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Promoting excellence or discouraging mediocrity – a policy framework assessment for precision agriculture technologies adoption

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Abstract
Precision Agriculture Technologies (PATs) are providing a great potential in alleviating adverse impacts arising from climate change. This study evaluates the decision-making process of farmers regarding the adoption and implementation of PATs in potato agricultural cooperative in Northern Greece. For this purpose, a bio-economic model utilizing mathematical programming techniques was designed and applied to three different farms producing Protected Geographical Indication (PGI) potato of Kato Nevrokopi. The proposed model aims to incorporate the existing management methods of farming systems and their associated characteristics. Its objective is to analyse the aspirations of farmers to adopt new practices, considering agronomic, environmental, and policy limitations. Special focus was paid to two distinct scenarios: (a) subsiding PATs adopters or (b) penalizing the non-adopters. Results indicated that subsidy provision 594–650€/ha would have a greater impact on PATs profitability. Lastly, based on the results, further explanations of incentives towards promoting the adoption of novel practices, ensuring the long-term viability of agricultural systems, are proposed.

Keywords Bio-economic modelling · Decision-making · Agricultural systems · Public policy

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Introduction

The agricultural sector faces dynamic challenges driven by population growth, the reduction of available resources and the ever-increasing consumer need for products that meet the principles of sustainability. The incorporation of modern technology into agricultural systems promotes production and efficiency, while minimizing natural resource exploitation. International Society of Precision Agriculture states the transformation of temporal, spatial and individual data towards the increase of agricultural performance can be perceived as Precision Agriculture (PA) (ISPAG, 2021). PA Technologies (PATs) can contribute to the economic, environmental, and social aspects of agricultural field, as the newly introduced Common Agricultural Policy (CAP) suggests. PATs can support the achievement of sustainable development by 2050 (Bucci et al., 2018), while contributing to circular economy transition at the same time (Kleisiari et al., 2021). Their contribution to each field of sustainability is considered essential to ascertain their importance towards the achievement of the CAP objectives.

More precisely, from an economic standpoint, PATs can enhance farm management and lead to more reasonable data-driven decisions (Rozenstein et al., 2023; Schimmelpfennig & Ebel, 2016).For instance, Al-Amin et al. (2023) have proved the feasibility of decreasing from 15€ to 45€/ton on wheat cultivation depending on field's shape, when autonomous machines were used. Labour cost minimization is another aspect that PATs be considered advantageous in comparison with conventional practises(Shang et al., 2023). Moreover, PATs can operate as a resiliency factor to the continual decline in human agricultural labour, ensuring the completion of each agricultural activity within a specific time range (Salimova et al., 2022). However, the initial investment cost should be regarded as a limiting factor in the PATs deployment. (Hanson et al., 2022; Yigezu et al., 2018).

Furthermore, the application of PATs is accompanied with agronomic and environmental benefits (Koutsos & Menexes, 2019) towards the achievement of sustainability. Environmental impact can be diminished by implementing only the quantities of resources needed in each case such as irrigation (Bwambale et al., 2022), fertilizers (de Lara et al., 2023) and pesticides (Shearer et al., 2021). Moreover, Life Cycle Assessment methodology has been applied to quantify the benefits of PATs adoption. Denora et al. (2023) have estimated an overall 10% decrease of environmental impacts, when applying variable rate technology on fertilizing compared to the conventional method. Another aspect of PATs is that they can operate with higher accuracy levels, conducing to the conservation of local biodiversity (Capmourteres et al., 2018).

Social dimension is the least explored one, when it comes to PATs adoption. Although numerous research were conducted to study the effect of socioeconomic determinants of adopters, which may be called social features, the interaction of PATs with rural communities can be further examined. For example, Pathak et al. (2019) in their extended literature review are assessing the influence of communication to farmers social network and social media, a crucial factor for providing appropriate incentives to non-adopters. Key findings of Busse et al. (2014) suggest that co-operation of all involved stakeholders (precision farming industries- consulors-farmers) should be examined thoroughly, to identify the barriers in late adoption stages.

Apart from the European Commission's (EC) guidelines, farmers ought to face numerous impacts of Climate Change (CC) such as higher temperatures, water scarcity etc. (Clapp et al., 2018). An adaptation needs to happen to maintain the sector's economic viability and mitigate CC effects. PATs adoption is capable of securing farmers income, cover the rising global food demand, while following more environmentally friendly farming practices. (Shafi et al., 2019). More precisely, Gardezi and Bronson (2020) have proven that the higher the environmental risks the higher the adoption rate of PATs. Greenhouse Gas Emissions (GHG) reduction is another area to which PATs may assist in both the agricultural and livestock sectors (Balafoutis et al., 2017; Soto et al., 2019).

Although precision agriculture creates opportunities to improve farm efficiency and long-term environmental and social benefits, its adoption rate among farmers remains quite low (Barnes et al., 2019a, b, c; Lowenberg-DeBoer & Erickson, 2019). The main reason of this is that adoption is a gradual process, which heavily depends on a large series of characteristics/incentives that influence the decision-maker (farmer) (Daberkow & McBride, 2003; Groher et al., 2020; Kendall et al., 2022; Vecchio et al., 2020). Economic factors can heavily influence farmers to non-adoption (Ammann et al., 2022). That is the reason why low cost applications and provision of monetary support are needed (Kendall et al., 2022). Barnes et al. (2019b) have performed a survey including 971 EU arable crop growers, concluding that the economic support and lower taxation can act as drivers towards PATs adoption, while they suggested policy expectations towards the same direction.

On top of the economic constrains, there are several other barriers for PATs adoption. For instance, Mozambani et al. (2023) have assessed 131 farmers to identify factors that affect adoption of PATs. Their findings indicate size of agricultural holding, increased requirements at the processing stage and the perception of farmer for higher yields can be effective predictors for PATs adoption from farmers' side. It should be mentioned thatGroher et al. (2020) have identified differences between crop types (e.g. vegetable and arable crop producers over fodder crops and grapes), signifying the importance of farmers specialisation and their products connection with final consumers on PATs adoption process. Additionally, Paustian and Theuvsen (2017) have found that experience, consultancy services and increased farm size are affecting PATs adoption as well. Lack of knowledge can be considered as a limitation factor as Khanna & Kaur (2023) suggest, especially of PATs of greater complexity (Vecchio et al., 2020).

The above mentioned studies examine the impact of external (social, organizational, and governmental) or internal (socioeconomic, attitudes, and beliefs) elements on PAT adoption. They do, however, conclude to the importance of enacting suitable legislative measures to further encourage PATs adoption. Predicting the adoption rate of new agricultural practices by farmers is a challenging procedure that includes farmers, agricultural experts/researchers, enterprises and policy makers (Kuehne et al., 2017).

Proposition of accurate policy measures that will increase PATs adoption, is a demanding and high skill process. Tey and Brindal (2012) provide potential policy implications in their literature evaluation, hence their methodology is purely qualitative, lacking a quantified impact of the proposed policy measures. Same qualitative approach is followed by Lajoie-O'Malley et al. (2020) after reviewing 23 documents for policymaking in digital agriculture era from high influential organizations/entities. However, quantified approaches are highly needed to describe current situation in an explicit way and propose target values that can be monitored after the activation of the proposed policy measure/framework (Huber et al., 2023). For instance, Shikur (2020) has explored the policy implementation of 4 different scenarios regarding irrigation management of Oronia region through Computable general equilibrium (CGE) model. The outcomes of this survey suggest that PATs adoption not only contribute to the enhancement of on-farm efficiency and productivity but also have a positive impact on local societies. Similarly, Schieffer and Dillon (2015) explored policy-farmer interactions to evaluate the impact of PAT adoption. Their results indicated that penalty policies have a negative effect on the new technologies adoption, meaning that a positive approach through subsidizing the adopters is recommended. However, it should not be neglected that efforts had been made to predict the adoption rate of PATs based on ADOPT technique.

This study incorporates the CAP (2023–2027) guidelines for the production of environmentally friendly products and the enhancement of rural development, while at the same time it assesses technology adoption in Kato Nevrokopi Potatoes, which is a Protected Geographical Indication (PGI) product (European Commission, 2021). In this context, a collaboration between the University of Thessaly, Nitlab, and NEVROCOOP – IKE (potato producers cooperative) allowed the development and testing of Precision Agriculture equipment, targeting water use efficiency and insecticide use optimization. In fact, Kato Nevrokopi is located is northern Greece and despite its cold winters, recent years it experiences water shortage (Petalas et al., 2018). Therefore, the objective of this study is to assess farmers' adoption decision process towards the proposed Precision Agricultural practices in potato production systems in Northern Greece. Based on the literature review results, there is a limited number of surveys that provide accurate policy guidelines. This is the reason why special focus is given on quantified policy suggestions and their impact to increase PATs adoption rates, through the implementation of a bio-economic model. Indeed, despite the advantages of bio-economic models in assessing farmers decision-making process, similar studies are rather scarce in the literature (e.g. Kleftodimos et al., 2021a, b; Ridier et al., 2013). In fact, in contrast with the aforementioned studies, bio-economic models simulate the complex interactions between biological processes, environmental factors, and economic decisions on a farm (e.g. Ridier et al., 2013; Mosnier et al., 2009). This allows for a more dynamic and realistic representation of farming systems compared to econometric models, which often rely on statistical analysis of historical data. Moreover, they consist a strong tool for decision-making via scenario simulations to better assess the potential outcomes of different management practices, policy changes or market conditions (Watzold et al. 2006). Thus. in this study, two scenarios are examined (penalize non-adopters or subsidizing adopters) with a view to assure a smooth transition from existing agricultural system to an innovative lower input one. Moreover, following the hydrological studies in the area (Petalas et al., 2018), we examined the above measures in the context of water scarcity.

The remainder of the paper is organized as follows. Section 2 describes the methodology followed for the bio-economic model, while Sect. 3 presents the acquired results for the potato farmers of the cooperative. Further discussion on the outcomes of this study can be found in Sect. 4. Section 5 summarizes the key findings and suggest future guidelines.

Methodology

In this section,: (i) the bio-economic model and its' constraints, (ii) the selected farms, and (iii) the proposed policy scenario are presented.

i. The structure of the bio-economic model.

The bio-economic model maximizes farmers' gross margins over one period under constraints for three selected farms in the region examined. At this point, the assumption that farmers were considered risk-averse towards the proposed management strategies should be underlined (Hardaker et al., 2015). The proposed model was constructed as a linear one by the use of mathematical programming methods in GAMS software (General Algebraic Modeling System).

The objective function has the following form:

$$U = \Sigma RAL_{c,n} - \Sigma\left(\varphi * std\right) \quad (1)$$

where *RAL* was the income, φ was the risk aversion coefficient, *std* was the standard deviation of the average income, and index *c* stood for the conventional practices, while index *n* was for the adoption of alternative management strategies. The standard deviation of average income was calculated as follows.

$$\mathrm{std} = \sqrt{\Sigma\left(RALrdt - gm_{c,n}\right)^2} \quad (2)$$

where *RALrdt* is the random income according to each state of nature.

Here, farmers behaviour was expressed via the E-V context. Hazell and Norton (1986) introduced the concept of the "Environmental Variability (E-V) Rule" in their work on farm-level decision making under risk and uncertainty. The E-V rule suggests that farmers' decisions regarding production and resource allocation are influenced by the variability of environmental conditions, particularly in relation to crop yields. In general, E-V rule refer to the mean-standard deviation model. In fact, the standard deviation describes the root of variance and consequently, the model represents the efficient set of crops that should be identical to the ones derived by the E-V model. The function number (2) has the advantage to be expressed in the same units as income, thus, it facilitates the interpretation of the findings. In addition, following Baumol (1963), it is assumed that income is normally distributed, and the risk aversion of the farmers is assessed by the use of a revealed preference approach (Charas and Holt, 1996).

In the estimation of the risk aversion coefficient, we tested several values within the interval of {0.5, 1.5], following the methodology outlined by Hazell and Norton (1987). These values were chosen to encompass a range of risk attitudes commonly observed in agricultural decision-making contexts. However, for the sake of brevity and clarity, we did not exhaustively list each individual value tested. During the calibration of the model, the Percentage of Absolute Deviation (PAD) was used as an indicator. The PAD takes the following form and evaluates the representativeness of our model by calculating crop-pattern variability:

$$PAD = \frac{\sum_{crop=1}^{n}\left|\bar{X}_{crop} - X_{crop}\right|}{\sum_{crop=1}^{n}\bar{X}_{crop}}$$

where, $\bar{X}_{crop}$ represents the value observed, X_{crop} the value simulated, and index crop represents the crop selection.

Following this methodology, a value of risk aversion coefficient equal to 1 was retained which corresponds to a moderate risk aversion according to the literature (Hardaker et al., 2015).

The bio-economic model constraints

These constraints regard a variety of economic, agronomic, environmental, and public policies.

Land constraint

The sum of the cultivated surfaces should be less or equal to the total area of the farmland.

$$\sum_{\text{crop,pc,s}} x\left(crop, pc, s\right) \leq farmland \tag{3}$$

where, *x* is the surface for each crop, associated with the previous crop (*pc*), for each type of soil (*s*).

Water constraint

The water resources in each farm-type were considered limited, hence the total use of water should be less or equal to the total water availability. Thus,

$$\sum_{c,m,pc,s,i,qs} cai\left(crop, m\right) \times x\left(crop, pc, s\right) \leq WATER) \tag{4}$$

where, *cai(crop, m)* is the water use per calendar month per crop (m^3 ha^{-1}), and *WATER* is the total water availability per farm. This constraint ensures that the total water consumption by all crops (summed over all crops, fields, and irrigation systems) does not surpass the available water resources on the farm. If the available water is insufficient to meet the water requirements of the selected crops, the constraint would indeed necessitate adjustments such as shifting to crops with lower water requirements or reducing the cultivated area to match the available water resources.

Labour constraint

The labour availability of each farm was composed of family labour and occasional seasonal workers. Hence,

$$\sum_{crop,cow,h} Labor_{crop,h} \leq workfam_h + workers_h \tag{5}$$

where, $Labor_{crop,h}$ is the total hours devoted to crop production, $workfam_h$ was the total family labour availabilities, and $workers_h$ was the hired labour.

Crop rotation

A crop rotation constraint was proposed as well, which restricts the selection of crops by the farmer. This constraint has been added to better represent the real case practices where potato growers alternate their cultivation with soft wheat, which is the commonly followed practice from Kato Nevrokopi potato farmers as arose as a feedback of local agronomists and its cultivation can be verified by Mavromatis (2015). According to this constraint, the cultivation surface of a crop is limited by its allowed precedents. To produce a matrix of crop precedents data obtained by personal interviews were used. Consequently, the constraint has the following form:

$$\sum_{\text{crop,s}} x\,(crop, s) \le \sum_{pc,s} x(pc, s) \tag{6}$$

where, $\sum_{pc,\text{s}} x\,(pc, s)$ is the surface of the precedent crop in each soil type.

Public policy constraints

The model includes all the necessary constraints of the Common Agricultural Policy in order to receive the Basic and Greening payments (European Parliament, 2015). Concerning crop production, the farmer has to follow the three constraints regarding permanent grasslands, crop diversity, and Ecological Focus Areas (EFA). Hence, the constraints have the following form:

- Permanent grasslands.

Permanent grassland must always be maintained in the agricultural systems and should be no less than 5% of the total area of the farm. Hence,

$$\sum\nolimits_{crop} x_{''gl''} \geq 0.95 \times \sum\nolimits_{crop^o} x_{''glo''} \tag{7}$$

where, $\sum_{crop} x_{''gl''}$ is the permanent grasslands, while the $\sum_{crop^o} x_{''glo''}$ is the permanent grassland observed in the baseline year, which is 2021.

- Crop diversity.

According to this constraint, every farm which exceeds 10 ha must cultivate at least two different crop species every season, where each crop must not exceed 75% of the total cultivated land. Following the article of (Kleftodimos et al., 2021a, b), the following constraint was adopted:

$$\sum\nolimits_{crop} x_{''m''} \le 0.75 \times LANDV \tag{8}$$

Table 1 Characteristics of the selected farms

Features	Farm 1 (n=30)	Farm 2 (n=15)	Farm 3 (n=5)
Total Agricultural Area (ha)	5.8	10.4	22.6
Crop Rotation	Yes	Yes	Yes
Gross-Margin (€/ha)	1,156	1,231	1,079.6
Operational costs (€/ha)	496	459	488
Potatoes surface (ha)	3.5	7.2	15.7
Soft-Wheat surface (ha)	2.3	3.2	6.9
Permanent Grassland	5%	5%	5%
EFAs	0%	0%	5%
Number of family workers	2	2.5	2.8
Family labour (hours/year)	1200.5	1424.2	1588.01

Table 2 Scenario characteristics and their impact on farm management and risk

	Policy measure	Impact on farm management after the adoption of the novel practices	Impact on risk after the adoption of the novel practices
Scenario 1	Subsidy / Premium	20–25% decrease in the following operations: water use for irrigation, insecticide use (Adeyemi et al., 2018) 10–20% increase in labour needs (van Evert et al., 2017)	0–10% yield increase & 15% decrease in yield variability; Risk aversion (Ahmad & Sharma, 2023; Akkamis & Caliskan, 2023; King et al., 2005)
Scenario 2	Penalty	20–25% decrease on the following operations: water use for irrigation, insecticide use (Adeyemi et al., 2018)10–20% increase in labour needs (van Evert et al., 2017)	0–10% yield increase & 15% decrease in yield variability; Risk aversion (Ahmad & Sharma, 2023; Akkamis & Caliskan, 2023; King et al., 2005)

where, $\sum_{crop} x''m''$ is the cultivated area of the main crop, and $LANDV$ is the total cultivated land of the farm.

Lastly, farms that exceed 15 ha are obliged to dedicate 5% of the total utilized area as an EFA. Hence, Eq. (8), for the farms with a size over 15 ha can be:

$$\sum_{crop} X_{crop} \leq 0{,}95 \times LANDV \tag{9}$$

ii. Farm-selection.

For the simulations of the proposed model, three farms characteristics were selected in the region of Kato Nevrokopi. With the guidance of 9 agricultural experts in total (5 agronomists of the region, 2 farmers of 20+years' experience and 2 experts on crop production from the University of Thessaly), three farms were selected, which represented the majority of the existing agricultural systems in the greater area of Kato Nevrokopi, based on the prevailing climatic conditions as well as the different agronomic characteristics such soil type and field capacity (Table 1).

In general, all the farms of the selected region follow a two-year crop rotation pattern, between potato and soft wheat; where the potato cultivation takes place during the spring-summer period of the first year, followed by the cultivation of soft wheat, during the spring-summer period of the next year. By way of explanation, a part of the total utilized area of the farm is cultivated with the main crop (potato) and the rest with the second crop (soft wheat); in the next year, the same will occur but vice versa: the part that has been cultivated with potato the first year will receive soft wheat and the part that used to have soft wheat will now be seeded with potato.

iii. Proposed management strategies and public policy incentives.

The proposed technologies aimed at alternative farm management. More specifically, there are two main sub-fields where the proposed PAT is expected to alter inputs used for the cultivation of potatoes; increasing the water for irrigation efficiency and the insecticide used to control the population of *Phthorimaea operculella*. The first sub-field is to be achieved through monitoring of weather conditions and soil moisture, with on-field sensors. The gathered data will provide the software user/farmer with a valuable real-time piece of information about the water state of the crop, to optimize the irrigation plan that he/she follows. Following an increasing great body of literature, the optimization of irrigation practices, especially via precision irrigation and the use of sensors, optimises as well the nutrient application that decreases yield variability (e.g. King et al., 2005). Moreover, the study of Ahmad and Sharma (2023) elaborated an intensive literature review on the economic and environmental benefits of Precision Agricultural Technologies on potato yields. According to this study, precision irrigation practices increase potato yield by up to 30%, averaging 8.5%. Thus, following this study, we assume conservatively that the adoption of the proposed practices will increase yield between 0 and 10%. Similarly, the study of Akkamis and Caliskan (2023), showed that irrigation variability has a significant impact on potatoes yield and quality. Indeed, proper irrigation by the use of PATs may reduce yield variability by 27.3%. Consequently, this study adopts conservatively a 15% reduction on potatoes yield variability after the adoption of the proposed practices (Akkamis & Caliskan, 2023).

Likewise, the latter sub-field is possible by an on-field matrix of “smart” traps that can count in real-time the population of the potato pest *Phthorimaea operculella*. If the population level of the insect is above the favourable set percentage, then insecticide needs to be applied. In this manner, it is expected that no insecticide for prevention purposes will be spread, if there is no necessity, as well as the applied doses, will be more precise, depending on each occasion. A noteworthy piece of information that was taken into consideration, due to its potential influence on the acceptance/adoption by the end-user (Barnes et al., 2019a) is the total cost for the installation and maintenance of the equipment; which in this case was €2,550/set and approximately 500€/year (maintenance cost). However, even though the proposed practices decrease significantly the operation costs and secure the yield, they require a significant increase in working hours and reallocation of these hours within the year which heavily affect the production costs and the working calendar of the farmers.

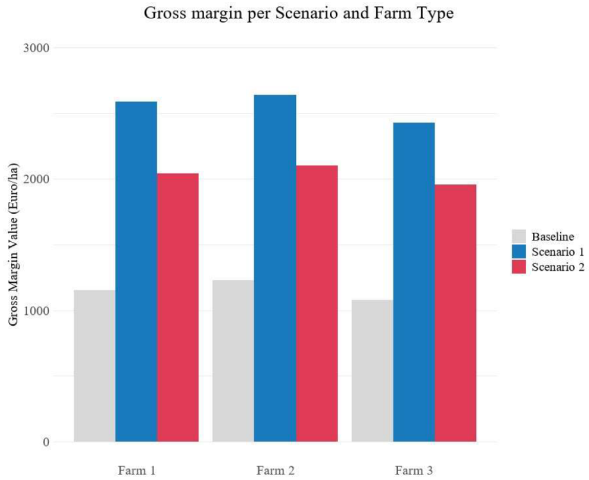
Two policy scenarios were tested to examine farmers’ adoption of the proposed PAT in Table 2. These scenarios examined the possibility to adopt through financial means; Scenario 1 included an incentive in a form of a subsidy and Scenario 2 imposed a penalty. More precisely, the first scenario was built, having in mind that precision farming practices that include the reduction of inputs and the improvement of irrigation efficiency are eligible to be financially supported by the upcoming Eco-schemes, which will be set by each Member State in light of CAP 2023–2027. Regarding Scenario 2 and having in mind the European Union’s short and long-term Green Deal targets, a penalty was introduced, that discourages farmers from upholding the same conventional farming practices and retaining the same volume of inputs since a more sustainable proposed solution exists and lower-input farming systems are required. Hence, here PAT technologies emerge as an alternative management to help the farmers attain the low-input goals. In addition, the above two scenarios were examined also in the context of water scarcity. As said it was above mentioned, following the study ofPetalas et al., (2018) severe droughts may occur in this area during the summer months, which affect the water availability of the examined production systems. This phenomenon may be aggravated in the future due to climate change. Hence, following the consultation of the local experts, simulations in a water scarcity context by adjusting the "irrigation constraint" were performed. A 10% reduction in water availability was tested for each policy measure/scenario, compared to the baseline situation (Scenario 1', Scenario 2').

The objective of both scenarios was the smooth transition from the current farming system to a novel lower input one that will meet the required environmental standards and deliver a satisfactory level, quantity/quality wise, of production, securing the income of the farmers. In the model, both scenarios were introduced as parameters. Therefore, we conducted an iterative process, systematically introducing various values ranging from €0/ha to €200/ha, to analyze farmers' adoption rates in optimizing crop mix decisions across different penalty levels and premiums, on top of the current financial support that they used to obtain from the previous CAP. Finally, the year 2021 has been retained as a baseline scenario as it was the year of data collection.

Results

The results obtained for the three farms were compared with the baseline scenario. Consequently, in this section findings are presented regarding the farm gross margins, and total costs of proposed subsidies or penalties. In general, according to the proposed scenario simulations, all farms seem to adopt alternative management practices and as a result, they experience higher gross margins and lower production costs. More specifically, the two simulated scenarios affect positively the farmer's gross margins (Fig. 1) since the average increased percentage of income is 10.95% and 5.7%, for scenario 1 and scenario 2, correspondingly. In the case of the 1st scenario, the gross margin increase derives mostly from the additional amount of subsidy and the decreased variable cost of inputs whereas, for the 2nd scenario, this increase stems solely from the latter.

Regarding policy measures, it seems that all farms are willing to adopt under certain circumstances. Regarding the 1st scenario, the additional subsidy needed, besides the existing subsidy scheme that farmers already receive, is between 594 and 645 (€/ha). In particular, the required subsidy level to encourage farmers to adopt the novel practices is 645, 626 and 594 €/ha, for Farm 1, Farm 2, and Farm 3, respectively. Analogously, for the 2nd scenario, the level of penalty that is enough to motivate farmers to prevent the loss of their income and reformulate their farming practices to the novel proposed ones is between 821 and 899 (€/ha). More specifically, the monetary point that the penalty (income loss) is sufficient to convert the existing farming system into the novel one is 899 (€/ha) for Farm 1, 867 (€/ha) for Farm 2 and 899 (€/ha) for Farm 3. Both scenarios indicate that Farm 1 demands a higher level of subsidy (or penalty) to alter its current farming system and install the proposed PAT. It could be assumed that this happens due to its small farm size and its limited labour



	Farm 1			Farm 2			Farm 3		
	Baseline	Scenario 1	Scenario 2	Baseline	Scenario 1	Scenario 2	Baseline	Scenario 1	Scenario 2
Gross margin(€/ha)	1,156	2,590	2,042	1,231	2,640	2,103	1,079.6	2,430	1,955
Gross margin variation (%)		11.2	6.08		10.4	5.02		11.28	6.02

Fig. 1 Economic outcomes of each scenario per farm

resources, which makes it harder to be persuaded to alter its farming system, in comparison to the other farms. More specifically, in the case of Farm 1, the family labour covers most of the standard tasks of the cultivation, in terms of farm operations so, by adopting the proposed PAT, an additional level of risk occurs, since the new farming practices are more labour-intensive. This means extra hired labour and therefore more labour cost. However, the one that is the most willing to adopt is Farm 3 which is the largest and wealthiest one. Such farms have the available capital to invest in novel technologies, especially when there is an opportunity to decrease input costs per unit of area. Even though, at first glance this reduction is small; considering the total farmland and its costs, owners of large farms could save a noteworthy amount of capital.

Regarding the simulations under water scarcity, the results highlighted that in both scenarios the farmers are adopting the novel practices for significant lower incentives (Fig. 2). More specifically, in Scenario 1, the proposed incentive is reducing by 32.5%, 23.6%, and 44.7% for Farm 1, Farm 2, and Farm 3, respectively. Similarly with the previous simulations, the necessary incentive to convince Farm 1 to adopt the novel practices is significantly higher in relation to other farms mostly due to the lower labour availabilities of this production system. As the proposed practices are labour intense, this farm requires to hire more seasonal workers, hence higher variable costs. On the contrary, Farm 3 adopt easier the novel practices with a much lower premium. In fact, as the water becomes scarcer, the farmers attribute higher values to the water constraint and consequently, they are more eager to adopt the proposed PAT for a lower premium.

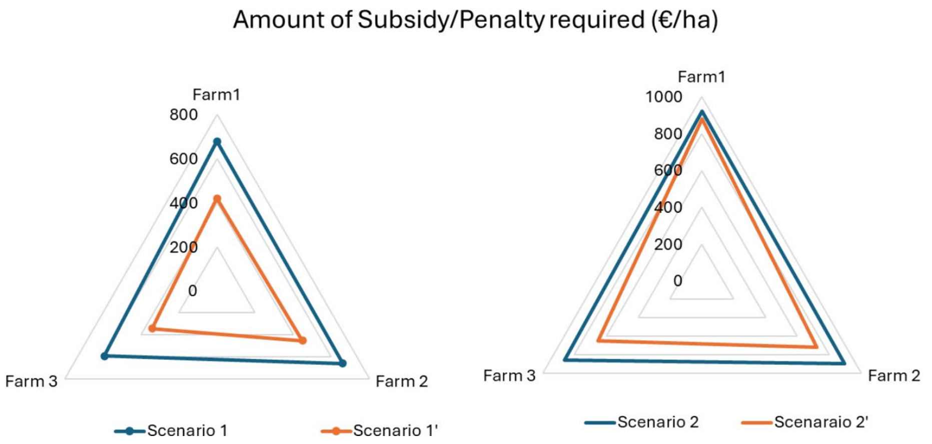


Fig. 2 Impact of the decrease in 10% water availability on farmers' intentions to adopt the proposed PAT (Scenario 1' and Scenario 2' represent farmers' adoption intentions under the 10% total water decrease constraint)

Concerning Scenario 2 similar findings were obtained. The implementation of the penalty motivates the farmers to adopt the novel practices for lower values in a range between 7.45% and 23%. However, even if lower penalty levels are required, this measure seems to be less effective than the premium. For instance, for Farm 1 there is no significant difference in the level of the premium compared with the initial simulations. This results from the fact that Farm 1 has limited investment capabilities and required higher labour costs. As a result, for lower penalty levels, they prefer to pay the penalty than to invest in the novel practices even in the context of water scarcity.

Discussion

The simulations performed by this bio-economic model for three different characteristic farms regarding the adoption of PAT under different policy measures and water scarcity highlighted different findings. In general, the scenario simulations showed that different levels of policy incentives can be efficiently targeted to convince the local farmer to adopt the PAT practices. Nevertheless, the proposed levels varies between farms and depend on the different farm characteristics, such as profitability and labour availability.

More specifically, farmers seem to be willing to adopt the proposed PAT under both simulated policy scenarios (subsidy/penalty), since they can attain a higher income, by decreasing their inputs. Based on the results of this study, for all three farms, the 1st scenario, which comes into a premium/subsidy form appears to be superior to the 2nd one (penalty) regarding its effectiveness in mobilizing farmers to adopt the proposed PAT; which is in line with several past studies that have drawn identical conclusions regarding the effectiveness of these two policy measures (Kleftodimos et al., 2021a, b; Kleftodimos, Kyrgiakos, Kleftodimos et al., 2021a, b). PA tools can decrease the overall use of inputs or ameliorate the efficiency of the existing ones, due to the fact that farmers can achieve better timing and more targeted applications for pesticides, irrigation or other agricultural practices. However, it still remains a limitation of this model that the proposed measures will have an horizontal impact on all farms and that the use of PA tools will affect the use and not the efficiency of the resources used.

According to the literature, wealthier farmers are more likely to be mobilized to adopt a novel technology/practice, which is justified by the study of Bocquého et al. (2013). In this case, Farm 3 is the wealthiest mainly because of its size, since the costs (€/ha) are similar across all the registered farms; it could be assumed that the farm size is proportionate to the gross margin. Farm size is a significant determinant that can heavily influence farmers' decision-making process toward the adoption of PAT, since larger farms may have access to equity and monetary resources to invest in novel technologies (Lambert et al., 2015; Wang et al., 2010). Most studies that assess the influence of farm size agree that its proportionate increase plays a major role in the increase of the PAT adoption rate (Tamirat et al., 2018).

Not surprisingly, Farm 1, which is the smallest one in the area, requires the most monetary resources/incentives (€), to adopt the proposed PAT. In such a small-sized farm, family/unpaid labour is the main source of labour. That is mainly because this type of labour can cover most of the farm's standard operational needs since every management operation is covered by the available family labour except the one of harvesting, which necessitates extra hired labour. High levels of unpaid/family labour to meet total labour needs can have a negative effect on PAT adoption, acting as a disincentive to take up the PAT (Schimmelpfennig, 2016). The number of studies that have identified labour availability and allocation as determinants influencing the adoption process of farmers follows an exponential trend in the literature. This is because farms with limited labour typically tend to focus on basic farm operations rather than investing and reallocating available labour to alternative practices which can be more technical and time-consuming (Kleftodimos et al., 2021a, b; Ridier et al., 2013).

Regarding the context of water scarcity, the results showed that in both scenarios the farmers are ready to accept lower payments or penalties to adopt PAT practices. As water becomes scarcer the adoption of the novel practices will optimize their irrigation management and adapt suitably to the new situation by building more resilient agricultural systems. These findings are in accordance with previous studies which highlighted that in a water scarcity context, stakeholders are willing to adopt water efficient practices for lower incentives (Dinar, 1992; Koundouri et al., 2006; Vermeer. J., 1951).

However, all the above proposed policy measure comes with a significant social cost (e.g. Kleftodimos et al., 2021a, b). In particular in Greece the existing payments, which all of them are under the 1st Pillar of CAP, varied between €100/ha and €1000/ha, while the median level of payments reaches the €610/ha which is the highest in EU (Kremmydas & Tsiboukas, 2022). Our findings are in this range and closest to the median which signifies that significant cost savings may occur if the above practices take the form of an Eco-Scheme. Moreover, as the above practices may contribute to different ecosystem services, such as water quality and soil quality, they may be supported by the 2nd Pillar of CAP and implement the first Agri-Environmental Measure in Greece (Kleftodimos, Kyrgiakos et al., 2021).

Conclusions

The aim of this study was to the efficiency and analyse the intentions of three representative farms in a case study, towards proposed technological equipment, under two specific simulated policy scenarios. To achieve this, a bioeconomic model was developed and applied through different policy scenarios.

Our main analyses and sensitivity analyses suggested that precision agriculture practices can improve potato cultivation for reducing the inputs used. By adopting these technologies and practices, farmers can preserve the overall amount of production while ameliorating the quality of final products. Subsidies to best performers seem to be a more appropriate practice than imposing penalties on the less efficient ones. Policymakers should be aware of this strategy when proposing new measures that include precision agriculture practices. This study contributes to a holistic approach to crop production, where decisions should be made based on real field data to reduce the risk of each decision, while on the other hand the proposed measures each time should have a realistic approach. Multiple scenarios should be studied for the same case to highlight the one with the greatest impact on the development of rural areas. Lastly, it should be stated that the knowledge and innovation CAP's goal will further promote precision agriculture practices and it is of paramount importance how this can be achieved in practice.

However, our approach is subject to several limitations. For instance, as shown also in the Introduction section, behavioural factors can greatly influence the final decision of the farmer (Dessart et al., 2019). Moreover, farmers' subjectiveness regarding PAT can vary, which is another factor, which has not been incorporated in this model (Malawska & Topping, 2016). The influence of counsellors on farmers' final decisions is a factor that poses a constraint to this study. Furthermore, the significance of agricultural cooperatives cannot be underestimated in these circumstances. They not only provide guidance to farmers regarding the adoption of PAT, but also facilitate cost-sharing and mitigate the risks associated with such investments. Lastly, it should be noted that all participants in our study were affiliated with the local agricultural cooperative, which unfortunately limited our ability to evaluate the extent of this influence.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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