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Modelling Lithuanian family farms' participation in agri-environmental subsidy schemes: a Neural Network Approach

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ABSTRACT: Properly targeted agri-environmental subsidies (AES) can ensure the implementation of the European Green Deal goals. Hence, it is important to know what factors encourage family farms to participate in the AES schemes in order to select appropriate political tools and properly use the allocated subsidies. We propose a Multilayer Perceptron neural network to examine 34 Lithuanian crop family farms and identify the factors affecting their participation in the AES. The results indicate that the decision by the Lithuanian family farms regarding the participation mainly depends on a few factors, including the agricultural production output of the farm and farmers' education, while other factors, such as farmer age and farm size, were less important.

Modelado de la participación de las granjas familiares lituanas en esquemas de subsidios agroambientales: un enfoque de red neuronal

RESUMEN: Los subsidios agroambientales (AES) adecuadamente dirigidos pueden garantizar la implementación de los objetivos del Pacto Verde Europeo. Por lo tanto, es importante saber qué factores alientan a las explotaciones familiares a participar en los esquemas de AES para seleccionar las herramientas políticas adecuadas y utilizar adecuadamente los subsidios asignados. Proponemos la red neuronal Multilayer Perceptron para examinar 34 granjas familiares de cultivos lituanos e identificar los factores que afectan su participación en AES. Los resultados indican que la decisión de participación de las granjas familiares lituanas depende principalmente de algunos factores: la producción agrícola de la granja y la educación de los agricultores, otros factores, como la edad del agricultor y el tamaño de la granja, no fueron tan importantes.

KEYWORDS / PALABRAS CLAVE: Agri-environmental Subsidy, Agricultural Practices, Common Agricultural Policy, Neural Network, Multilayer Perceptron. / Subsidio Agroambiental, Prácticas de la Agricultura, Política Agrícola Común, Red Neuronal, Perceptrón Multicapa.

JEL Classification / Clasificación JEL: Q18, Q58, C45.

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1. Introduction

Agricultural practices after World War II had a negative impact on the ecosystem. In order to tackle the post-war food shortage, agriculture was intensified and various chemicals (fertilizers, pesticides, etc.) were widely used. Agricultural chemicals allowed to kill pests and weeds and increased food production. Agricultural practices characterized by the growing use of agricultural chemicals persist, posing a threat to the environment (Puertas *et al*., 2023). Unfortunately, at the same time, large amounts of residual pesticides seep into the environment, polluting it (soil, water, air and food pollution) and adversely affecting human health (Mohammadi *et al.*, 2022; Tudi *et al.*, 2021; Wang *et al.*, 2022).

In order to reduce the negative effects of soil, water, air and food pollution arising from agricultural activities and to increase the positive effects, environmental subsidies were introduced into the environmental policy (Baylis *et al.*, 2008; European Commission, 2015). The aim of environmental subsidies is to support activities that protect the environment or reduce the use and extraction of natural resources and to meet the growing demand for public goods (European Commission, 2015; United Nations, 2017).

Although various agri-environmental subsidy (AES) schemes have been applied in the EU for more than 20 years, it remains unclear whether this environmental policy instrument is effective enough in terms of the delivery of environmental benefits (Baylis *et al.*, 2008; Coderoni & Esposti, 2018; European Commission, 2015; Tyllianakis & Martin-Ortega, 2021). Today we face the challenges of climate change, including the changing soil conditions, increasing temperature and precipitation. Agriculture is one of the main sectors contributing to climate change through GHG emissions and indirectly through its impacts on soil, forests and other land uses (Blandford & Hassapoyannes, 2018). The increase in the areas of agricultural land and number of livestock as well as the intensive use of chemical fertilizers and pesticides, aimed at meeting the growing demand for agricultural products, pose a danger to the environment (Agrimonti *et al*., 2021). Hence, the environmental pollution, degradation of ecosystem services, and human health risks are only increasing (Millennium Ecosystem Assessment, 2005; Puertas *et al.*, 2022; Tudi *et al.*, 2021).

The European Green Deal has set ambitious goals for Europe to become the first climate-neutral continent and to neutralize the effects of greenhouse gases (GHG) on climate change by 2050 (European Commission, 2019). Therefore, with the view towards these goals, it is necessary to analyse the actions leading towards them and to evaluate the role of the AES from an economic and environmental perspective. The European Green Deal is one of the key policy priorities for maintaining, protecting and enhancing “the EU’s natural capital, protecting the health and well-being of its citizens” from the harmful environmental effects and ensuring fair transformation (European Commission, 2019).

One of the instruments to implement part of the goals of the European Green Deal are well-targeted AES. However, if applied improperly, the subsidies may have adverse effects and cause harm to the environment. Withana *et al*. (2012) examined environmentally harmful subsidies (EHS) in EU Member States demonstrating the need for reform in numerous cases of EHS due to inefficient use of energy and natural resources, negative impact on biodiversity, air, and water quality. The interim assessment of the impact of Lithuanian AES subsidies revealed that, due to the insufficient targeting of measures in 2014-2018, significant areas of valuable meadows and habitats were destroyed in the areas participating in the program measures (ESTEP, 2019). The abandonment of detrimental and improper targeted subsidies is necessary to contribute to the implementation of the European Green Deal (European Commission, 2019). The AES are widely used in agriculture to promote environmentally friendly farming and environmental innovation, to maintain soil quality, to improve natural habitats, and to support activities to reduce GHG emissions (Biffi *et al.*, 2021; Henderson & Lankoski, 2019).

Previous studies have revealed diverse results. First, the negative environmental impacts were not mitigated because the AES were not targeted at the problem areas of greatest water scarcity, biodiversity loss, soil erosion, and nutrient runoff (Biffi *et al*., 2021). Second, the AES did not achieve long-term positive effects because monetary compensations were targeted without taking into account farmers' values and perceptions (identity, social capital, knowledge, experience, etc.) (Teff-Seker *et al.*, 2022). Third, it is difficult to involve family farms pursuing intensive agricultural activities in the AES schemes and to change their farming practices (Biffi *et al.*, 2021; Merckx & Pereira, 2015).

Given that the AES schemes are widely used to reduce the environmental impact of modern agricultural practices, their success depends on the extent of their application. Since the effectiveness of the Common Agricultural Policy (CAP) of the European Union (EU) is closely tied to the issue of family farm participation, it is also necessary to analyze the factors that influence their participation. This analysis will help to include the most polluting family farms in the AES schemes, enabling the policymakers to accurately target measures of the agri-environmental policy.

Research problem: How should AES schemes be designed to engage family farms' participation in those schemes and change farms' production decisions to more environmentally friendly ones?

Research aim: To examine what factors affect family farms' participation in the AES.

Research objectives:

- to explore the concept of AES and to analyse the factors influencing farmers enrolment in the AES;
- to identify the factors influencing the participation of Lithuanian family farms in the AES, applying the suggested research methodology using the neural network approach;
- to evaluate the importance of selected economic, social, and environmental factors on farmers' enrolment in the AES and to provide policy recommendations.

The next section (Section 2) of the paper discloses the concept of AES and analyses the factors leading family farms to participate or not participate in the AES schemes. Section 3 presents the research methodology based on the neural network approach and research results. The discussion and conclusions together with policy recommendations are presented in Section 4.

2. Literature review

2.1. The concept of AES

Agriculture performs essential environmental, economic, and social functions by providing ecosystem services, i.e., food supply, ensuring biological diversity, improving the quality of the environment, etc. On the other hand, the sector also causes negative externalities such as water and land degradation due to chemical pollution, GHG emissions, and high demands on water resources (Richterová *et al.*, 2021; Valsecchi *et al.*, 2009; Van Beers & Van den Bergh, 2001; Wang *et al.*, 2022). About a quarter of global GHG emissions come from the agricultural sector (Laborde *et al.*, 2021). In recent years, GHG emissions from agriculture have generally stopped declining or even increased in some cases (European Commission, 2019).

At the launch of the AES in the EU in 1980-1998, they were primarily focused on environmentally friendly practices and organic farming (Primdahl *et al.*, 2003; Tyllianakis & Martin-Ortega, 2021). However, with each new CAP, the application of AES schemes in the EU continued to expand (McGurk *et al.*, 2020; Tyllianakis & Martin-Ortega, 2021) with the implicit target to mitigate emissions from agriculture (Coderoni & Esposti, 2018). Puertas *et al.* (2023) stress the importance of continued support for sustainable and economically profitable agriculture in order to curb agricultural pollution and its consequences, such as rising air temperature and emissions. The AES are targeted to promote environmentally friendly farming and environmental innovation, to maintain soil quality, to improve natural habitats, and to support activities to reduce GHG emissions (Henderson & Lankoski, 2019; Laukkanen & Nauges, 2014). In the literature, the AES are described as a key agricultural policy tool which:

- aims to tackle the negative impact of agriculture activities on the environment through monetary compensation to farmers (Leonhardt *et al.*, 2022; McGurk *et al.*, 2020; Wittstock *et al.*, 2022);
- aims to support a positive impact on the environment (Coderoni & Esposti, 2018; McGurk *et al.*, 2020);
- aims to implement sustainable farming practices that promote biodiversity and ecosystem functions in agricultural landscapes through monetary compensation (Barghusen *et al.*, 2021; Puertas *et al.*, 2023; Tyllianakis & Martin-Ortega, 2021; Wittstock *et al.*, 2022; Wuepper & Huber, 2022);
- encourages farmers to supply organic goods in larger quantities (McGurk *et al.*, 2020);
- allows farmers to voluntarily choose whether or not to participate in the AES schemes, which typically last up to five years (McGurk *et al.*, 2020).

The AES are implemented through the EU CAP with the focus on the efficient use of resources, the transition to a climate-resilient low-carbon economy in agriculture, and the restoration and preservation of agriculture-related ecosystems. The CAP plays a key role in improving the environmental performance of agriculture, including the GHG emission reduction (Coderoni & Esposti, 2018). Nowadays, the environmental protection requirements are included in the EU's highest-level strategic documents where the European Green Deal is classified as one of the most important political priorities. It establishes the obligation to preserve and increase the EU's natural capital and protect citizens' health and well-being from climate and environment-related risks and impacts. The AES are among the political measures to reach the goals of the European Green Deal; therefore, the AES must be also analysed in the European Green Deal context.

EU Member States have prepared their initial national CAPs for 2023–2027. The effectiveness of CAP 2023-2027 depends on the uptake of adjusted and redesigned AES schemes, so research of factors that influence farmers' participation in AES is relevant when implementing the new CAP. Based on the European Green Deal, the list of potential supported practices was prepared (European Commission, 2021). These practices could serve as directions for a new AES schemes design (Table 1).

TABLE 1

Examples of agriculture practices subsidised by AES schemes for 2023-2027

Examples of agricultural practices	CAP strategic plan focus areas						
	Climate change mitigation	Climate change adaptation	Protection or improvement of water quality	Prevention of soil degradation	Protection of biodiversity	Actions for sustainable and reduced use of pesticides	Actions to enhance animal welfare
Organic farming practices		●	●	●		●	●
Integrated Pest Management practices		●	●	●	●	●	
Agroecology	●	●	●	●	●	●	●
Agroforestry	●		●	●	●	●	
Husbandary and animal welfare plans	●	●					●
High nature value farming	●	●	●	●	●	●	●
Carbon farming	●		●	●	●	●	
Precision farming	●	●	●	●	●	●	
Improve nutrient management			●	●	●		
Protecting water resources		●					
Other practices beneficial for soil		●		●	●		
Other practices related to GHG emissions	●						

Labelling: ● – the agricultural practices addressing CAP focus areas.
Source: Own elaboration based on European Commission (2021).

During the implementation of the EU CAP 2023–2027, the activities presented in Table 1 should be included in the national strategies of EU countries and accomplished through the AES schemes. This would encourage family farms to develop a sustainable food production system, contribute to the achievement of the EU's climate goals, and protect the environment. The AES are designed to directly contribute to the fulfilment of the several EU' Green Deal goals. Meanwhile, the listed activities (see Figure 1) are aimed at the reduction in the use of pesticides by 50 percent; ensuring 25 percent of land used for organic farming; significant increase of the organic aquaculture; reduction in the sales of antimicrobials by 50 percent; reduction in the use of fertilizers by 20 percent; and ensuring 10 percent of lands with high-diversity landscape features (European Commission, 2021).

Researchers distinguish different aspects of implementation of the AES goals. The ability to enrol the family farms and understand farmers' view on agri-environmental practices are referred to as the key principles for the successful adoption of the AES (Barghusen *et al.*, 2021; Teff-Seker *et al.*, 2022). One of the main reasons for the ineffectiveness of AES is the lack of research on the attitude of family farms, including their understanding of the agri-environmental practices and implementation thereof, and their willingness to apply the environmental management (Mettepenningen *et al.*, 2013; Teff-Seker *et al.*, 2022; Tyllianakis & Martin-Ortega, 2021). The factors behind the farmers' decision to participate in the AES schemes must be determined for the purpose of the investigation, and the next subsection is dedicated to this task.

2.2. Factors leading family farms to participate/not participate in the AES

The AES are more effective when a higher number of farmers are driven to participate in these schemes, as they influence the participants' actions in terms of environmental protection and conservation. One of the areas of research on agri-environmental measures focuses on the analysis of farmers' decision to take part in the implementation of agri-environmental measures (Galnaitytė, 2017). The aforementioned research suggests that the participation is largely driven by farmers' quest to maximize their profits. Carlisle (2016) studied the influence of farms differences in size and activity scope on their decision to uptake the AES schemes. Despite the higher motivation to adopt the AES, smaller farms with lower opportunity costs were less inclined to do so due to the transition costs in comparison to the farms larger in size and financial capacity. The choices of family farms are influenced by various economic and social factors as well as personal attitudes (Biffi *et al*., 2021; Galnaitytė, 2017; Henderson & Lankoski, 2019; Wittstock *et al*., 2022). Hence, the need for a wider analysis of factors influencing the participation decisions and farmers' preferences to enrol into the AES is emphasized (Tyllianakis & Martin-Ortega, 2021). Proper targeting of subsidies and greater participation of farms can help distribute the allocated funds more accurately and, at the same time, increase their impact on the improvement of the state of the environment.

Profitability of an economic activity is one of the sought-after elements of sustainable agriculture (Vitunskienė & Vinciūnienė, 2014). However, participation in the AES puts certain constraints on the farms land use, soil health, fertilization, and grazing practices. According to Bostian *et al.* (2020), the voluntary participation of farms in subsidy schemes provides environmental benefits, while at the same time reduces farm productivity due to the applied restrictions on the use of fertilisers and other activities. As a result, participation in the AES changes the production decisions of the farm and, at the same time, its economic objectives, i.e., the farm's profit must be ensured by providing environmental benefits. Farms adjust input and input sets and change the land use in order to maintain the desired farm profits (Bostian *et al.*, 2020; Henderson & Lankoski, 2019; Picazo-Tadeo *et al.*, 2011).

Despite the extensive analysis of the factors influencing farm participation decisions in crop insurance subsidy schemes over the past two decades (Akter *et al.*, 2016; Enjolras *et al.*, 2012; Finger & Lehmann, 2012; Santeramo *et al.*, 2016; Wąs & Kobus, 2018), the studies examining factors influencing farmers' participation in the AES are less common. Recent research findings include the studies analysing participation of Greek farms, Polish commercial farms, Dutch farms, Israeli farmers in AES issues and the adoption of soil health practices in United States (US). Nonetheless, no such studies on Lithuanian farms have been found. Giannakis (2014) investigated the determinants of farm participation in the AES schemes in Trikala region (Greece). According to the findings of the study, farmers of a younger age and with a better education were more likely to participate in these schemes. The impact of personal farmers attitudes was also stressed. The research of farms in Thessaly (Greece) by Damianos & Giannakopoulos (2002) showed that young and educated farmers were more likely to adopt environmental schemes and that agricultural education and bigger farm size also had a positive influence on the adoption. Wąs *et al.* (2021) analysis of Polish farms revealed that farms' participation in AES was mostly related to the economic interests of the farm. The findings of Barghusen *et al.* (2021) confirmed equal importance of both economic and environmentally-based factors for Dutch farmers regarding participation in the AES. Israeli farmers' willingness to participate in the AES was dictated by environmental, personal and social considerations as well as financial factors (Teff-Seker *et al.*, 2022). Farmers using the fertile lands in German Saxony prioritise decisions related to farms' operation processes over the decisions on the participation in the AES. The factors that influenced the decision were economic, routine and biophysical/geography-related, while the land of lower value to the farm from an economic point of view was allocated to the AES (Wittstock *et al*., 2022). Carlisle's (2016) research provides a detailed review of the agronomic and financial factors, policy and knowledge barriers found in independent US studies that are considered to influence farms' participation in the AES. Having conducted a systematic review of papers dealing with the analysis of factors, Tyllianakis & Martin-Ortega (2021) stress that the literature on the analysis of farms' willingness to participate in the AES is limited but growing. Their findings suggest that, in general, farmers are positive towards the participation in the AES, but the schemes do not seem to fit farmers preferences. This study also reveals that wealthier farms gain more from such participation than less wealthy farms and emphasizes the need to adapt the design of the schemes in order to attract smaller farms.

According to the findings of the analysis of empirical studies on the AES, most of research use both qualitative and quantitative indicators. In their research works, some authors (Teff-Seker *et al.*, 2022) grouped the factors into environmental, personal, and social motivation. Other authors (Mettepenningen *et al.*, 2013) grouped factors into farmer- and farm-related, social, and informational factors. Other authors (Wąs *et al.*, 2021) break the factors down into farm resources, farm structure, farm performance, farmer demographic and farmer beliefs system. Summarizing the empirical studies analysed, it can be concluded that the factors employed in the studies cover three dimensions, namely, economic, social, and environmental, also corresponding to the three dimensions of sustainable development. The summary of the most common factors used in the previous research on farm participation in the AES schemes is presented in Table 2.

TABLE 2

Factors affecting farms participation in the AES

Factors	McGurk *et al.* (2020), representative Irish farms	Leonhardt *et al.* (2022), Austrian crop farms and mixed farms	Wuepper & Huber (2022), Swiss farms	Mettepenningen *et al.* (2013), farms of Flanders region, Belgium; farms of Arkansas State , US	Teff-Seker *et al.* (2022), Israel farmers	Wąs *et al.* (2021), representative Polish farms	(Giannakis, 2014), farmers of Trikala region, Greece	Damianos & Giannakopoulos (2002), farmers of Thessaly region, Greece
Social factors:								
Age	●	●	●	●	●	●	●	
Education		●		●	●	●	●	●
Gender				●	●		●	
Ecological knowledge					●			
Settlement area (urban; rural)					●			
Quality of life					●			
Family members working on the farm (persons)						●		
Managing farm (years)						●		
Agricultural education				●			●	●
Social networks; contacts with public and private institutions				●			●	●

Factors	**McGurk *et al.* (2020), representative Irish farms**	**Leonhardt *et al.* (2022), Austrian crop farms and mixed farms**	**Wuepper & Huber (2022), Swiss farms**	**Mettepenningen *et al.* (2013), farms of Flanders region, Belgium; farms of Arkansas State , US**	**Teff-Seker *et al.* (2022), Israel farmers**	**Wąs *et al.* (2021), representative Polish farms**	**(Giannakis, 2014), farmers of Trikala region, Greece**	**Damianos & Giannakopoulos (2002), farmers of Thessaly region, Greece**
Economic factors:								
Agricultural activity type	●	●	●			●		
Farm size (UAA)	●	●	●	●		●	●	●
Labour hours; labour unit	●		●					
Income	●			●	●	●		
AES amount received		●	●					
Total subsidies amount (excl. on investment)						●		
Productivity (Outputs/Inputs)		●				●		
Economic prosperity					●			
Participation in land rental	●	●				●		
Assets value (without land)						●		
Environmental factors:								
Nature coherence (conservation; relatedness)					●			
AES participation	●			●				
Number of crops								
Livestock (units; density)			●			●		
Crop area			●					
Mineral fertilisers								
Pesticides								
Land quality						●		
Production zone (lowlands; mountain area)			●					
Area/land type (grassland area; forage crop area; abandoned land; fallow land; hedges)						●		
Region				●		●		

Labelling: ● – the decision influencing the factors analysed.
Source: Own elaboration.

The studies analysing farmers' decision-making behaviour concerning their participation in the support schemes often employ a utility function, i.e. utility maximization at farm level (Coderoni & Esposti, 2018; Damianos & Giannakopoulos, 2002; Giannakis, 2014; Henderson & Lankoski, 2019). The factors affecting it are not only economic but also social capital or the farmer's approach to environmental protection.

The review of the factors used in previous studies has suggested that the set of research factors often included both quantitative and qualitative factors related to social, economic, and environmental aspects of the farm or reflecting the farmer's attitude towards the matter. Age and education may be distinguished as the most commonly used social factors (Giannakis, 2014; Leonhardt *et al.*, 2022; Mettepenningen *et al.*, 2013; Wąs *et al.*, 2021). Economic factors commonly used in research included farm economic size and/or utilised agriculture area, activity type, and income level (McGurk *et al.*, 2020; Mettepenningen *et al.*, 2013; Wąs *et al.*, 2021). When a survey was used for farm data collection, social factors also included agricultural education and/or use of social networks or even membership in farmers' unions (Damianos & Giannakopoulos, 2002; Giannakis, 2014; Mettepenningen *et al.*, 2013); farmers' risk preferences or moral choices were analysed (Joao *et al.*, 2015).

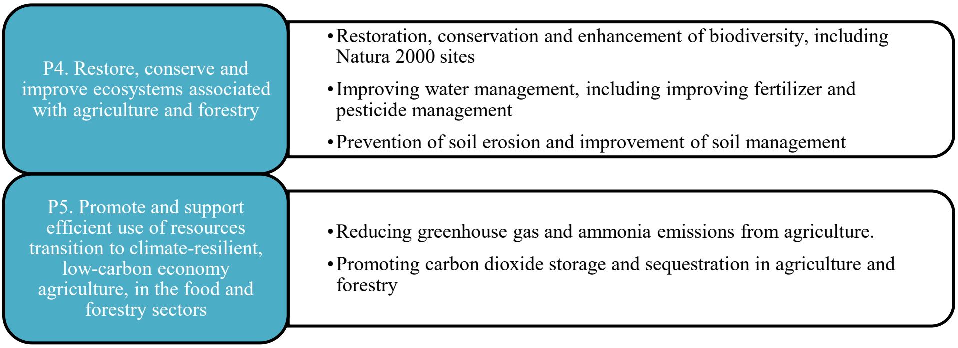
3. Research methodology and results

3.1. Lithuanian case study: environmental priorities implemented by the rural development program

The implementation of the environmental protection requirements in relation to agriculture began the Lithuanian agricultural policy in 1982, gradually integrating newly emerging ones. Since 2004, the implementation has been expanded with measures financed by the EU funds, adding the requirement to maintain the land in good agricultural and environmental conditions (Vitunskienė & Vinciūnienė, 2014). The goals of the Lithuanian Rural Development Programme 2014-2020 (hereinafter referred to as the RDP 2014-2020) were the modernization of farms, improvement of economic performance, improvement of soil management, efforts to preserve biological diversity, promotion of ecological farming, creation of new jobs, and development of rural areas and business. The priorities of the RDP were designed to meet and implement all six rural development priorities of the EU. Figure 1 below provides a summary of the environmental and climate change priorities and target areas of the RDP 2014-2020.

FIGURE 1

Priorities and target areas of support for environmental protection in agriculture according to the RDP 2014-2020



Source: Own elaboration based on Ministry of Agriculture of the Republic of Lithuania (2015).

The RDP strategy aims to meet the selected priorities. At the top of the list of priorities, ranked by significance, is the promotion of nature-friendly farming, conservation innovations, soil quality maintenance, improvement of natural habitats, promotion of environmentally friendly farming methods, and support to activities that reduce CO_2 emissions.

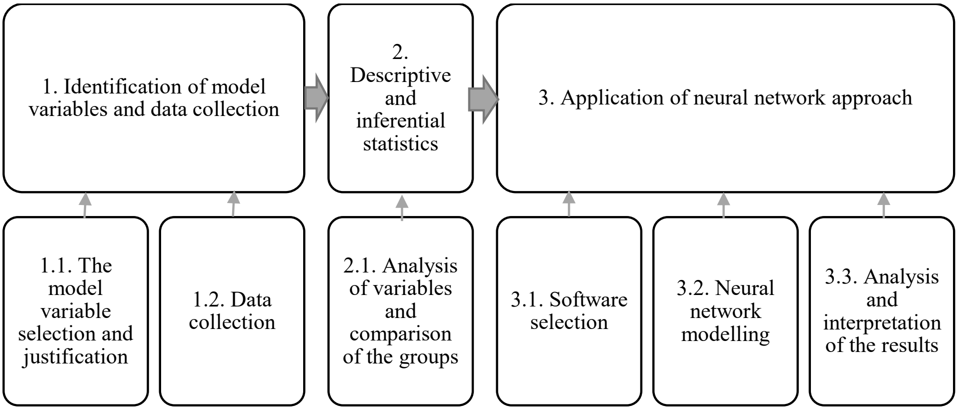
In order to achieve the goals of mitigating climate change, significant budget funds were allocated. For the implementation of agricultural environmental protection measures under the RDP 2014-2020, about 676 million euros were paid out, i.e., about 44 percent of the total disbursed RDP funds during the above-mentioned period. For the implementation of measures under the 4th priority "Environment – biodiversity, water and soil improvement", the largest part of the funds was disbursed, i.e. 630.4 million euros, and the financial level of implementation was the second highest in the programme, reaching 91 percent (ESTEP, 2021). Understanding the factors that influence the decisions of farms to participate in the AES is important in order to ensure the successful allocation of funds and their efficiency and effectiveness. To the authors' knowledge, this is the first empirical study aiming to assess the factors that influence the willingness Lithuanian farms to participate in the AES schemes.

3.2. Research methodology

The methodology of this research consists of three steps, which include variable selection, descriptive and inferential statistics of the data as well as neural network modelling (Figure 2).

FIGURE 2

The logical scheme of the research



Source: Own elaboration.

First, the analysis in Section 2.2 revealed the variables most commonly used when analysing farmers' participation in the AES. The selection of the research variables was also determined by dta availability in the EU Farm Accounting Data Network (FADN) at the farm level. FADN collects and compiles farm accounting data every year. It enables the researchers to monitor and compare the production and economic results of farms in the EU Member States and to assess the impact of the CAP on them.

The selection of crop farms in the present research is based on two assumptions. First, the studies reviewed showed that farms' specialisation influenced the decision whether or not to enrol in the AES (Leonhardt *et al.*, 2022; Wittstock *et al.*, 2022) and, in view of the heterogeneity of the farmers, they might have had different preferences (McGurk *et al.*, 2020). Second, based on the data by the Lithuanian Statistics Department, crop production is predominant in Lithuanian agriculture and comprises more than a half of total agricultural production. The type of farming analysed in the present research –crop farms– corresponds to the typology used in the FADN and covers farms with the types of "specialist cereals, oilseeds and protein crops" and "general field cropping, mixed cropping".

Participation in the AES schemes was carried out within the framework of the RDP 2014-2020; hence, 2017 was chosen as the interim year during the participation in the schemes. According to the statistical data by the Agricultural Data Center[1], there were 34,135 crop farms at the end of 2017. To provide 95 % confidence interval and meet the 0.05 error requirement in the empirical research, a sample of 380 family farms had to be reached. The Lithuanian Agricultural Advisory Service, responsible for collecting the FADN data, was contacted in order to request the consent of family

[1] Agricultural Data Center database. Access: https://ismain.vic.lt/VurapPublic/

farms to participate in the research. Consent was obtained from 34 farms that agreed to have their data submitted for the research, resulting in a margin of error of 16.46 %. The research farm level data covered 34 Lithuanian crop producing family farms in the year 2017, and 8 of those farms participated in the AES scheme under the RDP 2014-2020.

Six variables covering the social, economic, and environmental factors were selected in order to analyse their effects on family farms' participation in the AES schemes (Table 3).

TABLE 3

Description of variables

Variables		Marking	Unit
Economic factors	Utilised agriculture area	*UAA*	ha
	Output	*OutputEurha*	Euro/ha
	Debt ratio	*Debtratio*	%
Social factors	Farmer's age	*Age*	years
	Farmer's education	*Educ*	0 = practical; 1 = basic; 2 = full
Environmental factors	Land quality points	*Landquality*	Points
Dependent variable	Participation in agri-environmental subsidies	*Part_AES*	1 = participating farms; 0 = non-participating farms

Source: Own elaboration.

Farmer's age (*Age*) and education (*Educ*, divided into three education levels) stand for the social factors in the model. According to the previous studies, they may be considered the most common influencing social factors. In terms of education, certain legal requirements applied to those who wished to engage in farming. Hence, practical education (=0) stands for those farmers who only have practical experience, basic education (=1) stands for farmers who have acquired the basics of professional farming, full education (=2) stands for farmer's higher education.

Economic modelling factors are represented by the utilised agriculture area (*UAA*), farm output in euros per ha (*OutputEurha*), and debt ratio (*Debtratio*). The UAA describes the farm size, while output (*OutputEurha*) stands for wealth of the farm, is related to the intensity of farms' activity, and could be treated as an indicator of how a farmer allocates land to agricultural production (Wittstock *et al.*, 2022). Debt ratio (*Debtratio*), calculated as ratio of total debt to asset (Wąs & Kobus, 2018), is not a commonly used factor in studies that analyse farmer's participation in the AES. Nevertheless, it is widely used in the analysis of farms' decisions regarding the participation in crop insurance subsidy schemes (Santeramo *et al.*, 2016; Wąs & Kobus, 2018) and is also treated as one of the factors reflecting the level of farm risk (Wąs & Kobus, 2018).

Although land quality (*Landquality*) is not a common factor used in the analysis of participation, it was necessary to include it in the research as an environmental factor, as intensive agricultural activities are carried out on good quality land and produce the majority of farms' agricultural output, making these farms difficult to attract to the AES schemes (Biffi *et al.*, 2021; Wąs *et al.*, 2021). Environmental factors such as mineral fertilisers and pesticides were not included as the study covered both participating and non-participating farms, and participating farms had already implemented restrictions on the use of fertilisers. The dependent variable is farmers participation/non-participation in the AES scheme (*Part_AES*).

Second, it was decided to present descriptive statistics of the farm data in the research in order to draw reasonable conclusions about the characteristics of the sample regarding their means, medians, minima, and maxima with respect to the variables selected. Shapiro-Wilk tests were performed to analyse the normality of the distribution of the variables. Inferential statistics (t-tests and Mann-Whitney's U tests) were performed to reveal statistically significant differences between the farms in the sample.

Third, as presented in Figure 2, neural networks were employed in the research. It should be mentioned that discrete choice econometric models, i.e. probit, tobit, or logistic regression models, are often used to determine the factors influencing farmers' enrolment in the AES (Damianos & Giannakopoulos, 2002; Giannakis, 2014; Henderson & Lankoski, 2019; Laukkanen & Nauges, 2014; Wąs *et al.*, 2021). The aforementioned factors were tested empirically by running logistic regression with the SPSS™. Although the predictive power of the presented model was fairly good, the input variables were not statistically significant according to Wald's test. Hence, it was decided to adopt a neural network approach instead.

Since the phenomena in agriculture are based on multiple and unidirectional connections, advanced research methods are applied to their analysis and decision making. The artificial neural networks (ANN) are particularly useful when analysing complex phenomena due to the multifunctionality of the former. They are used as an alternative to classical mathematical methods to resolve agricultural problems, including investigation of the impact of weather conditions, crop pest identification, estimation of corn grain yield, and harvest prediction (Khairunniza-Bejo *et al.*, 2014; Kujawa & Niedbała, 2021).

Various ANN approaches are applied in agricultural research, mostly covering areas of agronomy (Khairunniza-Bejo *et al.*, 2014; Wang *et al.*, 2021) and management of agribusiness (Nosratabadi *et al.*, 2021). No studies were found where Multilayer Perceptron (MLP) would be applied to an agricultural economics research. However, the MLP method has an advantage if applied to the related fields of agricultural research. Previous research (Wang *et al.*, 2021) results showed that the MLP ANN was more efficient compared to linear regression, decision tree, support vector machine, etc. Comparing the Adaptive Network-based Fuzzy Inference System (ANFIS) with the MLP, the researchers (Nosratabadi *et al.*, 2021) came to the conclusion that the ANFIS model had a higher predictive power than the MLP model, but this could be affected by some factors (such as climate, government policies, and technological progress) that were considered as constant.

In the present research, the MLP neural network available at the SPSS was used because this network was appropriate for pattern recognition problems. The MLP consists of three parts: the input layer, the hidden layers, and the output layer. Each layer consists of one or more artificial neurons. Information in an MLP is transmitted in only one direction, from the input layer to the output layer (Delashmit & Manry, 2005). In each neuron, the weighted sum of its inputs is calculated, and its output is transferred to other neurons. In this way, the signals, or information, will move from the input layer, through the hidden layers to the output layer. Nonlinear activation functions are also used in these networks to modify the signals (Khairunniza-Bejo *et al.*, 2014). The construction of a neural network is usually more or less based on trial and error. In the case of this research, various versions of SPSS MPL were studied by changing the scaling of the variables, number of hidden layers, and number of neutrons. The final model was the one with minimum model error and performing sufficiently good classification of the farms in the sense of pattern recognition. The weights and importance ranking of our variables were based on the corresponding algorithm in the SPSS. Since the data set was small, the cross-validation, which is the usual procedure within the NN, was not justified in this context, and only training data were used in the model.

3.3 Research results

For general description of the farms participating in the study through the analysis of the explanatory variables, complete descriptive statistics are presented in Table 4. The descriptive statistics are divided into three parts to present separately the data for all farms (N = 34), the farms non-participating in the AES (N = 26), and the farms participating in the AES (N = 8).

TABLE 4

Descriptive statistics of variables

	All farms (34)				Farms non-participating in the AES (26)				Farms participating in the AES (8)			
	Mean	Median	SD	Min-Max	Mean	Median	SD	Min-Max	Mean	Median	SD	Min-Max
Educ	1.35	2	0.85	0 -2	1.15	1	0.88	0 - 2	2	2	0	2 - 2
Age	52.94	53.5	8.6	32 - 67	53.08	53.5	9.20	32 - 67	52.5	53.5	6.8	39 - 61
UAA	376.42	294.15	301.08	23 - 1,273	334.48	235.95	316.10	23 - 1,273	512.74	440.11	206.66	258 - 808
Debtratio	27.77	26.17	15.45	2 - 70	27.25	26.17	15.32	2 - 70	29.46	26.2	16.79	8 - 53
Landquality	46.83	47	5.1	35 - 55	47.37	47.90	5.59	35 -55	45.1	44.5	4.27	38 - 53
OutputEurha	1,067.09	1,045.47	337.54	381- 2,378	898.04	999.88	247.40	381 - 1,398	1,291.74	1,082.98	493.04	925 - 2,378

Source: Own elaboration.

The following observations could be made regarding the descriptive statistics:

- The mean values of the variables were higher in the *Farms participating in the AES* group, except for *Age* and *Landquality*, which had higher means in the *Farms non-participating in the AES* group.
- This also applied to the medians of the variables, where the participating group exhibited higher medians except for *Age* (it was the same as in the participating group, 53.5) and *Landquality*.
- When comparing the minima and maxima of the variables, the participating group stood out for having higher minimum and maximum values for *OutputEurha* and higher minimum values for the rest of variables, whereas the non-participating farms had higher maximum values for *Age*, *UAA*, *Debtratio,* and *Landquality.*
- Variable *UAA* indicated greater variation in the size of non-participating farms, as average-sized farms were engaged in AES. Non-participating farms included mainly small and very large farms.

Most of the variables in the sample were normally distributed, except for the *UAA* variable in the non-participating group and *OutputEurha* in the participating group. The t-tests between all group means did not indicate any statistically significant differences.

If the t-tests proved to be unreliable when group size was less than 30 observations, non-parametric Mann-Whitney's U tests were used instead (Table 5). The null hypotheses were rejected; hence, there were statistically significant differences in the case of variables *Educ* and *UAA*.

TABLE 5

Mann-Whitney's U Test results for the statistically significant differences

Variable	All farms (34)	
	Farms non-participating in the AES (26)	Farms participating in the AES (8)
Educ		
Mean Rank	15.35	24.50
Asymptotic Sig.(2-sided test)	0.010	
UAA		
Mean Rank	15.35	24.50
Asymptotic Sig.(2-sided test)	0.023	

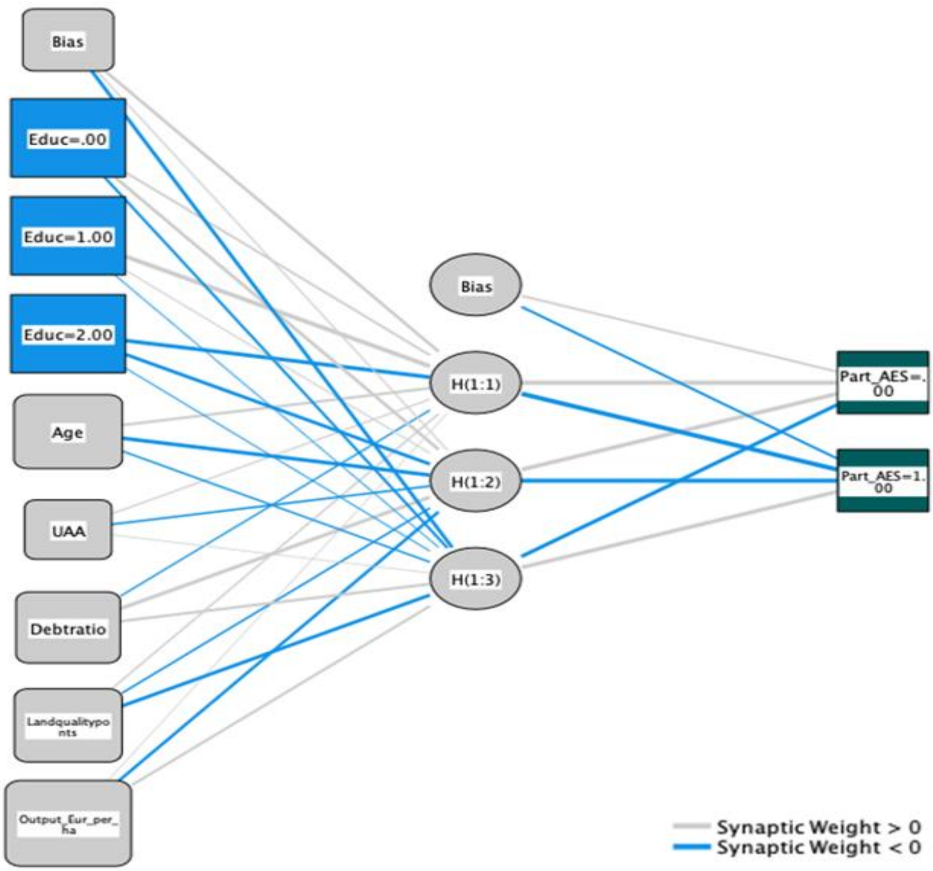
Source: Own elaboration.

As presented in Table 5, the participating farms had a significantly higher mean rank than the non-participating ones in the case of *Educ*. The crosstabulation of the variables *Part_AES* and *Educ* showed that all participants in group 1 had full education (=2), while non-participants (group 0) included farmers representing all levels of education. In the case of the *UAA* variable, the mean rank was generally lower in the non-participating group. A 2-sided test showed the smallest possible margin of error: 0.010 for *Educ* and 0.023 for *UAA*, indicating statistically reliable differences between the participating and the non-participating farms in relation to these variables.

At the following step, the MLP neural network was constructed with SPSS by using the standardised values of the variables. The MLP of the present research consists of three layers. The input layer contains eight neurons (five continuous variables and one categorical with three categories). They are used to distribute the inputs to the hidden layer. Three neurons are in the hidden layer, and their outputs are connected to the output layer. Information between the layers moves through the weighted connections, and the hidden layer uses the hyperbolic tangent activation function, while the output layer activation is based on SoftMax function (Figure 3).

FIGURE 3

The architecture of the three-layer MLP neural network used in the research



Source: Own elaboration using SPSS™.

In practice, the connections between the neurons are controlled by the strengths of these connections known as the synaptic weights. A single neuron may have multiple connections (synapses) with other neurons in the next layer, and these synapses will yield different signals to each neuron. Although SPSS provides an extensive table of estimated coefficients of the neural network, its information is still challenging to interpret. According to Khairunniza-Bejo *et al.* (2014), it is complicated to establish the "causal-effective relationship between input and output", and at this point the authors compare the ANN to the "black box". Hence, to interpret the MLP results of the present research, normalised importance of the variables (see Table 6) provided by SPSS is studied.

TABLE 6

Importance of input variables on the decision of participation in the AES

	Importance	Normalised importance
OutputEurha	0.224	100.0 %
Educ	0.188	83.8 %
Age	0.168	74.8 %
Landquality	0.166	73.8 %
Debtratio	0.155	69.1 %
UAA	0.099	44.3 %

Source: Own elaboration.

The *OutputEurha* of the farm appears to be the most significant variable affecting farmers' decision regarding participation in the AES, with its normalised importance being 100 percent. The importance of other variables was determined by comparing them to the most significant one. Hence, the second variable, *Educ,* had 83.8 percent importance compared to *OutputEurha*. *Age* and *Landquality* followed with the importance values of 74.8 percent and 73.8 percent, respectively. Apparently, *Debtratio* and *UAA* were the least important variables in determining the decision to participate in the AES.

Generally, the MLP neural network used in the research indicated high prediction power for the observations because the total of 100 percent correct predictions were obtained, and the area under the ROC curve was equal to 1. However, the small sample size was quite small, and only training data were used in our model.

4. Discussion and conclusions

Understanding the factors that influence farmers' participation in the AES schemes is key to enhancing the acceptance of such schemes as well as their effectiveness in reaching the goals pertaining to climate change mitigation. Most common factors used in the previous research works were identified by the analysis of scientific literature. The factors of the present research were selected on the basis of previous research, in view of the research aim and available data.

The research results have revealed that the output of the farm is the most important factor when it comes to the participation decision. Wittstock *et al*. (2022) view economic factors as predominant among the factors that influence decisions. The farms are not inclined to accept that they will lose part of their income by participating in the AES. Hence, before committing to the AES, they decide how the farm land will be allocated. The land that is not as important for farms' production would be designated to the AES (Wittstock *et al*., 2022), since compliance with agricultural environmental protection measures is a decision requiring the farmer to consider the related income and costs in order to avoid a reduction in the farm output and the resulting income (Galnaitytė, 2017; McGurk *et al*., 2020). The results of research on the Irish farmers indicated that the higher profit per hectare, the less eager the farm was to participate in the AES (McGurk *et al*., 2020). The results of the present research suggest that Lithuanian farms consider the possible influence of participation in the AES on their agricultural output, as the decision influences both the allocation of land for farm activities and the financial situation of the farm.

Education was found to be the second most important variable according to the MLP neural network results. The inferential statistics also revealed statistically significant differences between the research groups, where the participating group consisted only of farmers with full education. This coincides with the results obtained by Damianos & Giannakopoulos (2002) and Giannakis (2014). According to their findings, well-educated Greek farmers had positive views towards participation in the AES. Furthermore, the probability of participation in the AES among Israeli farmers increased with the level of education. (Teff-Seker *et al*., 2022), while the Austrian farmers with high educational level and farms situated in less favourable areas were associated with a higher participation in the AES (Leonhardt *et al*., 2022). This could be explained by the necessity to be knowledgeable not only in farm affairs, but also legal aspects of contract execution and scheme requirements in order to be able to participate in the AES. Nonethteless, the results on the influence of education on participation in the AES are ambiguous. Mettepenningen *et al*. (2013) analysed the influence of diferent levels of education and found it had no significant influence on the probability of participating in the AES for either Flemish (Belgium) or Arkansas (the U.S.) farmers. Education is one of the variables that is commonly analysed when it comes to adoption of the AES schemes. The concern about the farmers' education is reflected in the RDP 2014-2020 programme. Although those willing to engage in agricultural activities need to confirm their professional readiness for farming, their education and entrepreneurial competences are insufficient and could hinder economic and technological progress. Certain support programmes require the participants to have certain degree of education, and practical education does not pass as an eligibility criterion.

Age was a less important variable in this study (3^{rd} out of 6). However, Damianos & Giannakopoulos (2002) and Giannakis (2014) found opposite results when examining the factors determining farmers' participation in the AES in Greece. Age appeared to be statistically significant, and the younger the farmer, the more likely he/she was to enroll in the AES. Young farmers in these studies were considered individuals up to 39 and 40 years old, respectively. According to the results of descriptive statistics of the present research, the youngest age of the non-participating farmers was 32 years compared to the youngest participating farmers' age (39 years). Similarly, the oldest farmer (67 years) belonged to the non-participating farms' group, while the oldest age in the participating farms' group was 61 years. These findings correspond to the research results obtained by McGurk *et al*. (2020) from Irish farms, where younger farmers were less likely to participate in the AES up to a certain point, and older farmers after certain point became less likely to participate.

The importance of land quality was slightly lower than that of the age variable, although the production potential of the farm appears to depend on the fertility of the land. According to Wittstock *et al*. (2022), land quality is closely related to economic factors of the farm: the farmer assesses the quality of the available land and, accordingly, allocates the land for agricultural production and/or participation in the AES schemes. However, Wąs *et al*. (2021) assume there is a lack of explicit research data on how land quality affects farms' production potential and income.

The importance of the debt ratio turned out to be even lower. Financing agricultural activities with the resulting debt increases uncertainty about the future financial situation (Wąs & Kobus, 2018). However, in the sample of present research, the median of the debt ratio was similar for both groups and did not seem to have a significant influence on the decision of the farms to participate in the AES.

Farm size appeared to be a significant factor in previous studies, although it had diverse effect on farmers' willingness to consider participation. Earlier studies on farmers in Greece revealed a significant and positive impact of farm size on the participation in the AES (Damianos & Giannakopoulos, 2002; McGurk *et al*., 2020), while later it appeared to have a significant negative impact (Giannakis, 2014). But in the case of the present research, farm size was the least important factor, although our groups were significantly different in terms of UAA. Farms, depending on their size, evaluated the opportunities and benefits provided by the AES differently (Wittstock *et al*., 2022).

This study is the first to examine the Lithuanian family farms participating and non-participating in the AES and to identify the factors affecting their participation and their importance, using an advanced research method – the neural network. The results of the study reveal that the Lithuanian farms prioritise the decisions related to maintaining the farm's production level. Therefore, participation in the AES and provision of environmental benefits and ecosystem services are expected to result in not only compensation but also additional remuneration which would ensure the farm's profit. Farmers' education remains one of the key factors in enhancing participation in the AES and achieving more sustainable farming practices. Sustainable farming requires understanding and quick adjustment of production decisions, innovation adoption as well as knowledge of available schemes and benefits. Policymakers should therefore consider investing in farmer education and better dissemination of information on the AES, while incorporating active learning methods. This is especially important in relation to older farmers in order to address the issue of poor enrolment in the AES related to older age.

However, the factors behind the motivation to participate in the AES may differ. From the policy point of view, research should be conducted annually to assess the factors of participation in the AES, so that appropriate measures could be selected and adapted at the right time. This is also relevant when implementing the European Green Deal action plan towards the circular economy, the "Farm to Fork" strategy, to reduce the use of chemical pesticides, fertilizers, antibiotics, etc. Factors may be assumed to change over time due to other actions and policies. Regarding farmers' social factors, some of them could not be included in the present study because such data are not collected by the FADN, and this was the limitation of the research. Although the FADN database can provide extensive farm economic and environmental data, it is incomplete when it comes to farmers' social characteristics. We believe that the creation of a new database of Farm Sustainability Data Network (FSDN) will supplement the existing FADN and we will be able to revise our research in future.

In view of the concerns of the European Commission about the adaptation of agriculture to climate change, well-designed and well-targeted CAP schemes could help farmers to adapt faster.

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