering economic and socioeconomic criteria. Consequently, we do not model the life cycle of agents who enter farming, get old, and retire (Bert *et al.,* 2011).

Therefore, following each discrete optimization time-step (annual), every neighboring farm *nbf* decides whether to remain in the system or exit (see also Figure 1). Specifically, a neighboring farm is considered viable and remains in the production system when at the end of the year *t* meets both viability criteria, i.e., (i) the optimal Farm Net Profit after Tax ($FNPAT^{*}_{nbf,t}$) should be at least equal to the simulated average living expenditures of neighboring farms in year *t* ($\overline{LE_{NBF,t}^{sim}}$), and (ii) optimal farm growth in equity ($FGE^{*}_{nbf,t}$) should be at least equal to zero.

As regards the mathematical formulations of the specific profitability measures are as follows considering the relevant literature (GRDC, 2015):

$$FNPAT^{*}_{f,t} = \Pi^{*}_{f,t} - (DEP_{f,t} + LRC_{f,t} + SFNC_{f,t} + LFNC_{f,t} + SIC_{f,t} + FPTX_{f,t}) \quad (5)$$

$$FGE^{*}_{f,t} = FNPAT^{*}_{f,t} - LE_{f,t} \quad (6)$$

where $FNPAT^{*}_{f,t}$ is the optimal Farm Net Profit after Tax *f* in year *t;* $\Pi^{*}_{f,t}$ is the optimal gross profit of farm *f* in year *t*; $DEP_{f,t}$ is the depreciation of machinery of farm *f* in year *t*; $LRC_{f,t}$ are the land rental costs[7] of farm *f* in year *t*; $SFNC_{f,t}$ are the short-term finance costs which correspond to the interest paid for short-term loans of farm *f* in year *t*; $LFNC_{f,t}$ are the long-term finance costs which correspond to the interest paid for long-term loans of farm *f* in year *t;* $SIC_{f,t}$ are the social insurance contributions paid by farm *f* in year *t;* $FPTX_{f,t}$ is the farm profit tax paid by farm *f* in year *t;* $FGE^{*}_{f,t}$ is the optimal Farm Growth in Equity of farm *f* in year *t;* $LE_{f,t}$ are the living expenditures[8] of farm *f* in year *t*.

2.3.4. Re-initialization of resources and farm firm growth rules

The annual re-initialization of resources required for the farms' operation and growth/expansion process is conducted through the Endogenous Feedback Mechanism (EFM) (whose general structure has been presented in the 2.1 section). An essential part of the literature indicates that growth in equity determines the prospects for growth/expansion of the farm (e.g., Painter, 2005; Cittadini *et al.*, 2008; Bert *et al.*, 2011; GRDC, 2015), that is, that the acquisition of resources will be determined through this profitability measure. Hence, we consider that optimal farm growth in equity could be used as an alternative criterion of farm expansion/growth to tra-

[6] The literature on whom agents compete with for social status, i.e., who the Joneses are, is relatively limited (Mageli *et al.,* 2022). Nevertheless, it is conceivable that agents compare more intensely with agents who are socially proximate to them (Mageli *et al.,* 2022). For example, society serves as a socially distant reference group, whereas colleagues are socially close reference groups (Mageli *et al.,* 2022). In this framework, we could consider a socially close reference group to each agent (individual real-world farm), farms with the same productive specialization located in the same region, i.e., neighboring farms *(NBF)* correspond to arable crop farms of the regional unit of Karditsa (NUTS-3 level). In particular, farmers of this reference group could be considered colleagues due to their similar professional goals and intense professional interactions, which are expressed through their professional collective bodies, such as trade union bodies, groups of producers, and cooperatives, which are mainly made up of farmers of common productive specialization. From this perspective, the intense professional and, consequently, social interactions may provide each agent of the reference group (neighboring farm) with a comparatively better level of information about the economic performance of its neighbors and the livelihood level (consumption level, particularly for visual commodities that are connected to income or wealth, e.g., cars and houses) (Mageli *et al.,* 2022) than for socially distant reference groups (i.e., farms with different productive specializations compared to the agent). Consequently, this comprehensive information signals the process of forming social norms based on which a social group's social status or position is determined. In our case, the quest for social status is reflected in KUJ preferences (Fisher and Heijdra, 2009; Lombardo, 2021; Mageli *et al.,* 2022). Finally, we also relied on a strict definition of neighboring farms for this selection based on the relevant literature (Paroissien *et al.,* 2021), where only farms with the same specialization located in the same region are included in the socially close reference group (neighboring farms).

[7] In case that farm rents out part of owned farmland, then receives land rental income $LRINC_{f,t}$. Consequently the equation (5) is adapted as follows: $FNPAT^{*}_{f,t} = (\Pi^{*}_{f,t} + LRINC_{f,t}) - (DEP_{f,t} + SFNC_{f,t} + LFNC_{f,t} + SIC_{f,t} + FPTX_{f,t})$, indicating that a farm cannot simultaneously rent in and rent out farmland, a condition we also find in similar simulation models (e.g., Donati *et al.,* 2024).

[8] The estimation of living expenditures following the base year (2012) is carried out by utilizing the living expenditures index *(LEI)* of households in rural areas (ELSTAT, 2021). That is, heterogeneity between farms in the living expenditures in the base year (2012) is captured, but its evolution over time is based on the exogenously determined living expenditures index *(LEI)*. Since the available time series of the living expenditures index *(LEI)* does not meet the minimum required time horizon of 16 data points of the ARIMA model (Christodoulos *et al.,* 2010), we use a linear trend model instead of the ARIMA model to make post-sample forecasts.

ditional criteria such as the shadow values of resources (e.g., land, circulating capital) (Guinde *et al.,* 2005; Hennessy, 2007; Espinosa *et al.,* 2016).

However, given resource constraints, especially land, farm expansion is possible when neighboring farms decide to downsize or abandon agricultural production (Plogmann *et al.*, 2022). Essentially, the process of structural change drives the reallocation of the resources required for expansion, where the resources of non-viable neighboring farms (e.g., land) are reallocated to viable ones (see also Figure 1). Various modelers (e.g., Bert *et al.*, 2011; Sheng *et al.*, 2015; Herrera *et al.*, 2022; Sun *et al.,* 2022) highlight the role of relative profitability as a criterion/mechanism for the reallocation/allocation of resources between surviving farms. Within this context, our concern was how optimal farm growth in equity could be expressed as a criterion/mechanism for resource reallocation among viable farms and integrated into the EFM. To model this mechanism, we adapted the concept of efficient allocation (Ayerst *et al.*, 2020; Chen *et al.,* 2022). According to the proposed adaptation, we replace relative farming productivity with relative farm growth in equity. We consider this adjustment to be reasonable since Foster *et al.* (2008) found that "firms' self-selection behavior (in choosing an operating scale, or to enter or exit) is made based on firm profitability rather than firm productivity and consequently resource reallocation may not always align with firm productivity growth, particularly in the short run" (Sheng *et al.*, 2015: 75).

By incorporating the proposed resource reallocation/allocation mechanism into the EFM, each farm's annual level of resource is determined by the available level of the resource at the beginning of the previous growing season, the relative optimal growth in equity at the end of the previous growing season (indicating the optimal decisions), and by exogenous events[9] that will occur in the current growing season.

Since we have ensured (from the viability determination assumptions) that a viable farm will not reveal negative optimal growth in equity, the mathematical formulation of the share of any resource $r \in \{AL, CRC\}$ allocated or reallocated is as follows:

$$\Omega^{sim}{}_{r_{vf,nbf,t}} = \frac{FGE^{*}{}_{vf,nbf,t}}{\sum_{vf=1}^{VF}\sum_{nbf=1}^{NBF} FGE^{*}{}_{vf,nbf,t}}\,,\ for\ t = 1\ldots\ T,\quad 0 \le \Omega^{sim}{}_{r_{vf,nbf,t}} \tag{7}$$

[9] We assume that exogenous events are expressed through successive differences in the aggregate level of resources where the relative optimal growth in equity of the previous growing season allocates these positive or negative differences across farms.

where $\Omega^{sim}{}_{r_{vf,nbf,t}}$ is the simulated share of resource r allocated/reallocated to viable neighboring farm in year t; $FGE^{*}{}_{vf,nbf,t}$ is the optimal Farm Growth in Equity of viable neighboring farm in year t; $\sum_{vf=1}^{VF}\sum_{nbf=1}^{NBF} FGE^{*}{}_{vf,nbf,t}$ is the aggregate optimal Farm Growth in Equity of viable neighboring farms in year t.

Essentially the simulated share of resource r allocated to viable neighboring farm in period t ($\Omega^{sim}{}_{r_{vf,nbf,t}}$) expresses the part of EFM which corresponds to optimal decisions ($X_{jt}{}^{*}$) while considering the interdependence of optimal decisions of viable neighboring farms, indicating competitiveness for resources. It is also worth noting that the simulated share ($\Omega^{sim}{}_{r_{vf,nbf,t}}$) remains the same for each resource allocated/reallocated.

(i) Arable land

Therefore, considering the above, the EFM mechanism for the resource of arable land will be formulated as follows:

$$AL_{vf,nbf,t} = AL_{vf,nbf,t\text{-}1} + \Omega^{sim}{}_{AL_{vf,t\text{-}1}}\,[\textstyle\sum_{nvf=1}^{NVF}\sum_{nbf=1}^{NBF} AL_{nvf,nbf,t\text{-}1}{}^{sim} + (TAL_{NBF,t} - TAL_{NBF,t\text{-}1})],\ for\ t{=}2\ldots T \tag{8}$$

where $AL_{vf,nbf,t}$ is the available arable land of viable neighboring farm in year t; $AL_{nvf,nbf,t\text{-}1}$ is the available arable land of viable neighboring farm at the beginning of year $t\text{-}1$; $\Omega^{sim}{}_{AL_{vf,nbf,t\text{-}1}}$ is the simulated share of arable land reallocated to viable neighboring farm at the end of the year $t\text{-}1$, that is, following the annual optimization; $\sum_{nvf=1}^{NVF}\sum_{nbf=1}^{NBF} AL_{nvf,nbf,t\text{-}1}{}^{sim}$ is the simulated aggregate arable land of non-viable neighboring farms at the end of the year $t\text{-}1$, that is, following the annual optimization; $TAL_{NBF,t}$ is the actual total arable land of neighboring farms in year t; $TAL_{NBF,t\text{-}1}$ is the actual total arable land of neighboring farms in year $t\text{-}1$.

Essentially, the product $\Omega^{sim}{}_{AL_{vf,nbf,t\text{-}1}}(TAL_{NBF,t} - TAL_{NBF,t\text{-}1})$ corresponds to the vector V_{it} of EFM that allows for external changes in the resource restrictions due to exogenous events, and probably reflects the competition for resources with other types of farms or non-agricultural sectors which operate within the same region.

However, competitive pressures are likely to lead to an unfavorable situation, i.e., $TAL_{NBF,t} - TAL_{NBF,t\text{-}1} < 0$ and consequently to a decrease of available arable land for the viable neighboring farms, which will be reallocated among them utilizing the inverse form of the simulated share of arable land ($\Omega^{sim}{}_{AL_{vf,nbf,t\text{-}1}}{}^{-1}$), that is, less profitable albeit viable farms will abandon proportionately more of their arable land.

As can be easily understood by the reader, the above procedure is also applied to the available irrigated land

($IL_{vf,nbf,t}$), which is expressed as a share of the total arable land and is assumed to be constant at the base year level and equal to 80%.

Based on relevant literature (e.g., Bert *et al.,* 2011; Djanibekov and Finger, 2018; Donati *et al.,* 2024), the farmland is reallocated only on a rental basis through farmland rental arrangements between tenants and landowners, and the land rental price is exogenously determined [10].

(ii) Circulating capital

Similarly, we apply the EFM in the case of determining the available circulating capital on an annual basis. The noticeable difference lies in the fact that the circulating capital of non-viable neighboring farms is not reallocated to viable neighboring farms as in the case of arable land.

$$CRC_{vf,nbf,t} = CRC_{vf,nbf,t\text{-}1} + \Omega^{sim}{}_{CRC_{vf,nbf,t\text{-}1}} (TCRC_{NBF,t} - \sum_{vf=1}^{VF} \sum_{nbf=1}^{NBF} CRC_{vf,nbf,t\text{-}1}{}^{sim}), \textit{ for } t = 2 \ldots T \qquad (9)$$

$CRC_{vf,nbf,t}$ is the available circulating capital of viable neighboring farm in year *t*; $CRC_{vf,nbf,t\text{-}1}$ is the available circulating capital of viable neighboring farm at the beginning of year *t-1*; $\Omega^{sim}{}_{CRC_{vf,nbf,t\text{-}1}}$ is the simulated share of circulating capital allocated to viable neighboring farm at the end of the year *t-1*, that is, following the annual optimization; $\sum_{vf=1}^{VF} \sum_{nbf=1}^{NBF} CRC_{vf,nbf,t\text{-}1}{}^{sim}$ is the simulated total circulating capital of viable neighboring farms at the end of the year *t-1*, that is, following the annual optimization; $TCRC_{NBF,t}$ is the actual total circulating capital of neighboring farms in year *t*.

As before (in the case of available arable land), the product $\Omega^{sim}{}_{CRC_{vf,nbf,t\text{-}1}}$ ($TCRC_{NBF,t} - \sum_{vf=1}^{VF} \sum_{nbf=1}^{NBF} CRC_{vf,nbf,t\text{-}1}{}^{sim}$) reflects the effect of the external economic factors that can form the availability of financial resources at farm level, such as the financial system, the tax system, macroeconomic conditions (e.g., level of inflation), etc. These factors may create a healthy financial situation or financial stress. Financial stress could therefore lead to an unfavorable situation, i.e., $TCRC_{NBF,t} - \sum_{vf=1}^{VF} \sum_{nbf=1}^{NBF} CRC_{vf,nbf,t\text{-}1}{}^{sim} < 0$ and consequently to a decrease of the available circulating capital for the viable neighboring farms which will be allocated to them utilizing the inverse form of the simulated share of circulating capital ($\Omega^{sim}{}_{CRC_{vf,nbf,t\text{-}1}}{}^{-1}$), that is, less profitable, albeit viable farms, will lose proportionately more of their circulating capital[11].

2.3.5. Capital stock evolution at the farm level (Investment module)

The intertemporal evolution of capital stock at the farm level is assessed utilizing the Perpetual Inventory Method (PIM) where the capital stock (machinery and equipment) of the farm *f* in year *t* is equal to the non-depreciable capital stock of the year *t-1* plus gross investment in fixed assets that will be made through the year *t* (Weyerstrass, 2016). The mathematical formulation of PIM is as follows:

$$K_{f,t} = (K_{f,t\text{-}1} - DEP_{f,t\text{-}1}) + I_{f,t} \qquad (10)$$

where $K_{f,t}$ is the capital stock of farm *f* in year *t;* $K_{f,t\text{-}1}$ is the capital stock of farm *f* in year *t-1; $DEP_{f,t\text{-}1}$* is the depreciation of farm *f* in year *t-1,* which is obtained from the equation $DEP_{f,t\text{-}1} = \delta K_{f,t\text{-}1}$, where δ is the fixed depreciation rate equal to 5% (Weyerstrass, 2016; Femenia *et al.*, 2017), and $I_{f,t}$ is the gross investment on fixed asset of farm *f* in year *t*. Gross investment in fixed assets includes annual cash expenditures for the maintenance of capital stock due to economic depreciation and the acquisition of required investment capital for farm expansion (net investment on fixed assets) (Smale *et al.,* 1986).

Following similar modeling approaches (Kay, 1971; Freeman *et al.,* 2009), we assume a Leontief production relationship between capital stock and land. It is therefore assumed that the capital stock remains constant per hectare of arable land at the base year level ($\frac{K_{f,t=1}}{AL_{f,t=1}}$, so that the amount charged for depreciation in year *t-1* ($DEP_{f,t\text{-}1}$) is constantly reinvested in new capital stock (or gross investment on fixed assets) in year *t*($I_{f,t}$) (Freeman *et al.,* 2009). Essentially, the constant intertemporal relationship between capital stock and arable land renders the investment process a continuous process of investment or disinvestment (Britz *et al.,* 2016) determined by the arable land acquired or abandoned[12].

2.4. Farm data description and specification

For the empirical application of the proposed simulation model, a representative sample of arable crop farms

[10] Detailed information concerning land rental costs/land rental income estimation is provided in *Part C: Land rental costs/land rental income estimation* in the supplementary material.

[11] Detailed information concerning required borrowing circulating capital & short-term finance costs estimations is provided in *Part D: Borrowed capital & finance costs estimations /D1. Borrowed circulating capital & short-term finance costs estimations* in the supplementary material.

[12] Detailed information concerning required borrowing investment capital and long-term finance costs estimations is provided in *Part D: Borrowed capital & finance costs estimations/D2. Borrowed investment capital & long-term finance costs estimations* in the supplementary material.

in Karditsa (NUTS-3 level) is chosen. The regional unit of Karditsa is one of the five regional units of the region of Thessaly (NUTS-2 level) located southwest of it.

This study utilizes farm-level data provided by a research project that thoroughly investigated the perspective of a sample of farms of the regional unit of Karditsa that specialized in "Other fieldcrops/General field cropping" (according to the TF14 classification of FADN) to cultivate alternative crops such as energy crops. Initially, 70 farms were selected by stratified random sampling, and detailed data on production, revenues, fixed assets, and subsidies for 2005 and 2006 were collected through personal interviews. Two field surveys followed (after 2006) to update mainly data on production, revenues, fixed assets, and subsidies through personal interviews. Through these two follow-up surveys, we collected additional socio-economic information such as living expenditures and how agricultural subsidies were spent (e.g., living expenses, investments, production costs, loans).

The first follow-up field survey was conducted in 2012, where data from 48 remaining farms were updated (from the initial 70), and the second was in 2019, where data from 31 remaining farms (out of 48 in 2012) were updated. For the empirical application of the simulation model, the data of the most recent period (2012-19) are utilized to manage the complexity of the model at a computable level.

The sample represents at a satisfactory level the farm structure of 6,272 farms specializing in "Other fieldcrops/General field cropping" in the regional unit of Karditsa for 2012. Specifically, based on a comparison of our sample with the Farm Accountancy Data Network (FADN) data for the base year (2012), we found a significant degree of similarity in terms of farm size distribution, where the Finger–Kreinin (FK) similarity index (Finger and Kreinin, 1979) stands at 90.2% (see also Table 1). Consequently, although the farm sample size can be considered relatively small compared to the population, it sufficiently reflects the heterogeneity in farm structure[13].

Cotton and durum wheat are the main activities regarding total farmland area shares. All observed activities (i.e., cotton, processing vegetables, tobacco, maize, alfalfa) except durum wheat and set-aside require irrigation. The production of processing vegetables and tobacco is conducted through annual contracts with the industry, while for the activity of alfalfa (seed production), the farmers conclude a ten-year contract.

Table 1. Farm size distributions comparison of farms specialized in "Other fieldcrops/General field cropping" (according to the TF14 classification of FADN) in the region of Karditsa, 2012

Farm size class (ha)	Characterization	Sample farms	FADN
		Farms (%)	Farms (%)
<10	Very Small	37.46	36.28
10-<30	Small	43.75	53.68
30-<50	Medium	12.5	7.94
50-<100	Large	6.25	2.23
≥100	Very Large	-	-

Notes: The determination and characterization of farm size classes is based on Happe *et al.* (2008), and Huettel & Margarian (2009).
Source: Authors, based on sample data and FADN.

Since field survey through personal interviews is a very costly and slow process (Khanal and Omobitan, 2020), collecting data on an annual basis during the interim years of the period 2012-19 was not possible. This fact created the need to fill in the gaps in the time series of the model parameters. Model parameters were estimated for the period considered utilizing the available national times series setting 2012 as the base year. In addition, the available national times series provided the necessary input data for the ARIMA and linear trend models. The national time series are provided by various exogenous data sources[14]. However, it should be noted that for the activities cultivated under contract farming, we assume that prices remain constant at the base year levels for all simulation periods since sample farmers stated that they remained almost invariable for the period 2012-19.

2.5. Policy experiments

Simulation experiments for two alternative policy scenarios were performed. Additionally, we ran simulations for a combined (policy and geopolitical) scenario.

<u>Business as usual (BAU) scenario:</u> We assume that the baseline policy implemented from 2015 to 2022 (2013 CAP reform), will continue to be implemented until 2026. Expressly, we assume that decoupled and coupled payments will remain stable at the levels of 2022, as well as the greening obligations related to crop diversification and the ecological focus area (EFA) to receive decoupled payments (Greek Ministry of Rural Development and Food, 2014).

[13] Using a relatively small sample of farms is not unusual for relevant in-depth analyses in the context of farm-level mathematical programming models (e.g., Iglesias *et al.,* 2003; Viaggi *et al.,* 2010; Viaggi *et al.,* 2011; Djanibekov and Finger, 2018; Lairez *et al.,* 2023).

[14] For more details see the *Part E: Historical dataset and forecasting method of exogenously determined parameters* in the supplementary material.

CAP Post-2020 scenario: According to the Greek Strategic Plan proposal for the CAP 2023-27 (Greek Ministry of Rural Development and Food, 2022), the provisions of the CAP Post-2020 reform scenario apply from the year 2023. In the period 2023-26, internal full convergence will be implemented, i.e., the convergence of the value of payment entitlements at a single unit value (flat rate) at the agronomic region level[15](Greek Ministry of Rural Development and Food, 2022). The value of the payment entitlements in the agronomic region of interest, i.e., arable land, will equal 231.4 EUR/ha in 2026. Farms with available arable land of more than 10 hectares are obligated to apply ecological focus area to 4% of it to receive decoupled payments. It should be mentioned that is maintained the measure of diversification of crops for farms with available arable land larger than 10 hectares to receive decoupled payments, valid from 2015 in the context of the 2013 CAP reform. The proposed strategic plan also includes implementing the redistributive payment mechanism during the period 2023-27. Specifically, relatively small farms with available arable land between 2 and 11 hectares, will be considered beneficiaries of the redistributive support, equal to 117 EUR/ha.

In addition, the proposed national strategic plan aims to improve the environmental performance of arable crop farms by adopting voluntary environmental measures referred to as eco-schemes. One of the main measures is considered to be the extension of the application of the ecological focus areas, where farms with available arable land less than 10 hectares can apply ecological focus area to 5% of it, receiving an average eco-scheme payment equal to 200 EUR/ha. Additionally, farms with available arable land more than 10 hectares can apply ecological focus area to 10% of it receiving an average eco-scheme payment equal to 240 EUR/ha (Greek Ministry of Rural Development and Food, 2022).

CAP Post-2020 & Long War of Attrition (LWA) scenario: This combined scenario is a variant of the previous one, integrating the serious possibility that Russia's invasion of Ukraine will become a long war of attrition (Modern War Institute, 2022) with severe and prolonged consequences for the global economy.

Given the emerging upward trends in grain prices (maize, wheat) due to Russia's invasion of Ukraine and uncertainty over the future of the Black Sea Grain Initiative (European Council, 2022), we assume a high grain price scenario for the period 2022-26 combined with the provisions of CAP Post-2020 reform scenario described above. In particular, we consider the upper bound of the prediction intervals for durum wheat and maize prices provided by ARIMA model forecasts.

[15] Since the 2013 CAP reform, the process of payments convergence has started in the form of partial convergence.

3. RESULTS

3.1. Validation of the simulation model

The validation results presented in Table 2 confirm the ability of both models to reproduce the evolution of activities allocation to at least a satisfactory level (Percentage Absolute Deviation (PAD index): 8.05-29.6%; Finger–Kreinin (FK) similarity index (FK index): 85.2-96%) according to the relevant literature[16] (e.g., Gómez-Limón *et al.*, 2016), providing a good representation of reality. However, the NV&QR model is significantly superior in the base year.

Validations of the models on their ability to reproduce the actual farm size distribution and the actual number of farms are carried out for the year 2019 as it is the only year of observations available after the base year. In this context, both models simulate to at least a satisfactory level the evolution of farm size distributions (PAD index = 17.58%; FK index = 91.2%) and the number of viable farms (Absolute Percentage Error (APE) = 6.4%)[17] without revealing any difference in terms of forecasting accuracy (see also Table 3). As can be seen, both models slightly overestimate the rate of structural change, that is, the percentage change in the number of surviving farms, in the reference period (Simulated: 39.6% (from 48 to 29 farms) vs. Actual: 35.42% (from 48 to 31 farms)). Although both models are characterized by satisfactory forecasting accuracy, we will choose the best fitting model, the NV&QR Model, to assess the impact of policy and combined scenarios on structural change and land use change.

3.2. Forecasting models accuracy

After estimating the best-fitting ARIMA models for the exogenously determined parameters of interest (i.e.,

[16] Although there is no commonly accepted threshold in the international literature for these two indicators, Gómez-Limón *et al.* (2016) consider the values of PAD index = 33.2% and FK index = 83.4% satisfactory.

[17] Although there is no commonly accepted threshold for MAPE (Mean Absolute Percentage Error) in the international literature; however, some authors consider that a model is characterized by good forecasting accuracy (or goodness-of-fit) when MAPE (APE, in our case, due to a single year of observations available after the base year) does not exceed 20%, whereas when it does not exceed 10%, the forecasting accuracy is characterized as high or perfect (e.g., Quartey-Papafio 2021).

Table 2. Actual and simulated land allocation.

Activity	Actual 2012 Area (ha)	NV&QR Model 2012 Area (ha)	QR Model 2012 Area (ha)	Actual 2019 Area (ha)	NV&QR Model 2019 Area (ha)	QR Model 2019 Area (ha)
Cotton	467.9	454.36	365.48	305.1	296.52	266.15
Tobacco (Virginia)	58.6	83.74	94.02	82	109.15	105.56
Maize	27	11.82	11.82	27.15	14.83	48.95
Processing Tomato	31	23.11	23.11	52	55.57	55.53
Processing Pepper	30	25.66	37.06	68.8	70.95	71.33
Alfalfa (hay)	66.5	63.75	68.43	96.6	101.7	10
Alfalfa(seed production)	-	-	-	58.5	45.47	45.47
Durum Wheat	139	163.13	217.85	236.75	236.95	236.88
Set-aside	27.2	21.62	29.41	17.9	13.81	14.89
Total area (ha)	847.2	847.2	847.2	944.8	944.8	944.8
PAD index (%)	-	11.6	29.6	-	8.05	11.7
FK index (%)	-	94.2	85.2	-	96	94.15

Note: NQR model: Naïve and Quasi-Rational expectations Model; QR model: Quasi-Rational expectations Model
Source: Authors, based on sample data.

Table 3. Actual and simulated farm size distribution and number of farms.

Farm size class (ha)	Actual 2019 Farms (%)	Actual 2019 Farms (%)	NV&QR Model 2019 Farms (%)	NV&QR Model 2019 Farms (%)	QR Model 2019 Farms (%)	QR Model 2019 Farms (%)
<10	22.57	7	13.79	4	13.79	4
10-<30	45.15	14	48.27	14	48.27	14
30-<50	12.9	4	13.79	4	13.79	4
50-<100	16.12	5	17.24	5	17.24	5
≥100	3.22	1	6.89	2	6.89	2
Total number of sample farms (N)	-	31	-	29	-	29
APE (%)	-	-	-	6.4	-	6.4
PAD index (%)	-	-	17.58	-	17.58	-
FK index (%)	-	-	91.2	-	91.2	-

Note: NV&QR model: Naïve and Quasi-Rational expectations Model; QR model: Quasi-Rational expectations Model. The determination of farm size classes is based on Happe *et al.* (2008), and Huettel & Margarian (2009).
Source: Authors, based on sample data.

costs, prices, crop yields, total arable land, total circulating capital, and interest rate), we measured their forecasting accuracy by in-sample forecasts according to the MAPE measure. Most ARIMA models are characterized by high forecasting accuracy; the MAPE does not exceed 10%, while the other models are characterized by good forecasting accuracy[18] (e.g., Quartey-Papafio *et al*., 2021). A high forecasting accuracy also characterizes the utilized linear trend model for the rural households' living expenditure index *(LEI)*.

3.3. Simulated structural change

Figure 2 depicts the evolution of the number of viable/surviving farms and the average farm size over time[19]. The simulated number of farms decreases by

[18] For more details, see the *Part F: ARIMA and linear trend models estimations* in the supplementary material.

[19] The initial number of farms is normalized to 100.

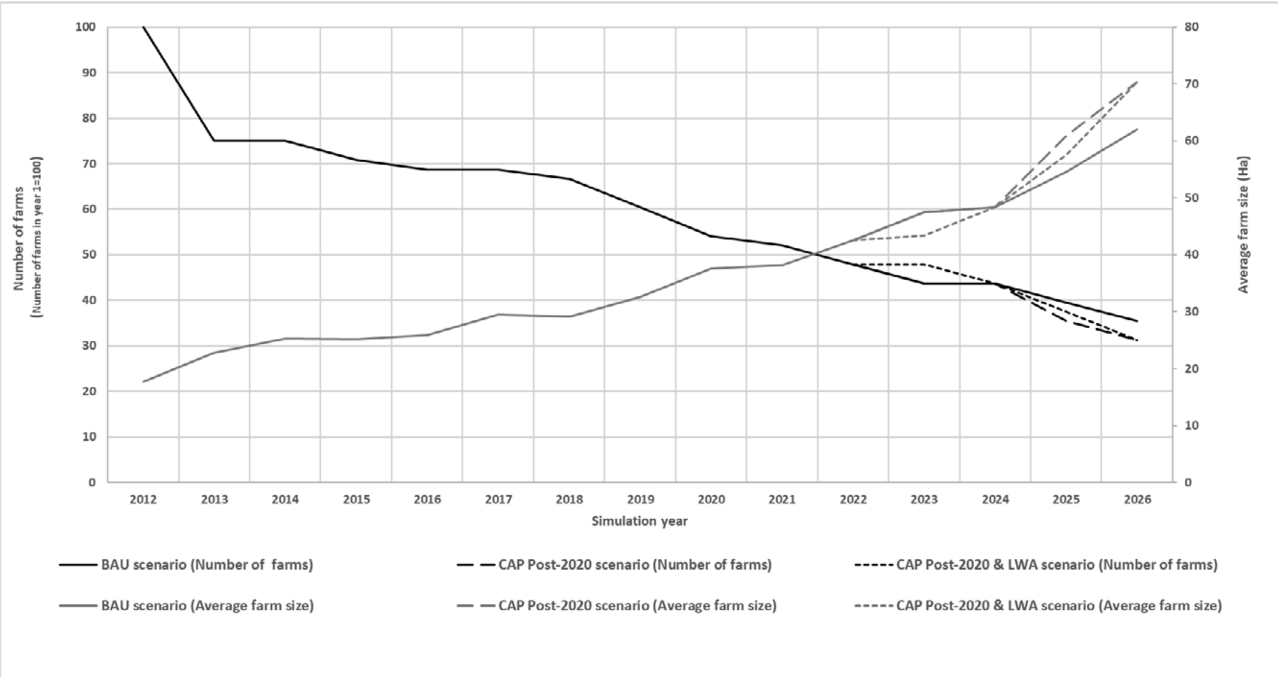


Figure 2. Simulated number of farms and average farm size by scenario. *Note:* The provisions of the CAP Post-2020 scenario apply from the year 2023. *Source:* Authors, based on sample data.

39.6% for the reference period 2012-19, while the average farm size increases from 17.65 hectares to 32.58 hectares. As we can see, the process of structural change continues after 2019, when the simulation model forecasts a further reduction in the number of viable farms. According to the BAU scenario, for the period 2019-2026, a decrease in the number of farms by 41.4% and an increase in the average farm size from 32.58 hectares to 62.76 hectares are foreseen. For the CAP Post-2020 reform and CAP Post-2020 & LWA scenarios, the simulation model forecasts a comparatively higher rate of structural change. Specifically, for 2019-26 the number of farms decreases by 48.3%, and the average farm size increases from 32.58 hectares to 70.35 hectares. This simulation result almost coincides with the estimates of some farmers in the sample, who consider that by 2026 the studied farms will be reduced by 50% compared to 2019 (when the most recent survey was conducted). Therefore, regardless of the scenario, the model predicts an increase in the rate of structural change compared to that simulated in the period 2012-19.

Examining the dynamics of structural change from the perspective of farm size distribution, we observe a decrease over time in the percentage of very small (farm size class: <10 hectares) and small farms (farm size class: 10-< 30 ha) (see Figure 3). A decline over time is also foreseen for the share of the farmland area of these farms. On the contrary, for the large (farm size class: 50-<100 ha), and very large farms (farm size class ≥100 ha), an increase in the shares of the farms and farmland area is foreseen. Medium-sized farms (farm size class: 30-<50 ha) show a weak upward trend in the share of farms and a weak downward trend in the share of farmland area.

A very high concentration of farmland in very large farms (farm size class ≥100 ha) is foreseen since, according to all examined scenarios, almost only 10% of farms will concentrate about 50% of the total farmland area. It is worth noting that the CAP Post-2020 and CAP Post-2020 & LWA scenarios (although they do not show substantial differences in the rate of structural change), compared to the BAU scenario, negatively impact the viability of small and very small farms. The above findings are in line with the estimates of the sample farmers who claim that in the region of Karditsa will gradually prevail, arable crop farms with a size of at least 30 hectares since such a farm size can ensure a decent standard of living for the rural household as well as growth prospects.

Regarding the evolution of farm profitability, the simulation results depicted in Figure 4 reveal a gradual increase in the average Farm Net Profit after Tax (FNPAT) for all scenarios. This development can be considered reasonable since, through the structural change, the comparatively less profitable farms exit and release resources such

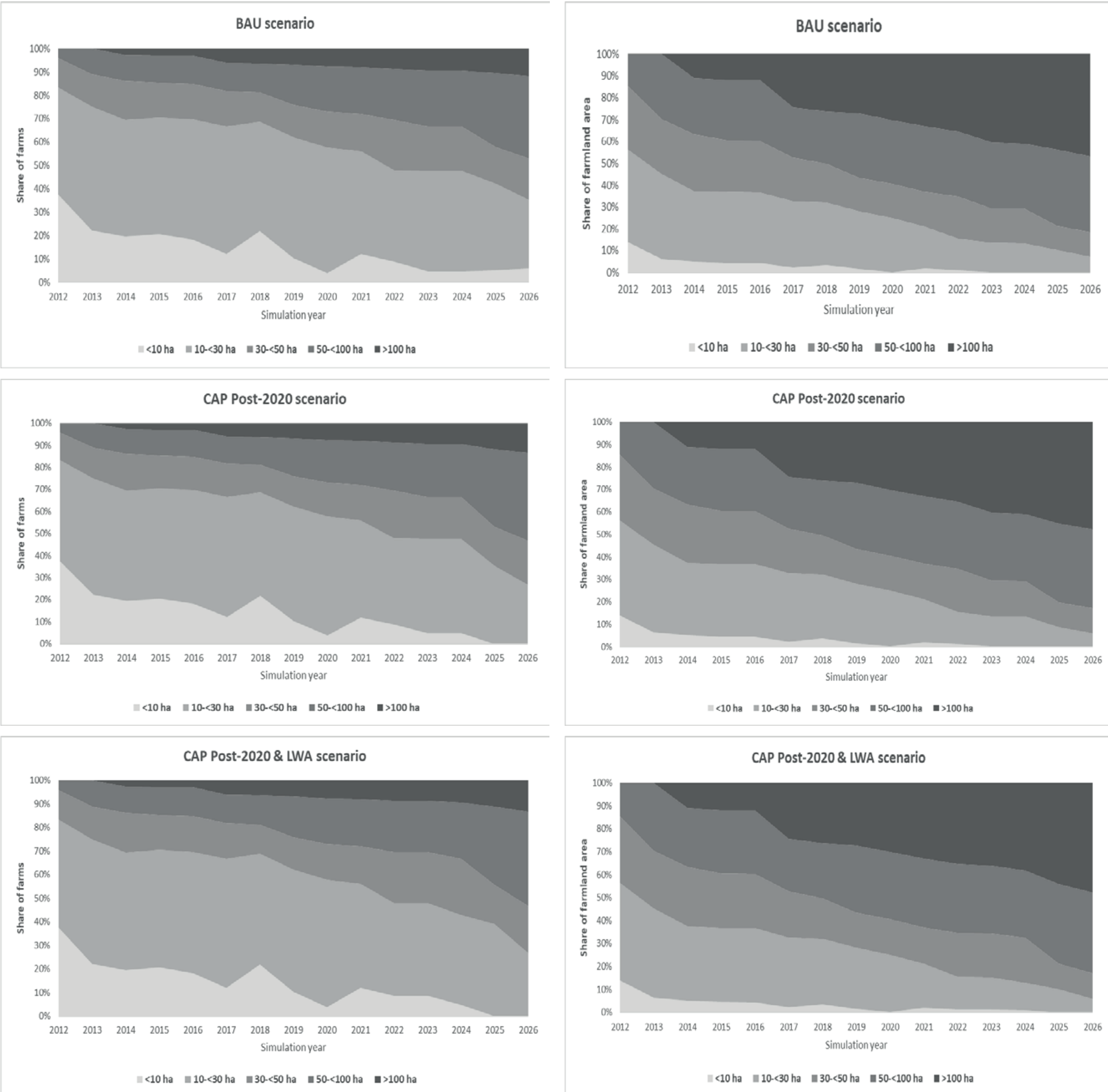


Figure 3. Share of farms and farmland area by farm size classes and scenario. *Note:* The provisions of the CAP Post-2020 scenario apply from the year 2023. *Source:* Authors, based on sample data.

as land, which the comparatively more profitable farms acquire. In this framework, surviving and consequently growing farms tend to make more efficient use of available resources, allocating them to comparatively more profitable productive activities, as we will see below.

Although there are no significant differences between the scenarios, in the last two years of the simulation (2025-26), a clear distinction is simulated in favor of the CAP Post-2020 and CAP Post-2020 & LWA scenarios, which is probably due to the higher rate of structural change. Further analyzing the evolution of average profitability by farm size class, the simulation results provided in Table 4 show an increase in profitability for farms with a size of at least 30 hectares, explaining the claim of the sample farmers that shortly the arable crop farms with a size of at least 30 hectares will be able to remain in the production system. Even more, implementing the CAP Post-2020 and CAP Post-2020 & LWA

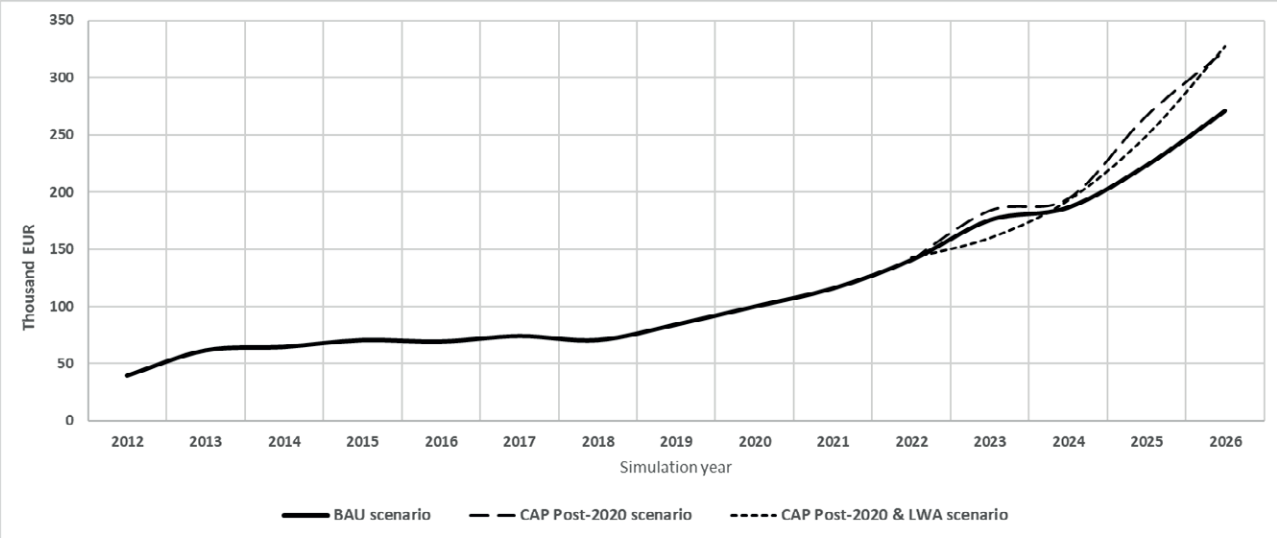


Figure 4. Evolution of simulated average Farm Net Profit after Tax (FNPAT) by scenario. *Note:* The provisions of the CAP Post-2020 scenario apply from the year 2023. *Source:* Authors, based on sample data.

Table 4. Simulated mean Farm Net Profit after Tax (FNPAT) in EUR by farm size classes (2012-2026).

Farm size class in ha (Characterization)	2012	2019	2026 (BAU scenario)	2026 (CAP Post-2020 scenario)	2026 (CAP Post-2020 & LWA scenario)
<10 (Very Small)	18,156	13,706	12,196	-	-
10-<30 (Small)	41,931	26,707	25,989	24,987	25,010
30-<50 (Medium)	59,829	68,250	98,608	104,309	107,964
50-<100 (Large)	110,370	69,918	115,803	122,013	126,539
≥100 (Very Large)	-	695,181	1.738,668	1.855,216	1.865,563
Aggregate	39,526	84,644	271,183	323,692	327,622

Note: The determination and characterization of farm size classes is based on Happe *et al.* (2008), and Huettel & Margarian (2009).
Source: Authors, based on sample data.

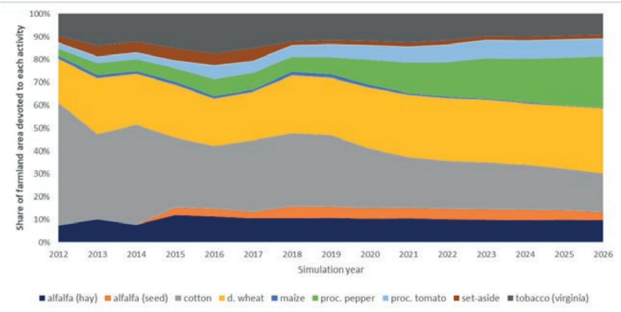
scenarios is projected to enhance the profitability of these farms further. It is also worth noting that between these two scenarios, no substantial differences can be found in the evolution of profitability.

3.4. Simulated land use change

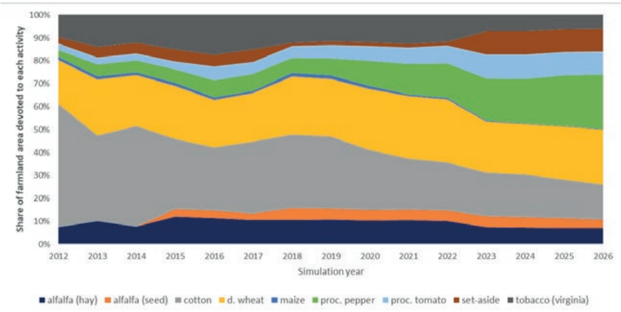
As regards the simulated land use change dynamics illustrated in Figure 5, the main change can be seen in the progressive expansion of the processing vegetable area and especially for processing pepper. This finding thoroughly verifies farmers' expectations for the further expansion of these crops. In particular, the processing pepper farmers of the sample state that their export activity will increase significantly in the coming years since they receive more than double commodity prices compared to domestic prices. Processing tomato farmers aspire to a significant expansion of their productive activity due to the positive growth prospects of the local tomato processing industry, as they also consider the role of the local group of processing tomato farmers to be particularly beneficial. An increasing trend in the processing vegetable area is simulated for both scenarios. Still, a more significant upward trend is simulated for the CAP Post-2020 reform scenario, possibly due to the increased rate of structural change leading to more efficient use of resources, in the sense that surviving farms tend to allocate farmland area to comparatively more profitable activities[20].

Conversely, we simulated a significant gradual decrease in the cotton and tobacco areas. In fact, for the CAP Post-2020 reform scenario, we observe a fur-

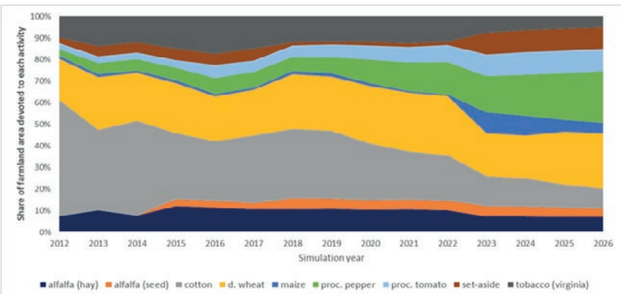
[20] Details are provided in Table A1 in the Appendix.



(a) BAU scenario



(b) CAP Post-2020 scenario



(c) CAP Post-2020 & LWA scenario

Figure 5. Simulated arable land allocation by scenario. *Note:* The provisions of the CAP Post-2020 reform scenario apply from the year 2023. *Source:* Authors, based on sample data.

ther reduction of the cotton and tobacco areas. Durum wheat area increases significantly over time for the BAU scenario, while for the CAP Post-2020 reform scenario, a decrease after 2022 is foreseen due to the set-aside applied by the vast majority of sample farms (more than 90%) in the context of eco-scheme payments. Based on this finding, we conclude that farms have a strong incentive to adopt eco-schemes since the majority exceed 10 hectares and, therefore, would be required to implement set-aside on 4% of arable land without extra payment. In the CAP Post-2020 & LWA scenario, an expected increase is simulated for the area of the grain (durum wheat, maize), especially maize, due to the possible increase and maintenance of farm gate prices at high levels due to the Ukrainian crisis. Accordingly, a further reduction in cotton and tobacco areas is simulated.

4. DISCUSSION AND CONCLUSIONS

Dynamic modeling methodologies are deemed crucial for comprehending the evolution of economic agents' behaviors in response to shifts in the economic environment or policies (Gardebroek and Oude Lansink, 2008). Considering the volatile economic environment in which farms operate due to recent international developments, such assessments gain significant weight when using simulation models like the one we propose herein since they can support policy analysts in formulating and specifying the appropriate policy measures.

In this context, this study described the conceptual framework of a newly developed farm-level recursive linear programming model primarily aiming at simulating the impact of policy reform on structural change in the arable production system of the region of Karditsa (NUTS-3 level), one of the central growing regions of arable crops in Greece. While managing to capture mainly endogenously the dynamics of structural change adaptation, the proposed simulation model can simultaneously be characterized by a comparatively low level of modeling complexity compared to other simulation models, such as agent-based models.

From a general perspective, this paper seeks to contribute to the debate on dynamic assessments of the multidimensional effects in the context of the CAP Post-2020 reform while considering recent geopolitical developments in the context of the Ukrainian crisis.

Validation results demonstrate satisfactory performance of the simulation model in reproducing past changes. Therefore, we can use the model to assess the effects of various scenarios on the agricultural production system. By carrying out policy experiments for two different policy scenarios and a combined scenario (policy and geopolitical) we estimated an increased rate of structural change compared to the reference period (2012-19), and especially for the CAP Post-2020 and CAP Post-2020 & Long War of Attrition (LWA) scenarios. The proposed model simulated an evident gradual concentration of farmland in relatively large farms (farm size ≥50 ha), accompanied by a decrease in the number of relatively small farms (farm size < 30 ha), making these findings consistent with the results obtained from simulation models (e.g., Happe *et al.*, 2008; Bert *et al.*, 2011; Donati *et al.,* 2024) and other dynamic modeling approaches (Herrera *et al.*, 2022; Schuh *et al.*, 2022).

Regardless of the examined scenario, the simulated average farm profitability shows a gradual increase, which is partly explained by the fact that relatively more profitable farms remain in the production system confirming previous findings obtained from simulation models (Happe *et al*., 2008; Bert *et al*., 2011) and other dynamic modeling approaches (Herrera *et al*., 2022; Schuh *et al*., 2022). Obviously, the surviving farms which achieve growth in equity tend to allocate their growing resources (such as farmland, circulating capital and fixed assets) more efficiently, i.e., to relatively more profitable productive activities (in our case, processing vegetables), further enhancing average farm profitability (Bert *et al*., 2011). However, a downward trend is simulated for the average profitability of relatively small farms (farm size < 30 ha).

In terms of land use change dynamics, regardless of the scenario, our model simulated an increasing trend of the land allocated to food crops such as processing vegetables and a simultaneous decreasing trend of the farmland allocated to industrial crops such as cotton and tobacco. The rationale explains this result discussed earlier, namely that surviving farms tend to expand productive activities with comparatively higher profitability, a finding that is also consistent with findings obtained from a simulation model applied to the agricultural system of the Argentine Pampas (Bert *et al*., 2011). Additionally, Bert *et al.* (2011) consider that this behavior of the farms is interpreted by their survival strategy. Considering the above, it could be said that a correlation of land use change with structural change emerges, in the sense that the viability of farms is strongly dependent on the land use chosen (Bert *et al*., 2011) and is expressed through their survival strategy to allocate their farmland area and capital to the most profitable cropping activity gradually.

Focusing on the paper's main finding – namely, the agricultural production concentration in relatively large farms (farm size ≥ 50 ha) – it is found that this has some significant policy implications. In particular, an intensifying continuation of pressures towards fewer but larger farms (i.e., an increasing rate of structural change) could lead to a breakdown of social cohesion, a prerequisite for addressing rural communities' challenges (Knutson et al., 1986). From this perspective, appropriate policy measures could focus, for example, on the enhancement of farmers' market access since small and medium-sized farms have issues accessing markets, achieving a proper share in the EU food chain, including value-added processing, and maintaining bargaining power (Schuh et al., 2022). In this vein, cooperatives are one way to improve farmers' access to markets and strengthen bargaining power, primarily through vertical integration, which can often play a significant role in increasing the economic benefits of farmers (Schuh et al., 2022). Therefore, it is essential to prioritize examining exemplary cooperative practices and supporting the adoption of similar operational models through policy actions (Schuh et al., 2022).

Even if essential insights were gained, this modeling exercise is characterized by several caveats, where we will focus on the main ones. First, although the proposed recursive linear programming model utilizes input data of representative individual real-world farms, effectively capturing the heterogeneity in farm structure and replicating varied farm behavior, it does not explicitly capture the interaction between individual farms in the sense of not incorporating an endogenous price formation mechanism for the market of locally available resource like land (Berger, 2001; Troost and Berger, 2015; Kremmydas, 2019). Additionally, it does not fully consider spatial relationships, overlooking the imperfect land allocation among farms by disregarding internal transport costs and the physical immobility of land (Berger, 2001; Troost and Berger, 2015; Kremmydas, 2019). In this context, the determination of the regional level at which farms can be regarded as competitors for the farmland offered is left to the subjectivity of the modeler. Although administrative units are often used as a realistic approach (in our case, the regional unit of Karditsa (NUTS-3 level)), ideally, the regional level could be defined by the viewpoint of active farmers who operate the land (Plogmann *et al.,* 2022). Consequently, these weaknesses of the proposed model limit its ability to fully capture interactions between farms and spatial dynamics, limiting its explanatory power in policy analysis. Especially, the model cannot provide detailed insights into the impacts of policy scenarios/options on farm structure due to their effects on local resource markets (Kremmydas, 2019). Furthermore, the incomplete incorporation of spatial dynamics curtails the model's explanatory capacity regarding policy effects on the environment, where spatial aspects hold considerable importance (Kremmydas, 2019).

Second, although the proposed simulation model considers the differences in profits among neighboring farms cultivating different farmland areas in the base year, providing a reasonable representation of the farm growth process, it does not consider economies of scale in an intertemporal context. The capture of economies of scale at a longitudinal level by the proposed model was not carried out to maintain its computational complexity. However, a more detailed model that considers this dimension could enhance the representation of farm heterogeneity and, consequently, policy representation towards a more realistic framework. Therefore, future developments of the proposed simulation model could incorporate cost reductions as a function of farm expansion and/or technological progress (Happe *et al.,* 2008; Bert *et al.,* 2011).

Third, due to the lack of farm-level data for the interim years of the reference period, we were forced to use the available national-level time series for parameters of interest to bridge the time series data gap at the farm level. However, various authors have highlighted and documented the statistical differences between regional/national and farm-level time series data associated with underestimation of variability (e.g., Debrah and Hall, 1989). In particular, aggregated data tends to underestimate the variability of parameters such as prices and yields at the farm level (Debrah and Hall, 1989), which may lead to a less adequate representation of reality regarding farms' behavior and adaptation.

This modeling exercise has identified many avenues for further research, highlighting only a few. First, the geographical and sectoral coverage should be expanded. Second, it is of particular importance to run simulations using alternative allocation/reallocation mechanisms of resources, such as relative shadow values of resources. Third, an interesting avenue for further research is to conduct an environmental impact assessment by utilizing mean- and effect-based indicators (Lebacq *et al.,* 2013; Donati *et al.,* 2024) but also to incorporate social indicators, allowing us to assess sustainability performance at the farm level (e.g., Lairez *et al.,* 2023). Finally, further research could be conducted on the investigation of farm viability using alternative monetary and socio-economic viability criteria.

To conclude, although our modeling results may not represent all Greek regions, they may be particularly informative for trends that may emerge due to structural and land-use changes in rural areas with similar arable production systems, not only in the country but also in the wider Mediterranean area.

ACKNOWLEDGEMENTS

This research is co-financed by Greece and the European Union (European Social Fund-ESF) through the Operational Programme "Human Resources Development, Education and Lifelong Learning" in the context of the project "Strengthening Human Resources Research Potential via Doctorate Research" (MIS-5000432), implemented by the State Scholarships Foundation (IKY).

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APPENDIX

Table A1. Simulated average gross margin for each cropping activity (EUR/ha).

	2012	2019
Cotton	1,176	1,549
Tobacco (Virginia)	4,750	4,757
Maize	2,300	1,409
Processing Tomato	6,370	4,863
Processing Pepper	17,331	27,800
Alfalfa (hay)	807.3	817.6
Alfalfa (seed production)	-	509.5
Durum Wheat	258.2	207.3

Source: Authors, based on sample data.

SUPPLEMENTARY MATERIAL TO "SIMULATING FARM STRUCTURAL CHANGE DYNAMICS IN THESSALY (GREECE) USING A RECURSIVE PROGRAMMING MODEL"

Part A: Conceptual framework of ARIMA modeling

The Box-Jenkins method for Autoregressive Integrated Moving Average (ARIMA) models is considered one of the most efficient time series forecasting methods utilizing almost any set of data (Christodoulos et al., 2010). In this framework, other authors consider that ARIMA models have been remarkably successful with an excellent performance on small data sets (Garnier, n.d.). According to various modelers, ARIMA models can provide acceptable results when at least 16-time series data points are available (Gottardi & Scarso, 1994; Christodoulos et al., 2010).

An important class of stochastic models for describing time series are called stationary models or Autoregressive-Moving Average (ARMA) models varying about a fixed constant mean level and with constant variance (Box et al., 2016).

An ARMA (p,q) model is formulated as follows:

$$Y_t = \sum_{i=1}^{p}\varphi_i Y_{t\text{-i}} + \varepsilon_t - \sum_{j=1}^{q}\theta_j\varepsilon_{t\text{-}j}, \tag{A1}$$

where $\varphi_1 ,\ldots, \varphi_p$ are the autoregressive (AR) parameters to be estimated, $\theta_1 ,\ldots,\theta_q$ are the moving average (MA) parameters to be estimated, and $\varepsilon_1\ldots\varepsilon_t$ are a series of unknown random "shocks" (or residuals) that are assumed to follow a normal distribution (Pardoe, n.d.).

The model can be simplified by introducing the Box-Jenkins backward shift operator[21] where $B^iY_t = Y_{t\text{-}i}$ and $B^j\varepsilon_t = \varepsilon_{t\text{-}j}$; $Y_1,\ldots,Y_t$ is any time series ; $p<t$ and $q<t$ (Pardoe, n.d.).

Substituting backward shift operators in equation (A1), we obtain the following form:

$$(1 - \textstyle\sum_{i=1}^{p}\varphi_i B^i)Y_t = (1 - \sum_{j=1}^{q}\theta_j B^j)\varepsilon_t \tag{A2}$$

Which is often reduced further to (Pardoe, n.d.):

$$\varphi_p(B)Y_t = \theta_q(B)\varepsilon_t \tag{A3}$$

Many series encountered in industry or business reveal nonstationary behavior [22]and do not vary about a fixed mean, showing a stochastic trend (Box et al., 2016). We should therefore convert a non-stationary time series to a stationary one by differencing the ARMA (p,q) model.

Then the ARMA (p,q) model can be extended and written using differences $\Delta Y_t = (1 - B)^d Y_t = \nabla^d Y_t$ as follows:

$$\varphi_p(B)(1 - \mathrm{B})^d Y_t = \theta_q(B)\varepsilon_t \tag{A4}$$

where d is the order of differencing. Replacing in the ARMA model with the differences above, we obtain the formal ARIMA p,d,q) model (Pardoe, n.d.).

To detect non-stationarities, we utilize one of the most well-known tests, which corresponds to the augmented Dickey-Fuller (ADF) test (Asteriou & Hall, 2007; Mahan et al., 2015; Box et al., 2016). The identification of possible model orders (p,q) is approached through the utilization of Autocorrelation function (ACF) and Partial Autocorrelation function (PACF) plots (Mahan et al., 2015; Box et al., 2016; Garnier, n.d.) while trying to keep the model orders at low levels (≤ 2) for most of the estimated models (Gottardi & Scarso, 1994). After estimating several models, we test whether the condition of invertibility (Asteriou & Hall, 2007; Garnier, n.d.) and statistical significance of the AR and MA parts of the model are satisfied (Mossad & Alazba, 2015). The estimated models are then compared according to the Akaike information criterion (AIC) by selecting the model with the lowest value (Mahan et al., 2015; Box et al., 2016; Garnier, n.d.).

The diagnostic check of the model is then performed, which is applied to residuals to detect whether they exhibit

[21] The Backward shift operator is a useful notational device expressing the length of previous data the model uses to provide forecasts (Christodoulos et al., 2010).

[22] ARIMA modeling requires that the time series be stationary (Schaffer et al., 2021). A stationary series is characterized by three properties: a constant mean, constant variance, and constant covariance that depends only on the time intervals (Schaffer et al., 2021). Time series with trends or changing variance is non-stationary.

autocorrelation, utilizing the Breusch-Godfrey Lagrange Multiplier (LM) test (Mahan et al., 2015; Weyerstrass, 2016; Ayele et al., 2017). The null hypothesis of the LM test is that there is no autocorrelation in the residuals series up to the pre-determined lag order (p=2 in our analysis) at the 5% level of significance (Weyerstrass, 2016; Ayele et al., 2017). Regarding the measurement of the forecasting accuracy of ARIMA models, there is no universally preferred measure; however, according to various modelers (Gottardi and Scarso, 1994; Christodoulos et al., 2010), particular emphasis is given to the measure of Mean Absolute Percentage Error (MAPE). At this point, we would like to point out that there is no commonly accepted threshold for MAPE in the international literature; however, some authors consider that a forecasting model is characterized by good forecasting accuracy (or goodness-of-fit) when MAPE does not exceed 20%, whereas when it does not exceed 10%, the forecasting accuracy is characterized as high or perfect (e.g., Quartey-Papafio et al., 2021). Estimates and statistical tests of ARIMA models were performed using EViews statistical package.

Part A: References

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Part B: Structure of the model's objective function and constraints

The following describes the objective function's structure and the constraints typical to each sub-model. The objective function of the expected gross profit of the farm f in year t is defined as follows:

$$Max\ E\{\Pi_{f,t}\} = \sum_{j=1}^{n} X^{T}_{f,j,t}\ [E\{p_{f,j,t}\}\ E\{y_{f,j,t}\} - vc_{f,j,t} + ls_{j,t} + e_{f,t}ecop1_{f,j,t} + \varepsilon_{f,t}ecop2_{f,j,t}] + DP_{f,t}DL_{f,t} + b_{f,t}NP_{f,t}NL_{f,t} + \beta_{f,t}\ OP_{f,t}OL_{f,t} + r_{f,t}RP_{f,t}AL_{f,t} \quad \text{(B1)}$$

Subject to:

Arable land constraint

$$\sum_{j=1}^{n} X_{f,j,t} = AL_{f,t} \quad ,for\ t = 1,\ldots,T,\ \ j \in J \quad \text{(B2)}$$

Irrigated land constraint

$$\sum_{wj=1}^{n} X_{f,wj,t} \leq IL_{f,t} \quad ,for\ t = 1,\ldots,T,\ \ wj \in WJ,\ WJ \subseteq J \quad \text{(B3)}$$

Circulating capital constraint

$$\sum_{j=1}^{n} X_{f,j,t}vc_{f,j,t} \leq CRC_{f,t} \quad ,for\ t = 1,\ldots,T,\ \ j \in J \quad \text{(B4)}$$

$$X_{f,j,t} \geq 0 \quad ,for\ t = 1,\ldots,T \quad \text{(B5)}$$

where $E\{\ \}$ denotes the expectation operator; $E\{\Pi_{f,t}\}$ denotes the expected gross profit of the farm f which is maximized in year t ; $X_{f,j,t}$ is the $J\ x\ 1$ vector of decision variables and denotes the level of cropping activity j (hectares for crops) of the farm f in year t; $E\{p_{f,j,t}\}$ denotes the $J\ x\ J$ diagonal matrix of expected price of the output from cropping activity j in EUR/kg of the farm f in year t; $E\{y_{f,j,t}\}$ denotes the $J\ x\ 1$ vector of expected yield of cropping activity j in kg/ha of the farm f in year t; $vc_{f,j,t}$ is the $J\ x\ 1$ vector of variable cost of cropping activity j in EUR/ha of the farm f in year t[23], $ls_{i,t}$ is the $J\ x\ 1$ vector of land subsidy of cropping activity j in EUR/ha in year t.

$ecop1_{j,t}$ is the $J\ x\ 1$ vector of potential eco-scheme payment of cropping activity j in EUR/ha of the farm f with a size of less than or equal to 10 hectares in year t under the CAP Post-2020 reform; $ecop1_{f,j,t}$ is the $J\ x\ 1$ vector of potential eco-scheme payment of cropping activity j in EUR/ha in year t of the farm f with a size greater than 10 hectares in year t under the CAP Post-2020 reform[24]; $e_{f,t}$ denotes the binary variable that corresponds to the farm f in year t and is equal to 1 when the farm adopts the eco-schemes[25] and the size of the farm does not exceed 10 hectares, while it gets the value 0 when the farm does not adopt the eco-schemes or when it exceeds 10 hectares; $\varepsilon_{f,t}$ denotes the binary variable that corresponds to the farm f in year t and is equal to 1 when the farm adopts the eco-schemes and the size of the farm exceeds 10 hectares , while it gets the value 0 when the farm does not adopt the eco-schemes or when it does not exceed 10 hectares (obligations concerning eco-schemes adoption are explained in constraints (B9)-(B12)).

$DP_{f,t}$ is the entitlement value of decoupled payments in EUR/ha of the farm f in year t; $DL_{f,t}$ is the eligible farmland area of decoupled payments in hectares of the farm f in year t; $NP_{f,t}$ is the agri-environmental payment in EUR/ha of the nitrate pollution reduction programme of the farm f in year t; $NL_{f,t}$ is the farmland area in hectares included in the nitrate pollution reduction programme of the farm f in year t; $OP_{f,t}$ is the agri-environmental payment in EUR/ha of the organic farming programme of the farm f in year t; $OL_{f,t}$ is the farmland area in hectares included in the organic farming program of the farm f in year t; $b_{f,t}$ denotes the binary variable that corresponds to the farm f in year t, and is equal to 0 when the farm does not participate in the nitrate pollution reduction programme, while it gets the value 1 when it participates[26]; $ß_{f,t}$ denotes the binary variable that corresponds to the farm f in year t and is equal to 0 when the farm does not participate in the organic farming programme, while it gets the value 1 when it participates[27]. In addition, when the binary variable $b_{f,t}$ takes the value 1, the binary value $ß_{f,t}$ will take the value 0 and vice versa, indicating that a farm cannot simultaneously participate in the two different agri-environmental measures of pillar B of the Common Agricultural Policy[28] (obligations concerning agri-environmental measures are explained in constraints (B13)-(B16)).

$r_{f,t}$ denotes the binary variable that corresponds to the farm f in year t, and is equal to 0 when the size of the farm exceeds 11 hectares or when it is less than 2 hectares ; $RP_{f,t}$ is the redistributive payment in EUR/ha of the farm f in year t under the CAP Post-2020 reform; $AL_{f,t}$ is the available arable land in hectares of the farm f in year t; J is the set of potential activities[29]; $X_{f,wj,t}$ is the level of irrigated cropping activity wj in hectares of the farm f in year t; WJ is the set of potential irrigated activities[30] $IL_{f,t}$ is the available irrigated land in hectares of the farm f in year t; $CRC_{f,t}$ is the total available circulating capital in EUR of the farm f in year t.

The remaining constraints are specific to the farm and correspond to policy and flexibility constraints:

2013 CAP reform constraints (greening obligations)

Crop diversification obligation for farm f with total available arable land ($AL_{f,t}$) > 10 hectares:

$$X_{f,j,t}\ h_{f,t} \le h_{f,t}\ 0.75\ AL_{f,t} \qquad \text{for } t = 2015,\ldots,T \qquad \text{(B6)}$$

[23] where $vc_{f,j,t} = ic_{f,j,t} + hlc_{f,j,t} + mrc_{f,j,t}$; $ic_{f,j,t}$ denotes the input cost ic of cropping activity j in EUR/ha of the farm f in year t; $hlc_{f,j,t}$ denotes the cost of hired labour hlc of cropping activity j in EUR/ha of the farm f in year t ; $mrc_{f,j,t}$ denotes the machinery rental costs of cropping activity i in EUR/ha of the farm f in year t.

[24] The provisions concerning the voluntary measures of eco-schemes are included in the *Greek Strategic Plan proposal for the CAP 2023-2027* (https://ead.gr/wp-content/uploads/2022/01/cap_sp_proposal_30_12_2021.pdf).

[25] To determine which farms are likely to adopt the eco-schemes (based only on economic criteria) for 2023-26, we estimate the average annual difference in the optimal farm net profit after tax (FNPAT*) for each farm due to adopting the eco-schemes. Therefore, the farm will adopt the eco-schemes if this annual average difference is positive.

[26] A farm's participation in the nitrate pollution reduction programme (Agri-Environmental measure of the Rural Development Programme) is determined through *a priori* information provided from sample farms.

[27] A farm's participation in the organic farming programme (Agri-Environmental measure of the Rural Development Programme) is determined through *a priori* information provided from sample farms.

[28] Of course, it may be true that $b_{f,t} = ß_{f,t} = 0$, which indicates the non-mandatory nature of the specific agri-environmental policy measures.

[29] where *J= {cotton(ct); tobacco(tb); maize(mz); pr. tomato(pt); pr. pepper(pp); alfalfa(aa); alfalfa-seed(aasd); durum wheat(dw); set-aside(st)}*, if $b_{f,t} = 0$ then $st \notin J$

[30] where *WJ = {cotton(ct); tobacco(tb); maize(mz); pr. tomato(pt); pr. pepper(pp); alfalfa(aa); alfalfa-seed (aasd}*

where $h_{f,t}$ denotes the binary variable that corresponds to the farm f in year t, and is equal to 0 when the available arable land ($AL_{f,t}$) ≤ 10 hectares, while it gets the value 1 when the available arable land ($AL_{f,t}$) > 10 hectares.

Ecologic focus area obligation for farms f with total available arable land ($AL_{f,t}$) > 15 hectares:

$$0.7[\![\sum_{lgj=1}^{n} X_{f,lgj,t}]\!] + X_{f,st,t} \geq g_{f,t} 0.05 AL_{f,t} \quad \text{for } t = 2015,\ldots,T,\ lgj \in LGJ,\ LGJ \subseteq J \qquad \text{(B7)}$$

where $X_{f,lgj,t}$ is the level of legume crops (*lgj*) in hectares of the farm f in year t; *LGJ = {alfalfa-hay (aa); alfalfa-seed (aasd)}*; $g_{f,t}$ denotes the binary variable that corresponds to the farm f in year t, and is equal to 0 when the available arable land ($AL_{f,t}$) ≤ 15 hectares, while it gets the value 1 when the available arable land ($AL_{f,t}$) > 15 hectares.

Crop diversification obligation for farm f with total available arable land ($AL_{f,t}$) > 30 hectares:

$$[X_{f,L1\,j,t}{}^{*} + X_{f,L2\,j,t}{}^{*}] u_{f,t} \leq u_{f,t}\, 0.95 AL_{f,t}) \quad \text{for } t = 2015,\ldots,T,\ \ L1\,j \in J,\ L2\,j \in J \qquad \text{(B8)}$$

where $X_{f,L1\,j,t}{}^{*}$ the optimal level of cropping activity in hectares, to which the largest share (*L1 j*) of the available arable land ($AL_{f,t}$) of farm f in year t is allocated; $X_{f,L2\,j,t}{}^{*}$ the optimal level of cropping activity in hectares, to which the second largest share (*L2 j*) of the available arable land ($AL_{f,t}$) of farm f in year t is allocated; $u_{f,t}$ denotes the binary variable that corresponds to the farm f in year t, and is equal to 0 when the available arable land ($AL_{f,t}$) ≤ 30 hectares, while it gets the value 1 when the available arable land ($AL_{f,t}$) > 30 hectares.

CAP Post-2020 reform scenario constraints

Crop diversification obligation for farm f with total available arable land ($AL_{f,t}$) > 10 hectares:

$$X_{f,j,t} \leq h_{f,t}\, 0.75\, AL_{f,t} \qquad \text{for } t = 2023,\ldots,T,\ \ j \in J \qquad \text{(B9)}$$

CAP Post-2020 reform scenario constraints- (adoption of eco-schemes)

Eco-schemes adoption: Extension of EFA application by farm f with total available arable land ($AL_{f,t}$) ≤ 10 hectares:

$$X_{f,st,t} = e_{f,t}\, 0.05\, AL_{f,t} \qquad \text{for } t = 2023,\ldots,T,\ \ st \in J \qquad \text{(B10)}$$

Eco-schemes adoption: Extension of EFA application by farm f with total available arable land ($AL_{f,t}$) > 10 hectares:

$$X_{f,st,t} = \varepsilon_{f,t}\, 0.1\, AL_{f,t} \qquad \text{for } t = 2023,\ldots,T,\ \ st \in J \qquad \text{(B11)}$$

CAP Post-2020 reform scenario constraints- (non-adoption of eco-schemes)

EFA application by farm f with total available arable land ($AL_{f,t}$) > 10 hectares:

$$X_{f,st,t} = \varepsilon_{f,t}\, 0.04\, AL_{f,t} \qquad \text{for } t = 2023,\ldots,T,\ \ st \in J \qquad \text{(B12)}$$

Nitrate pollution reduction program constraints (Agri-Environmental measure of the Rural Development Programme):

$$\sum_{nwj=1}^{n} X_{f,nwj,t} b_{f,t} \geq b_{f,t}\, 0.75\, NL_{f,t}, \quad \text{for } t = 1,\ldots,T,\ nwj \in NWJ,\ NWJ \subseteq J \qquad \text{(B13)}$$

where $X_{f,nwj,t}$ is the level of irrigated cropping activity included in the nitrate pollution reduction program (*nwj*) in hectares of the farm f in year t; *NWJ = {cotton(ct); maize(mz); pr. tomato(pt); pr. pepper(pp) }*

$$\sum_{ndj=1}^{n} X_{f,ndj,t} \geq b_{f,t}\, 0.2\, NL_{f,t}, \quad \text{for } t = 1,\ldots,T,\ ndj \in NDJ,\ NDJ \subseteq J \qquad \text{(B14)}$$

where $X_{f,ndj,t}$ is the level of non-irrigated cropping activity included in the nitrate pollution reduction program (*ndj*) in hectares of the farm f in year t; *NDJ = {durum wheat (dw)}*

$$X_{f,st,t} \geq b_{f,t}\, 0.05\, NL_{f,t}, \quad \text{for } t = 1,\ldots,T,\ st \in I \qquad \text{(B15)}$$

where $X_{f,st,t}$ is the level of set-aside *(st)* included in the nitrate pollution reduction program (hectares) of the farm f in year t.

We want to point out that from the year 2018 onwards, the vast majority of sample farms implemented the nitrate pollution reduction program as follows: the share of 0.75 of constraint (B13) was set to 0.7; the share of 0.2 of constraint (B14) was set to 0.3, and the share of 0.05 of constraint (B15) was set to 0.

Organic farming program constraint (Agri-Environmental measure of the Rural Development Programme):

$$\sum_{orj=1}^{n} X_{f,orj,t} \geq OL_{orgf,t} \beta_{f,t}, \quad \text{for } t = 1,\ldots,T,\ \ orj \in ORJ,\ ORJ \subseteq J \qquad \text{(B16)}$$

where $X_{f,orj,t}$ is the level of organic cropping activity included in the organic farming program (*orj)* in hectares of the farm *f* in year *t*; *ORJ = {alfalfa (aa)}.*

Flexibility constraint of multiannual contract farming

$$0.85\ CL_{f,t}\ c_{f,t} \leq X_{f,aasd,t}\ c_{f,t} \leq 1.15\ CL_{f,t}\ c_{f,t}, \quad \text{for } t = 2015,\ldots,T,\ \ aasd \in I \tag{B17}$$

where $X_{f,aasd,t}$ is the level of *alfalfa-seed (aasd)* in hectares of the farm *f* in year *t*; $CL_{f,t}$ is the available land of the farm *f* in year *t* included in the multiannual contract farming program; $c_{f,t}$ denotes the binary variable that corresponds to the farm *f* in year *t*, and is equal to 0 when the farm does not participate in the program of multiannual contract farming , while it gets the value 1 when it participates.

Part C: Land rental costs/land rental income estimation

As mentioned in the main text, land is reallocated only on a rental basis through farmland rental arrangements between tenants and landowners. LaPorte et al. (2020) state that "the most popular and frequently used farmland rental arrangement is a fixed cash rent agreement, where the landowner receives a predetermined fee to be paid by the tenant regardless of agricultural commodity price or crop yield" (p. 1). This type of landowners' rental agreement is also maintained for the case under consideration, where the farmers pay after harvesting and selling the agricultural commodities in the market. The following is an estimate of land rental costs for each year after the initial one, where $LRC_{vf,nbf,t}$ are the land rental costs of viable neighboring farm in year *t*; $LRC_{vf,nbf,t\text{-}1}$ is the rented land of viable neighboring farm in year *t-1;* LRI_t is the land rental price index in year *t*; $\overline{LRP_{NBF,t=1}}$ is the average land rental price per land unit (EUR/ha) in base year (*t=1*) applicable to the region where the neighboring farms operate; $\overline{LRP_{NBF,t}}$ is the average land rental price per land unit (EUR/ha) in year *t* applicable to the region where the neighboring farms operate; $\Omega^{sim}{}_{AL_{vf,nbf,t\text{-}1}}$ is the simulated share of arable land reallocated to viable neighboring farm at the end of the year *t-1*, that is, following the annual optimization; $\sum_{nvf=1}^{NVF}\sum_{nbf=1}^{NBF} AL_{nvf,nbf,t\text{-}1}$ is the simulated aggregate arable land of non-viable neighboring farms at the end of the year *t-1*, that is, following the annual optimization; $TAL_{NBF,t}$ is the actual total arable land of neighboring farms in year *t*; $TAL_{NBF,t=1}$ is the actual total arable land of neighboring farms in year *t*-1; $AL_{vf,nbf,t}$ is the available arable land of viable neighboring farm in year *t*.

$$LRC_{\ vf,nbf,t} = \ RL_{vf,nbf,t-1}\ \underbrace{LRI_t\ \ LRP_{\ NBF,t=1}}_{\overline{LRP}_{\ NBF,t}}$$
$$+\ \underbrace{LRI_t\ \ \overline{LRP_{\ NBF,t=1}}}_{\overline{LRP}_{\ NBF,t}}\ \ \Omega^{sim}{}_{AL_{vf,nbf,t-1}}\ \ [\sum_{nvf=1}^{NVF}\sum_{nbf=1}^{NBF} AL_{nvf,nbf,t-1}{}^{sim}$$
$$+\left(TAL_{NBF,t} - TAL_{NBF,t-1}\right)]$$
$$for\ t = 2\ldots T,\ RL_{vf,nbf,t} \subseteq AL_{vf,nbf,t} \tag{C1}$$

The average land rental price (applicable to the region where the neighboring farms operate) ($\overline{LRP_{NBF,t}}$) was used as a single land rental price for all farms to simplify the modeling process, considering that the observed differences in payable land rental prices between farms are negligible. Since the land rental price is exogenously determined in this model version[31], updating its variance for each year after the base year is conducted using the land rental price index (LRI_t) (ELSTAT, 2019b). Additionally, we must mention that product $RL_{vf,nbf,t\text{-}1}\ \overline{LRP_{NBF,t}}$ indicates that land rental prices are renegotiated every cropping cycle.

To simplify the presentation of the estimation of land rental costs on an annual basis, we did not separate the land into irrigated and non-irrigated. It is worth mentioning that the average land rental price of non-irrigated land is about 50% lower.

To make post-sample forecasts in the medium term, the exogenously identified average land rental price per land unit ($\overline{LRP_{NBF,t}}$) is estimated through ARIMA stochastic process.

Although rare in our analysis, there is the case of viable farms that rent out part of owned land because the estimated reduction of the land attributed to them due to exogenous reasons[32] [$\Omega^{sim}{}_{AL_{vf,nbf,t\text{-}1}}{}^{-1}$ ($TAL_{NBF,t}$ – $TAL_{NBF,t\text{-}1}$)] exceeds (i) the previous year rented land ($RL_{vf,nbf,t\text{-}1}$) and (ii) the land that accumulated endogenously, i.e., the released land available for rent, derived from

[31] Following similar simulation models (Bert et al., 2011; Djanibekov & Finger, 2018; Donati et al., 2024), the land rental price is exogenous in the suggested model. Unfortunately, this version of the model does not fully consider the interaction between farms and the spatial relationships to include a land rental market with the endogenous formation of the rental price through an auction mechanism (Bert et al., 2011) as it is usually applied in agent-based models. However, land rental price endogeneity could be approximated to some extent through shadow values, for example, using the distribution of shadow value for the land of viable farms based on the exogenously determined land rental price, but this aspect requires further investigation.

[32] Competitive pressures from other farm types or non-agricultural sectors are likely to lead to an unfavorable situation, i.e., $TAL_{NBF,t}$ – $TAL_{NBF,t\text{-}1}$ < 0 and consequently to a decrease of available arable land for the viable neighboring farms, which will be reallocated among them utilizing the inverse form of the simulated share of arable land ($\Omega^{sim}{}_{AL_{vf,nbf,t\text{-}1}}$), that is, less profitable albeit viable farms will abandon/release proportionately more of their arable land.

non-viable neighboring farms [$\Omega^{sim}{}_{AL_{vf,nbf,t\text{-}1}}$ ($\sum_{nvf=1}^{NVF}\sum_{nbf=1}^{NBF}$ $AL_{nvf,nbf,t\text{-}1}{}^{sim}$)].

In this case, land rental costs are negative ($LRC_{vf,nbf,t} < 0$), equal to land rental income for the viable neighboring farm ($LRINC_{vf,nbf,t} > 0$). Consequently, the equation $FNPAT^*_{f,t} = \Pi^*_{f,t} - (DEP_{f,t} + LRC_{f,t} + SFNC_{f,t} + LFNC_{f,t} + SIC_{f,t} + FPTX_{f,t})$ (5) (in section *2.3.3.Determining farm viability* of the main text) is adapted as follows:

$$FNPAT^*_{f,t} = (\Pi^*_{f,t} + LRINC_{f,t}) - (DEP_{f,t} + SFNC_{f,t} + LFNC_{f,t} + SIC_{f,t} + FPTX_{f,t}) \quad \text{(C2)}$$

indicating that a farm cannot simultaneously rent in and rent out farmland, a condition we also find in similar simulation models (e.g., Donati et al., 2024).

Part C: References

Bert, F. E., Podestá, G. P., Rovere, S. L., Menéndez, Á. N., North, M., Tatara, E., Laciana, C. E., Weber, E., & Toranzo, F. R. (2011). An agent-based model to simulate structural and land use changes in agricultural systems of the argentine pampas. *Ecological Modelling*, *222*(19), 3486–3499. https://doi.org/10.1016/j.ecolmodel.2011.08.007

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Part D: Borrowed capital & finance costs estimations

D1. Borrowed circulating capital & short-term finance costs estimations

Farm growth in equity is the surplus income available to put back into the business by either purchasing assets or debt repayment (Hofstrand, 2009; Bert et al., 2011; GRDC, 2015). Therefore, the current level of short-term borrowing will be determined by the optimal farm growth in equity of the year *t-1* minus the sum of the existing debt and the required circulating capital of the current year. More specifically, if the optimal farm growth in equity of the previous year is enough to serve: 1) the scheduled principal repayment of existing debt of farm f in year t-1 ($DPRP_{f,t\text{-}1}$) which consists of (i) the borrowed circulating capital of farm f ($BCRC_{f,t}$) to be repaid within the same year received and (ii) the borrowed investment capital of farm f ($BINVC_{f,t}$) to be repaid within a predetermined duration of years (T_L)[33] 2) and the required circulating capital of farm f of the current year ($CRC_{f,t}$), then the farm f will not take out a short-term loan, otherwise the farm will be led to short-term borrowing. The mathematical formulation of the condition is as follows:

$$BCRC_{f,t} = \begin{cases} 0, if \;\; FGE^*_{f,t-1} \; - \; DPRP_{f,t-1} - CRC_{f,t} \; \geq 0 \\ > 0, if \;\; FGE^*_{f,t-1} \; - \; DPRP_{f,t-1+j} - CRC_{f,t} \; < 0 \end{cases}$$
$$for\ t = 2,\ldots,T \quad \text{(D1)}$$

where $BCRC_{f,t}$ is the borrowed circulating capital of farm f in year t; $DPRP_{f,t\text{-}1}$ is the principal repayment of existing debt of farm f in year t-1.

In the case of a short-term loan, the level of borrowed circulating capital will be calculated as follows:

$$BCRC_{f,t} = (CRC_{f,t} + DPRM_{f,t\text{-}1}) - FGE^*_{f,t\text{-}1} \quad \text{(D2)}$$

Respectively the short-term finance costs will be estimated as follows:

$$SFNC_{f,t} = BCRC_{f,t}\ SIR_{f,t} \quad \text{(D3)}$$

where $SFNC_{f,t}$ are the short-term finance costs of farm f in year t and $SIR_{f,t}$ is the short-term interest rate in year t. According to the Greek banking system, the short-term interest rate is based on the BFR (Basic Rate for Farmers).

[33] We assume an equal annual repayment which corresponds to the ratio $\frac{BINVC_{f,t}}{T_L}$

D2. Borrowed investment capital & long-term finance costs estimations

Farm growth in equity is the surplus income available to put back into the business by either purchasing assets or debt repayment (Hofstrand, 2009; Bert et al., 2011; GRDC, 2015), and hence the current level of long-term borrowing will be partially determined by the optimal farm growth in equity. Therefore, the following conditions determine the need or not for borrowed investment capital in year *t* ($BINVC_{f,t}$):

$$BINVC_{f,t} = \begin{cases} 0, if \ \ FGE^*{}_{f,t-1} + DEP_{f,t-1} - DPRP_{f,t-1} - CRC_{f,t} - I_{f,t} \geq 0 \\ > 0, if \ \ FGE^*{}_{f,t-1} + DEP_{f,t-1} - DPRP_{f,t-1} - CRC_{f,t} - I_{f,t} < 0 \end{cases}$$

$$for\ t = 2,\ldots,T \qquad \text{(D4)}$$

In case the sum of optimal farm growth in equity of year *t-1* ($FGE^*_{f,t-1}$) and depreciation of year *t-1* ($DEP_{f,t-1}$) exceeds the sum of scheduled principal repayment of existing debt in year *t-1* ($DPRP_{f,t-1}$), the required level of circulating capital of year *t* $CRC_{f,t}$ and the required gross investment on fixed assets in year *t* ($I_{f,t}$), then the farm will not take out a long-term loan. Alternatively, the farm will have to take out a long-term loan.

In the case of a long-term loan, the level of borrowed investment capital ($BINVC_{f,t}$) will be calculated as follows:

$$BINVC_{f,t} = (CRC_{f,t} + DPRP_{f,t-1} + I_{f,t}) - (FGE^*_{f,t-1} + DEP_{f,t-1}) \qquad \text{(D5)}$$

Respectively the long-term finance costs will be estimated as follows:

$$LFNC_{f,t} + \frac{BINVC_{f,t}}{T_L} LIR_t \qquad \text{(D6)}$$

where $LFNC_{f,t}$ are the long-term finance costs of farm *f* in year *t* and LIR_t is the long-term interest rate in year *t*. Based on literature (DAFWA, 2014), we consider that the repayment duration of borrowed investment capital (T_L) should be equal to 15 years. The long-term interest rate is based on the BFR (Basic Rate for Farmers) according to the Greek banking system.

Part D: References

Bert, F. E., Podestá, G. P., Rovere, S. L., Menéndez, Á. N., North, M., Tatara, E., Laciana, C. E., Weber, E., & Toranzo, F. R. (2011). An agent-based model to simulate structural and land use changes in agricultural systems of the argentine pampas. *Ecological Modelling*, *222*(19), 3486–3499. https://doi.org/10.1016/j.ecolmodel.2011.08.007

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Part E: Historical dataset and forecasting method of exogenously determined parameters

Table E1. Data sources of times series and forecasting method of exogenously determined farm model parameters

Farm model parameter of interest	Range	Data source	Forecasting method
Hired labor costs ($hlc_{f,j,t}$)	[2001-2018]	ELSTAT (2019b)	ARIMA model
Input costs ($ic_{f,j,t}$)	[2000-2019]	ELSTAT (2019c)	ARIMA model
Machinery rental costs ($mrc_{f,j,t}$)	[2000-2019]	ELSTAT (2019b)	ARIMA model
Land rental price ($LRP_{NBF,t}$)	[2000-2018]	ELSTAT (2019b)	ARIMA model
Interest rate (SIR_t; LIR_t)	[2000-2020]	ELSTAT (2019b)	ARIMA model
Cotton yield ($y_{f,ct,t}$)	[1961-2017]	Greek Ministry of Rural Development and Food;	ARIMA model
D. wheat yield ($y_{f,dw,t}$)	[1961-2017]	Greek Ministry of Rural Development and Food; Greek Ministry of Rural Development and Food (2019)	ARIMA model
Tobacco yield ($y_{f,tb,t}$)	[1979-2017]	Greek Ministry of Rural Development and Food; Greek Ministry of Rural Development and Food (2019)	ARIMA model
Pepper yield ($y_{f,pp,t}$)	[1961-2007]	Greek Ministry of Rural Development and Food	ARIMA model
Tomato yield ($y_{f,ptm,t}$)	[1961-2007]	Greek Ministry of Rural Development and Food	ARIMA model
Legumes crops yield ($y_{f,aasd,t}$; $y_{f,aa,t}$)	[2000-2017]	Greek Ministry of Rural Development and Food (2019)	ARIMA model
Maize yield ($y_{f,mz,t}$)	[1981-2017]	Greek Ministry of Rural Development and Food; Greek Ministry of Rural Development and Food (2019)	ARIMA model
Cotton price ($p_{f,ct,t}$)	[2000-2019]	ELSTAT (2019c)	ARIMA model
D. wheat price ($p_{f,dw,t}$)	[2000-2019]	ELSTAT (2019c)	ARIMA model
Legume crops price ($p_{f,aasd,t}$; $p_{f,aa,t}$)	[2000-2019]	ELSTAT (2019c)	ARIMA model
Maize price ($p_{f,mz,t}$)	[2000-2019]	ELSTAT (2019c)	ARIMA model
Total arable land ($TAL_{NBF,t}$)	[2004-2019]	FADN Public Database*	ARIMA model
Total circulating capital ($TCRC_{NBF,t}$)	[2004-2019]	FADN Public Database*	ARIMA model
Living expenditures ($LE_{f,t}$)	[2008-2020]	ELSTAT (2021)	Linear trend model

Notes: * The available Farm Accountancy Data Network (FADN) time series were filtered to include Greek farms specialized in “Other fieldcrops” (according to the TF14 classification of FADN), utilizing the parameters of Arable land (SE026) and Other circulating capital (SE480), which were multiplied by the parameter Farms represented (SYS02) to obtain values at an aggregate level. *Source:* ELSTAT (2019b), ELSTAT (2019c), ELSTAT (2021), FADN Public Database, Greek Ministry of Rural Development and Food, Greek Ministry of Rural Development and Food (2019).

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Part F: ARIMA and linear trend models estimations

Table F1. ARIMA models of exogenously determined parameters of interest

Exogenously determined parameter of farm model (Y_t)	Time series data points [period]	ARIMA Model (p,d,q)	Φ_1	Φ_2	Φ_3	Θ_1	Θ_2	Θ_3	μ	MAPE (%)	AIC	Augmented Dickey-Fuller t-Statistic	Breusch-Godfrey Serial Correlation LM Test [$Prob.\ X^2\ (p)$]
Hired labor price index	19 [2001-2018]	(2,0,1)	1.64*** (0.05)	-0.82*** (0.04)	-	-0.99*** (0.09)	-	-	92.79*** (0.59)	0.95	3.84	-3.55*	Prob. X^2 (2)=0.059
Input price index	20 [2000-2019]	(1,1,1)	0.87*** (0.06)	-	-	-0.99*** (0.12)	-	-	-	3.78	6.19	-4.29**	Prob. X^2 (2)=0.44
Machinery rental price index	20 [2000-2019]	(0,2,1)	-	-	-	-0.50** (0.21)	-	-	-	1.29	4.09	-7.00***	Prob. X^2 (2)=0.92
Land rental price index	19 [2000-2018]	(1,0,1)	0.53** (0.20)	-	-	0.99*** (0.06)	-	-	99.05*** (1.57)	1.05	3.76	-4.01**	Prob. X^2 (2)=0.40
Interest rate index	21 [2000-2020]	(0,2,1)	-	-	-	-0.91*** (0.07)	-	-	-	5.51	6.49	-6.92***	Prob. X^2 (2)=0.99
Cotton yield (Kg/Ha)	57 [1961-2017]	(1,0,1)	0.92*** (0.01)	-	-	-0.97*** (0.03)	-	-	299.23*** (5.36)	7.55	9.21	-4.21***	Prob.X^2 (2)=0.54
D. wheat yield (Kg/ 0.1 Ha)	57 [1961-2017]	(2,0,1)	0.50*** (0.15)	0.43*** (0.14)	-	-0.62*** (0.14)	-	-	278.04*** (51.51)	11.30	9.83	-3.47**	Prob.X^2 (2)=0.98
Tobacco yield (Virginia) (Kg/0.1 Ha)	39 [1979-2017]	(1,0,3)	0.87*** (0.02)	-	-	-1.00*** (0.15)	0.48** (0.21)	-0.46*** (0.15)	336.52*** (8.17)	6.73	9.40	-4.21***	Prob.X^2 (2)=0.35
Pepper yield (Kg/0.1 Ha)	47 [1961-2007]	(1,0,2)	0.98*** (0.09)	-	-	-0.66*** (0.14)	-0.29** (0.14)	-	4396.72*** (1079.63)	6.28	13.21	-4.10***	Prob.X^2 (2)=0.81
Tomato yield (Kg/0.1 Ha)	47 [1961-2007]	(1,1,0)	-0.44*** (0.14)	-	-	-	-	-	81.27** (31.97)	5.5	14.34	-7.21***	Prob.X^2 (2)=0.36
Legumes crops yield [Alfalfa (hay & seed)] (Kg/0.1 Ha)	18 [2000-2017]	(0,0,2)	-	-	-	0.31*** (0.08)	0.93*** (0.02)	-	740.24*** (26.53)	4.69	10.83	-4.82***	Prob.X^2 (2)=0.10
Maize yield (Kg/0.1 Ha)	37 [1981-2017]	(2,0,0)	0.54*** (0.16)	0.33*** (0.16)	-	-	-	-	1086.85*** (122.19)	3.77	10.67	-4.18**	Prob.X^2 (2)=0.36
Cotton price (EUR/kg)	20 [2000-2019]	(1,0,1)	0.85*** (0.06)	-	-	-0.96*** (0.04)	-	-	0.48*** (0.048)	15.17	-2.19	-3.39*	Prob.X^2 (2)=0.16
D. wheat price (EUR/kg)	20 [2000-2019]	(3,0,0)	0.84*** (0.23)	-0.62** (0.29)	0.44* (0.22)	-	-	-	0.19*** (0.02)	10.81	-4.08	-3.19*	Prob.X^2 (2)=0.32
Legume crops price (Alfalfa-hay) (EUR/kg)	20 [2000-2019]	(1,1,0)	-0.43* (0.22)	-	-	-	-	-	-	6.00	-6.36	-4.36**	Prob.X^2 (2)=0.80
Maize price (EUR/kg)	20 [2000-2019]	(1,0,1)	0.83*** (0.06)	-	-	-0.99*** (0.10)	-	-	0.18*** (0.00)	8.48	-4.70	-3.40*	Prob.X^2 (2)=0.08

(Continued)

Table F1. (Continued).

Exogenously determined parameter of farm model (Y_t)	Time series data points [period]	ARIMA Model (p,d,q)	Φ_1	Φ_2	Φ_3	Θ_1	Θ_2	Θ_3	μ	MAPE (%)	AIC	Augmented Dickey-Fuller t-Statistic	Breusch-Godfrey Serial Correlation LM Test [*Prob.* $X^2(p)$]
Total arable land index	16 [2004-2019]	(0,1,3)	-	-	-	-1.26^{***} (0.28)	1.17^{***} (0.22)	-0.82^{***} (0.14)	3.19*** (0.89)	3.67	6.98	-7.75^{***}	Prob.X^2 (2)=0.64
Total circulating capital index	16 [2004-2019]	(0,1,1)	-	-	-	-0.93^{***} (0.06)	-	-	29. 7*** (2.31)	10.91	10.24	-3.75^{**}	Prob.X^2 (2)=0.19

Notes: $\nabla^d Y_t = \mu + \phi_1 \nabla^d Y_{t-1} + \cdots \phi_p \nabla^d Y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q}$;
$\Phi_1, \ldots, \Phi_p$: autoregressive (AR) model parameters of order p; $\Theta_1, \ldots, \Theta_q$: moving average (MA) model parameters of order q (Martínez-Acosta et al., 2020) ; ε_t is white noise; μ= a constant equal to the mean of the series if d = 0 (Narayana & Parikh, 1981); * indicates significance at 0.1 level, ** indicates significance at 0.05 level, *** indicates significance at 0.01 level; The null hypothesis H_0 of the Breusch-Godfrey Serial Correlation LM Test is that there is no autocorrelation in the residuals series up to pre-determined lag order ($p=2$ in our analysis) at the 0.05 level of significance (Weyerstrass, 2016).
Source: Authors, based on ELSTAT (2019b), ELSTAT (2019c), FADN Public Database, Greek Ministry of Rural Development and Food, Greek Ministry of Rural Development and Food (2019).

Table F2. Linear trend model regression statistics of rural households' living expenditure index (LEI)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.954777	0.019644	48.60363	0.0000
@TREND	-0.023925	0.002778	-8.612057	0.0000
R-squared	0.870843	Mean dependent var		0.811226
Adjusted R-squared	0.859101	S.D. dependent var		0.099846
S.E. of regression	0.037479	Akaike info criterion		-3.589453
Sum squared resid	0.015451	Schwarz criterion		-3.502538
Log likelihood	25.33145	Hannan-Quinn criter.		-3.607318
F-statistic	74.16753	Durbin-Watson stat		0.642814
Prob(F-statistic)	0.000003			

Source: Authors, based on ELSTAT (2021) data.

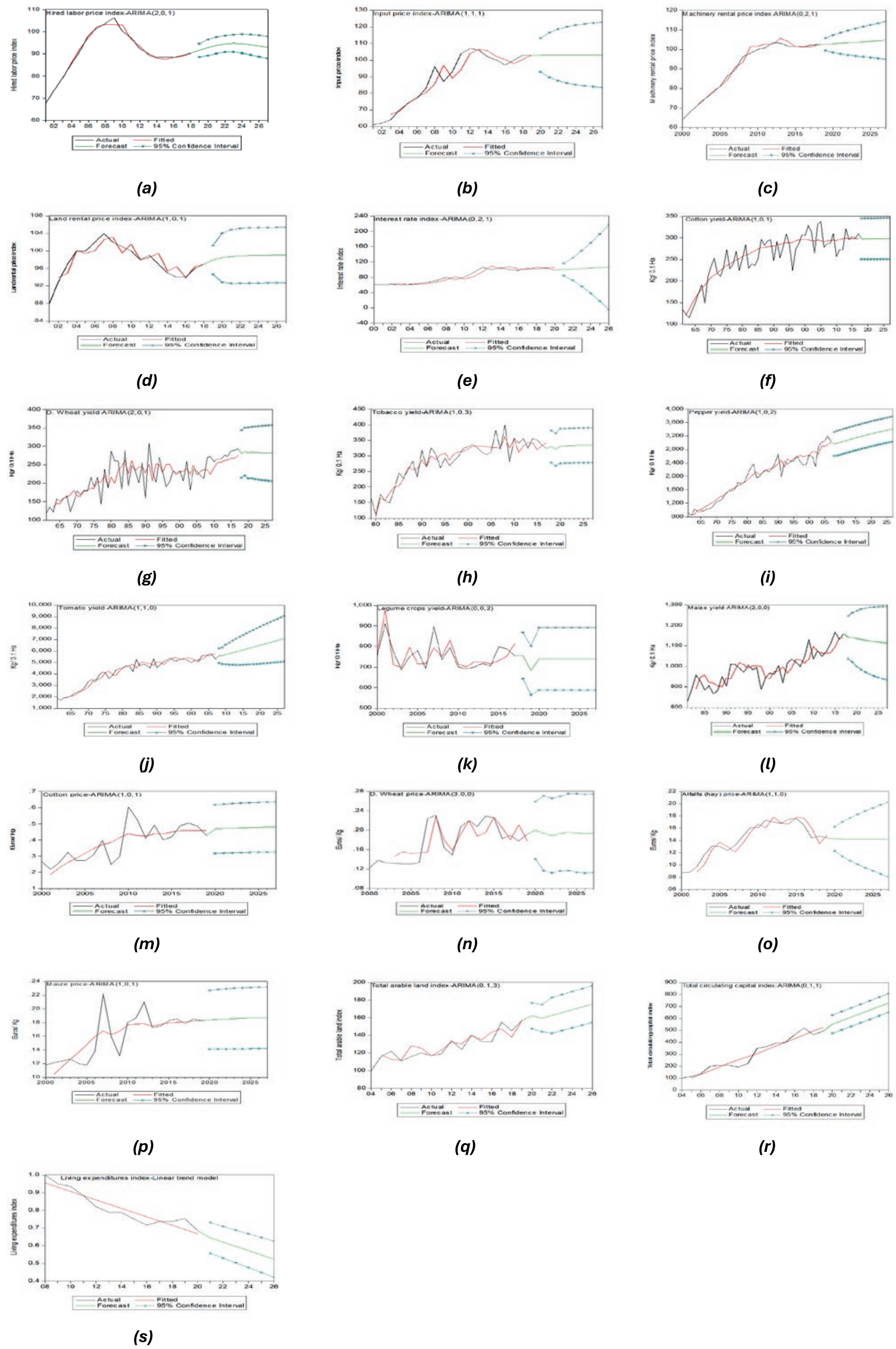

Figure F1. ARIMA and linear trend models of the exogenously determined parameters of interest. *Notes:* the horizontal axis indicates the year; 0.1 Ha (hectare) =1 stremma is the Greek unit of land area. (*a*) Hired labor price index; (*b*) Input price index; (*c*) Machinery rental price index; (*d*) Land rental price index; (*e*) Interest rate index; (*f*) Cotton yield (kg/0.1 Ha); (*g*) Durum wheat yield (kg/0.1 Ha); (*h*) Tobacco yield (kg/0.1 Ha); (*i*) Pepper yield (kg/0.1 Ha); (*j*) Tomato yield (kg/0.1 Ha); (*k*) Legume crops yield (kg/0.1 Ha) including Alfalfa (hay & seed); (*l*) Maize yield (kg/0.1 Ha); (*m*) Cotton price (EUR/kg); (*n*) Durum wheat price (EUR/kg); (*o*) Alfalfa (hay) price (EUR/kg); (*p*) Maize price (EUR/kg); (*q*) Total arable land index; (*r*) Total circulating capital index; (*s*) Living expenditures index. *Source:* Authors, based on ELSTAT (2019b), ELSTAT (2019c), ELSTAT (2021), FADN Public Database, Greek Ministry of Rural Development and Food, Greek Ministry of Rural Development and Food (2019).

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OPEN ACCESS

Citation: Dehghan, M., Moosavi, S.N., & Zare, E. (2024). Analyzing the impact of government subsidies on household welfare during economic shocks: A case study of Iran. *Bio-based and Applied Economics* 13(4): 387-396. doi: 10.36253/bae-15105

Received: September 8, 2023
Accepted: September 2, 2024
Published: December 31, 2024

Data Availability Statement: All relevant data are within the paper and its Supporting Information files.

Competing Interests: The Author(s) declare(s) no conflict of interest.

Editor: Fabio Bartolini

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Analyzing the impact of government subsidies on household welfare during economic shocks: A case study of Iran

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Abstract. The study evaluates the effectiveness of Iranian government subsidies for households by comparing the welfare impact of food price shocks with the subsidy payments they receive. This helps us assess the government's efforts to reduce poverty in Iran. The household income and expenditure survey in 2020 was used to calculate compensated price elasticities using the Quadratic Almost Ideal Demand System (QAIDS). Results showed negative and less than 1 own-price elasticities for all food items, with a sensitivity to changes in income greater than one for demand of cereals, cooking oil, and fruits. Then, compensated variations (CV) welfare index was used to evaluate the effectiveness of government support payments in reducing household vulnerability due to food price increases. The results showed that the CV fluctuates between 8.05-80.46 $ under different scenarios. In other words, consumers are in a worse situation in terms of welfare and their expenditure increases. The vulnerability index of low-income households, after applying different food price scenarios, is in the range of 1.46-14.67%, which is reduced to 1.35-14.53% by implementing the cash-targeted subsidy policy. In other words, the effectiveness of the government's subsidy policy of $19 per person could reduce the vulnerability of these households by only 0.14%.

Keywords: poverty, vulnerability, welfare, subsidies, food, demand system.
JEL Codes: D12, D60, I3, I32, Q18.

INTRODUCTION

Social protection programs like subsidies aim to prevent poverty and social crisis and promote justice, even if it means sacrificing some economic efficiency (Barr, 2020). However, poor subsidy payment methods can cause inefficiency and injustice. There is currently a heated debate among economists and policymakers about the link between targeting subsidies and poverty reduction (Amegashie, 2006). Price changes wield considerable influence over resource allocation and consumer behavior, thereby shaping the implementation of economic welfare policies (Khodaparast Shirazi *et al*., 2018). The surge in food prices, both domestically and globally, has become a pressing global concern (FAO, 2021). Although the COVID-19 pandemic exacerbated the issue by disrupting supply chains and inflating prices further (Elleby *et al*., 2021), the trend of rising food prices predates the pandemic, originating in 2018 (Panzone *et al*., 2021). In Iran, where food accounts for a substantial portion of household consumption, the anticipated impact of food inflation on household welfare is pronounced (Layani *et al*., 2020). Iran's persistent struggle with high inflation underscores the gravity of the situation, with efforts ongoing to identify and address underlying causes (Ilias, 2010). Notably, between 2010 and 2019, Iran witnessed an increase in spending on essential items like food and housing, exacerbating the economic strain on households (Salehi Isfahani, 2020). Despite the reformed social protection policy in Iran, the adverse effects of food price shocks could disproportionately affect low-income households in due to their vulnerable economic structures (Pawlak and Kołodziejczak, 2020).

To contextualize the analysis of price shocks on household vulnerability and welfare across diverse countries, it is imperative to understand the intricate dynamics of consumer behavior and demand systems. For instance, studies utilizing sophisticated models such as Translog, Almost Ideal Demand System (AIDS), and Quadratic Almost Ideal Demand System (QAIDS) offer valuable insights into the responsiveness of consumers to price changes. Take, for example, Deaton and Mulbaer's (1980). There has been a growing body of literature regarding the impact of price shocks on household vulnerability and welfare effects across various countries in recent years (e.g. Aziz *et al*., 2016; Arfini & Aghabeygi, 2018; Adekunle *et al*., 2020; Lugo *et al*., 2022). Karagiannis *et al*.'s (2000) analysis on Greece, Abdulai's (2002) examination of Switzerland, Mazzocchi *et al*.'s (2004) investigation on Italy, Tefera's (2010) exploration of Ethiopia, Ahn *et al*.'s (2018) study on Korea, Yuzbashkandi and Mehrjo's (2020) research on Iran and Abdullah and Mohammed (2023) study on Iraq. Specifically, Ivanic and Martin (2008) and Ivanic *et al*. (2012) researched the correlation between global food price escalation and poverty in low-income countries, considering world and local prices' impact on poverty. Arfini and Aghabeygi (2018) found that increasing food import prices in Italy affected the welfare index by 1061.48 billion USD in the entire food group. The meat group was most affected and the fruit group was least affected. A recent study (Layani *et al*. 2020) found that rising food prices in Iran have a significant impact on rural households, with 10.63% of them falling below the poverty line. Anindita *et al*. (2022) used various methods to examine the impact of price and income changes on demand and welfare in urban Indonesia. They found that households substitute some food items as a coping mechanism. Rossen *et al*. (2022) have conducted a study that examines the effect of price shocks on different household groups based on income and age. Their research found that households with lower income and older individuals experience more significant welfare losses and a decrease in tax burdens compared to lower-income households with younger individuals. These studies provide valuable insights into the demand system and price elasticities of goods and offer useful implications for policymakers and practitioners in the field.

However, these prior studies have solely focused on analyzing the welfare impacts that arise from changes in prices. However, they fail to address a fundamental question: to what extent can the government's welfare policies, such as cash transfers, effectively mitigate the decrease in welfare and prevent households from falling below the poverty line. Therefore, this current research aims to address this research gap by assessing the impact of the Iranian government's subsidy policy for poor households.

In 2017 year, the Iranian government introduced a new social protection program by replacing universal subsidies with targeted subsidies while implementing support policies for vulnerable groups as a way to reduce poverty (Hosseini *et al*., 2017). A subsidy reform program replaced energy subsidies with direct cash payments. Recently, to protect Iranian households from vulnerability caused by price liberalization, the government provides additional subsidies to consumers and eliminates cash subsidies for high-income groups. Although the amount of cash subsidy increased significantly from 2011 to 2019, the share of this cash payment of household average income decreased from 22% to 5%. This Government assistance includes official transfers from the Ministry of Health, Labour and Welfare and Komite Emdad. Although the poor benefited significantly from the monthly transfers, their real value diminished rapidly due to high inflation. The reformed social protection programs are targeted, particularly prioritizing poor households headed by women, using a targeting algorithm developed jointly with the World Bank. Government welfare payments decreased from $35.4 in 2018 to $19.8 per person in 2019 due to economic sanctions and reduced revenue, resulting in less support for people in need (Salehi Isfahani, 2020).

The study calculates the welfare effects of changes in food prices and evaluates the effects of these changes on the poverty line and the number of poor households in Iran. Unlike previous studies, this research considers the vulnerability index, which has received insufficient attention in assessing the effects of price shocks on consumer behavior.

The paper is divided into distinct sections. Firstly, the theoretical fundamentals and materials, and methods are presented. Secondly, the results of calculating the price and income elasticities of food demand for Iranian households are reported, along with an examination of the effects of various food price increase scenarios. Finally, the fourth section provides conclusions and suggestions.

METHODOLOGY

Data

In this study, to estimate the demand system and calculate the price and income elasticities of food items, the latest cost-income data of 2878 Iranian households supported by the government, which was published by the Iranian Statistics Center, was used. These data include the amount of consumption of each food item and their corresponding price. Also, to estimate the AIDS system, the size of the household, and the education level of the head of the household were used in the estimation of the demand system. Table 1 presents the socio-economic characteristics of the sample under study. The average age of the head of the household in government-supported households is 52.32 years, while the average number of years of education of the head of the household is 5.27 years. The average size of households in the sample was 3.89 individuals. The government-supported households included in the study are categorized as low-income households, with an average monthly income of $53.65. It has been observed that the group of households under consideration here has an average per capita food expenditure of $14.05 per month, which constitutes around 26% of the per capita income.

Table 1. Socio-economic characteristics of the studied households.

Variables	Average
Age of household head (year)	52.32
Education of household head (year)	5.27
Family size	3.89
Per capita Food expenditure ($)	14.05
Per capita income per month ($)	53.65

* Source: Iranian Statistics center in 2020 (1$=208000 Rial).

Welfare analysis

The evaluation of the efficacy of providing subsidies to low-income households is determined by comparing the ratio of the Compensated Variation (CV) index to the per capita income with the ratio of cash subsidies to monthly income (Eq. 1).

$$Vulnerability\ index\ \text{after}\ subsidy\ policy = \frac{CV}{monthly\ income} - \frac{\text{cash subsidy}}{monthly\ income} \quad (1)$$

Where CV is the household's welfare index as a result of different price shocks. the ratio of the Compensated Variation (CV) index to the monthly income is known as the vulnerability index (Azzam and Rettab, 2012).

$$Vulnerability\ index\ before\ subsidy\ policy = \frac{Welfare\ effects\ of\ price\ shock}{monthly\ income} \quad (2)$$

By following Khodadad Kashi *et al.* (2005), Arshadi and Karimi (2013) and Layani *et al.* (2020), the 66 percent of the average household food expenditure is defined relative poverty line:

Poverty Line=66 percent × (average food expenditure) (3)

After computing the poverty line, we can divide urban households into two groups: The households that have a food expenditure higher than poverty line (above the poverty line), and the households that have a food expenditure lower than poverty line (below the poverty line). The reason for this is because poverty lines are highly elastic to relative food prices (Bresciani and Valdes, 2007), and changes in food prices result in variations of poverty prevalence. Furthermore, we then compute a new poverty line, after accounting for the rise in food prices (Rodriguez-Takeuchi and Imai, 2013):

Secondary Poverty Line= Poverty Line + Welfare Index-Subsidy policy (4)

Different indexes measure welfare changes due to policy implementation. Economic conditions like price changes can affect consumer utility rates. To determine the impact of economic conditions on consumer utility, criteria like Consumers Surplus (CS), Compensated Variation (CV), and Equivalent Variation (EV) are used. We use CV to determine the minimum amount that Iranian consumers are willing to accept to tolerate higher food prices. Studies suggest that the CV is the most suitable criterion for our analysis (Tefera, 2012 and Cranfield

2007). Compensated Variation was utilized in the study, as indicated by research conducted by Azzam and Rettab (2012), Tefera (2012), Layani *et al.* (2020), and Roosen *et al.* (2022).

$$CV = \sum_{i=1}^{n} p_i^0 x_i^0 \left(\frac{dp_i}{p_i^0} + \frac{dx_i^*}{x_i^0} + \frac{dp_i}{p_i^0}\frac{dx_i^*}{x_i^0}\right) \quad (5)$$

Where p_i^0 and x_i^0 correspond to price and quantities before price shock and dx_i^* is the compensated quantity change in demand following the price shock using the compensates elasticities. The percentage change of x_i^* is not available. However, by the total differential of the Hicksian demand functions $x_i^*(.)$ for i = 1, 2,…, N i.e., an approximation of the change is obtained.

$$\begin{aligned} \frac{dX_1^*}{X_1^0} &= \epsilon_{11}^H \frac{dp_1}{p_1} + \epsilon_{12}^H \frac{dp_2}{p_2} + \cdots + \epsilon_{1N}^H \frac{dp_N}{p_N} \\ \frac{dX_2^*}{X_2^0} &= \epsilon_{21}^H \frac{dp_1}{p_1} + \epsilon_{22}^H \frac{dp_2}{p_2} + \cdots + \epsilon_{2N}^H \frac{dp_N}{p_N} \\ &. \\ &. \\ \frac{dX_N^*}{X_N^0} &= \epsilon_{N1}^H \frac{dp_1}{p_1} + \epsilon_{N2}^H \frac{dp_2}{p_2} + \cdots + \epsilon_{NN}^H \frac{dp_N}{p_N} \end{aligned} \quad (6)$$

where ε_{ij}^H is the Hicksian price elasticity for i = 1, 2,…, N and j = 1,2,…, N.

To estimate the Hicksian price elasticities as shown in (6), we estimate a QAIDS model for N commodities by imposing the usual restrictions: Adding-up, homogeneity, and symmetry. The QAIDS model developed by Banks *et al.* (1997), which has budget shares that are quadratic in log total expenditure, is an example of the empirical demand systems that have been developed to allow this expenditure nonlinearity.

$$s_i = a_i + \sum_{j=1}^{n} \gamma_{ij} log p_j + \beta_i log\left[\frac{M}{f(p)}\right] + \frac{\lambda_i}{g(p)}\left[log\frac{M}{f(p)}\right]^2 + \delta_i z_i \quad (7)$$

Where S_i is the share of food group i in total expenditure on the N food groups, for i=1,2,..,N; and p_j is a vector of prices; M is total expenditure and Z Vector of statistical variables dependent on household characteristics. Also, *f(p)* is the Laspeyres Price Index defined by $logf(p)^* = \Sigma_i s_i log p_i$.

The restrictions are:

$$\sum_{i=1}^{n}\alpha_i = 1. \sum_{i=1}^{n}\gamma_{ij} = 0. \sum_{i=1}^{n}\beta_i = 0 \quad .\gamma_{ij} = \gamma_{ji} \quad i.j = 1.2 \ldots N \quad (8)$$

The formulae for the elasticities in the QUAIDS are given by Banks, Blunbell and Lewbel (1997). They are obtained by first differentiating equation (7) with respect to logM and $logp_j$, respectively, to obtain:

$$\mu_i = \frac{\delta s_i}{\delta log M} = \beta_i + \frac{2\lambda_i}{g(p)} log\left[\frac{M}{f(p)}\right] \quad (9)$$

$$\mu_{ij} = \frac{\delta s_i}{\delta log p_j} = \gamma_{ij} - \mu_i(\alpha_j + \sum_k \gamma_{jk} log p_k) - \frac{\lambda_i \beta_j}{g(p)}\left[\log\left(\frac{M}{f(p)}\right)\right]^2 \quad (10)$$

The expenditure elasticities are then derived as $e_i = m_i/s_i + 1$. The uncompensated or Marshallian price elasticities are given by $e_{ij}^m = m_i/s_i - d_{ij}$, where d_{ij} is the Kronecker delta, which is equal to one when i=j, otherwise $d_{ij} = 0$. Using the Slutsky equation, $e_{ij}^m = e_{ij}^m + s_j e_i$, the compensated or Hicksian elasticities can be calculated and used to assess the symmetry and negativity conditions by examining the matrix with elements $s_i \left[e_{ij}^h\right]$, which should be symmetric and negative semi-definite in the usual way.

Definition food price shocks

There are several methods to define the price increase scenario. The first method is to use previous studies. Another method is to use time series data for food. For this purpose, the price of food taken and the price growth during the studied years were first calculated for each group, and the average rate of change of price growth was calculated and defined as the scenario for food price change. The scenarios of increasing food prices in this study are shown in Table 2. In addition to food price fluctuations, global statistics were also considered according to the Statistics Center of Iran. The first scenario studied is food price changes based on the reports of the Statistics Center of Iran (2021). It can be seen that meat has the highest price fluctuations and vegetables have the lowest price fluctuations. The second scenario in this study is the price fluctuations of food imports to Iran. On this basis, information on food import prices was collected, and the average annual fluctuations in food import prices were used as the basis

Table 2. Different food prices shock scenarios (%).

Food	First scenario	Second scenario	Third scenario	Fourth scenario
Cereals	34	15.31	9.64	6.07
Meat	124.4	16.26	4.33	3.83
Dairy	56.7	15.56	3.63	6.88
Oil and fat	54.4	9.60	26.27	8.22
Fruit	27.5	11.96	9.87	5.38
Vegetables	25.4	30.22	8.22	5.35
Sugar	28.5	19.03	13.15	8.08
Tea and coffee	31	10.09	9.87	5.38

for the price scenario. Finally, the third and fourth scenarios were defined based on the FAO predicted price changes. Accordingly, the food price index reported by FAO was examined for the period 2003-2021. The annual changes in the food price index were calculated, and the average changes in the price index during 2019-2021 were used as the third scenario and the average changes in the price index during 2003-2019 were used as the fourth scenario.

RESULTS

Table 3 displays the average food expenditure and expenditure share of eight main food groups. Cereals have the highest expenditure share, while tea and coffee have the lowest. On average, the expenditure allocated to tea and coffee is $4.50 per month, and the expenditure allocated to cereals is $41.70 per month. Meat has the second-highest food expenditure share among all food groups, accounting for 23.52% of the total expenditure. According to Layani et al.'s (2020) study on urban households, the average monthly expenditure on food indicates that cereals and meat are the top two priorities, with respective spending of $43.69 and $41.01. Additionally, households allocated an average of $4.69 on tea and coffee. A comparative analysis with the current study suggests that these households face challenges in maintaining a healthy nutritional status and are more vulnerable to price fluctuations. These findings highlight the need to address the nutritional inadequacies of these households and to develop interventions that support better dietary practices.

This study focuses on the Iranian agricultural market and aims to measure the impact of price changes on household expenditures. Specifically, we seek to answer the question: How will a price shock in the agricultural market affect the expenses of Iranian households that receive government support? this research explores whether payment of cash subsidies can effectively compensate for the reduction of welfare caused by such price shocks. To address the given query, it is imperative to compute the changes in the consumption patterns of various food products that ensue due to fluctuations in their prices. This can be accomplished by calculating the own-price and cross-price elasticities of the different food categories. The following section presents the results of the price and income elasticities.

Table 3. Average food consumption expenditure and share of food expenditure

Food	Average monthly food expenditure ($)	Food Expenditure Share (%)
Cereals	41.699	29.68
Meat	33.045	23.52
Dairy	16.238	11.56
Oil and fat	8.591	6.12
Fruit	12.506	8.90
Vegetables	16.297	11.60
Sugar	7.600	5.41
Tea and coffee	4.504	3.21

* Source: Iranian Statistics center in 2020 (1$=208000 Rial).

Price and income elasticities of food

After estimating the coefficients of the systems of equations based on the equations presented in the previous section, the price and income elasticities were obtained (Table 4). The compensated own-price and cross-price elasticities of food are shown in Table 4. As can be seen, all compensated elasticities of the studied food are negative as expected, and this is consistent with the behaviour that maximizes the utility of rational consumers.

In terms of absolute values, the highest own-price elasticity is related to oil, and the lowest own-price elasticity is related to dairy. The own-price elasticity of cereals is -0.398%. Therefore, 1% increase in cereal prices, assuming other conditions are constant, can reduce demand for this commodity by 0.398%. The compensated own- price elasticity of meat is calculated as -0.529%. Actually, the demand for meat and cereals are inelastic. It is worth noting that the own-price elasticity of oil and fat is (-0.729%) and the own-price elasticity of dairy products is (-0.006%). In other words, with a 1 % increase in the price of oil and fat (or dairy) assuming other conditions are constant, the demand for this food item decreases by 0.729% (or 0.006%). Own-price elasticity of fruits, vegetables and sugar are very close in terms of absolute value as -0.634 %, -0.608 % and -0.633 %, respectively.

According cross-price elasticities, there is a poor complementary relationship between cereals and other food groups. However, the effect of changes in cereal prices on demand for other foods is more pronounced. This result may be due to the higher importance of cereal for the poor households or the higher expenditures share of cereal. For instance, the effect of rising dairy prices on cereal demand is negative. In other words, with a 1 % increase in dairy prices, the demand for cereals decreases by 0.093 %, and this indicates a complementary relationship between the two prod-

Table 4. Price and income elasticities for each food groups.

	Cereals	Meats	Dairy	Oil cooking	Fruits	Vegetables	Sugar	Tea and coffee
Cereals	-0.398	0.086	-0.093	0.073	0.065	0.016	0.005	0.321
Meats	0.196	-0.529	0.175	0.048	0.084	0.119	0.061	-0.071
Dairy	0.177	0.715	-0.006	0.065	0.203	0.523	0.367	-1.044
Oil cooking	0.285	-0.106	-0.382	-0.729	-0.001	-0.048	-0.082	0.565
Fruits	0.258	-0.026	-0.385	0.021	-0.633	-0.054	-0.060	0.560
Vegetables	0.144	0.199	0.188	0.068	0.069	-0.608	0.068	-0.035
Sugar	0.159	0.236	0.284	0.043	0.088	0.175	-0.633	-0.219
Tea and coffee	0.206	-0.147	-0.429	0.011	-0.071	-0.117	-0.093	-0.243
Income Elasticities	1.303	0.918	0.136	1.210	1.392	0.998	0.774	0.836

* Source: Authors' calculations.

ucts. However, these households add cereals to their food portfolio as a substitute for dairy products. This result is expressed based on the elasticity coefficient of 0.177%. Although other foods are considered meat substitutes for households, the effect of meat price change on the demand for oil and fat, fruit and tea, and coffee is negative and is equal to -0.106%, -0.026% and -0.429%, respectively, and this indicates the complementarity of meat for these food groups. The cross-elasticity between oil and fat and other food groups such as meat, dairy, fruits, vegetables, and sugar are negative and it shows the existence of a complementary relationship between oil and fat with other food. However, the increase in oil and fat prices leads to an increase of 0.048 %, 0.065 %, 0.021 %, 0.068% and 0.043 % demand for meat, dairy, fruits, vegetable, and sugar, respectively. The cross-elasticity of other commodities with oil and fat suggests a substitution relationship between them. The highest substitute for fruit is tea and coffee (cross price elasticity is 0.560). Also, the highest complementary relationship between fruit and dairy products was obtained (cross price elasticity is -0.385). For households supported by the Relief Committee, compensated cross-sectional elasticity of vegetables indicates the existence of a substitution relationship between vegetables and other food groups (except tea and coffee). Indeed, if the decision is made to include foods such as cereals, dairy products, meat, oil and fat in the consumption basket containing vegetables, these foods are added to the poor households' consumption basket as a substitute. The highest and lowest substitution relationships are for vegetables-meat (0.199%) and vegetables-sugar (0.067%), respectively. It is worth to mention that vegetables themselves are considered as a complementary commodity for oil and fat (elasticity - 0.048 %), fruits (elasticity - 0.054 %). In other words, increasing the price of vegetables reduces the demand for oil, fat and fruits. Interestingly, vegetables are considered as a complementary commodity for oil and fat (cross-price elasticity is -0.048 %), fruits (cross-price elasticity is -0.054 %). In other words, increasing the price of vegetables reduces the demand for oil, fat and fruits.

The estimated total income elasticities presented in Table 4 have the expected positive signs in all eight commodities. The values for cereals (e=1.303), oil cooking (e=1.210), and fruits (e=1.392) are much greater than others. This implies a fairly large response of demand for these food groups to changes in total food expenditure. Actually, the demand for cereals, oil cooking, and fruits are elastic with respect to total food expenditure. The estimated income elasticities of meats, dairy, vegetables, sugar and tea and coffee are less than unity, so these goods are fairly inelastic with respect to total food expenditure.

Welfare effects of food price shocks

Evaluating the impact of price shocks on consumer welfare can provide valuable insights into the effectiveness of government support policies aimed at reducing poverty and vulnerability. Table 5 shows the effect of food prices shock on household expenditures. As shown, Under the first price scenario, CV welfare index fluctuates between 0.98-29.15%. The highest CV index is related to meat and the lowest welfare index is related to tea and coffee. The total Compensated variations index in this scenario is 57.28%. In other words, as a result of changes in food prices, the food expenditure of households supported by the government will increase by \$80.461. Therefore, if the government-supported households want to choose and consume the same food basket before the price change, their expenditure will increase by 57%. Under the second price scenario, the total wel-

Table 5. Welfare effect of multiple meat price shocks.

Food Groups	Expenditure	Scenario 1		Scenario 2		Scenario 3		Scenario 4	
		CV ($)	CV (%)	CV ($)	CV (%)	CV ($)	CV (%)	CV ($)	CV (%)
Cereals	41.699	14.502	10.32	6.457	4.60	4.079	2.90	2.563	1.82
Meats	33.045	40.947	29.15	5.417	3.86	1.436	1.02	1.279	0.91
Dairy	16.238	9.172	6.53	2.526	1.80	0.568	0.40	1.111	0.79
Oil cooking	8.591	4.642	3.30	0.824	0.59	2.239	1.59	0.702	0.50
Fruits	12.506	3.453	2.46	1.497	1.07	1.229	0.88	0.672	0.48
Vegetables	16.297	4.194	2.99	4.910	3.50	1.334	0.95	0.878	0.63
Sugar	7.600	2.169	1.54	1.441	1.03	0.991	0.71	0.611	0.44
Tea and coffee	4.504	1.381	0.98	0.450	0.32	0.451	0.32	0.242	0.17
Total	140.478	80.461	57.28	23.523	16.74	12.327	8.78	8.058	5.74
Vulnerability index before subsidy policy		14.67%		4.28%		2.29%		1.46%	
Vulnerability index after subsidy policy		14.53%		4.14%		2.15%		1.35%	

* Source: Authors' calculations (1$=208000 Rial).

fare index of Compensated variations was $23.523, which is 16.74% of the baseline food expenditure of households. The CV index of food items in this scenario fluctuates between 0.32-4.60%. With the simultaneous change of food prices based on the third and fourth scenarios, CV welfare index was equal to $12.327 and $8,058 respectively, which is 8.78% and 5.74% of household food expenses in the base year, respectively. The highest CV index in the third scenario is related to cereals (2.90%) and the lowest is related to tea and coffee (0.32%). In the fourth scenario, the welfare index of food items fluctuates in the range of 0.17-1.82%.

The vulnerability index of poor households fluctuates between 1.46-14.67% in different price scenarios. The highest vulnerability index was obtained after applying the first price scenario and the lowest was obtained as a result of the fourth price scenario. Given that the average monthly income of poor households is 548.31$, the total welfare loss due to rising food prices is equivalent to 14.67% of average household income in first scenario, which is an indicator of the vulnerability of households as a result of multiple food price shock. This index decreases to 1.46% in the fourth scenario. In order to support low-income households and establish social justice, the Iranian government pays a cash subsidy of about $19 per person per month to the head of the household's account. The amount of cash subsidy received by the households is equivalent to 0.14% of the average monthly income of the households. In other words, the Iranian government has only been able to reduce the vulnerability of low-income households by 0.14% by implementing this policy. Therefore, after the implementation of the targeted subsidy policy and supporting the low-income groups, the vulnerability index of households will be in the range of 1.35-14.53% in different price scenarios.

Finally, table 6 presents the secondary poverty line after the price increase and the subsidy policy. As can be seen, the secondary food poverty line varies between $26.88-99.29 under the different price shock scenarios. The results show that the subsidy policy was not efficient and some low-income households are still at risk of food poverty. The highest number of households below the poverty line will occur in the first price scenario.

Table 6. Effect of price shock on poverty line.

	Scenario 1	Scenario 2	Scenario 3	Scenario 3
Secondary food poverty line	99.29	42.35	31.15	26.88
% of households above poverty line	37.18	49.57	58	61
% of households below the poverty line	62.82	50.43	42	39

* Source: Authors' calculations.

DISCUSSION

Economic welfare measurement is crucial for policy-making. Demand analysis and consumption patterns help predict future situations. It's crucial to assess the impact of economic policies like subsidies and price changes on food security, health, and consumer welfare. We can gauge their effectiveness by observing consumer behaviour. In this study, an attempt was made to investigate the effectiveness of the policy of paying subsidies to poor households on reducing the vulnerability of poor households. For this purpose, use the household expenditure and Income survey of households supported by the government (under the support of the Komite Emdad) and the QUAIDS model and CV welfare index. The CV showed that the lost welfare of the low-income households in Iran under different price shock scenario. The welfare index of compensated variations of low-income households fluctuates between 8.05-80.46 $ under different scenarios. In other words, consumers are in a worse situation in terms of welfare and their expenditure increases. This finding was also reported by Arfini and Aghabeygi (2018) for Italian consumers and Layani *et al.* (2020) for Iranian urban households. The largest decline in household welfare due to price changes is related to two groups of cereals and meat. The CV index for the cereal fluctuates between 10.32-1.82% under different price scenarios. For meat, CV is between 0.91-29.15%. Roosen *et al.* (2022) showed that a general rise in the value-added meat tax from 7% to 19% leads to a welfare loss of 0.83 euros per household per month in Germany.

Based on the results, the degree of welfare lost by the studied households in 2020 as a result of different price shock scenarios, considered on average about 14.67%, 4.28%, 2.29% and 1.46% of their income in this year. Comparison of the findings with those of other studies (e.g. Layani *et al.*, 2020) confirms that the vulnerability of low-income households is more than others. The results indicated that a significant number of households have lower food expenditures than the estimated food poverty line, and they suffer from malnutrition. Therefore, the government's support policies (including the payment of cash subsidies to the head of the household) have not been able to eliminate the vulnerability of low-income households caused by food price inflation, and some of these households are still below the poverty line. The government has tried to play an effective role by supporting vulnerable households with appropriate assistance programs or paying subsidies to offset the impact of price increases. The results of this study show that cash subsidy payments offset only a small portion of the welfare loss. Thus, if the government's goal is to support vulnerable households, regulating the market for these products can play an important role in food security and support implementation.

Iran's goods and services subsidy policy has been criticized for being inefficient despite being a consumer-supportive policy for the past 40 years. The poverty index is still high and standard welfare is not achieved for households. It is costly, potentially distorts the market, and benefits some groups that do not require support. Currently, the Iranian government provides a uniform subsidy to all individuals irrespective of their distinctive characteristics. However, empirical evidence demonstrates that the vulnerability of different individuals varies based on their demand structure. Therefore, undertaking such studies can aid the government in providing targeted subsidies based on the income of each person and minimizing the adverse effects of price shocks. For instance, individuals with lower income exhibit different behavioral patterns than those with higher income. Thus, the subsidy granted to them should be calculated based on their demand and welfare effects. This study is a significant step towards targeted subsidies, reducing governmental resource wastage, and promoting efficient allocation of resources. The current study was conducted on low-income households that are supported by the government, commonly known as relief committee member households. The findings of this study suggest that the government's existing support packages require a redesign to enhance the living conditions of these households. To achieve the desired outcome of improving the livelihoods of these households, policymakers are advised to consider increasing the amount of cash subsidy provided to these individuals. Alternatively, policymakers may also consider implementing sound policies that create stable employment opportunities for these individuals, which may lead to an improvement in their income status.

On the other hand, the demand for various types of meat, cereals, dairy products, and other food products will increase for various reasons, including population growth, which can be met by domestic production or foreign sources. Considering the significant results and effects that changes in global prices can have on household expenditure, the most logical policy is to support domestic production. More specifically, if food production does not keep pace with population growth, per capita food production will decrease as a result. Therefore, increasing demand should be met by increasing food imports or reducing exports, or resorting to both measures, which may affect domestic food prices. The increase in food imports definitely leads to greater dependence on foreign sources. This leads not only to a financial burden, but also to a number of economic, social, and political problems, including the impact of global price fluctuations on the domestic market. Considering the increasing trend of global food prices in recent years, and taking into account the welfare losses due to this price increase as an indirect tax imposed on consumers, it is possible to accurately identify vulnerable households and pay support. The cost played a more effective role in offsetting the impact of the price increase and supporting them. Given the impact of the rise in food prices on the well-being of the population and the need to respond to the increase in demand for food resulting from the rise in prices and to pay attention to food security, it may be important to improve the quality of people's diets through measures such as increasing the production of appropriate foods and creating diversity in food production, especially for foods that account for a significant portion of household food expenditures.

CONCLUSION

This study set out price elasticities of eight food groups to evaluate the impact of food price changes on Iranian households. Using the Quadratic Almost Ideal Demand System (QAIDS), we investigated how increasing food prices affects the welfare of Iranian urban consumers and the poverty line. The estimated price and expenditure elasticities align with expectations, with own elasticities being negative and expenditure elasticities being positive. The research has also shown that the rise in food prices has led to a decline in the purchasing power of households, resulting in a loss of welfare. The findings of a cost-of-living analysis indicate that the consumer welfare of different scenarios varied between \$8.05 to \$80.46. This is equivalent to approximately 5.74% to 57.28% of the total food expenditure of eight food groups in 2020. While the impact of food price changes varied across food groups, the majority of households experienced significant difficulties in accessing food due to such price changes. It is noteworthy that after food price shocks, there was an increase in the number of households that fell below the poverty threshold.

Therefore, the government can play a crucial role in supporting the vulnerable households and households below the poverty line, considering the increasing trend of food prices in recent years with appropriate support programs or by paying subsidies to compensate for the effect of the price increase. However, the findings of the present study indicate that the extant cash subsidy payment policy is insufficient to compensate for the decline in welfare resulting from the surge in food prices in recent years. The outcome of such research endeavors can significantly contribute to the policymakers' ability to develop comprehensive and targeted support packages for households susceptible to economic vulnerabilities. By incorporating the results of these studies into their policy formulation process, policymakers can design effective measures to address the needs of vulnerable households and facilitate their economic stability and overall well-being.

However, there are some limitations in the present study that should be considered to make appropriate policy. This limitation is using the main food groups instead of using food separately in this study. Further research can also focus on calculating welfare effect separately for each food item and for different income deciles in order to determine exactly the extent of government support for vulnerable and poor households. The application of price elasticities, segmented by income, age, and education, can provide an accurate framework to determine consumer behavior. Such a framework can facilitate the formulation of effective policy designs, which can be further explored through future research. It is important to note that the simulations conducted in this study were based on cross-sectional data. To gain a better understanding of the long-term effects of food price shocks on poverty levels, future research must utilize panel data and examine poverty dynamics in conjunction with household livelihood strategies.

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Citation: Fraser, I., Fountain, M.T., & Holland, J.M. (2024). Crop production, the pollinator deficit and land use management: UK farm level survey results. *Bio-based and Applied Economics* 13(4): 397-417. doi: 10.36253/bae-15333

Received: November 13, 2023
Accepted: August 2, 2024
Published: December 31, 2024

Data Availability Statement: All relevant data are within the paper and its Supporting Information files.

Competing Interests: The Author(s) declare(s) no conflict of interest.

Editor: Simone Cerroni

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Crop production, the pollinator deficit and land use management: UK farm level survey results

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Abstract. In this paper, we address a gap in the literature concerning pollination management, the pollinator deficit, and conservation objectives. By employing a farm level survey of UK farmers, we examine farmers' attitudes, understanding and management of pollinators. Based on descriptive statistics and regression analysis, we found significant variation in interest and understanding of the impact of pollinators on commercial crops meaning that many respondents did not consider they had a pollinator deficit in terms of crop quality, quantity, or financial impacts. At the same time, many farmers are willing to adopt environmentally beneficial land-use measures if suitable advice and financial incentives are offered. However, there is little evidence of coordination of actions between farms to support wild pollinators. These findings indicate a potential disconnect between a farmer's understanding of the impact on agricultural output from a pollinator deficit and the agricultural benefits from the adoption of specific environmental measures.

Keywords: agri-environment policy, bees, wildflower strips, soft fruit, top fruit, arable.
JEL Codes: Q15, Q576.

1. INTRODUCTION

Ensuring sufficient crop pollination is essential if yields are to be maximised. This is particularly the case as we are seeing significant growth in demand for pollinator-dependent crops, at the same time that there is a decline in wild pollinators within the farming environment (Jordan et al., 2021; Gazzea et al., 2023) with research indicating that many crops may be experiencing a pollination deficit (PD) resulting in sub-optimal levels of production (Garibaldi et al., 2016; Reilly et al., 2020). For example, as part of an economic analysis of landscape configuration to support pollinators Kirchweger et al. (2020) assume that no insect pollination means that the optimal yield for oilseed rape (OSR) will be 79% of the maximum with pollination. Warnings about the economic impact of sub-optimal levels of crop pollination are frequent in the literature (e.g., Cardoso et al., 2020). Many studies

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examine the impact of pollination on the production of specific crops such as Perrot et al. (2018) (OSR), Fountain et al. (2019) (pears), Samnegård et al. (2019) (apples), Bishop et al. (2020) (faba beans), Eeraerts et al. (2019) (sweet cherry) and Garratt et al. (2023) for orchards (especially apples).

At the same time there are numerous studies examining farm level management options to support wild pollinators (Albrecht et al., 2020; Fountain, 2022; McHugh et al, 2022; Nicols et al., 2019 and 2023). In this literature, pollinator management can refer to measures that support both "managed" and "wild" pollinators. This distinction is important when considering how farmers think about the role of pollination in production. Managed pollination services (e.g. bee hives) which can be purchased or rented are equivalent to any other agricultural input and can reduce the uncertainty and risk of relying on wild pollinators. However, in many cases wild pollinators can provide the same or a better service than managed pollinators (e.g. Mateos-Fierro et al., 2022).

In response many governments including the UK have adopted pollinator friendly policy initiatives often embedded in agri-environmental policy (AEP) that explicitly aim to reverse the decline in wild pollinators in agricultural landscapes. For example, the UK government published the UK National Pollinator Strategy (NPS) in 2014, a 10-year plan to enhance and improve the status of all pollinating insects in England that includes the Wild Pollinator and Farm Wildlife Package (Defra, 2022).

Despite all this research and government policy it is somewhat surprising that there is limited research examining the knowledge and understanding that farmers have of the PD in crop production and the associated adoption of appropriate pollinator management activities (Hevia et al., 2021; Nalepa et al., 2021; Osterman et al., 2021). It remains unclear to what extent farmers consider or understand the potential for a PD to exist, and this is unlikely to change anytime soon because farmers rarely monitor the degree of crop pollination unlike yields (Garibaldi et al., 2020; Gemmill-Herren et al., 2021).

In this study, our key objective was to understand the degree to which UK farmers consider current levels and quality of pollinator activity and its impact on agricultural production, and to generate evidence on the extent to which farmers consider the PD to be a significant issue. In addition, we wish to examine the mix and type of management activities being implemented to support wild pollinators as well as the level of knowledge about pollinators. We also examine the degree to which AEP are enabling on farm management activities to support wild pollinators.

To address our research objectives, we developed a survey instrument that examine UK farmers knowledge of pollinator management for crop production together with wider environmental objectives. Our survey instrument was developed in collaboration with our project partners (academic and industry) from the North Sea Region Interreg project BEESPOKE.[1] In designing the survey, we took a bottom-up approach focussing on farmers to understand their knowledge of the PD as well as the use of AEP options. Our survey collected data (n=228) on farmers knowledge and understanding of the PD, pollinator habitat and management and AEP engagement. It was distributed to farmers growing at least one crop that is pollinator dependent in terms of yield. The survey yielded both qualitative and quantitative data.

By undertaking this survey our research contributes to the existing literature in several ways. First, we present evidence on the extent to which UK farmers perceive there to be a PD. Understanding farmers views about crop pollination and the associated, quality, quantity and financial implication reveals the extent to which they considered the PD to be important. Second, as noted there is limited existing research examining farmer understanding of pollinators and farmers' needs (e.g., Osterman et al., 2021; Busse et al., 2021; Nalepa et al., 2021). We add to this literature using our survey data for UK farmers. Third, within economics, much of the existing research has focussed on generating estimates of the value of pollination services (Feuerbacher et al., 2024) or the non-market values society derives from experiencing pollinators (use value), knowing that they exist (non-use existence value) as well as the indirect benefits they provide such wild-flowers and greater biodiversity (Moreaux et al., 2023). Therefore, there remains a need for more research examining on-farm adoption of pollinator conservation measures. Finally, there is a knowledge gap around our understanding of current levels of farm level pollinator management activities and whether this is driven by crop production and/or AEP.

The paper is structured as follows. In section 2, we briefly review the antecedent literature focussing on the significance of the PD, farmer knowledge and understanding of crop pollination, and AEP adoption. Next in Section 3, we describe our survey instrument and the statistical methods employed to analyse the data collected. Next, we present the results of our analysis and in Section 5, we discuss implications. Finally, in Section 6, we conclude.

[1] This research was funded by Interreg grant: Beespoke (Benefitting Ecosystems through Evaluation of food Supplies for Pollination to Open up Knowledge for End users) https://northsearegion.eu/beespoke

2. LITERATURE REVIEW

2.1. Significance of the pollinator deficit

The potential for a PD or pollination limitation to exist in agricultural production has been a reoccurring theme with the literature (Garratt et al., 2014; Garratt et al., 2023). Identification and measurement of the PD has been examined in a wide array of crops in both field studies (Reilly et al., 2020) and meta-analysis of existing research (Gazzea et al., 2023). Economic research on the PD often reports the yield dependence ratios which measures how much of the crop (quality and quantity) is lost if there is no pollination (Feuerbacher et al., 2024). When a PD has been identified researchers typically express this in terms of sub-optimal production and consequent reduction in financial returns. For example, Garratt et al. (2023) report (for 24 commercial apple orchards in Kent, UK), that average PD was 22% in 2018 and 2.6% in 2019 which equated to an average reduction of £15,000 per hectare. The extent of the PD is also highlighted by Reilly et al. (2020) who report that five out of seven major pollinated crops in the USA exhibit a PD. And with this potential level of sub-optimal production being identified the economic consequences have also been examined (Jordan et al., 2021). However, Breeze et al. (2016) and Baylis et al. (2021), both note that economically valuing the PD or more generally valuing pollination services has proven to be complicated given the difficulties in identifying key parameters such as the extent to which crop output depends on pollination services.

2.2. Farmer knowledge and understanding of pollinators

Despite the existence of a significant body of research examining and attempting to measure the PD there is far less research that considers the extent to which farmers knowledge and understanding of pollinators or the PD. A particularly relevant study is Osterman et al. (2021) who examined the decline of pollinators in agricultural landscapes highlighting the existence of a knowledge gap between understanding the issues around pollinator decline and farmer willingness to adopt science informed land use interventions. They interviewed 560 farmers across 11 countries all growing at least one of four pollinator-dependent crops (including 25 UK OSR farmers). Osterman et al. (2021) report that many survey participants know about non-bee pollinators via observation in the field but there remains a significant knowledge gap regarding non-bees and crop pollination (Rader et al., 2020). In terms of OSR and government incentives for AEP, they report that 70% of farmers implemented hedgerows when financial incentives are available and 20% without. They found similar results for floral strips. Clearly, the motivation for many famers to implement land use interventions such as flower strips is because they receive financial payments.

Another relevant study is provided by Hevia et al. (2021) who surveyed Spanish farmers in four areas to understand perceptions about pollinators and practices to promote them. They collected 376 face-to-face questionnaires, although between 59% and 87% of the responses collected are from respondents who are either part-time farmers or non-professional farmers. Like Osterman et al. (2021) honeybees, then bumble bees and wild bees are the main pollinators with other pollinators not viewed as being as important. Respondent attitudes about declines in pollinators informed their views about what needs to be done to reverse the decline. Employing stepwise multiple regression Hevia et al. (2021) examined what influenced knowledge about pollinators reporting that education, concern about the pollinator crisis and farmer type (i.e. full time) are positively correlated whereas age was negative. They also note that reported actions to promote pollinators are less use of insecticides, crop diversification and fallow fields, and that the level of education is positively correlated with maintaining wild-flowers and reduced spraying.

Similarly, Busse et al. (2021) report that adoption of insect-friendly farming measures, especially integrated pest and pollination management (IPPM) (Lundin et al., 2021) is only implemented if sufficient financial incentives are available. Also, farmers regard insect biodiversity typically in terms of ecosystems services as they relate to agricultural production and not as part of the wider ecosystem. Furthermore, farmers appear to implement specific types of agricultural practices without understanding the potential benefits they have on pollinators. For example, flowering catch cropping is used without many farmers realizing the benefits for pollinators. Cole et al. (2022) discusses how planting a legume mixture can help support wild pollinators. Improving farmers' understanding of this issue is, as Busse et al. (2021) argues, a precondition to the adoption of new land use management techniques that will support pollinators (and insects more generally).

Other relevant research is presented by Eeraerts et al. (2020), who surveyed 24 sweet cherry farmers in Flanders, Belgium employing semi-structured interviews. They report that the farmers understood the importance of insects as wild pollinators although as is common in the literature there was undue emphasis placed on the importance of specific types of bees. Eeraerts et al. (2020) also note that almost all respondents pay for honey beehives. This choice can be understood as a short-term solution to their crop pollination requirements whereas making changes to the landscape (e.g., the introduction of wildflower strips) are longer term strategies. More generally, the relationship between wild pollinators and the use of beehives can be understood as a pollination diversification strategy (Nalepa et al., 2021).

Finally, using an online survey of 75 Canadian apple growers Nalepa et al. (2021) examine the influence of farm characteristics and farmer perceptions about bees and how this influences the adoption of pollinator supporting management practices. Employing logistic and Poisson regression models they found a positive relationship between grower awareness of pollinators and the number of pollinator supporting practices adopted on-farm.

2.3. AEP and pollinator management

Agricultural production and land-use choices that necessitate the need for AEP to support wild pollinators is evidence that agricultural intensification is generally negatively correlated with pollinator diversity and associated services (Deguines et al., 2014). Increased intensification of crops that require pollination necessitates the need to support pollinators with suitable living habitats in the wider landscape. In addition, Kleijn et al. (2015) argue that society cannot rely on crop pollination as motivation for providing meaningful support for wild pollinators. Therefore, the importance of AEP in promoting and financially supporting wild pollinator management is clear. In the UK, there are a several AEP initiatives with specifically designed elements to support pollinators such as the Countryside Stewardship Scheme (CSS) that offers financial support for undertaking various pollinator supporting activities. Defra (2023a) report that popular CSS on-farm activities that support wild pollinators include management of hedgerows, the provision of winter bird food and flower-rich margins. The flower-rich margins option has been implemented on 32,000 hectares. Importantly, AEP pollinator options are targeted at conservation objectives and not agricultural production although there can be positive production externalities.

When it comes to AEP design, McCullough et al. (2021), Eeraerts (2023), and Pindar and Raine (2023) all conclude there needs to be more land maintained as natural/semi-natural habitat. Similarly, Image et al. (2023) argue that AEP needs to complement wildflower strips with other landscape features such as hedgerows and woodland margins. McCullough et al. (2021) suggested that planting small areas may provide some benefits for pollinators (bees) under specific settings but policy, with a focus on the landscape scale, is likely to be more important. Wood et al. (2015) also explains that an interaction between landscape features, AEP interventions and crops being grown needs to be considered when assessing landscape modifications to support pollinators. Gardner et al. (2021) note that wild pollinator populations are more stable in landscapes that have a greater number of boundary features and/or semi-natural features.

In terms of explaining adoption of AEP (in general) the literature frequently cites opportunity cost (Hejnowicz et al., 2016) and the fit of the AEP options with existing farm level practices (Bartkowski et al., 2023). Other explanatory factors identified in the literature as positively influencing adoption include tenure (Bartkowski et al., 2023), farm size (Wool et al., 2003) and farm type (grassland compared to specialized arable farms) (Paulus et al., 2022). In a systematic review of quantitative literature on AEP participation Canessa et al. (2024) report that binary choice models such as logits and probits are often used to explain adoption, although very few studies examine adoption in relation to biodiversity (7% of models). In these studies, frequently employed independent variables include age, education, farm size, farm type, information sources, and neighbour participation. However, it is noted by Tsakiridis et al. (2022) in studies that examine AEP and adoption that self-selection bias can be an issue in terms of sample composition. This in turn means that there will likely be higher levels of adoption in sample data such that any statistical signal will be likely stronger and positive.

2.4. Summary and key research questions

Given our review of the antecedent literature and the objectives of our research, the following research questions will be addressed:

i. How important do farmers consider the PD to be for crop production?

Given the existing literature researchers consider the PD to be a significant issue, but it remains unclear if farmers share this view.

ii. What types of farm management actions and activities do farmers adopt to support pollinators?

The existing literature on the type of actions and activities that farmers adopt to support pollinators is limited and an enhanced understanding will give important insights into pollinator management. In particular, understanding the extent to which farmers employ short term (i.e., bee hives) versus long term (i.e., wild pollinators) solutions for pollination services is important. In addition, understanding the extent to which farmers employ AEP to supports pollinators and the reasons why. This will also enable us to better understand the degree to which farmers coordinate with neighbours in supporting pollinators.

iii. What knowledge do farmers have of pollinators?

A reoccurring theme in the literature is the limited knowledge and understanding that farmers appear to have regarding pollinators in terms of types and potential contributions to crop production.

iv. What do farmers consider to be their main pollinator management priorities and what advice and information sources will inform these priorities?

Finally, we examine key priorities in terms of pollinator management and who farmers turn to for advice and information.

3. MATERIAL AND METHODS

3.1. Survey design and implementation

Our data collection strategy involved the design and implementation of a farm level survey instrument that enabled us to address the research questions raised. The design of our survey enabled us to collect information to address the issues identified in the Introduction as well as key themes that emerged from the antecedent literature. In particular, the survey was designed to examine the extent to which farmers understand the required actions and activities to support pollinators and its impact on crop production, knowledge and understanding of pollinators, and appropriate management.

The survey (see Appendix C) began by requesting information for the most important pollinated crop from each respondent. We wanted to examine attitudes towards crop production and pollination. We asked a series of questions to reveal information regarding farm level production and the PD. The survey then asked about current levels of pollinator land management activities and how these are influenced by participation in AEP. We also sought information about farmer knowledge regarding pollinators as well as sources of advice and information used in crop production. Given the importance of landscape scale land use decision for wild pollinators, we asked about the extent to which respondents cooperate with neighbouring farmers regarding pollinators.[2]

The survey instrument was initially trialed by distributing to a small group of farmers involved with the BEESPOKE project who gave feedback. The final version was distributed online in two waves during 2021 and 2022 by an agricultural research company (i.e. Map of Ag Analytics Limited - https://mapof.ag/). To be included in the survey, we required respondents to grow at least one pollinator dependent crop. Survey participation was incentivized yielding 200 responses. In addition, to ensure adequate survey returns from soft and top fruit producers, we also distributed the survey via industry contacts, yielding a final sample of 228 responses.

3.2. Descriptive statistics

Our sample of respondents (n=228) were drawn from farmers across England and Scotland with the largest number of responses being recorded for Kent (n=32), Scotland (n=14), Herefordshire and Norfolk (both n=13), North Yorkshire and Suffolk (both n=13), Lincolnshire (n=12), Shropshire and Cambridgeshire (both n=11). By mapping the survey data onto the International Territorial Levels (ITLs) adopted by the UK government we could assess the representativeness of our sample of farmers by crop (three most common reported) and region.[3] The results are shown in Table 1.

The results in Table 1 reveal that in terms of regional distribution by crop type, our sample of respondents appears to be relatively similar in terms of OSR and apples. However, for strawberries our sample maps less well, however, as shown in Table 2, that presents sample descriptive statistics, strawberries only account for 7.5% of survey returns. We note, however, that the non-standard composition of the farms being surveyed means that it is difficult to accurately assess the representativeness of our sample.

The descriptive statistics shown in Table 2 present information for key variables side by side as well as by column.

From Table 2, we observe that in terms of years of farming experience, it is unsurprising that almost 80% have more than 25 years given the age profile of respondents (median age of over 50 years). The age profile of our respondents is typical for England, although

[2] The survey also collected qualitative information using open-ended questions. Although these are not referred to in this paper a small selection of responses are provided in Appendix B.

[3] For details see: https://www.ons.gov.uk/methodology/geography/ukgeographies/eurostat#south-west-england-

Table 1. Percentage of survey respondents by region and three main crops compared against England farm census data for 2021.

	Sample Data			England Census Data 2021[1]		
Region	OSR[2]	Apples	Strawberries	OSR	Apples	Strawberries
South-East	17	43	6	14	44	50
East of England	19	8	35	25	7	14
West Midlands	14	33	12	11	30	21
Yorkshire	17	0	0	16	0	1
East Midlands	13	0	12	19	2	4
South-West	5	15	6	9	16	9
North-East	4	0	0	6	0	0
North-West	1	3	6	1	1	1

[1] Source: Defra (2024). Structure of the agricultural industry in England and the UK at June 2021 www.gov.uk/government/statistical-data-sets/structure-of-the-agricultural-industry-in-england-and-the-uk-at-june; [2] OSR = Oilseed Rape.

Table 2. Descriptive data.

Variable	Categories	Percentage	Variable	Categories	Percentage
Years Farming	Less than 5	1.3	Age	Age Under 35	3.9
	5-10	3.9		36-45	12.3
	11-15	4.4		46-55	18.4
	16-25	11.8		56-65	39.0
	More than 25	78.5		Over 65	26.3
Farm Management	Farm Owner	75.4	Farm Type	Top Fruit	15.4
	Farm Manager	11.8		Mixed	15.5
	Tenant Farmer	9.2		Soft Fruit	7.3
	Other	3.5		Livestock	3.9
				Arable	57.9
How Crop Sold	Producer Organisation	19.3	Agri-Environmental Policy	Yes	54.0
	Contract	22.4		No	46.0
	Spot Market	45.2			
	Other	13.2			
Crops Grown	Oilseed Rape	59.2	Crops Grown	Blackcurrants	0.9
	Apples	17.5		Blueberries	0.9
	Strawberries	7.5		Plums	0.4
	Cherries	2.6		Linseed	0.4
	Field beans	4.8		Spring Beans	0.9
	Pears	1.3		Borage	0.9
	Raspberries	0.9		Parsley	0.4
				Sunflowers	0.4

we have less farmers aged 65 and over compared to recent farm statistics (DEFRA, 2023b). In terms of farm management, 75.4% of respondents are farm owners and 9.2% are tenant farmers, which compares to 54% being owner occupied and 14% being tenanted in 2021 in England (DEFRA, 2023b). In terms of the area of pollinated crops grown, we have an average of 51 hectares with a median of 30 hectares.

Our sample has 54% of respondents participating in AEP. It is difficult to establish if this is high or low compared to national data. Within England in 2022, it is reported by DEFRA (2023c) that 34,500 AEP agreements were implemented. Given that there are almost 200,000 agricultural holdings in England this means 18% are participating, although 80,000 holdings are under 20 hectares and participation amongst small farms is known to be significantly lower. Also, the participation rate in our sample is significantly below the levels seen at the peak of earlier AEP e.g. Entry Level Scheme had 70% participation. Wool et al. (2023) report that in the

Humber region of the UK AEP adoption rates are relatively low with only 11% of farms adopting.

Finally, the mix of crops reported in Table 2, shows that the most frequent is winter oilseed rape (59.2%), apples (17.5%) and strawberries (7.5%). Also, as we would expect, our sample does have a high proportion of arable producers which reflects current agricultural land use in England (DEFRA, 2021). In 2021, 3.7 million hectares of land was used to grow arable crops with cereals and oilseed crops (various) accounting for 80%. The area used to grow oilseed crops was 313,000 hectares in 2021. In contrast, horticulture accounted for 131,000 hectares of land. The land area devoted to orchards and small fruit was 31,000 hectares (DEFRA 2021) with orchards accounting for almost 70% of this area.

3.3. Data analysis, methods, and statistical software

We began by examining descriptive statistics for our survey for the set of questions we wished to address. In addition, we implemented a statistical test between pairs of proportions for responses by crop type. We also estimated several regression model specifications to further examine the questions we raised regarding attitudes and knowledge of the PD and pollinators, and farm management and pollinators.

In terms of regression model specifications, for example, when we had a binary dependent variable, we employed a logit specification. Most data collected by the survey, is either a yes or no responses (e.g., Is crop yield lower than expected? See Table 5). When employing a binary logit model, it utilises a latent variable approach to determine the probability of an event. This approach retains a linear regression model but utilises a framework to determine the value of a latent or unobserved variable (y^*) which in turn determines the outcome observed for the binary dependent variable y. Formally,

$$y_i^* = X_{ik}\beta_k + u_i$$

where

$$y_i = 1 \text{ if } y_i^* > 0$$

$$y_i = 1 \text{ otherwise}$$

where $i = 1,\ldots,N$, X_{ik} is a i by k data matrix, $ß$ is vector of independent variables $(k=1,\ldots,K)$ to be estimated and u_i is the error term assumed to be independently identically distributed with mean zero and constant variance.

In contrast, when our dependent variable takes the form of a count variable, we employed a Poisson specification. An example is a count of the number of farm management practices adopted to support wild pollinators (see Table 7). In this case, the model is specified as

$$f(Y|y_i) = Pr(Y = y) = \frac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i!} = \frac{e^{X_{ik}\beta_k}\lambda_i^{y_i}}{y_i!}$$

where λ is the Poisson distribution parameter. The Poisson regression model can be specified in log-linear form:

$$\text{Ln } \lambda_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k$$

Finally, when the dependent data was an ordered response, we estimated an ordered Probit model.

All regression models were estimated using LIMDEP Version 11 (Greene, 2016). Our regression analyses do not reveal causality, but potentially important correlations between aspects of farm level activities, crop types and pollinator management. The selection of explanatory variables we employ is informed in part by reference to the antecedent literature. For example, as

Table 3. Explanatory variables used in statistical analysis.

Variable	Description	Units
Experience	Number of years farming	Years*
Area	Size of farm	Hectares
AEP	In an AEP scheme supporting pollinators	Yes = 1, No = 0
Records	Keep records of crop pollination	Yes = 1, No = 0
Soft Fruit	Type of crop produced	Yes = 1, No = 0
Top Fruit	Type of crop produced	Yes = 1, No = 0
Arable	Type of crop produced	Yes = 1, No = 0
Low Yield	Farmer thinks current levels of pollination are negatively impacting crop yield	Yes = 1, No = 0
Collaborate	Collaborate with neighbours in supporting wild pollinators	Yes = 1, No = 0

* In some regression model specifications, we employed experience squared to capture the potential non-linear relationship between experience and the dependent variables.

noted by Canessa et al. (2024), experience, farm type, size and collaboration with neighbours are frequently employed in studies examining adoption of AEP. The set of explanatory variables used in the regression analysis are presented in Table 3.

4. DATA ANALYSIS

4.1. Attitudes about crop pollination

We first asked respondents' questions about their attitudes to current crop pollination (Table 4).

Many of the farmers in our sample do not consider a lack of pollination (i.e. PD) to be an issue that impacts yield, quality, or financial return (Table 4). However, by crop type, top fruit growers appear less concerned than either soft fruit growers or arable farmers, illustrating the issues confronting efforts to induce greater on farm pollinator management motivated by economic concerns alone. Furthermore, testing the null hypothesis of equality of proportions of responses by crop type, there is a difference at the 10% level of statistical significance between: soft fruit and top fruit (Z=2.18, p=0.074) for crop quality; between arable and soft fruit (Z=-2.136, p=0.055) for crop quality; and arable and soft fruit (Z=-2.34, p=0.052) for financial return. However, even for soft fruit producers the highest level of concern was only 25% for financial returns, meaning, either a large proportion of farmers are generally unaware of PD and its impact on production or PD is less important to farmers compared to other aspects of crop production.

To further examine the responses reported in Table 4, we estimated logit regression models (Table 5).

Farm experience was negatively correlated with a positive response to the questions for crop quality and the impact on finance (Table 5), implying that older farmers appear less likely to express concern about aspects of insect pollination on production. In contrast, larger farms were more likely to respond 'Yes' to the question about the negative impact of insect pollination on yield and crop quality. For crop type (a dummy variable) the excluded category is arable meaning a negative estimate for top fruit (yield and finance) and a positive response for soft fruit (quality) are both relative to arable. These results indicate a

Table 4. Attitudes to pollinator management and crop production (%).

Question	Response	All Crops	Top Fruit	Soft Fruit	Arable
Do you believe the yield of your crop is currently lower than it could be because of a lack of insect pollination?	No	84.2	92.0	79.2	83.2
	Yes	15.8	8.0	20.8	16.8
Do you believe the quality of your crop is currently lower than it could be because of a lack of insect pollination?	No	92.1	96.0	79.2	92.9
	Yes	7.9	4.0	20.8	7.1
Do you believe the financial return of your crop is currently lower than they could be because of a lack of insect pollination?	No	86.8	94.0	75.0	86.4
	Yes	13.2	6.0	25.0	13.6

Table 5. Is crop yield, quality, or financial return lower than it could be, due to a lack of insect pollination? (Yes=1; No=0).

	Low Yield			Low Quality			Low Finance		
Variables	Coeff	SE	P value	Coeff	SE	P value	Coeff	SE	P value
Constant	-0.883	0.999	0.377	-1.332	1.220	0.275	-0.731	1.027	0.476
Experience	-0.313	0.198	0.114	-0.406*	0.245	0.098	-0.369*	0.204	0.071
Farm Area	0.004*	0.002	0.079	0.005*	0.003	0.064	0.003	0.002	0.214
Soft Fruit	0.138	0.591	0.816	1.127*	0.644	0.080	0.641	0.563	0.255
Top Fruit	-1.138*	0.636	0.074	-1.281	0.979	0.191	-1.159*	0.704	0.100
AEP	0.567	0.411	0.168	0.114	0.546	0.835	0.455	0.431	0.292
Records	1.27**	0.546	0.020	1.638**	0.657	0.013	1.177**	0.575	0.041
LL	-88.45			-53.21			-80.46		
Chi^2	18.6***			19.5***			16.6***		
McFadden Pseudo $^R2$	0.10			0.15			0.09		

Notes: Coeff = Coefficient; SE = Standard Error; ***, **, * Significance at 1%, 5% and 10% level; LL = Log-Likelihood.

Table 6. Hire crop pollination services (Yes =1/No=0).

Variables	Pollinator Service		
	Coeff	SE	P value
Constant	-2.05**	0.95	0.03
Experience	0.07	0.19	0.71
Top Fruit	1.33***	0.36	0.00
Soft Fruit	1.65***	0.47	0.00
Low Yield	-0.19	0.47	0.69
AEP	0.44	0.32	0.17
Records	0.26	0.51	0.62
LL	-124.3		
Chi^2	23.96***		
McFadden Pseudo R^2	0.088		

Notes: Coeff = Coefficient; SE = Standard Error; ***, **, * Significance at 1%, 5%, 10% level; LL = Log-Likelihood.

mixed response for crop type and how insect pollination impacts crop performance. Next, if a farmer keeps pollinator records, then they are more likely to have responded 'Yes', such that recording crop pollination is likely to heighten awareness of potential issues stemming from crop deficiencies. Finally, we note that the McFadden Pseudo R^2 for all models is relatively low and as such we should treat these results with a degree of caution.

Finally, we also asked respondents if they hire contract pollination services. This was confirmed by 35% of respondents. To examine this decision in more detail, we estimated a logit regression model with the results shown in Table 6.

The results in Table 6 reveal that soft fruit and top fruit producers are more likely to employ this type of service compared to arable farmers.

4.2. Farm management and wild pollinators

Next, we asked respondents about farm management practices they employ to encourage and support wild pollinators (Table 7).

Most respondents undertake some type of activity to support wild pollinators (Table 7), although these estimates may be subject to a degree of selection bias i.e. responses from farmers interested in pollinators or biodiversity. Given the responses on crop quantity, quality and financial returns, the motivation for adoption of practice listed in Table 7 are unlikely to be driven by crop production and instead by environmental attitudes, AEP requirements, retailer requirements and insecticide container labelling that stipulates how to avoid impacts

Table 7. Farm management supporting wild pollinators (%).

Farm Management Practice	Yes
Improve management of existing habitats	89.0
Establish new flower-rich habitats	73.2
Maintain hedgerows by not cutting annually	80.3
Time insecticide spraying to reduce impact on pollinators	93.9
Time pesticide applications to reduce impact on pollinators	81.6
Reduce number of chemical applications to protect beneficial insects	88.2
Spot spraying instead of treating an entire crop	46.1
Provide nesting and/or overwintering habitat	79.4

Table 8. Adoption and non-adoption of pollinator supporting activities.

	Adopt			Not Adopt		
Variables	Coeff	SE	P value	Coeff	SE	P value
Constant	1.712***	0.156	0.000	1.072***	0.306	0.001
Experience	-0.002	0.032	0.949	-0.107*	0.063	0.089
Soft Fruit	0.119	0.085	0.159	-0.105	0.187	0.575
Top Fruit	0.086	0.065	0.187	-0.693***	0.175	0.000
Low Yield	0.062	0.073	0.392	-0.105	0.166	0.527
Collaborate	0.107	0.068	0.118	-0.155	0.166	0.350
AEP	0.147***	0.055	0.007	-0.271**	0.119	0.023
LL	-458.75			-356.74		
Chi 2	15.1***			25.8***		
McFadden Pseudo R^2	0.016			0.035		

Notes: Coeff = Coefficient; SE = Standard Error; P = P Value; ***, **, * Significance at 1%, 5%, 10% level; LL = Log-Likelihood.

on pollinators. When we asked respondents their reasons for not adopting practices that support wild pollinators; time (28%), experience (20%) and cost (17%) were the main justifications.

To further examine adoption, we estimated a Poisson count data regression model by creating a dependent variable for the number of practices adopted/not adopted (see Table 7). These results are presented in Table 8.

The number of adoptions of pollinator beneficial on-farm management activities was only explained by whether a farmer was in AEP. In the case of not adopting practices, this was negatively related to farmer experience, if they produced top fruit, and if they were in an AEP. More analysis on the proportion of arable and fruit farmers in AEP is required. However, there is no published data available and only limited statistics regarding overall land use by farm type. This represents an important information gap.

Table 9. Adoption of on-farm pollination supporting activities.

Variables	Improve Habitat[a]			New Flower[b]			Hedge[c]			Time Fungicide[d]			Spot Spray[e]		
	Coeff	SE	P value	Coeff	SE	P value	Coeff	SE	P value	Coeff	SE	P value	Coeff	SE	P value
Constant	-3.12	2.754	0.257	-6.41**	2.665	0.016	-5.93**	2.515	0.018	1.26	2.585	0.625	-4.89**	2.259	0.030
Experience	3.24*	1.879	0.084	5.06***	1.722	0.003	3.93**	1.564	0.012	0.58	1.559	0.709	2.63**	1.305	0.043
Experience^2	-0.46*	0.275	0.092	-0.74***	0.245	0.002	-0.51**	0.219	0.020	-0.12	0.216	0.590	-0.36**	0.176	0.041
Soft Fruit	1.64**	0.787	0.037	0.27	0.389	0.494	0.85*	0.494	0.084	0.29	0.451	0.518	0.99***	0.352	0.005
Top Fruit	1.31	1.057	0.215	0.99	0.665	0.135	0.33	0.605	0.582	0.56	0.661	0.394	0.53	0.462	0.246
Low Yield	0.87	0.777	0.260	0.94*	0.553	0.091	1.39**	0.691	0.044	-0.82*	0.445	0.065	0.63	0.399	0.116
Collaborate	1.03	0.772	0.181	1.08**	0.523	0.039	0.55	0.528	0.299	1.18*	0.639	0.063	0.67*	0.378	0.075
Records	-0.26	0.814	0.751	0.64	0.667	0.337	0.69	0.794	0.379	0.29	0.680	0.670	0.47	0.503	0.352
LL	-70.3			-118.5			-104.1			-103.8			-147.9		
Chi^2	12.72*			25.79***			18.36**			10.12			18.9***		
McFadden Pseudo R^2	0.083			0.098			0.081			0.046			0.06		

Notes: Coeff = Coefficient; SE = Standard Error; ***, **, * Significance at 1%, 5%, 10% level; LL = Log-Likelihood; a = Improve management of existing habitats; b = Establish new flower-rich habitats; c =Maintain hedgerows by not cutting annually; d = Time insecticide spraying to reduce impact on pollinators; e = Spot spraying instead of treating an entire crop

We also examined the individual on-farm practices using logistic regression models. These results are presented in Table 9.

Improved management of existing habitats was positively related to being a top fruit producer, and experience, but negative for experience squared, implying that as farmers gain more experience (i.e. years in farming) they have a decreasing likelihood of adoption. For those establishing new flower-rich habitats, experience was positively related, and experience squared negative. Farmers who considered levels of pollination to be having a negative impact on crop yield and who collaborated with their neighbours regarding pollinators are positively related. For farmers who maintain hedgerows, experience was positively related, but experience squared was negative. However, being a top fruit producer and considering existing levels of pollination as having a negative impact on crop yield were positively related. The timing of fungicide applications was negatively related for those farmers who consider that existing levels of pollination are having a negative impact on crop yield, but positive for those who collaborate with neighbours. Spot spraying was positively related to farmer experience and collaborating with neighbours if producing top fruit but negative for experience squared. Finally, when asked about reducing the number of chemical applications to protect beneficial insects, this was positively related to collaboration with neighbours. Similarly, farmers who provided nesting and/or overwintering habitat, were also likely to be collaborating with neighbours. Our results regarding any aspect of collaboration with neighbours could be a function of pre-existing farm clusters. Examining the influence of farm clusters on farm level cooperation warrants further examination.

4.3. Knowledge of pollinator types

We asked respondents if they knew which pollinators their crops depended on (Table 10).

Most respondents indicated Honeybees, Bumblebees and Solitary bees were the main pollinators. The potential lack of understanding regarding the other pollinators, for example Syrphine hoverflies in strawberries (Hodgkiss et al., 2018) does indicate a need for greater provision of information for farmers. Also, the percentages of respondents indicating the specific type does not vary significantly by crop. Examining the average number of pollinator types by crop type reveals little varia-

Table 10. Which types of pollinators do your crops depend on (%).

Pollinator group	Overall Yes	Overall No	Yes if Top Fruit	Yes if Soft Fruit	Yes if Arable
Honeybees	80.3	19.7	88.0	87.5	76.6
Bumblebees	77.2	22.8	82.0	87.5	74.0
Solitary bees	53.9	46.1	80.0	50.0	46.1
Hoverflies	28.5	71.5	46.0	25.0	23.4
Flies	22.4	77.6	24.0	33.3	20.1
Butterflies	25.4	74.6	24.0	16.7	27.3
Moths	20.2	79.8	30.0	12.5	18.2

Table 11. On-farm pollination monitoring activities (Yes =1; No=0).

Variables	Traps in Crop			Walk Crop			Agronomist		
	Coeff	SE	Pvalue	Coeff	SE	Pvalue	Coeff	SE	Pvalue
Constant	-3.02**	1.22	0.01	-0.49	0.84	0.56	-1.57*	0.90	0.08
Experience	-0.03	0.24	0.89	-0.01	0.17	0.93	0.05	0.18	0.80
Top Fruit	0.90*	0.49	0.07	1.07***	0.37	0.00	0.55	0.37	0.13
Soft Fruit	0.73	0.64	0.26	0.72	0.48	0.13	0.72	0.48	0.14
Low Yield	0.58	0.54	0.28	-0.25	0.42	0.56	0.91**	0.41	0.03
AEP	0.83*	0.47	0.07	0.68**	0.29	0.02	0.11	0.31	0.72
Records	1.76***	0.53	0.00	2.11***	0.77	0.01	1.71***	0.52	0.00
LL	-74.5			-142.4			-130.4		
Chi^2		24.68***		29.1***		25.18***			
McFadden Pseudo R^2	0.142			0.093			0.088		

Notes: Coeff = Coefficient; SE = Standard Error; ***, **, * Significance at 1%, 5%, 10% level; LL = Log-Likelihood.

tion: top fruit farmers identified 3.74 groups; soft fruit farmers 3.13 groups; and arable farmers 2.86 groups. One result of significance was the importance placed on solitary bees by top fruit producers, suggesting that efforts to increase awareness about the importance of solitary bees in pollinating top fruit is having an impact. For each pollinator type, we ran a logit regression and found that the only positive and statistically significant regressors were either being a top fruit producer or coordinating with a neighbour regarding pollinators, and only for Honeybees, Solitary bees, and Moths.

We next asked if respondents undertook any active monitoring of pollinators. Results indicated that most respondents relied on crop walks to assess crop pollination requirements (55%). There was also a significant proportion who relied on advice from agronomists and consultants (32%) but most farmers did not monitor pollinators using traps (13%). We also examined on-farm pollination monitoring by employing logit model specifications. These results are presented in Table 11.

Both crop walks and employing traps within crops are positively related with being a top fruit producer, AEP participation, and keeping pollinator records. The probability growers who took advice on pollination from agronomists and consultants was more likely if existing pollination levels are low, and they were keeping pollinator records. Overall, there was a strong and positive relationship between keeping pollination records and on-farm pollination monitoring activities.

We also asked farmers about other aspects of pollination management. 9.6% indicated that they collected records of crop pollination by pollinator type, 17.1% actively managed their farm for wild pollinators in collaboration with neighbours and 49.1% think that they benefit from pollinators by the actions being undertaken by their neighbours. These findings are important given that accurate records of crop pollination are required if changes to production or land use are to be evaluated in terms of supporting wild pollinators.

4.4. Pollinator management priorities

We next asked respondents their priorities in relation to pollination management (Table 12).

Many respondents indicated “Always” or “Often” in terms of priorities for pollination management regarding consistent and reliable crop pollination and increased economic returns (Table 12). This contradicts the answers reported in Table 4 about understanding how crop pollination relates to quantity, quality, and

Table 12. Main priorities for pollination management (%).

Pollination management main priorities	Always	Often	Maybe	Never
Consistent and reliable crop pollination	67.5	18.9	10.5	3.1
Increased economic return	62.7	22.4	12.3	2.6
Availability of managed pollinators for rental or purchases	14.9	13.2	31.1	40.8
Reported declines in wild pollinator populations	20.2	28.5	26.8	24.6
Diversification of pollination strategies	22.4	25.9	33.8	18.0
Minimising uncertainty and risk in crop pollination	43.0	27.6	22.8	6.6
Effectiveness of pollinator species	36.4	24.6	30.7	8.3

Table 13. Sources of advice used by respondents.

Variables	Published			Government			NGO			Local Groups		
	Coeff	SE	P value	Coeff	SE	P value	Coeff	SE	P value	Coeff	SE	P value
Constant	3.739	2.447	0.127	5.275*	2.705	0.051	-0.674	1.980	0.734	4.189*	2.275	0.066
Experience	-1.876	1.424	0.188	-2.916*	1.586	0.066	0.217	1.216	0.858	-2.337*	1.367	0.087
Experience^2	0.179	0.193	0.353	0.309	0.215	0.151	-0.102	0.170	0.550	0.246	0.189	0.192
Low Yield	1.011**	0.407	0.013	0.315	0.447	0.481	1.132**	0.418	0.007	-0.333	0.464	0.473
Top Fruit	-0.466	0.522	0.372	0.174	0.526	0.741	-0.131	0.562	0.816	-0.646	0.582	0.267
Soft Fruit	-0.487	0.406	0.231	-0.436	0.467	0.351	0.389	0.411	0.344	-0.692	0.445	0.120
Records	-0.220	0.539	0.683	0.513	0.546	0.347	0.121	0.538	0.822	1.258**	0.507	0.013
AEP	0.452	0.312	0.148	0.133	0.352	0.705	0.767**	0.353	0.030	0.314	0.337	0.351
LL	-130.69			-122.42			-127.1			-129.29		
Chi^2	27.45		0.000	22.98		0.000	26.82		0.002	21.54		0.003
McFadden Pseudo R^2	0.095			0.094			0.11			0.083		

Notes: Coeff = Coefficient; SE = Standard Error; ***, **, * Significance at 1%, 5%, 10% level; LL = Log-Likelihood.

financial returns. These results are also hard to reconcile with data around maintaining records about crop pollination. Potentially, it is correlated with crop pollination monitoring and walking the crop, but unless a coherent and meaningful assessment of pollinator presence is related to crop quality/quantity it remains unclear how informative walking a crop can be regarding pollination requirements. Thus, whilst most respondents understand the economic significance of crop pollination it is unclear how this is manifesting in current agronomic practices. For the other types of pollination management priorities, there were much lower levels of importance. Given the clear correlation between these priorities and the supply of pollinator services either from wild or managed pollinators, these results provide more evidence of inconsistent understanding regarding crop pollination and farm level activity.[4]

4.5. Advice and investment in pollination services

Our survey revealed that by far the most important source for seeking advice on crop pollination were agronomists and other commercial suppliers (74%). Next were published advice (33%) and sources including government, NGOs and local environmental groups (at or below 25%), partly relating to the answer about the role of agronomists in monitoring pollinators. For the crop pollination information source, we estimated logit model specification. These results are presented in Table 13.

Table 14. Increased investment in pollination services (%).

Invest in Pollination Services	Yes
Research Evidence on Financial Benefits	63.2
Research Evidence on Environmental Benefits	60.5
Research Evidence on Landscape Benefits	28.9
Farm Assurance Schemes	31.6
Customer Assurance Schemes	22.8
Higher Payments for AEP	54.8
Decrease in Natural Pollinators	39.0

The results shown in Table 13 reveal that there is only weak statistical evidence between the source type of information and the set of explanatory variables. For example, published sources were positively related to reporting a negative yield effect from a lack of pollination. When asked about government sources of information we found only a negative result for experience. For NGOs we found a positive relation for AEP participation and reporting a negative yield effect.

Finally, we asked what would make a farmer increase investment in pollination services (Table 14).

Evidence regarding financial benefits, higher payments associated for AEP participation and evidence on environmental benefits will all lead to an increase in investment of pollination services (Table 14).

[4] We also analysed these responses employing an ordered probit where the dependent variable was coded: Never = 0, Maybe =1, Often = 2 and Always =3. All models yielded relatively weak statistical results. See Appendix A for details.

5. DISCUSSION

5.1. The Significance of the Pollinator Deficit

Our survey results indicated that most respondents were not concerned about the financial consequences of inadequate pollination (i.e. the PD). This means that the answer to our first question (How important do farmers consider the PD to be for crop production?) is not very much, there are only low levels of concern about crop pollination and the associated PD. This result is somewhat surprising given the apparent importance of the of the PD within the existing literature. There are several possible explanations for this result.

First, any variation in crop yield and/or quality that occurs because of the PD are small and as such considered negligible compared to other factors. Within the extensive economic efficiency literature and related farm level benchmarking literature, it was very difficult to identify existing research considering pollination. Examples include Tariq et al. (2018) and Wijayanti et al. (2020) who consider strawberry production and note that variation in pollination as a possible reason for differences in farm level performance. However, the lack of literature on farm level efficiency and productivity that mentions pollination or pollinators likely occurs either because pollination is assumed to be constant, or that the importance of pollination in commercial systems has not been investigated sufficiently to know whether it is optimal and so it has generally been overlooked.

Second, 35% of our sample of respondents employ crop pollination services (i.e. honeybee hives). As observed by Garibaldi et al. (2020), if there are too few pollinators this could be resolved using managed hives in the short term with longer term landscape planning including enhancement and conservation of semi-natural habitats and flower strips. In fact, a decision to deploy honeybee hives can be understood as a risk averse approach to pollination, and many farmers see wild pollinators as additional (or secondary) to honeybees (Eeraerts et al., 2020), even when honeybees are not the most effective or efficient pollinator.

Third, there are trade-offs in land use as it relates to agricultural production and pollination management that means that a PD will always occur. Micro economic analysis assumes that economic agents will equate net marginal benefits from all activities such as crop production and provision of landscape (e.g. wildflower strips) to support wild pollinators that in turn enhance crop returns (Fezzi and Bateman, 2011). Assuming we have a single farm, and they can allocate a small land parcel to either production of apples or production of pollinators (e.g., wildflower strips). On this piece of land farmers are equating the return from the crop and the return from supporting pollinators. If the increase in production on the marginal piece of land more than compensates for the reduction in yield from lower pollinator numbers, then the farmer will plant the crop.

Fourth, our results reveal that the current levels of monitoring and record keeping about crop pollination and pollinators are limited. This means that awareness of the existence of a PD is likely to be low. In addition, this result also answers our third question regarding knowledge of pollinators (What knowledge do farmers have of pollinators?). As noted from the literature, limited knowledge and understanding of pollinators by farmers is frequently reported. In part this could be a result of there being too little monitoring of pollinators, without which it will be difficult for farmers to fully appreciate if existing levels of crop pollination are sufficient. To enable farmers to monitor pollinators requires them to understand how to measure pollination activity as well as be able to identify pollinators. Garibaldi et al. (2020) have described a protocol that farmers could employ to assess if current levels of pollination are too low and research projects such as Beespoke provide extensive guidance on pollinator identification and land management options.[5] The need for this type of protocol is supported by our results in that respondents consider bees to be the most important pollinator, even though many other insects play a significant role in crop pollination. There is a significant body of research demonstrating that insects, in general, are in decline (Cardoso et al., 2020; Mancini et al., 2023). Hall and Martins (2020) note that although pollinator decline and its consequences are understood, and bees have played a key role in knowledge enhancement, there is a need enhance understanding to include insects in general. Basset and Lamarre (2019) and Goulson (2019) argue that we require adoption of activities to protect all insects given the rapid declines in population levels being observed. Basset and Lamarre (2019) also observe that specific species i.e., bees and butterflies have provided an initial focus, but protection needs to go beyond a small group of iconic species. Potentially, bees could be a "flagship species" as happened with the short-haired bumblebee project in south-east England (Gammans, 2013). Conversely, flagship species can mean that other insects are marginalized in terms of conservation efforts

[5] Beespoke (https://northsearegion.eu/beespoke/) has developed protocols to enable farmers to measure insect pollination by crop type. Other examples of research projects supporting farmers in understanding how to count pollinators are the Flower-Insect Timed (FIT) Counts app (https://fitcount.ceh.ac.uk/) that is part of the UK Pollinator Monitoring Scheme (PoMS: https://ukpoms.org.uk/).

and understanding other insects that are critical to ecosystem survival.

Finally, benefits of pollinator monitoring are not confined to individual farmers. There is the need for more general pollinator monitoring such as advocated by Breeze et al. (2021). They demonstrated that costs of monitoring are significantly less than losses from poor pollination. Identifying the potential economic benefits of monitoring needs to examine if the costs of dealing with sub-optimal levels of pollination are economically meaningful.

5.2. Farm level management to support pollinators

In relation to our second question (What types of farm management actions and activities do farmers adopt to support pollinators?) our results align with the existing literature. We find that participation in AEP is positively correlated with the adoption of pollinator supporting activities such as habitat improvements, establishment of flower strips and hedgerow management. There are several reasons why AEP is so important for supporting pollinators on farms.

First, when it comes to key farm level priorities to support pollinators financial reward is the most important motivation for adopting appropriate practices. However, the financial driver is unlikely to be because of agricultural production and the PD given our results. That said, our results also reveal that if the financial benefits in terms of crop production from greater levels of pollination can be shown then farmers would invest in pollination services. Without this evidence payments offered for AEP participation will continue to be the main motivation for adoption. Existing research unambiguously demonstrates that higher AEP payments attract great levels of participation as there are clearly significant costs involved in creating habitats that support pollinators. If we assume that a farmer creates a wildflower strip, then they will incur costs in terms of soil preparation prior to planting the seed which also needs to be bought as well as ongoing management to ensure the wildflower strips yields sufficient flowering plants that will attract and support pollinators. There may also be an opportunity cost where the land used to produce the flower strip is no longer in conventional production (Silva et al., 2023). These costs can reduce the attractiveness of allocating land for pollinators. There may be land that is not currently in production that can be used to support pollinators. In this case, when there is minimal opportunity cost, planting wildflower strips may be an appropriate land use choice, especially if there is also an increase in crop yield (Blaauw and Isaacs, 2014).

Second, even though higher rates of payment for AEP will likely induce higher participation, not all farmers will participate in AEP. As explained by Gaines-Day and Gratton (2017), there may be factors that prevent participation including awareness of policy options, a lack of knowledge to enable participation and a need for farmers' *"to experience a shift in their beliefs, values, or attitudes regarding environmental conservation"* (p. 2). Nalepa et al. (2021) also argue that increasing farmer awareness and understanding of wild pollinators could see increased levels of adoption of appropriate land use practices. An important element that is required to ensure improved identification of pollinators, is more emphasis on farmer education and extension service to enable them to monitor pollinators and undertake land management practices that support pollinators (Nichols et al., 2022). Clearly, AEP design and implementation needs to recognize the important role that education and extension services play if AEP is to be successful. Much in the same way that there is growing evidence about the PD, greater efforts are still needed to communicate scientific research findings to farmers such as the importance of specific wildflower seed mixes, appropriate management for floral establishment and on-going management to ensure longevity of the resource (Nichols et al., 2022).

Third, another important finding regarding farm level management emerged when we asked respondents about the extent to which they coordinate activities in support of wild pollinators. Only 17% responded positively whereas almost 50% acknowledged that they benefited from the actions of neighbouring farmers. There is significant evidence that many pollinator species are reliant on landscape management and therefore require land-use management at a scale beyond an individual farmers' control. From a policy perspective, given that many pollinator species are reliant on wider landscape features, and this requires management at a scale beyond an individual farmers' control, collective action is needed, with policy support. Therefore, there is a need to align wild pollinator management with AEP design. From an economic perspective, Cong et al. (2014) show, using an Agent Based Model (ABM), that an individual farmer will have little incentive to manage their farm for wider landscape objectives that can support wild pollinators. A solution to this problem, proposed by economists, is the agglomeration bonus (Bareille et al., 2020, 2021). This is a payment, that could be made via AEP, that increases as the number of farmers coordinating increases. On a practical level, farm level coordination could be enabled by the development of farm cluster groups and these groups have been growing in importance in the UK (Prager, 2022). If the focus of a farm cluster is based purely on pollinators it might not be induce sufficient participation, whereas improving wider biodiversity, and/or pest control, may be more of an incentive. Interestingly, the reintroduction of the shorthaired bumble bee (*Bombus subterraneus*) into south-east England does suggest that focusing on a single species can work and in turn yield wider biodiversity benefits (Gammans, 2013; Sampson et al., 2020). However, the current prescriptive nature of AEP design has been noted by Arnott et al. (2019) as a limitation enabling longer-term behavioural change. By allowing AEP implementation to be more flexible not only might this induce higher levels of participation, but it may also support farm level coordination that in turn generates a landscape that is beneficial for wild pollinators.

5.3. Limitations of the current research

Although our research has revealed important insights into farm level knowledge and understanding of the PD and pollinators within the UK there are several limitations that need to be acknowledged. First, although our regression models yielded interesting results, in general statistical significance is quite low (e.g., low McFadden Pseudo R^2 values). Therefore, our results do need to be treated cautiously and would be best interpreted as exploratory as opposed to definitive. One way to address this limitation would be to collect a bigger sample of data. It would also be important to ensure that the sample is representative of the type of farm level behaviour and practices we are focussing on. To be able to statistically demonstrate sample representativeness would constitute an important development on the research presented here. Second, our sample although does not capture the regional variation in strawberry production as well as that for OSR and apples. In part, this limitation could again be addressed by increasing sample size but with a clear emphasis on mapping crop composition by regional production. Third, with a different approach to sampling it would be possible to deal with the issues arising from sample selection bias in relation to AEP participation.

6. CONCLUSIONS

In this paper, we present findings from a farm-level survey undertaken to examine farmer knowledge and understanding of the PD, and pollinator management. Overall, our results indicate that identifying a PD at the farm level is difficult and is maybe considered less important than other yield limiting factors that can affect output on an annual basis. Our findings also indicate that many respondents are actively undertaking farm level management activities that support wild pollinators. Therefore, although respondents recognize the importance of pollinators in crop production, they do not seem as concerned with pollination management in relation to crop production, and the PD. This may be because many do not consider there to be issues around crop production and existing levels of crop pollination. Or it could be because pollinator monitoring is too difficult or time consuming or that the benefits from monitoring are not understood. There are clearly some crops for which the relationship between crop quantity and quality is positively correlated with levels of pollination, e.g. apples and strawberries. Potentially, with an enhanced understanding of crop pollination and provision of simple protocols for assessing levels of pollination (such as those developed by BEESPOKE) farmers might begin to actively monitor pollination of crops. Even if the extent of the PD becomes more widely understood, how farmers use their land, and the associated marginal costs and benefits means that increasing pollination levels may not be considered of sufficient economic importance. This land-use trade-off makes pollination decisions more complex than simply looking for margins of improvement in crop production from applying agricultural chemicals.

Given the existing set of financial incentives determining production there is a negative externality in terms of biodiversity provision which in turn necessitates the need for AEP. The challenge in this context is that the land-use activities that support wild pollinators are only part of a wider mix of policies that farmers can adopt. Evidence to date suggests farmers are not adopting the right mixes and as such there is an under provision. This implies that the relative "prices" for the mix of land use options is "wrong". This can be rectified if the relative prices are changed or if some additional benefits from the land use management can be perceived or achieved by farmers.

Our findings confirm that efforts to inform and provide incentives to farmers to adopt farm management practices that support pollinators will likely be more successful if channeled via AEP rather than appealing to the profit motive. If farmers are experiencing PDs, then there is likely to be a high correlation with it and potential exit from the industry. However, there is little or no research pointing to a serious PD in crop production and resulting farm level industry exit. Until such evidence is forthcoming the desired changes in land-use practices that will support wild pollinators will have to come via AEP.

ACKNOWLEDGEMENTS

We thank two reviewers for their extensive and very insightful comments on earlier versions of the manuscript. This research was conducted as part of BEE-SPOKE, an Interreg project supported by the North Sea Programme of the European Regional Development Fund of the European Union. (https://northsearegion.eu/beespoke/). We also thank the growers and farmers who participated in our survey.

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APPENDIX A

Table A1. Priorities for pollination management (Ordered Probit - dependent variable: Never = 0, Maybe =1, Often = 2 and Always =3) Only statistically significant estimates and associated marginal effects are reported.

Variables	Reliable Crop[a] Coeff/ME	Managed Pollinators[b] Coeff/ME	Declines Pollinators[c] Coeff/ME	Diversify Management[d] Coeff/ME	Minimise Risk[e] Coeff/ME	Effectiveness Pollinators[f] Coeff/ME
Top Fruit	1.07***	1.36***				0.47*
Y=0	-0.03***	-0.38***				-0.05**
Y=1	-0.01***	-0.12*				-0.12*
Y=2	-0.15***	0.07***				-0.02
Y=3	0.28***	0.43***				0.18*
Soft Fruit	0.48**	0.5***		0.55***		0.71***
Y=0	-0.02**	-0.18***		-0.12***		-0.07***
Y=1	-0.06**	0.004		-0.1***		-0.17***
Y=2	-0.08**	0.06***		0.04***		-0.03
Y=3	0.16**	0.12**		0.18***		0.27***
AEP	0.31		0.25*	0.43***	0.52***	
Y=0	-0.02*		-0.08*	-0.11***	-0.06***	
Y=1	-0.04*		-0.02*	-0.06***	-0.11***	
Y=2	-0.05*		0.03*	0.05***	-0.02*	
Y=3	0.11*		0.07*	0.12***	0.2***	
Records				0.44*		
Y=0				-0.09**		
Y=1				-0.08		
Y=2				0.03***		
Y=3				0.14		
LL	-201.4	-273.5	-311.3	-298.9	-274.6	-292.3
Chi^2	18.3**	36.4***	5.89	22.3***	13.79*	20.28***
McFadden Pseudo R^2	0.043	0.062	0.01	0.036	0.025	0.035

Notes: Coeff = Coefficient; ***, **, * Significance at 1%, 5%, 10% level; ME = Marginal Effects [Y=0,1,2,3]. MEs for dummy variables are Pr[Y|X=1]-Pr[Y|X=0]; LL = Log-Likelihood; a=Consistent and reliable crop pollination; b=Availability of managed pollinators for rental or purchases; c=Reported declines in wild pollinator populations; d=Diversification of pollination strategies; e=Minimising uncertainty and risk in crop pollination; f=Effectiveness of pollinator species.

In terms of delivery of consistent and reliable crop pollination, top fruit, soft fruit, and AEP participation was positively related. For availability of managed pollinators for rental or purchase, and effectiveness of pollinator species, both top fruit and soft fruit growers are positively related. Declines in wild pollinator populations and minimizing uncertainty and risk in crop pollination were positively related to AEP participation, indicating that either these farmers have an increased awareness of crop pollination or because farmers are more likely to participate in AEP if are interested in the environment. For diversification of pollination strategies there was a positive association with soft fruit, AEP participation and keeping pollinator records but increased economic return yielded no statistically meaningful results.

APPENDIX B: EXAMPLES OF QUALITATIVE RESPONSES

To further investigate this issue, we sought feedback on each of these questions raised. Several respondents assess yields (compared to historical levels or national averages) and suggest deficit might be due to a PD, although several noted that measuring a PD is difficult in practice.

- "Very difficult but think that the crop could always yield better and maybe it is down to not enough pollinators"
- "I think it is very difficult to assess how I can say how much the yield is down due to pollinators"
- "I don't think you can truthfully"
- "Very difficult to assess yield deficit"

- In addition, a few respondents indicated that they employed measures to support pollinators (floral strips, and honeybee and bumblebee hives) and some examined seed set and flower counts. In terms of the crop quality and pollination the responses were like those for crop production. Most respondents provided no specific feedback although a few indicated that it is difficult to assess the pollination/crop quality relationship and a couple suggested that fruit shape and crop quality indicate issues regarding lack of pollination.
- These results echoed many of the qualitative comments for increased investment in pollination services. Increased payments for AEP for an increase in pollinator beneficial land use management was a frequently articulated response:
- "If there was more financial rewards for providing habitats for pollinators, no questions it would be more poplar. Money always talks."
- "If there was financial help to allow us to not grow as many crops and put it down to wild flowers."
- "More finical support and advice."
- "Help with a grant."
- "Grants or financial support."
- "Financial incentives to purchase wildflower seed, and schemes to reward farmers for leaving dedicated habitats for wild pollinators."

APPENDIX C: COPY OF SURVEY INSTRUMENT

Attached as separate file.

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The journal *Bio-based and Applied Economics* (*BAE*) provides a forum for presentation and discussion of applied research in the field of bio-based sectors and related policies, informing evidence-based decision-making and policy-making. It intends to provide a scholarly source of theoretical and applied studies while remaining widely accessible for non-researchers.

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