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). Nevertheless, 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

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

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 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:

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

Subject to:

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

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

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_{it}) 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:

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

where the vector of available resources (b_{it}) 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 ($X_{j,t-1}{}^{*}$) 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[3] (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 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[4].

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

[4] 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.

Each sub-model (based on representative individual real-world farm) optimized recursively[5] 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[6] 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.

[5] The model is written in GAMS language.

[6] 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).

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).

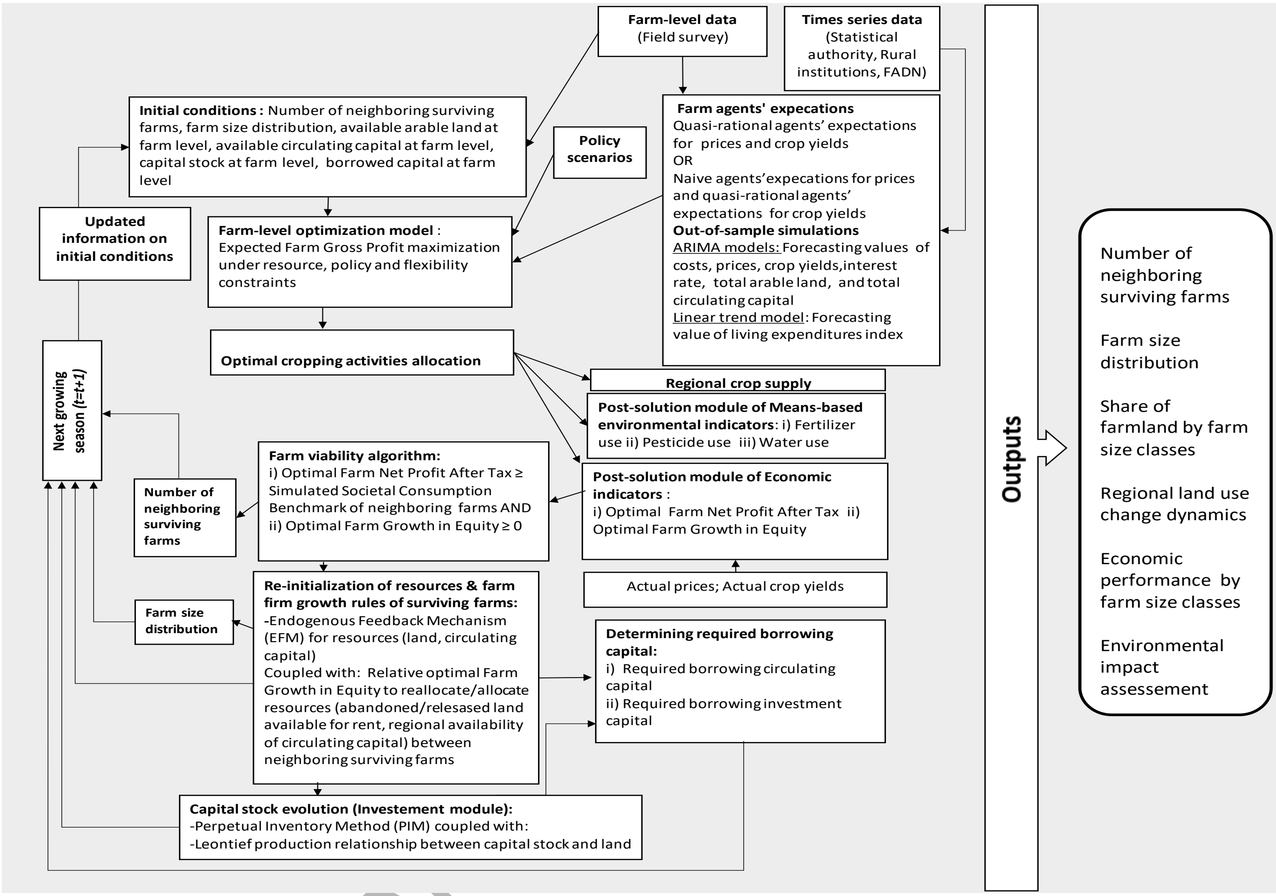


Figure 1. Conceptual diagram of the proposed modeling framework

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

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 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)*[7] 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):

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

[7] 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).

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

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[8] 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[9] 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 traditional 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

[8] In case that farm rents out part of owned farmland, then receives land rental income $\left(LRINC_{\ f,t}\right)$. 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).

[9] 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.

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[10] 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* ∈ $\{AL,\ CRC\}$ allocated or reallocated is as follows:

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

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.*

[10] 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.

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:

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

where $AL_{vf,nbf,t}$ is the available arable land of viable neighboring farm in year *t*; $AL_{vf,nbf,t-1}$ is the available arable land of viable neighboring farm at the beginning of year *t-1*; ${\Omega^{sim}}_{AL_{vf,nbf,t-1}}$ 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; $\sum_{nvf=1}^{NVF}\sum_{nbf=1}^{NBF} {AL_{nvf,nbf,t-1}}^{sim}$ 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*.

Essentially, the product ${\Omega^{sim}}_{AL_{vf,nbf,t-1}}$ $(TAL_{NBF,t} - TAL_{NBF,t-1})$ 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., $TAL_{NBF,t} - TAL_{NBF,t-1} < 0$ 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 (${{\Omega^{sim}}_{AL_{vf,nbf,t-1}}}^{-1}$), 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 [11].

(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.

$$CRC_{vf,nbf,t} = CRC_{vf,nbf,t-1} + {\Omega^{sim}}_{CRC_{vf,nbf,t-1}} \left(TCRC_{NBF,t} - \sum_{vf=1}^{VF} \sum_{nbf=1}^{NBF} {CRC_{vf,nbf,t-1}}^{sim}\right),$$

for t=2…T

(9)

$CRC_{vf,nbf,t}$ is the available circulating capital of viable neighboring farm in year *t*; $CRC_{vf,nbf,t-1}$ is the available circulating capital of viable neighboring farm at the beginning of year *t-1*; ${\Omega^{sim}}_{CRC_{vf,nbf,t-1}}$ 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; $\sum_{vf=1}^{VF} \sum_{nbf=1}^{NBF} {CRC_{vf,nbf,t-1}}^{sim}$ 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 ${\Omega^{sim}}_{CRC_{vf,nbf,t-1}}$ $(TCRC_{NBF,t} - \sum_{vf=1}^{VF} \sum_{nbf=1}^{NBF} {CRC_{vf,nbf,t-1}}^{sim})$ 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

[11] 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.

inflation), etc. These factors may create a healthy financial situation or financial stress. Financial stress could therefore lead to an unfavorable situation, i.e., $TCRC_{NBF,t} - \sum_{vf=1}^{VF}\sum_{nbf=1}^{NBF} CRC_{vf,nbf,t-1}{}^{sim} < 0$ 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 (${\Omega^{sim}}_{CRC_{vf,nbf,t-1}}{}^{-1}$), that is, less profitable, albeit viable farms, will lose proportionately more of their circulating capital[12].

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:

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

where $K_{f,t}$ is the capital stock of farm *f* in year *t;* $K_{f,t-1}$ is the capital stock of farm *f* in year *t-1;* $DEP_{f,t-1}$ is the depreciation of farm *f* in year *t-1,* which is obtained from the equation $DEP_{f,t-1} = \delta\, K_{f,t-1}$*,* 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* ($DEP_{f,t-1}$) is constantly reinvested in new capital stock (or gross investment on fixed assets) in year *t* $\left(I_{f,t}\right)$ (Freeman *et al.,* 2009). Essentially, the constant

[12] 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.

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[13].

2.4. Farm data description and specification

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

[13] 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.

compared to the population, it sufficiently reflects the heterogeneity in farm structure[14].

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

		Sample farms	FADN
Farm size class (ha)	Characterization	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.

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.

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[15]. However, it should be noted that for the activities cultivated under contract farming, we assume that prices remain

[14] 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).

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

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.

Business as usual (BAU) scenario: 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).

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[16] (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

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

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.

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[17] (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%)[18] without revealing any difference in terms of

[17] 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.

[18] 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

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.

Table 2. Actual and simulated land allocation

	Actual 2012	NV&QR Model 2012	QR Model 2012	Actual 2019	NV&QR Model 2019	QR Model 2019
Activity	Area (ha)	Area (ha)	Area (ha)	Area (ha)	Area (ha)	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

	Actual 2019	Actual 2019	NV&QR Model 2019	NV&QR Model 2019	QR Model 2019	QR Model 2019
Farm size class (ha)	Farms (%)	Farms (n)	Farms (%)	Farms (n)	Farms (%)	Farms (n)
<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

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).

⩾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.

3.2. Forecasting models accuracy

After estimating the best-fitting ARIMA models for the exogenously determined parameters of interest (i.e., 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[19] (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[20]. The simulated number of farms decreases by 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

[19] For more details, see the *Part F: ARIMA and linear trend models estimations* in the supplementary material.
[20] The initial number of farms is normalized to 100.

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.

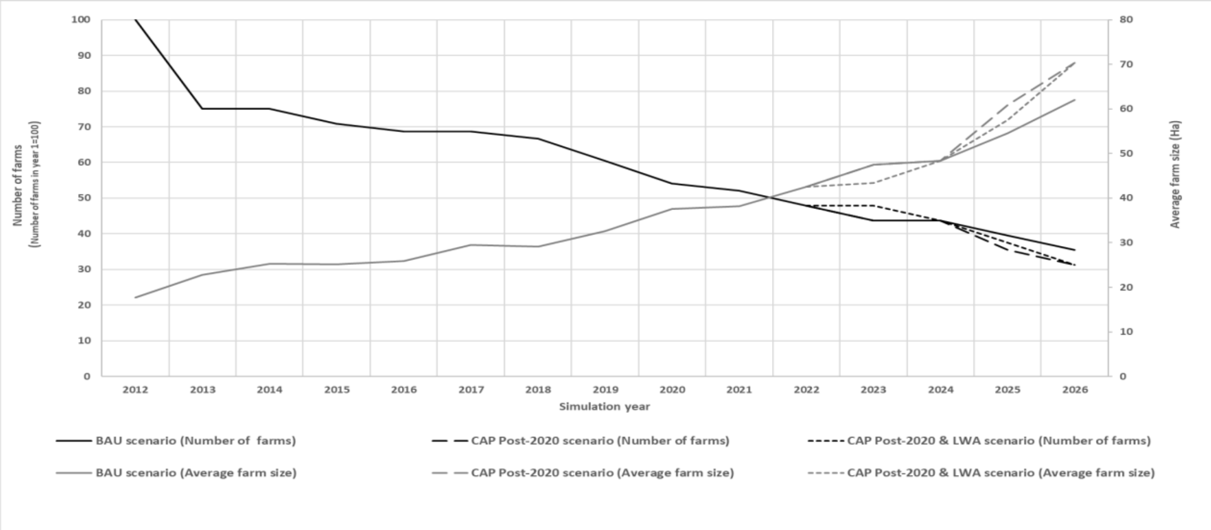


Figure 2. Simulated number of farms and average farm size by scenario

Note: The provisions of the CAP Post-2020 scenario apply from the year 2023.

Source: Authors, based on sample data.

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.

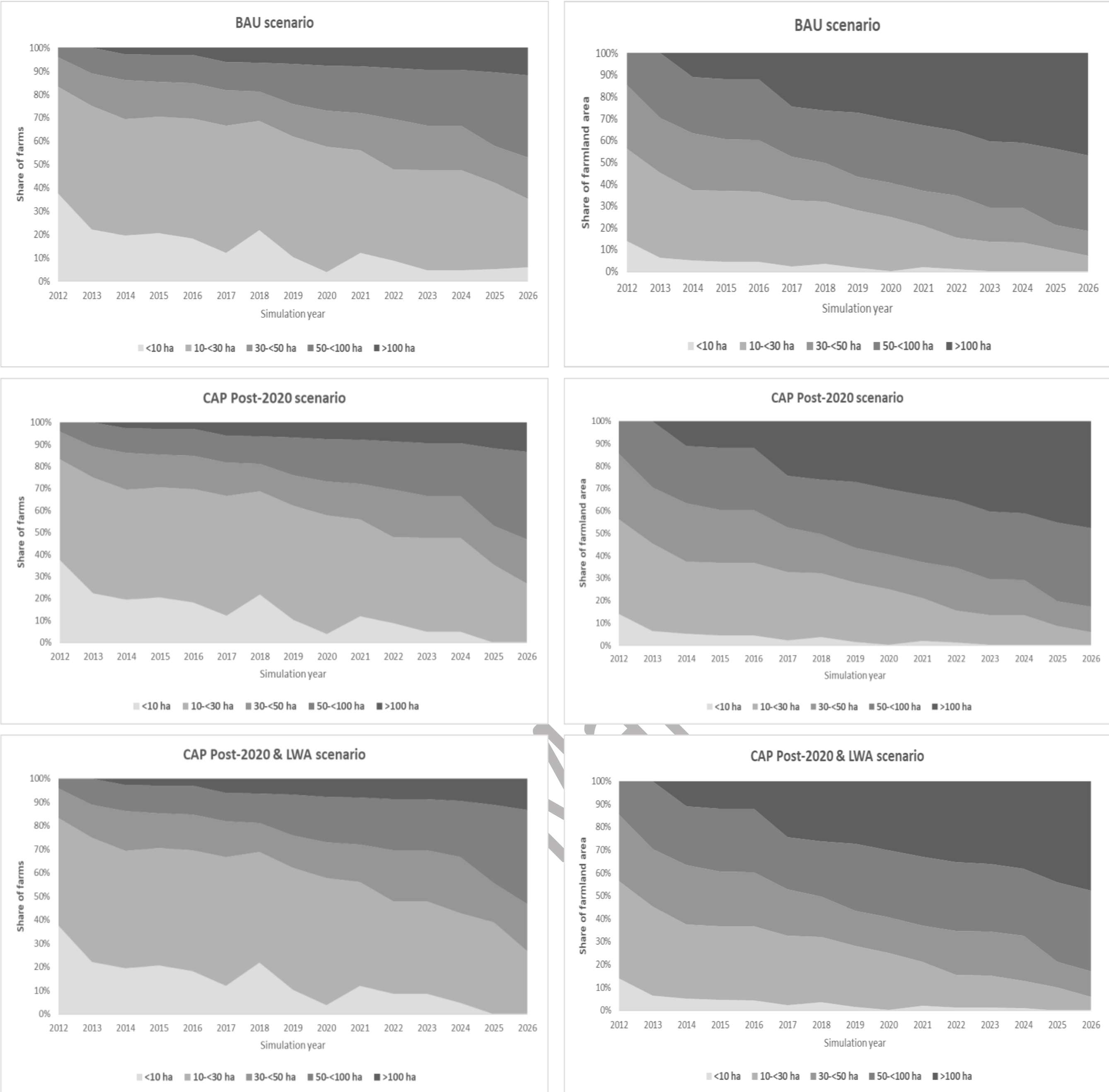


Figure 3. Share of farms and farmland area by farm size classes and scenario

Note: The provisions of the CAP Post-2020 scenario apply from the year 2023.

Source: Authors, based on sample data.

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 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 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.

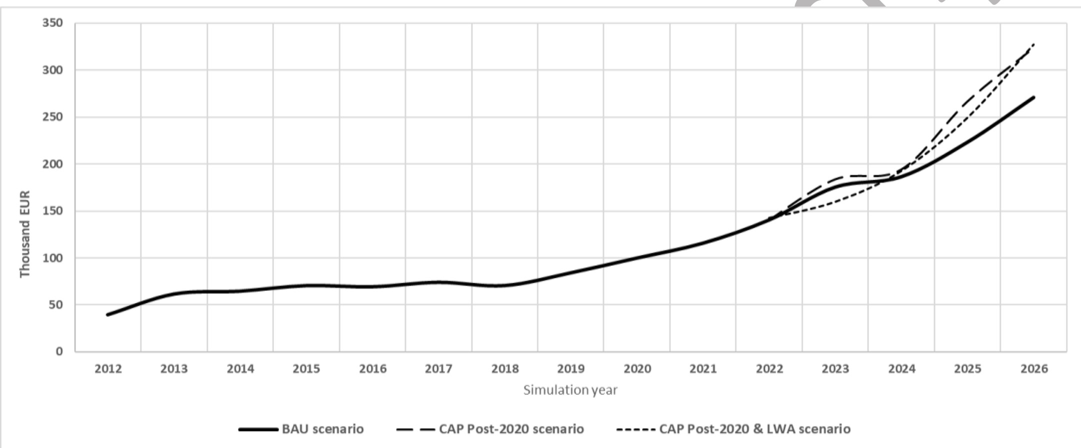


Figure 4. Evolution of simulated average Farm Net Profit after Tax (FNPAT) by scenario

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.

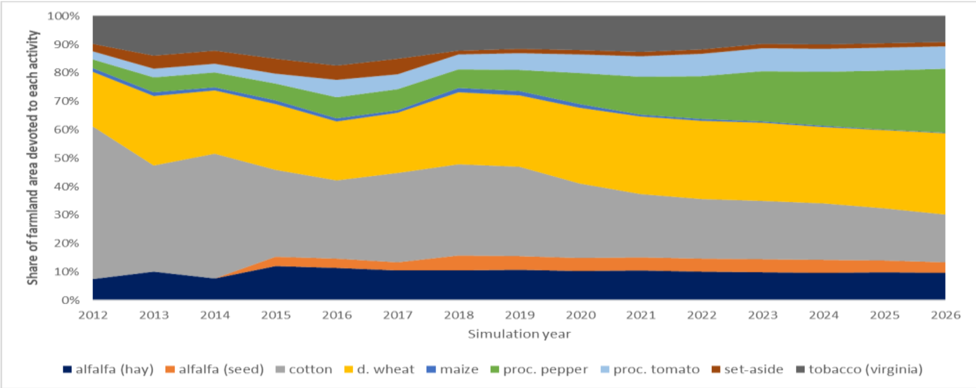
3.4. Simulated land use change

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[21]. 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[22].

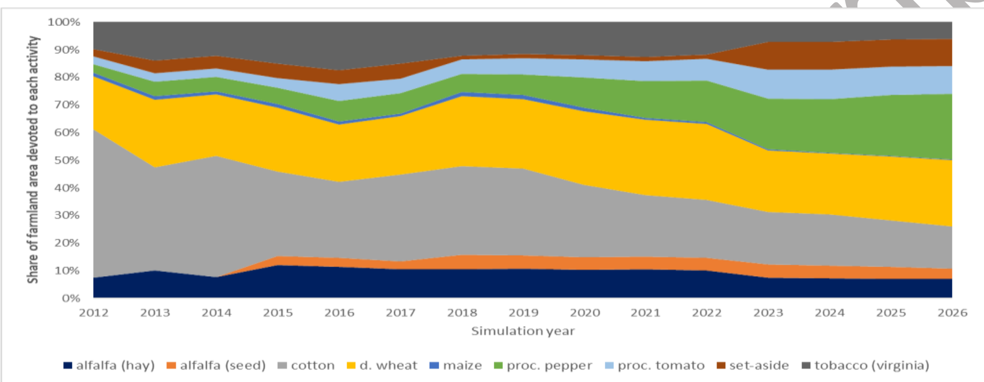
Conversely, we simulated a significant gradual decrease in the cotton and tobacco areas. In fact, for the CAP Post-2020 reform scenario, we observe a further reduction of the cotton and tobacco areas. Durum wheat area increases significantly over time for the BAU scenario, while for the CAP Post-2020 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

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

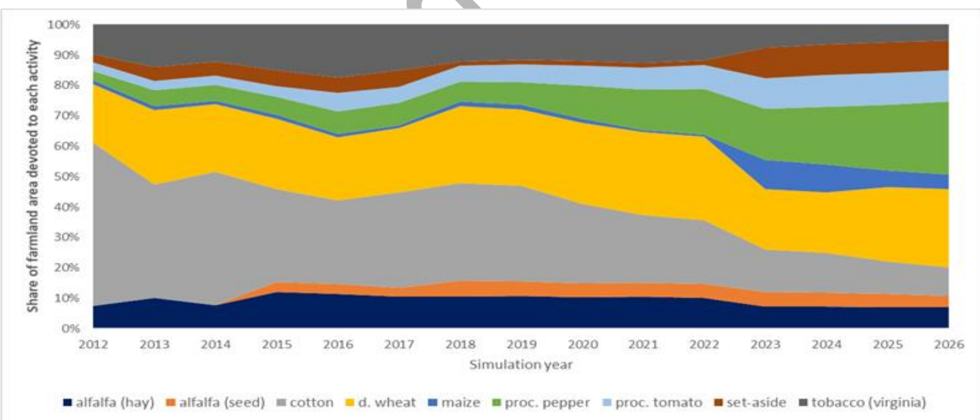
prices at high levels due to the Ukrainian crisis. Accordingly, a further reduction in cotton and tobacco areas is simulated.



(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.

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.

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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:

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

where $\varphi_1 \ldots, \varphi_p$ are the autoregressive (AR) parameters to be estimated, $\vartheta_1,\ldots,\vartheta_q$ 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[23] where $B^i Y_t = Y_{t-i}$ and $B^j \varepsilon_t = \varepsilon_{t-j}$; $Y_1, \ldots, Y_t$ is any time series ; $p<t$ and $q<t$ (Pardoe, n.d.).

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

$$\left(1 - \sum_{i=1}^{p} \varphi_i \, B^i\right) Y_t = \left(1 - \sum_{j=1}^{q} \theta_j \, B^j\right) \varepsilon_t \quad \text{(A2)}$$

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

[23] 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).

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

Many series encountered in industry or business reveal nonstationary behavior [24]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:

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

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 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%

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[24] 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.

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.

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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:

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

Subject to:

Arable land constraint

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

Irrigated land constraint

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

Circulating capital constraint

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

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

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*[25], $ls_{i,t}$ 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 ; $ecop2_{f,j,t}$ is the *J x 1* vector of potential eco-

[25] 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;*

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[26]; $e_{f,t}$ 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[27] 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[28]; $\beta_{f,t}$ 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[29]. In addition, when the binary variable $b_{f,t}$ takes the value 1, the binary value $\beta_{f,t}$ 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 [30]

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[26] 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).

[27] 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.

[28] 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.

[29] 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.

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

(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[31] ; $X_{f,wj,t}$ *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[32] $IL_{f,t}$ 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:

$$X_{f,j,t} \;\; h_{f,t} \;\leq\; h_{f,t}\, 0.75\, AL_{f,t} \qquad \text{for } t = 2015, \ldots, T$$

(B6)

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 $(AL_{f,t}) \leq$ 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:

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

(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

[31] 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 $st \notin J$

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

$(AL_{f,t}) \leq 15$ 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:

$$[X_{f,L1j,t}{}^{*} + X_{f,L2j,t}{}^{*}]\, u_{f,t} \leq u_{f,t}\ 0.95\ AL_{f,t} \quad \text{for } t = 2015, \dots, T,\ L1\,j \in J,\ L2\,j \in J$$

(B8)

where $X_{f,L1j,t}{}^{*}$ *is* 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; $X_{f,L2j,t}{}^{*}$ *is* 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 $(AL_{f,t}) \leq 30$ 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:

$$X_{f,j,t} \leq h_{f,t}\, 0.75\, AL_{f,t}, \quad t = 2023, \dots, T, j \in J$$

(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 $(AL_{f,t}) \leq 10$ hectares:

$$X_{f,st,t} = e_{f,t}\, 0.05\, AL_{f,t},\ t = 2023, \dots, T, st \in J$$

(B10)

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

$$X_{f,st,t} = \varepsilon_{f,t}\, 0.1\, AL_{f,t}, \quad t = 2023, \dots, T, st \in J$$

(B11)

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

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

$X_{f,st,t} = \varepsilon_{f,t}\, 0.04\, AL_{f,t}, \quad t = 2023, \dots, T, st \in J$

(B12)

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

$\sum_{nwj=1}^{n} X_{f,nwj,t}\, b_{f,t} \geq b_{f,t}\, 0.75\, NL_{f,t}$, for $\quad t = 1, \dots, T$, $nwj \in NWJ$, $NWJ \subseteq J$

(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) }*

$\sum_{ndj=1}^{n} X_{f,ndj,t} \geq b_{f,t}\, 0.2\, NL_{f,t}$, for $\quad t = 1, \dots, T$, $ndj \in NDJ$, $NDJ \subseteq J$

(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)}*

$X_{f,st,t} \geq b_{f,t}\, 0.05\, NL_{f,t}$, for $\quad t = 1, \dots, T$, $st \in I$

(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):

$$\sum_{orj=1}^{n} X_{f,orj,t} \geq OL_{orgf,t}\ \beta_{f,t}\ \text{,for } t = 1, \dots, T,\ orj \in ORJ\ ,\ ORJ \subseteq J$$

(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

$$0.85\, CL_{f,t}\, c_{f,t} \leq X_{f,aasd,t}\ c_{f,t} \leq 1.15\, CL_{f,t}\, c_{f,t} \qquad \text{for } t = 2015, \dots, T,\ aasd \in I$$

(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;* $RL_{vf,nbf,t-1}$ 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; $\Omega^{sim}{}_{AL_{vf,nbf,t-1}}$ 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; $\sum_{nvf=1}^{NVF}\sum_{nbf=1}^{NBF} AL_{nvf,nbf,t-1}{}^{sim}$ 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.

$$
\begin{aligned}
LRC_{vf,nbf,t} = {} & RL_{vf,nbf,t-1}\ \underbrace{LRI_t\ \overline{LRP}_{NBF,t=1}}_{\overline{LRP}_{NBF,t}} \\
& + \underbrace{LRI_t\ \overline{LRP}_{NBF,t=1}}_{\overline{LRP}_{NBF,t}}\ \Omega^{sim}{}_{AL_{vf,nbf,t-1}} \left[\sum_{nvf=1}^{NVF}\sum_{nbf=1}^{NBF} AL_{nvf,nbf,t-1}{}^{sim} \right. \\
& \left. + \left(TAL_{NBF,t} - TAL_{NBF,t-1}\right) \right]
\end{aligned}
$$

for t=2…T, $RL_{vf,nbf,t} \subseteq AL_{vf,nbf,t}$

(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[33], 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 $RL_{vf,nbf,t-1}\ \overline{LRP}_{NBF,t}$ 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.

---

[33] 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.

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[34] [${\Omega^{sim}}_{AL_{vf,nbf,t-1}}{}^{-1}\ (TAL_{NBF,t} - TAL_{NBF,t-1})$] exceeds (i) the previous year rented land $(RL_{vf,nbf,t-1})$ and (ii) the land that accumulated endogenously, i.e., the released land available for rent, derived from non-viable neighboring farms $[{\Omega^{sim}}_{AL_{vf,nbf,t-1}}\ (\sum_{nvf=1}^{NVF} \sum_{nbf=1}^{NBF} {AL_{nvf,nbf,t-1}}^{sim})]$.

In this case, land rental costs are negative ($LRC_{\ vf,nbf,t} < 0$), equal to land rental income for the viable neighboring farm $\left(LRINC_{\ vf,nbf,t} > 0\right)$. 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:

$$FNPAT^*{}_{f,t} = (\Pi^*{}_{f,t} + LRINC_{f,t}) - (DEP_{f,t} + SFNC_{f,t} + LFNC_{f,t} + SIC_{f,t} + FPTX_{f,t})$$
(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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[34] Competitive pressures from other farm types or non-agricultural sectors are likely to lead to an unfavorable situation, i.e., $TAL_{NBF,t} - TAL_{NBF,t-1} < 0$ 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 (${\Omega^{sim}}_{AL_{vf,nbf,t-1}}{}^{-1}$), that is, less profitable albeit viable farms will abandon/release proportionately more of their arable land.

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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* $(DPRP_{f,t-1})$ 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)[35] 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:

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

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

for t=2…T

(D1)

where $BCRC_{f,t}$ is the borrowed circulating capital of farm *f* in year *t;* $DPRP_{f,t-1}$ 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:

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

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_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).

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…T

(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:

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

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

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

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 ($\overline{LRP}_{NBF,t}$)	[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).

Part E: References

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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

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.X²(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.X²(2)=0.19

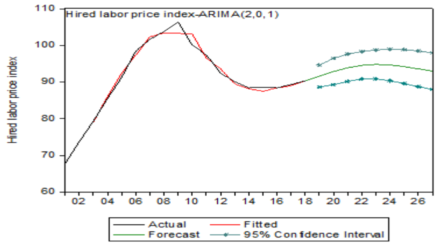
Notes : $\nabla^d Y_t = \mu + \phi_1 \nabla^d Y_{t-1} + \cdots \phi_p \nabla^d Y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q}$;
$\Phi_1, \ldots, \Phi_p$: autoregressive (AR) model parameters of order p; $\Theta_1, \ldots, \Theta_q$: moving average (MA) model 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)

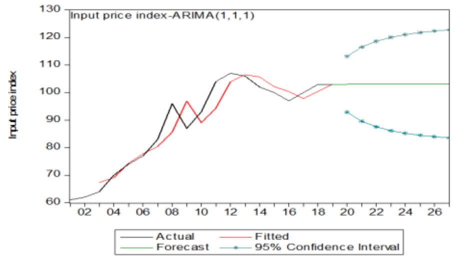
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.954777	0.019644	48.60363	0.0000
@TREND	-0.023925	0.002778	-8.612057	0.0000

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		

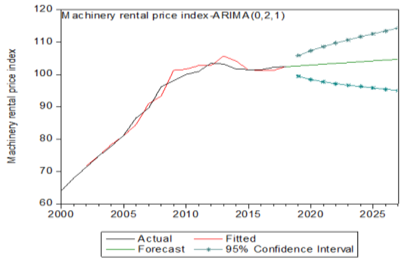
Source: Authors, based on ELSTAT



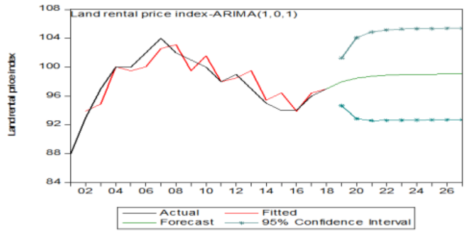
(a)



(b)



(c)



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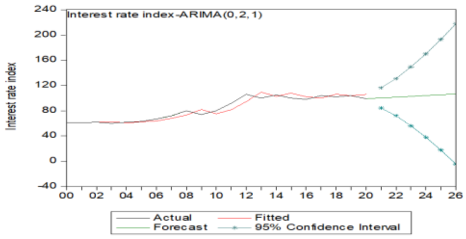

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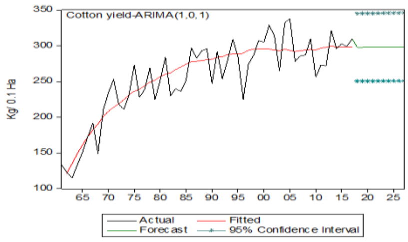

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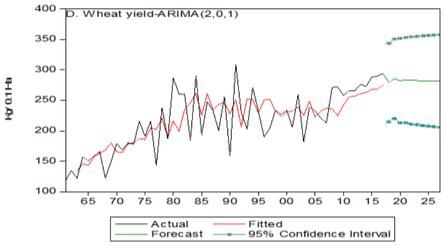

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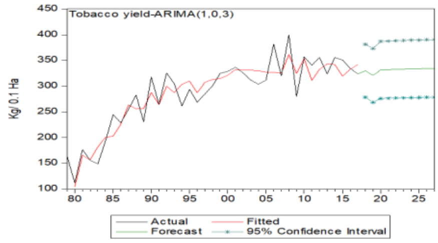

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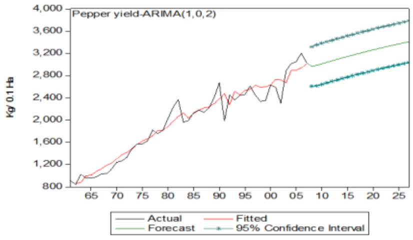

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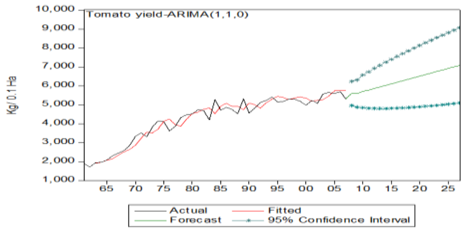

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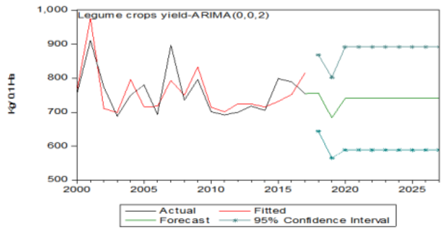

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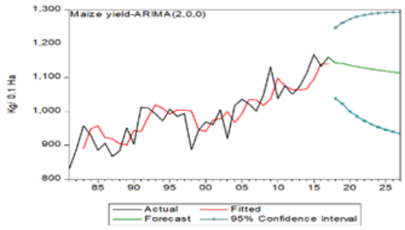

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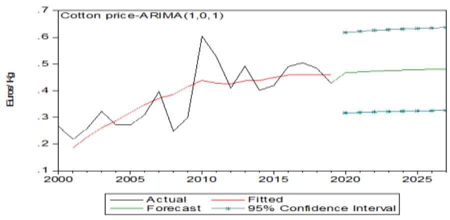

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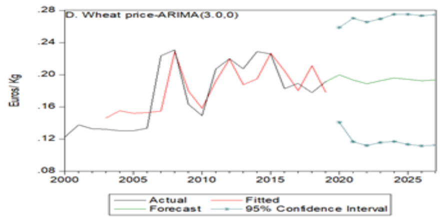

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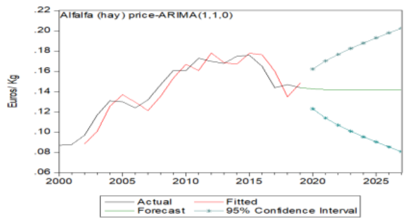
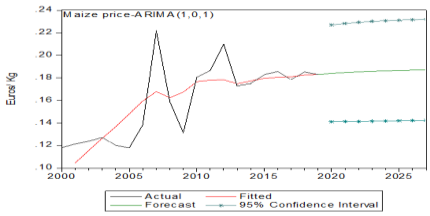


(o)



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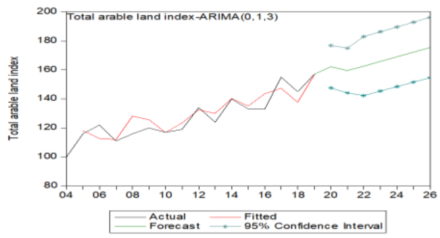

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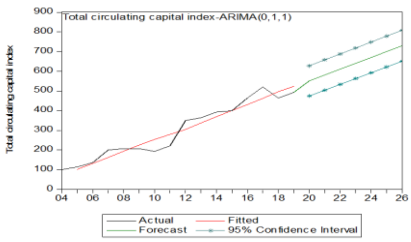

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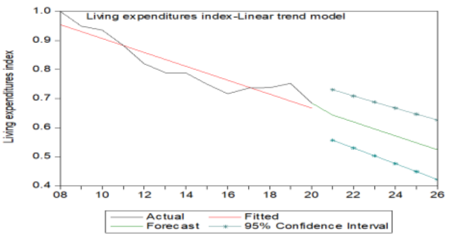

(s)

Fig. 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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