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Building a typology of farms based on their performance: a tool to support agricultural policy-making

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Within the same agricultural system, there is substantial heterogeneity in farms' performance depending on farms' structural features and farmers' decision-making. This paper proposes a policy-oriented farm typology-building approach that groups farms in the same agricultural system into categories based on their economic and environmental performance. For this purpose, latent profile analysis (LPA) is used, since it enables both the assessment of profile-specific synergies/trade-offs among performance indicators and the implementation of a three-step procedure to account for the covariates that characterize the resulting farm profiles. As an illustrative case study, this methodological proposal is applied to categorize Spanish farms included in the rain-fed field crops agricultural system. The results show that the proposed typology-building approach is useful for agricultural policy-making, as it allows for a better evaluation of how farms contribute to the achievement of policy objectives and the design of differentiated policy instruments accounting for the performance synergies/trade-offs across farm profiles (i.e. policy tailoring and targeting).

Keywords: agricultural holdings; field crops; latent profile analysis; performance trade-offs; agricultural policy

1. Introduction

Around the world, agricultural activity is conducted in a wide variety of climates, landscapes, and human cultures. The vast area of land covered by agriculture gives rise to multilevel heterogeneity, starting at the highest level with the diversity of agricultural systems. At this level, the heterogeneity is characterized by several factors, such as the environment (quantity and quality of the natural resources available – e.g. climate and edaphoclimatic conditions), production technology, market conditions, legal frameworks, and local know-how (Giller 2013). For instance, in the case of the European Union (EU), there are 155 million hectares (ha) of agricultural land, where agricultural systems range from highland grassland-based livestock farming to intensive horticulture under greenhouses.

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Likewise, it must be noted that each agricultural system is made up of thousands of farms. Thus, although these production units operate under the same productive framework, a second level of heterogeneity can be observed. Within a common agricultural system, differences at the farm level are related to factors that are (or can be) controlled by farmers, such as farms' structural features (e.g. farm size and the number of plots), production management (involving a wide range of production intensity), and farmers' socio-demographic characteristics (e.g. agricultural training) and psychological traits (e.g. risk aversion or environmental concerns). This farm heterogeneity within the same agricultural system has been found worldwide, as shown, for instance, by Weltin *et al.* (2017), Guarín *et al.* (2020), and Stylianou, Sdrali, and Apostolopoulos (2020) in Europe; Arbuckle *et al.* (2017) and Upadhaya, Arbuckle, and Schulte (2021) in the United States of America (USA); Botero *et al.* (2021) and Benitez-Altuna, Trienekens, and Gaitán-Cremaschi (2023) in Latin America; Kansiime, van Asten, and Sneyers (2018) and Alvarez *et al.* (2018) in Africa; or Goswami, Chatterjee, and Prasad (2014) in Asia.

All the aforementioned sources of heterogeneity lead to substantial variation in farms' economic, environmental, and social performance (e.g. Gómez-Limón and Sanchez-Fernandez 2010; Modernel *et al.* 2018; Bánkuti *et al.* 2020), which poses a challenge for agricultural policy-making. In this heterogeneous setting, policy efforts to promote more sustainable food production should be based on an accurate design (i.e. tailoring) of policy instruments effectively targeted at specific agricultural systems and farm types, aiming to achieve trade-offs between different farm dimensions in a way that properly reflects society's preferences (Graskemper, Yu, and Feil 2021; Huber *et al.* 2024).

There is growing societal concern about the negative environmental externalities of agriculture (e.g. contribution to climate change, biodiversity loss, or water pollution) (Pe'er *et al.* 2020). Therefore, to meet society's demands and make agriculture more environmentally friendly, current agricultural policy objectives go beyond the classical economic rationale and incorporate ecological issues (Guerrero 2021). The EU's Common Agricultural Policy (CAP) is a good example of this shift, as it has progressively been incorporating environmental and sustainable development objectives since the 1990s. Key reforms in 1992, 2003, and 2013 introduced agri-environmental policy instruments such as agri-environment-climate measures, cross-compliance, and green direct payments, respectively, to promote environmentally sustainable farming practices (Alons 2017; Doukas, Vardopoulos, and Petides 2024).

At a global level, these environmental concerns about agriculture have been translated into the United Nations' 2030 Agenda and the Sustainable Development Goals (SDGs) (FAO, 2017). Established in 2015, these goals hold global agricultural activity responsible for producing enough food to meet SDG 2 (Zero Hunger), while at the same time contributing to the achievement of SDG 6 (Clean Water and Sanitation), SDG 12 (Responsible Consumption and Production), SDG 13 (Climate Action) and SDG 15 (Life on Land) (Pe'er *et al.* 2019).

The EU's plan to achieve the SDGs is the European Green Deal (EGD) (European Commission 2019). The EGD includes Farm-to-Fork and Biodiversity strategies focused on transitioning to more sustainable agriculture (Boix-Fayos and de Vente 2023). Both strategies aim to achieve concrete environmental targets at the EU level (e.g. reduce the use and risk of chemical pesticides by 50%, reduce fertilizer use by at least 20%, or ensure that 25% of total farmland is under organic farming by 2030). They seek to do so without compromising farms' economic performance, as this represents a *sine qua non* for the continuity of agricultural activity. However, as many authors have pointed out (e.g. Matthews 2020; Pe'er *et al.* 2020; Scown and Nicholas 2020), the CAP design should be further improved to provide policy support that boosts farms' performance, in order to ensure they fulfill their widely touted potential to contribute to the SDGs.

Within this context, policy decision-making focused on new environmental targets must necessarily account for the marked heterogeneity in farms' economic and environmental performance. The usual way of dealing with farm-level heterogeneity within agricultural systems is through farm typologies, which seek to classify agricultural holdings into homogenous groups based on multiple features (Andersen *et al.* 2007; Huber *et al.* 2024).

Following van der Ploeg *et al.* (2009), two main types of farm typologies can be identified. On the one hand, there are ordinary typologies based on *farms' structural characteristics* and/or *farmers' socio-demographic features*. The EU's farm typology (European Commission 2021) is an excellent example of this, as it relies on criteria relating to geographical location (i.e. administrative regions), economic size (i.e. total standard output), and types of farming (i.e. the relative contribution of the various different production activities to the total standard output). These kinds of typologies are built based on an economic rationale, serving as valuable tools for assessing farms' economic performance and comparing this performance across farm types. However, they fail to account for farms' environmental performance, which is a key issue for policy evaluation and policy-making (Rega *et al.* 2022). On the other hand, there are typologies based on *farming styles*; that is, accounting for farmers' opinions, attitudes, and/or decision-making as factors influencing how the farming activity is carried out. In this category, several policy-oriented typologies have been proposed to summarize the farm-level heterogeneity concerning specific political issues (see next section). The ultimate purpose of these typologies is to facilitate the monitoring of how policy objectives are achieved and the design of new policy instruments by categorizing farm-level heterogeneity beyond economic performance (Bartkowski, Schüßler, and Müller 2022).

Following the latter approach, this study proposes a method for developing a policy-oriented typology that identifies a manageable number of farm categories within a specific agricultural system, where each category contains farms exhibiting similar economic and environmental performance, quantified through key performance indicators. To illustrate its empirical implementation, the Spanish rain-fed field crops agricultural system has been chosen as a case study.

The proposed methodological approach is relevant in the current policy-making context, in which agricultural policy aims to satisfy societal demands by improving farms' environmental performance (e.g. achieving the policy objectives established in the EGD) while ensuring the economic sustainability of these agricultural holdings. In this respect, the suggested approach of grouping farms with similar economic and environmental performance is helpful, since it can be used to identify specific synergies and trade-offs among the different key performance indicators within each farm group, and to characterize the different farm categories according to farms' specific structural features and farmers' socio-demographic characteristics. Thus, the delineated farm types could be useful for differentiating groups of farms to evaluate how they contribute to the achievement of policy objectives and for designing and implementing more effective and efficient policy instruments (i.e. policy tailoring and targeting). In this way, policy action would enable distinct changes in farming styles within each farm category (i.e. farms' performance) to ensure an optimal trade-off between farms' economic and environmental performance.

2. Contributions to existing literature on farm typologies

Farm typologies are a prevalent topic in the literature due to their strategic importance for agricultural policy-making. Although existing farm typologies differ systematically in terms of context, purpose, variables employed, and methods (e.g. Bartkowski, Schüßler, and Müller 2022), most previous studies converge on the two main approaches described in the previous section. These approaches are discussed below, examining the methodology in order to identify possible research gaps to be addressed by the proposed farm classification procedure.

Most previous empirical studies on farm heterogeneity have developed farm typologies based on structural variables relating to farms (e.g. Weltin *et al.* 2017, considering farm size, location, or production specialization), farmers' socio-demographic characteristics (e.g. Morris, Henley, and Dowell 2017, accounting for age, gender, or type of agricultural training), or a mixture of both (e.g. Benitez-Altuna, Trienekens, and Gaitán-Cremaschi 2023). The most commonly used methods for this purpose have been traditional cluster techniques because of their simplicity and effectiveness. Analyses based on k-means and hierarchical clustering algorithms are the most extensively used approaches in this avenue of research (e.g. Stylianou, Sdrali, and Apostolopoulos 2020; Vogel and Beber 2022), although other approaches have also been used (e.g. Graskemper, Yu, and Feil 2021, who used the Partitioning Around Medoids – PAM – procedure). The main advantage of these studies is that they tend to be comparable and reproducible because they are based on structural and economic variables generally available in official statistics. However, these structural typologies neither provide information about farms' environmental performance nor allow adequate monitoring to evaluate how current policy objectives are actually achieved (Rega *et al.* 2022). For this reason, they do not fully support agricultural policy-making, especially when farms' environmental performance is the key issue to be tackled.

A more recent approach consists of using variables related to farming styles to classify farms, summarizing the heterogeneity of farmers' perceptions, attitudes, and/or decision-making. Specifically, these typologies have mainly sought to classify farmers based on their opinions on environmental issues or the uptake of ecological management practices (Bartkowski, Schüßler, and Müller 2022). These farmer typologies are policy-oriented tools as they allow for a more specific design and communication of agri-environmental policy instruments depending on the various farmer profiles. Although clustering algorithms have also been used to construct this kind of typology (e.g. Bánkuti *et al.* 2020), finite mixture modeling methods represent the most suitable statistical technique in this research line. In short, these techniques assume the existence of a latent categorical variable in the distribution of a dataset, which allows the classification of observations (i.e. farms/farmers) into homogeneous groups (i.e. farm/farmer types) in terms of farming styles. Generally, these typology exercises rely on farmers' subjective opinions and decisions, gathered through *ad hoc* surveys using categorical or ordinal variables (e.g. Likert scale-based variables to reflect farmers' opinions or dichotomic variables related to the adoption of ecological practices). For this reason, the most common approach for developing these typologies is Latent Class Analysis (LCA), which identifies observation classes (i.e. farm/farmer profiles) based on similar distributions of a set of polytomous explanatory variables capturing farmers' responses. It must be noted that finite mixture modeling methods such as the LCA approach partially solve some of the shortcomings of traditional clustering techniques as the decision on the number of classes is based on more formal statistical criteria (i.e. goodness-of-fit statistics) and is thus less arbitrary (Vermunt and Magidson 2002).[1] Recent examples of applications of LCA to develop farmer typologies can be found in the studies by Daxini *et al.* (2019) and Barnes, Thompson, and Toma (2022).

Nonetheless, although these policy-oriented typologies usually employ more advanced statistical approaches than their structural counterparts, they face a notable constraint. As explained above, most of these typologies address particular issues of interest regarding farmers' perceptions, attitudes, or decision-making (e.g. personal opinions on environmental policy objectives or the adoption of specific farming practices), which involve the design of study-specific questionnaires and surveys. Consequently, the data collection processes are expensive and time-consuming, limiting the comparability of these typologies, since the case studies are difficult to update or replicate elsewhere. Moreover, although these typologies can improve the tailoring and targeting of agricultural policy instruments by identifying behavioral patterns, they do not allow the achievement of policy objectives to be monitored, as they are not based on farm performance indicators.

Based on the literature review conducted and the gaps in the knowledge on the topic identified by Bartkowski, Schüßler, and Müller (2022) and Huber *et al.* (2024), this study adds to the existing literature by proposing a novel farm typology-building approach that fulfills key criteria to effectively support policy evaluation and the design of better tailored and targeted policy instruments. Specifically, the criteria for the typology are as follows: (a) it is based on a comprehensive set of farm economic and environmental performance indicators, (b) it is developed using readily available, regularly updated official data, (c) it is built employing a method that assesses heterogeneous synergies and trade-offs among different indicators across farm types, and (d) it enables the characterization of farm types based on farm and farmer characteristics. To the best of the authors' knowledge, the farm typology presented in this paper is the first to meet all four criteria simultaneously.

First, our approach differs from most existing typologies that classify farms according to similar structural variables or farmer typologies based on subjective opinions, as they do not necessarily provide information about farms' actual performance (i.e. their contribution to achieving policy objectives). Conversely, the approach for constructing a farm typology proposed here relies on a comprehensive set of farm-level economic (productivity, profitability, and viability) and environmental (biodiversity and carbon emissions) performance indicators to assess how farms contribute to achieving policy objectives. In this sense, it is worth noting that many previous studies developed farm typologies based on structural variables and/or farmers' socio-demographic characteristics, and after having defined the farm types, then assessed their economic and environmental performance (e.g. Modernel *et al.* 2018). However, only a few studies have actually developed farm typologies based on farm performance indicators (e.g. Haileslassie *et al.* 2016). Among them, only Sauer and Moreddu (2020) have considered a broad enough set of indicators to accurately measure individual performance for the economic and environmental dimensions of sustainability.

Second, the farm typology proposed is based on the microdata provided by the *Red Contable Agraria Nacional* (RECAN, the Spanish branch of the European Farm Accountancy Data Network – FADN). This source of farm data is public and accessible to analysts at no cost, thus avoiding the need for costly and time-consuming collection of new data. Moreover, this data source is updated and published annually on a timely basis and ensures transparency, comparability, and replicability at the EU level, addressing the lack of reproducibility mentioned above. The suitability of this database for building typologies is confirmed by the many previous empirical studies that use it for classifying farms (e.g. Sauer and Moreddu 2020; Rega *et al.* 2022).

Third, it is worth pointing out that the main innovation of the typology approach proposed is the finite mixture modeling method used for the clustering. Considering that the variables we use to construct the typology (i.e. farm performance indicators) are continuous (not polytomous), using LCA as a statistical method for the analysis is unfeasible. Instead, this study employs Latent Profile Analysis (LPA). This technique has the same central assumptions and benefits as LCA but allows the use of continuous explanatory variables to identify categories (farm profiles) and estimate membership probabilities. Consequently, LPA has been deemed the most suitable statistical method for our case study. To the best of the authors' knowledge, only two previous studies have used LPA to develop a policy-oriented farm typology. Höglind, Hansson, and Manevska-Tasevska (2021) used LPA to explore the heterogeneity in adopting ecological management practices among Swedish farmers. However, the most direct antecedent to this research is the work by Barnes *et al.* (2023), who employed LPA to classify farms based on their performance. Nonetheless, the present paper advances the research beyond the aforementioned studies, in that the LPA model we run estimates full variance-covariance matrices for each farm profile without considering any constraint. This has allowed us to provide a novel assessment of profile-specific synergies/trade-offs among the different economic and environmental indicators used in the classification.

Finally, another noteworthy methodological innovation of this paper is the implementation of a three-step procedure to account for the covariates that explain farms' profile membership in the LPA model (i.e. farms' structural features and farmers' socio-demographic characteristics). This is highly useful for policy decision-making, as it relates farm performance profiles with variables capturing farms'/farmers' characteristics, allowing a more targeted implementation of policy instruments.

3. Data source and case study

3.1. The source of data: the Spanish farm accountancy data network (RECAN)

The empirical application of the proposed typology-building approach to any agricultural system requires the use of farm-level information, since it is the only type of information that can reflect the potential heterogeneity in farms' economic and environmental performance. In this respect, the FADN is considered the best source of farm-level data at the EU level (Kelly *et al.* 2018). The RECAN (Spanish brand of the FADN) collects data annually for a large sample of Spanish farms (around 9,000 farms annually). These farms are selected using a quota sampling procedure based on the European farm typology (European Commission 2021), guaranteeing that the annual RECAN samples adequately represent all agricultural subsectors (i.e. types of farming, TF) in Spain. The resulting RECAN database mainly collects farms' annual accounting information, such as output, production costs, subsidies, and balance sheets. However, it also gathers data on several productive (e.g. crop mixes), structural (e.g. size or land ownership), and environment-related (e.g. fertilizer and pesticide use) variables that are useful for assessing farms' performance; all these data are also updated annually. Moreover, since this source of microdata is harmonized at the EU level, the methodology proposed for building the farm typology is fully reproducible elsewhere in the

EU. All this explains why FADN/RECAN microdata have already been used in many empirical applications aimed at assessing heterogeneous farm performance (e.g. Sauer and Moreddu 2020; Rega *et al.* 2022), and also justifies their use in our case study.

Nonetheless, the use of FADN/RECAN microdata also entails several drawbacks. First, this farm network only includes "commercial farms," which in the case of Spain (RECAN) are those with a total annual standard output above 8,000 Euros. Despite this, RECAN is actually representative of the Spanish farm population, given that commercial farms represent more than 92% of the utilized agricultural area (UAA) in Spain and 97% of the value of its agricultural production. Second, it must be noted that the FADN/RECAN was primarily designed to collect accounting data to assess farms' economic performance. In fact, only a few variables collected in this database focus on environmental issues at the farm level. Although this makes the assessment of farms' environmental performance challenging, this source of microdata provides enough information to allow the calculation of proxy indicators measuring this sustainability dimension at the farm level, as evidenced in previous studies (e.g. Buckley *et al.* 2016; Stetter and Sauer 2022; Robling *et al.* 2023). In any case, both limitations imply that the results of the analysis and the policy implications drawn from them should be taken with caution.

3.2. Rain-fed field crops in Spain

Field crops (i.e. cereals, oilseeds, protein crops, and root crops) occupy over half of the world's harvested area and account for a substantial part of global crop production (see FAO 2022), meeting basic human and animal food needs worldwide. Therefore, a large share of the natural resources used in farming activities (e.g. soil, water, and energy) are allocated to these crops, which represent a key agricultural production sector for ensuring global food security.

According to the statistics published by the Spanish Ministry of Agriculture, Fisheries, and Food referring to 2022 (MAPA 2023), the agricultural area devoted to field crops in Spain covers 9.1 million ha, representing more than a third of the national UAA. In terms of total area, cereals are the most important crops, with barley covering the largest area (2.5 million ha), followed by soft wheat (1.9 million ha), oats (504,000 ha), and durum wheat (259,000 ha). Also, forage crops such as alfalfa and fodder vetch account for a significant area within the sector, covering 1.1 million ha. Other relevant field crops are sunflower (631,000 ha), protein crops for livestock feeding purposes (mainly field peas, vetch, and sweet lupins, with 161,000 ha), and legumes for human consumption (pulses such as lentils, chickpeas, or beans, accounting for 158,000 ha).

Notwithstanding, the production of field crops differs notably under rain-fed and irrigated conditions, in terms of both economic (e.g. productivity) and environmental (e.g. intensity of input use) performance (e.g. Sinisterra-Solís *et al.* 2023). Accordingly, we consider specialized farming in rain-fed field crops as a distinct agricultural system (i.e. similar resource availability, production technology, market conditions, and legal framework) suitable for the proposed empirical analysis. Thus, the target farm population analyzed was limited to the Spanish farms classified as TF 15 (specialist cereals, oilseeds, and protein crops) and TF 16 (general field cropping), where the entire farm area is rain-fed. According to the Spanish agricultural census, the agricultural system chosen for the analysis accounts for 3.1 million ha operated by 34,852 farms.

The boundaries established for the rain-fed field crops agricultural system allowed us to draw a representative panel sample from the RECAN microdata ($n = 559$) for the three-year period 2019–2021.[2] This panel sample enabled us to assess farms' economic and environmental performance as structural features, accounting for the mean values of the indicators considered across the three years, thus minimizing potential biases due to abnormal agricultural years.

For informative purposes, the main descriptive statistics for the RECAN variables characterizing the sample of farms included in the rain-fed field crops agricultural system (farmers' and farm characteristics, economic variables, and environment-related variables) for the last year analyzed (2021) are shown in Table S1, included in Appendix A as supplementary material. Overall, high values of dispersion measures for all variables highlight the heterogeneity of the farms within this agricultural system. Cases worth mentioning are the variability in the farms' physical size (ranging from 8 to 971 ha), total output (from 6,400 to 626,312 Euros), and profitability (farm net income, FNI, varying between −€314/ha and €7,412/ha). The same applies to the environmental variables assessing input use, all of which range from €0/ha to large values (e.g. €682/ha spent on fertilizers), indicating markedly different environmental pressures.

All the data introduced above justify the selection of the Spanish rain-fed field crops as a suitable case study for this research, since the typology built will allow the classification and characterization of the highly heterogeneous farm performance in this agricultural system, enabling improved governance.

4. Typology building

4.1. Farm performance indicators and covariates

This section details and justifies the farms' economic and environmental performance indicators included as classificatory variables for constructing the proposed policy-oriented typology.

To ensure a reasonable ratio between the number of parameters to be estimated by the LPA model and the sample size, accounting for statistical parsimony (i.e. a good fit of the explanatory model with the minimum number of regressors), only five key performance indicators were chosen (see Table 1), as explained below.

Making sure that farms achieve and maintain reasonable farm-level economic performance is a policy priority, since only by fulfilling this requirement can the continuation of this productive activity be guaranteed, and along with it, food security, the vitality of rural areas, and the provision of ecosystem services (Finger and El Benni 2021). In fact, the first specific objective guiding the design and implementation of the CAP is "to support viable farm income and resilience of the agricultural sector across the Union to enhance long-term food security and agricultural diversity." However, farm economic performance is a multidimensional concept, the assessment of which involves several indicators (e.g. Coppola *et al.* 2022; Robling *et al.* 2023). Consequently, our assessment approach accounts for the three main economic dimensions analyzed in the literature (Spicka *et al.* 2019): productivity, profitability, and viability.

Productivity is defined as the relationship between a farm's total production and the inputs used to achieve that level of output. Various indicators have been used to assess farms' productivity and/or technical efficiency (e.g. Rada and Fuglie 2019;

Table 1. Farm performance indicators.

Dimension	Indicator (ACRONYM)	Formula	Formula based on RECAN microdata	Units
Economic performance indicators				
Productivity	Land productivity (LAND_ PROD)	$\frac{\text{Total output}}{\text{UAA}}$	$\frac{\text{SE131}}{\text{SE025}}$	€/ha
Profitability	Return on Assets (ROA)	$\frac{\text{EBIT}}{\text{Total assets}}$	$\frac{\text{SE420} + \text{SE380} + \text{SE390}}{\text{SE436}}$	%
Viability	Economic viability (VIABILITY)	$\frac{\text{FNI}}{\text{Total Opport. Costs}}$	$\frac{\text{SE420}}{\text{OC}_{\text{land}}+\text{OC}_{\text{labor}}+\text{OC}_{\text{non-land assets}}}$	Dimensionless
Environmental performance indicators				
Biodiversity	Shannon Diversity Index (SDI)	$-\sum p_i \times \ln(p_i)$	p_i based on RECAN microdata regarding farmland use[a]	Dimensionless
GHG emissions	GHG emissions (GHG_EM)	$\frac{\text{GHG emissions}}{\text{UAA}}$	$\frac{\sum_i \text{input}_i \times \text{kg CO}_2\text{e/unit}_i}{\text{SE025}}$	kg CO_2e/ha

Note: [a]p_i is the share of the total farm area devoted to the following land uses: cereals, oilseeds, protein seeds and legumes, forage crops, other field crops, vineyards, olive groves, other permanent crops, permanent grassland, non-cultivated land, and forest land.

Gaviglio *et al.* 2021). For our case study, land productivity (LAND_PROD, measured in euros per hectare) was chosen as the most suitable indicator for a farm classification based on this dimension of economic performance.

Profitability relates the farm's level of profits to the capital invested in operating the farm. A wide variety of indicators to assess farm profitability can be found in the literature (Coppola *et al.* 2022). For this study, the Return on Assets (ROA), computed as the farm's Earnings Before Interests and Taxes (EBIT) divided by its total assets, expressed as a percentage, was deemed the most suitable indicator for assessing farms' capacity to generate profits.

A farm can be considered economically viable when it achieves a level of income that is enough to cover all farm operating costs while also ensuring an appropriate return to production factors owned and provided by the farmer (e.g. Špička and Dereník 2021). Hence, in line with prior research utilizing data from the FADN (e.g. Coppola *et al.* 2022; Gómez-Limón *et al.* 2023), the indicator used to assess farm *viability* (VIABILITY) was computed by dividing the Farm Net Income (FNI) by the total opportunity costs generated by the use of inputs provided by the farmer (i.e. land, labor, and non-land assets).[3]

Table 1 shows how each economic indicator has been calculated using RECAN microdata.

On the other hand, the assessment of farms' environmental performance has been based on several specific CAP objectives. Accordingly, two dimensions were used to measure the farms' environmental performance: biodiversity and greenhouse gas (GHG) emissions. This choice reinforces the policy-oriented nature of the proposed farm typology.

Bearing in mind the constraints of the FADN/RECAN data concerning farms' environmental information, a comprehensive literature review was conducted to find the most suitable FADN indicators to account for the heterogeneity in farms' environmental performance dimension (e.g. Robling *et al.* 2023).

Regarding farm *biodiversity*, the chosen indicator should capture the contribution the farms make to ecosystem services by preserving wildlife, habitats, and landscapes. For this purpose, the Shannon Diversity Index (SDI) was chosen. SDI quantifies the landscape heterogeneity (i.e. land use) at the farm level, which is positively related to farm biodiversity since it creates diverse habitats suitable for different organisms (Belfrage, Björklund, and Salomonsson 2015).

At this point, it is worth noting that although the farms analyzed are the ones included in the rain-fed field crops agricultural system (i.e. those whose farming activity mainly involves this kind of crop), they could have some plots cultivated with other crops (e.g. permanent crops) or dedicated to livestock activities (e.g. grassland). Also, a share of their farmland could be devoted to non-agricultural uses, such as non-cultivated land or forest. In this regard, RECAN provides information on the farmland area devoted to the following groups of crops and other land uses: cereals, oilseeds, protein seeds and legumes, forage crops, other field crops, vineyards, olive groves, other permanent crops, permanent grassland, non-cultivated land, and forest land. Thus, the SDI was calculated at the farm level based on the shares of these land uses in farms' total farmlands (p_i), applying the formula included in Table 1. Accordingly, the SDI obtained is a suitable proxy of the biodiversity supported by the farm (e.g. Uthes, Kelly, and König 2020; Dabkiene, Balezentis, and Streimikiene 2021), yielding dimensionless values for each farm analyzed, where the higher the score, the greater the level of expected biodiversity on the farm.

Since climate change is a key issue, *GHG emissions* were also used to assess farms' environmental performance. Unfortunately, RECAN information does not allow for a direct assessment of this environmental pressure at the farm level (Kelly *et al.* 2018). However, GHG emissions can be estimated by adapting the methodology proposed by the Intergovernmental Panel on Climate Change, linking RECAN data to external information, as proposed by Baldoni, Coderoni, and Esposti (2017) and Stetter and Sauer (2022). In this respect, the emissions assessed were limited to the farm gate level to account for the emissions directly associated with farmers' decision-making (i.e. farm performance) (Coderoni and Esposti 2018). Following this approach, GHG emissions from farms included in the rain-fed field crops agricultural system primarily stem from energy consumption (i.e. CO_2 emissions from fuels and electricity) and fertilizer use (i.e. nitrous dioxide emissions from nitrogen fertilizers). Hence, based on each farm's energy and fertilizer use, the sum of the total kg of CO_2 equivalent (CO_2e) emitted was computed to quantify farms' GHG emissions. The different types of GHG emissions were converted into CO_2e according to their updated Global Warming Potential (GWP) coefficients provided by the IPCC Sixth Assessment Report.

Thus, to estimate farms' total GHG emissions, the physical quantity of each input i (AI_i, measured in liters for fuel, kWh for electricity, and kg of nitrogen for fertilizers) was multiplied by a specific emission factor (EF_i, measured in kg of CO_2e per input unit), as shown in expression (1):

$$\text{GHG emissions } = \sum_i AI_i \times EF_i = \sum_i \frac{CI_i}{p_i} \times EF_i \tag{1}$$

However, since the RECAN only provides monetary values for the use of fuel, electricity, and organic fertilizers (i.e. fuel, electricity, and organic fertilizer costs), the physical quantities were estimated by dividing each input cost (CI_i) by its mean price

(p_i). The RECAN codes used in the calculation of these emissions were 1040 (cost of motor fuels and lubricants), 5020 (cost of electricity), 5030 (costs of heating fuels), SE296 (amount of nitrogen in mineral fertilizers),[4] and 3034 (cost of organic fertilizers such as manure, slurry, or compost). Mean prices for fuel and electricity were sourced from official Spanish statistics (MINTUR 2023; MITECO 2023). In the case of organic fertilizers, these prices were calculated using RECAN annual information.

Thus, the proposed GHG emissions indicator (GHG_EM, measured in kg of CO_2e per hectare) captures each farm's contribution to climate change. Consequently, a lower value of the ratio means better performance regarding climate change mitigation.

Table 1 also shows how each environmental indicator has been calculated using RECAN microdata and other sources of information.

The set of indicators used to build the proposed typology ensures a comprehensive assessment of farms' economic and environmental performance, considering their most relevant dimensions for the analysis. These indicators effectively account for the diversity in farms' performance, providing farm profiles with relatively homogenous performance gaps and synergies/trade-offs between economic and environmental indicators. Identifying these profiles can be helpful for policy evaluation and for enhancing the design and targeting of policy instruments to address key issues.

It is worth noting that all economic and environmental performance indicators were calculated for the 559 farms sampled for each of the three years considered (2019–2021). However, the variables used to build the farm typology were the mean values of the indicators over the three-year period analyzed. This decision ensures a more robust classification, as it treats farms' performance assessment as a structural feature, accounting for prevailing agricultural practices (e.g. Guo, Marquart-Pyatt, and Robertson 2023) and interannual variability of weather conditions affecting crop yields (e.g. Coppola *et al.* 2022).

Additionally, the proposed methodology includes the implementation of a three-step procedure (see next section), which will allow us to account for a set of covariates that explain farms' membership in the profiles defined in the typology. Table 2 provides information on the description and calculation of the 17 covariates considered for this purpose, which are related to farmers' characteristics, farms' structural characteristics, and farms' resources. Descriptive statistics for the complete set of covariates are shown in Table S2 included as supplementary material (see Appendix B).

The results of this three-step procedure can significantly facilitate the implementation of agricultural policy. In fact, these covariates will provide the information needed to appropriately target policy instruments to ensure the policy objectives set for each farm category (differentiated by performance) are more efficiently achieved.

4.2. Latent profile analysis (LPA)

LPA is a type of finite mixture modeling approach that focuses on identifying an underlying unobserved categorical variable, allowing the classification of a population of individuals into several subpopulations (i.e. latent profiles, classes, or groups) based on a specific set of continuous variables. In our case, LPA was used to classify farms based on the economic and environmental performance indicators defined in the previous section, thereby identifying several groups of farms exhibiting similar performance.

This statistical technique has been extensively used in person-centered analyses in psychology (Williams and Kibowski 2016) and organizational sciences (Woo *et al.* 2018), and more recently in agricultural and resource economics (e.g. Morgan *et al.*

Table 2. Set of covariates considered for the three-step procedure.

Covariates (ACRONYMS)	Formula / codification	Formula based on RECAN microdata	Units
Farmer's characteristics			
Age (AGE)	–	–	Years
Gender (GENDER)	1 = female, 0 = male	–	–
Agricultural training (TRAIN)	1 = formalized, 0 = practical experience	–	–
Full-time farmer (FULL_FARM)	1 = yes, 0 = no	–	–
Farm's structural characteristics			
Total farm area (F_AREA)	–	SE025	ha
Decoupled payments (DEC_PAY)[5]	$\frac{\text{Decoupled payments}}{\text{UAA}}$	$\frac{\text{SE630}}{\text{SE025}}$	€/ha
Environmental subsidies (ENV_SUB)	$\frac{\text{Environmental subsidies}}{\text{UAA}}$	$\frac{\text{SE621}}{\text{SE025}}$	€/ha
Other CAP pillar 2 subsidies (OTHER_2P)	$\frac{\text{Other CAP pillar 2 subsidies}}{\text{UAA}}$	$\frac{\text{SE624-SE621}}{\text{SE025}}$	€/ha
Owned land (OWN_LAND)	$\frac{\text{UAA}-\text{Rented UAA}}{\text{UAA}}$	$\frac{\text{SE025-SE030}}{\text{SE025}}$	%
Located in Castilla y León (REG_CYL)	1 = yes, 0 = no	–	–
Located in Castilla-La Mancha (REG_CLM)	1 = yes, 0 = no	–	–
Located in Andalucía (REG_AND)	1 = yes, 0 = no	–	–
Location in less favored areas (LFA)	1 = yes, 0 = no	–	–
Farm's resources			
Non-land fixed assets (NL_FASSET)	$\frac{\text{Total fixed assets}-\text{Land assets}}{\text{UAA}}$	$\frac{\text{SE441-SE446}}{\text{SE025}}$	€/ha
Outsourcing (OUTSOURC)	$\frac{\text{Contract work costs}}{\text{UAA}}$	$\frac{\text{SE350}}{\text{SE025}}$	€/ha
Labor input hours (LABOR_H)	$\frac{\text{Total labor input hours}}{\text{UAA}}$	$\frac{\text{SE011}}{\text{SE025}}$	hrs/ha
Debt ratio (DEBT)	$\frac{\text{Total liabilities}}{\text{Total assets}}$	$\frac{\text{SE485}}{\text{SE436}}$	%

2015; Villanueva, Vernaza-Quiñónez, and Granado-Díaz 2023). However, to the best of the authors' knowledge, only Höglind, Hansson, and Manevska-Tasevska (2021) have used it previously for farm classification purposes.

LPA uses probabilistic models to identify underlying groups (i.e. profiles) by estimating the probability that individuals belong to them. This method starts with the definition of a probability density function (*f*) for a set of independent multivariate observations (y_i, farm i characterized by j performance indicator values), as follows (Masyn 2013):

$$f(y_i) = \sum_{k=1}^{G} \pi_k f_k(y_i|\theta_k) \tag{2}$$

with f_k being the density function defined for profile k, θ_k the parameters of that density function, π_{ki} the probability of an observation belonging to that particular profile (where $\pi_k \geq 0$ and $\sum_{k=1}^{G} \pi_k = 1$), and G the number of profiles.

The parameters of this model (θ_k, π_k) for a given number of G profiles can be estimated by maximizing the following likelihood function (Fraley and Raftery 2002):

$$L(\theta_k, \pi_k|y_i) = \prod_{i=1}^{n} \sum_{k=1}^{G} \pi_k f(y_i|\theta_k) \tag{3}$$

A multivariate normal distribution is typically assumed for f_k, with their parameters being the means of the classifying variables considered for each profile k (μ_k) and their variance-covariance matrices (Σ_k). Consequently, each profile is centered around its multivariate mean, while the variance-covariance matrix defines its geometry. Generally, the variance-covariance matrices are parametrized by imposing certain simplifying assumptions or constraints among profiles to reduce the number of parameters to be estimated. The possible combinations allow the estimation of up to 14 different models according to the volume, orientation, and shape of the profiles and the differences among them (Celeux and Govaert 1995). In our case, the variance-covariance matrices were estimated without considering any constraint, allowing each profile to have its own geometry. In doing so, we obtained different covariances between every pair of classifying variables (farm performance indicators) for each profile, allowing us to analyze the specific synergies and trade-offs among the different economic and environmental performance indicators within each farm group identified.

Further detailed descriptions of LPA models are available in Vermunt and Magidson (2002) and Masyn (2013).

As mentioned above, one of the outcomes of the chosen LPA modeling approach was the variance-covariance matrices of the indicators for each profile. However, variance and covariance values are strongly influenced by the units of measurement used for the performance indicators, meaning they are not a suitable measure to assess the trade-offs or synergistic relationships between them. Instead, single linear regression coefficients combining every pair of indicators (X and Y) were obtained using the following expression:

$$Y = a_{x,y} + b_{x,y}\ X + \varepsilon \rightarrow b_{x,y} = \frac{dY}{dX} = \frac{cov(X,Y)}{var(X)} \tag{4}$$

The coefficients $b_{x,y}$ measure the average change in indicator Y (response variable) for one unit of change in indicator X (explanatory variable) while holding the remaining indicators constant (i.e. the *ceteris paribus* condition). The coefficients and their corresponding standard errors, from which the significance levels were obtained, were calculated using the Delta method. This method allows the estimation of exact standard errors for functions of parameters obtained through maximum likelihood, provided that the function used is invertible and differentiable, as is our case (the ratio of two parameters) (Oehlert 1992).

The LPA models provide parameter estimates for every profile k and membership probabilities for every individual i. The latter results can be used to relate the probabilities of profile membership with several covariates (Nylund-Gibson and Masyn 2016). For this purpose, the three-step approach developed by Vermunt (2010) and Bakk, Tekle, and Vermunt (2013) was applied, thereby avoiding problems associated with the alternative one-step approach, including the undesirable influence of auxiliary variables on class membership, incorrect estimates, and incorrect standard errors (Bakk, Oberski, and Vermunt 2016; Collier and Leite 2017).[6] The three-step approach involves, first, the estimation of the LPA model without covariates (step 1); then, the posterior membership probabilities of each individual to each profile are calculated from the previous LPA model (step 2); and, finally (step 3), a regression model (three-step model shown next) is used to determine the association between the posterior class membership probabilities obtained and external variables such as farms' and farmers' characteristics (i.e. covariates shown in Table 2). By including these variables as covariates in the three-step model, we can better understand the factors that affect farms' profile membership. Starting with the full set of covariates shown in Table 2, following a backward stepwise procedure, non-statistically significant covariates were sequentially eliminated until a fully significant model was obtained.

The probability of being assigned to a specific profile a_i based on farm-specific covariates z_i was calculated using the expression provided by Vermunt and Magidson (2016):

$$P(a_i|z_i) = \sum_{x=1}^{K} P(x|z_i)P(a_i|x) \tag{5}$$

with x being the true profile membership obtained from the LPA posterior classification, $P(x|z_i)$ the probability of farm i being assigned to the true profile x for this farm's specific information z_i, and $P(a_i|x)$ the conditional probabilities of responses between assigned and true profile memberships. For our case study, we employed proportional class assignment and the maximum likelihood adjustment method to rectify biases introduced by classification errors, as proposed by Vermunt and Magidson (2016).

LatentGOLD 6.0 (Vermunt and Magidson 2021) was used to estimate all models for LPA and the three-step approach.[7]

5. Results

5.1. Performance indicators

As explained above, the three-year means of the five key performance indicators were calculated for the 559 Spanish farms in the rain-fed field crops agricultural system that make up the panel sample. Table 3 shows their main descriptive statistics, confirming the expected high degree of heterogeneity among farms in terms of their economic and environmental performance. In fact, all values of the coefficient of variation are greater than 30%, with extreme maxima and minima for every indicator. Thus, these results support the idea that within the same agricultural system (e.g. Spanish rain-fed field crops), farms vary widely in terms of their performance and suggest that this heterogeneity could be better understood by defining different farm types.

5.2. Farm typology

Taking farm performance indicators as classification variables, LPA models were run for different numbers of profiles (from $k = 1$ to $k = 10$). For each LPA model, an array of fit indices was obtained (see Table S3 in Appendix D, included as supplementary material). Comparing the goodness-of-fit statistics, various different numbers of

Table 3. Descriptive statistics for farm performance indicators ($n = 559$).

Variable	Mean	St. Dev.	CV (%)	Max	Min
Economic performance indicators					
LAND_PROD (€/ha)	565.6	323.9	57.26	1,575.3	141.5
ROA (%)	11.41	9.32	81.71	47.31	−1.69
VIABILITY (dimensionless)	1.075	0.868	80.77	4.070	−0.225
Environmental performance indicators					
SDI (dimensionless)	0.789	0.242	30.66	1.331	0.211
GHG_EM (kg CO_2e/ha)	277.2	112.0	40.40	621.1	57.7

Source: Own elaboration based on RECAN microdata.

Table 4. Characterization of farm profiles according to their performance indicator statistics.

	Profile 1 ($n = 226$)		Profile 2 ($n = 202$)		Profile 3 ($n = 131$)		Overall ($n = 559$)	
Indicator	Mean	S.E.	Mean	S.E.	Mean	S.E.	Mean	S.E.
LAND_PROD (€/ha)	523.5 ^{b}	4.521	816.7 ^{c}	30.92	251.8 ^{a}	6.026	565.6	13.70
ROA (%)	8.437 ^{a}	0.363	16.92 ^{b}	0.889	8.041 ^{a}	0.534	11.41	0.394
VIABILITY (dimensionless)	0.777 ^{b}	0.035	1.798 ^{c}	0.074	0.475 ^{a}	0.036	1.074	0.037
SDI (dimensionless)	0.867 ^{b}	0.014	0.719 ^{a}	0.021	0.760 ^{a}	0.021	0.789	0.010
GHG_EM (kg CO2e/ha)	299.9 ^{b}	4.117	310.2 ^{b}	10.79	187.3 ^{a}	6.090	277.2	4.738
Profile size	0.405 ^{b}	0.024	0.361 ^{b}	0.025	0.235 ^{a}	0.019		

Note: Superscript letters show significant differences between the mean of the performance indicators among profiles. Differences are shown at the 5% level, with shared letters indicating no statistically significant difference, using the Wald test for pairwise comparisons.

profiles could be chosen as the most suitable solution (Nylund-Gibson and Choi 2018). However, the decision about the most appropriate number of profiles for the empirical analysis should also be based on the parsimony principle, selecting the model that achieves a desired level of goodness-of-fit with the fewest number of profiles possible, since parsimonious models can be more easily interpreted and understood. According to the goodness-of-fit statistics and parsimony criteria, the model with three profiles ($k = 3$, with 62 parameters to be estimated) was considered the most suitable result for the proposed empirical analysis.

As shown in Table 4, the three-profile solution identifies two large groups of farms (Profiles 1 and 2, each comprising around 40% of the farms in the sample) and one medium-sized group (Profile 3, with around 20% of the sampled farms). This table also shows the means of the farm performance indicators for each profile, allowing us to provide the following descriptions of farm types:

- *Profile 1* shows the best performance for the SDI indicator. Regarding LAND_PROD and VIABILITY indicators; their mean values are intermediate between the other two profiles. Furthermore, it is similar to Profile 3 in terms of its poor mean values for ROA and to Profile 2 in its poor GHG_EM values. This profile was labeled "mixed performance farms" based on these results.
- *Profile 2* has the best mean performance for all economic indicators while showing the worst performance for SDI and GHG_EM indicators. Thus, this profile was characterized as "economically sustainable farms."
- *Profile 3* has an outstanding climate-related performance (the best mean values for GHG_EM) but the worst results for all economic indicators. In contrast to Profile 2, this was labeled "climate-sustainable farms."

5.3. Farm performance indicators: synergies and trade-offs

Table 5 shows the variance-covariance matrices estimated for the three-profile LPA solution, showing the synergies and trade-offs between the key performance indicators

Table 5. Variance-covariance matrices for the three-profile solution LPA model.

		LAND_PROD	ROA	VIABILITY	SDI	GHG_EM
Profile 1	LAND_PROD	3,493***				
	ROA	29.50	24.53***			
	VIABILITY	−0.10	1.52***	0.19***		
	SDI	−1.70*	0.07	0.01*	0.04***	
	GHG_EM	364.5	−22.59	−6.74***	−3.19***	3,086***
Profile 2	LAND_PROD	155,450***				
	ROA	190.1	143.9***			
	VIABILITY	82.3**	4.19***	0.92***		
	SDI	−16.20*	−1.07***	−0.05**	0.07***	
	GHG_EM	26,070***	−442.5***	−1.40	5.38*	21,792***
Profile 3	LAND_PROD	4,000***				
	ROA	150.8***	33.31***			
	VIABILITY	7.22**	1.67***	0.14***		
	SDI	−1.28	0.22*	0.02**	0.05***	
	GHG_EM	1,674***	−35.17	−6.80**	−3.99**	4,012***

Note: ***, **, and * indicate statistical significance at 0.1%, 1%, 5%, respectively.

for each profile. Synergies (trade-offs) are found when a beneficial impact on a given indicator involves a beneficial (detrimental) impact on another indicator (Kanter *et al.* 2018). These beneficial or detrimental impacts are assessed by considering the signs of the covariance values (positive or negative) and the polarity of the performance indicators. That is, a higher indicator value can mean either a better (LAND_PRO, ROA, VIABILITY, and SDI) or a worse (GHG_EM) farm performance, as pointed out in the following paragraphs.

One pattern shared by all profiles is that there are statistically significant positive covariances suggesting synergies between ROA and VIABILITY. However, there are differences between profiles in other significant covariances.

For instance, synergies between other economic performance indicators are only found in Profile 2 (positive significant covariance between LAND_PROD and VIABILITY) and Profile 3 (positive significant covariates between LAND_PROD and ROA and between LAND_PROD and VIABILITY). Similarly, synergistic relationships are shown between environmental performance indicators for Profile 1 and Profile 3 (negative significant covariances between SDI and GHG_EM). However, in the case of Profile 2, the positive significant covariance between GHG_EM and SDI suggests a trade-off between these two indicators.

There are also interesting differences among profiles regarding covariances between economic and environmental indicators. In the case of Profile 1, there is no significant relationship between ROA and the two environmental indicators, but for the VIABILITY indicator, significant synergistic relationships are found with SDI (positive significant covariance) and GHG_EM (negative significant covariance). In the case of Profile 2, there are trade-offs between SDI and the three economic performance indicators (negative significant covariances). Moreover, despite the trade-off evidenced by the positive significant covariance between farm productivity (LAND_PROD) and carbon emissions (GHG_EM), Profile 2 shows synergistic relationships between farm profitability (ROA) and GHG_EM (negative significant covariances). Finally, in the case of Profile 3, although LAND_PROD and GHG_EM also show a

Table 6. Linear regression coefficients ($b_{x,y}$) for the combination of indicators X and Y in each profile.

Indicator Y \ Indicator X		LAND_PROD	ROA	VIABILITY	SDI	GHG_EM
Profile 1	LAND_PROD					
	ROA	0.0084				
	VIABILITY	−0.0000	0.0618***			
	SDI	−0.0005*	0.0028	0.0681*		
	GHG_EM	0.1044	−0.9206	−34.7671***	−87.51***	
Profile 2	LAND_PROD					
	ROA	0.0012				
	VIABILITY	0.0005**	0.0291***			
	SDI	−0.0001*	−0.0074***	−0.0560**		
	GHG_EM	0.1677***	−3.0742***	−1.5173	71.83*	
Profile 3	LAND_PROD					
	ROA	0.0377***				
	VIABILITY	0.0018***	0.0500***			
	SDI	−0.0003	0.0067*	0.1678***		
	GHG_EM	0.4187***	−1.0559	−47.9112**	−76.48**	

Note: ***, **, and * indicate statistical significance at 0.1%, 1%, 5%, respectively.

trade-off relationship (positive significant covariance), significant synergies are found between ROA and SDI (positive significant covariance), and between VIABILITY and the two environmental indicators (positive significant covariance for SDI and negative significant covariances for GHG_EM).

Table 6 shows the linear regression coefficients ($b_{x,y} = dY/dX$) for every pair of indicators in each farm profile.[8] These coefficients can be compared across profiles to assess which one has the lowest trade-offs or the highest synergistic relationships. For instance, this information indicates that the objective of reducing GHG emissions (GHG_EM) can be achieved in Profile 2 and Profile 3 alongside a decrease in production (LAND_PROD). However, the decrease in production per unit of pollution avoided is lower in the case of Profile 3. In any case, it is also true that a reduction in farms' emissions potential (GHG_EM) in the case of Profiles 1 and 3 has no cost in profitability terms (ROA) and even involves synergistic relationships regarding farms' viability (VIABILITY). Likewise, it is worth noting that in the case of Profile 2, although production reduction trade-offs are the highest, a reduction in GHG_EM would lead to an increase in profitability (ROA) and no significant impacts on farms' viability (VIABILITY). Moreover, carbon emissions (GHG_EM) could also be reduced through an increase in farm biodiversity (SDI) in Profile 1 and Profile 3, although not in the case of Profile 2.

Similarly, it can be observed that an increase in farmland biodiversity (SDI) can be achieved in Profile 3 at no cost in terms of economic performance (no significant or synergistic relationships found), while it would involve a slight decrease in farm productivity (LAND_PROD) in Profile 1. In any case, SDI shows synergistic relationships with economic indicators in Profile 1 (VIABILITY) and Profile 3 (ROA and VIABILITY). However, in the case of Profile 2, increasing SDI would involve a decrease in farm productivity (LAND_PROD), profitability (ROA), and viability (VIABILITY).

5.4. Factors explaining farm profiles' membership

Implementing the three-step approach allowed us to relate the profile membership to policy-relevant covariates. Table 7 shows the final set of covariates included in the model achieved after running the backward stepwise procedure. The model shows an acceptable goodness-of-fit, since the included covariates explain a substantial portion of the variability in class membership (Pseudo-$R^2 = 0.608$).[9]

First, it should be noted that all covariates related to farmers' characteristics (i.e. AGE, GENDER, TRAIN, and FULL_FARM), all CAP subsidies other than decoupled payment (ENV_SUB and OTHER_2P) and one farms' resources covariate (DEBT) turned out to be non-statistically significant and were therefore eliminated from the final model. The signs of the coefficients obtained and their magnitude indicate the effect of each covariate on the probability that a farm is included in a profile, relative to Profile 3, which was taken as the reference profile. Thus, a positive (negative) coefficient indicates a higher (lower) probability of membership in a profile relative to Profile 3. For example, regarding REG_CYL, the positive coefficient for Profile 1 indicates a higher probability that a farm located in this region belongs to this profile, while the negative coefficient for Profile 2 indicates the opposite. Consequently, a farm located in Castilla y León (REG_CYL = 1) has, *ceteris paribus*, a higher probability of belonging to Profile 1 and a lower probability of belonging to Profile 2, with Profile 3 showing an intermediate membership probability.

Farm membership in Profile 2 (economically sustainable farms), compared to membership in Profile 3 (climate-sustainable farms), is positively influenced by higher decoupled payments per hectare (DEC_PAY) and a higher level of outsourcing (OUTSOURC). However, those farmers with a higher share of owned land (OWN_LAND) are less likely to be included in this profile. Meanwhile, farm membership in Profile 1 (mixed performance farms), compared to membership in Profile 3, is positively influenced by higher shares of non-land fixed assets (NL_FASSET). In addition, the model indicates that farms with less total farm area (F_AREA), a lower share of owned land (OWN_LAND), located in less favored areas (LFA), and a lower share of labor input hours (LABOR_H) are more likely to belong to Profile 1.

Profile membership is also related to the regions where sample farms are located. Compared to Profile 3, farms located in Castilla y León (REG_CYL = 1) have a higher probability of being included in Profile 1 and a lower probability of being included in Profile 2. Those operating in Castilla-La Mancha (REG_CLM = 1) are more likely to be included in Profile 1. Finally, farms located in Andalucia (REG_AND = 1) have a much lower probability of being included in Profile 1.

6. Discussion and concluding remarks

The case study conducted here provides evidence that the methodological proposal for building a policy-oriented farm typology can be empirically implemented, resulting in categories of farms that are similar in terms of economic and environmental performance. Consequently, this new farm typology-building approach can significantly improve the understanding of agricultural systems, in turn helping to support policy analysis and decision-making by identifying the specific policy interventions needed (i.e. differentiated by farm profiles). Moreover, the quantitative methods used to estimate synergies/trade-offs among the different performance indicators within each group of farms identified (analyzed by means of variance-covariance matrices) and the

Table 7. Results of the three-step procedure to estimate the effect of latent profile predictors using profile 3 as reference profile.

	Profile 1		Profile 2		Profile 3		
Covariate	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Wald
Intercept	0.076 *a*	1.785	0.665 *a*	1.199	. *a*	.	0.401
F_AREA	−0.014 *a*	0.004	0.004 *b*	0.002	. *b*	.	20.279***
DEC_PAY	−0.001 *a*	0.003	0.015 *b*	0.003	. *a*	.	27.642***
OWN_LAND	−0.051 *a*	0.010	−0.048 *a*	0.012	. *b*	.	27.121***
REG_AND = 1	−3.929 *a*	0.993	−0.189 *b*	0.557	. *b*	.	20.248***
REG_CYL = 1	3.657 *c*	0.792	−3.346 *a*	0.774	. *b*	.	84.335***
REG_CLM = 1	3.725 *b*	0.802	1.056 *a*	0.486	. *a*	.	21.563***
LFA = 1	2.806 *b*	0.916	−1.153 *a*	0.746	. *a*	.	21.663***
NL_FASSET	0.003 *b*	0.001	0.003 *a,b*	0.001	. *a*	.	7.007*
OUTSOURC	0.015 *a,b*	0.011	0.025 *b*	0.006	. *a*	.	15.277***
LABOR_H	−0.036 *a*	0.014	0.021 *b*	0.014	. *b*	.	12.278**
Goodness-of-fit							
LL	−333.63						
BIC	806.44						
Pseudo-R^2	0.608						

Note: The Wald test in the last column refers to the entire row, with significant values indicating that at least one coefficient for that variable differs from 0. Letters in italics show the results of the pairwise comparisons among profiles also implemented using the Wald test. Differences are shown at the 5% level, with shared letters indicating no statistically significant difference.

characterization of the different farm profiles according to their specific characteristics (three-step procedure) are worth commenting as an interesting methodological contribution to the existing literature (Kanter *et al.* 2018).

However, prior to translating the results obtained into guidelines for policy analysis and the design of new instruments, two methodological issues should be acknowledged regarding the interpretation of observed synergies/trade-off relationships (see Schaafsma and Bartkowski 2020). The first one is that synergy/trade-off relationships based on time- and spatial-specific statistical covariances between performance indicators do not necessarily demonstrate the existence of stable or causal relationships. The second one is that the observed synergy/trade-off relationships are shaped by farm inefficiencies in resource use (i.e. farms' position relative to the production possibility frontier, PPF). Thus, it could be argued that observed synergies simply point to the possibility of eliminating these inefficiencies. These general limitations in assessing synergies and trade-offs also apply to this specific case, necessitating a cautious interpretation of the results obtained. In any case, it has been assumed that observed covariances still provide valuable insights for analyzing potential synergy/trade-off relationships in farm performance, since they give us information about the covariances of actual indicators, which can be used to predict the direction of the relationships between them (Breure *et al.* 2024).

Bearing in mind that the main challenge of agricultural policy is improving farms' environmental performance while ensuring their economic sustainability, the results yielded by the proposed methodological approach can be used to evaluate the application of current agricultural policies and to enhance agricultural policy tailoring, allowing the design of policy instruments to be fine-tuned to harness potential synergies/trade-offs across farm profiles. Moreover, these results can also help to improve agricultural policy targeting by focusing differentiated policy instruments on the farms that are more likely to belong to each profile according to their specific structural features and farmers' socio-demographic characteristics. The empirical case study analyzed in this paper is illustrative in this sense, as explained below.

For instance, the results show that higher decoupled payments increase the probability of belonging to the economically sustainable profile of farms. This suggests that decoupled payments have achieved the objective of ensuring viable farm income. On the contrary, environmental subsidies and other pillar two payments are non-significant when it comes to farm profiling, which might indicate that these schemes did not fulfill any specific objective in the Spanish rain-fed field crops agricultural system. This suggests the need to improve their design to enhance environmental and economic development in this agricultural system. In this regard, the changes introduced in the 2023–2027 CAP, especially its new green payments architecture, could be expected to improve the tailoring of these instruments and enhance their impact in terms of the efficient achievement of environmental sustainability. However, this hypothesis should be tested once information from 2023 onward becomes available.

In any case, decoupled payments do not seem to be efficiently allocated in the Spanish rain-fed field crops agricultural system, given the heterogeneity in farms' profitability and viability. In this case study, redistributing the total direct payment envelope could make sense, since reducing the higher payments granted to Profile 2 farms (those with the highest productivity levels) would not jeopardize their economic sustainability, but it would enable an increase in the lower payments received by farms in Profile 3 (climate-sustainable farms with the lowest productivity levels), in an effort to boost their profitability and viability levels. In this regard, the three-step approach helps to identify key structural characteristics of farms related to profile membership, such as the region in which the farm is located, its LFA status, or its physical size. Using these characteristics to distribute decoupled payments could contribute to a more efficient distribution of these payments in this agricultural system, helping to create a new balance between economic and environmental performance that would enhance social welfare.

Similarly, the results obtained could be used to fine-tune the design of agricultural income taxation. In Spain, this tax is levied on the basis of a flat-rate scheme estimating agricultural net income as a percentage (tax rate) of farmers' revenues (sales plus direct payments). Thus, the farm typology built could also be used to establish differentiated tax rates depending on the farms' profile. Some economic characteristics of the farms related to profile membership, such as outsourcing or non-land assets, could be helpful in this regard. This would allow for the introduction of specific deductions, taxes, or exemptions to align fiscal policy with the general objectives of the agricultural policy.

The results obtained for rain-fed field crops in Spain could also support the improvement of the agri-environmental policy implemented within this agricultural system. This study suggests that agri-environmental policy could be reinforced for farms belonging to Profiles 1 and 3 to improve their environmental performance further, as the trade-offs between economic and environmental performance in these profiles are lower than in Profile 2. This would make it possible to generate greater environmental benefits at a lower economic cost (i.e. lower payment requirements). As a result, the redirection of policy support toward more diversified farms—for example, through the new eco-schemes—could be a good way to bolster both the economic and environmental performance of these types of farms. These measures should focus on farms whose structural characteristics (e.g. region, LFA status, or farm area) make them more likely to belong to such profiles. In the event that environmental objectives were not achieved by focusing only on Profiles 1 and 3, higher payments for Profile 2 might be necessary, taking into account the higher opportunity costs for this profile (i.e. higher trade-off relationships between economic and environmental performance indicators).

GHG emissions reduction does not seem to affect farm profitability and viability, as no significant trade-offs are found in any of the profiles. This suggests that it may not be necessary to economically compensate farmers for cutting emissions. Instead, using compulsory measures (such as enhanced conditionality) could be an efficient way to achieve these reductions. However, it should be noted that both the profile definition and the trade-off and synergies analysis suggest that the reduction of GHG emissions in the rain-fed field crops system would come at the expense of productivity (i.e. food supply). On a larger scale, this could negatively impact global food markets and food security and, ultimately, could lead to production reallocation (i.e. increased food production in other countries driven by lower production costs and less stringent legal constraints), jeopardizing the objective of reducing GHG emissions at a global level. In this regard, in order to reduce GHG emissions while having the smallest possible impact on farms' productivity, profitability, and viability, it is suggested that greater efforts (e.g. higher environmental payments) should be focused on less intensive farms (Profiles 1 and 3) since the implementation of agri-environmental policy instruments in these farms is more efficient than in Profile 2.

Finally, it should be noted that this proposal of a new policy-oriented farm typology and the analysis of its outcomes is not free of limitations. The most noteworthy one is probably the limited suitability of the environmental indicators built, given the lack of detailed environmental information in the FADN/RECAN microdata. This constraint calls for careful handling of the conclusions and policy recommendations derived from the analysis. Nonetheless, many of these data limitations may be solved in the near future with the upgrade of the FADN into the Farm Sustainability Data Network (FSDN), which will provide more data on farm-level environmental performance and will allow more accurate and robust ecological indicators to be calculated. For instance, this update will make it possible to access information about farm performance regarding the presence of high natural value areas and the biocide potential of the agrochemical used (relating to biodiversity), soil management practices (concerning soil functionality), or nutrient balances (linked to pollution emissions). This additional information will be available from 2026, when microdata gathered from the 2025 farm sample are to be published.

The second potential drawback that is also worth mentioning is the static nature of the typology proposed. Profile sizes, synergies/trade-off estimates, and farm characteristics in each profile are obtained using recent data, reflecting the situation at a specific time in the past. However, the economic, technological, or policy changes affecting the farm population mean that any farm typology should be considered a dynamic classification evolving over the years. This calls for ongoing updates of farm typologies to account for these changes in profile membership. Likewise, further research analyzing individual farms' longitudinal data, employing suitable statistical methods such as Latent Class Growth Analysis (LCGA) or Latent Transition Analysis (LTA), could be of interest to assess groups of farms that display similar economic and environmental performance evolution patterns.

Finally, it should be noted that using farm types or profiles as target groups to design and implement differentiated policy instruments is challenging, as it raises issues about perceived fairness and legitimacy that could reduce their acceptance among farmers (Huber *et al.* 2024). Accordingly, the contributions of this typology-building approach to assist policy design and implementation should be complemented with further research focused on differentiating farmers' attitudes, opinions, and behavior across profiles (Dessart, Barreiro-Hurlé, and van Bavel 2019). This sort of empirical study might help to identify which policy instruments are more suitable for implementation among the different profiles, considering the objectives to be achieved, their expected efficiency and efficacy of the instruments, and their understanding and acceptance by targeted farmers.

Notes

1. In any case, qualitative criteria related to parsimony and interpretability of the results also need to be met, which reproduces some of the discretionary problems associated with traditional clustering techniques.
2. According to Spurk *et al.* (2020), a sample size above 500 individuals is large enough for an LPA model. Therefore, the sample size of 559 farms is considered to be adequate for this research.
3. To calculate the opportunity cost of land (OC_{land}), the farm's owned area was multiplied by the annual regional rental fee for rain-fed cropland based on official statistics. The opportunity cost of unpaid labor (OC_{labor}) was estimated as the product of this labor input and the mean annual wage paid for labor in the RECAN sample used for the analysis. To calculate the opportunity cost of non-land assets provided by the farmers ($OC_{non\text{-}land\ assets}$), the value of these assets was multiplied by the annual interest rate of 10-year Spanish government bonds.
4. RECAN provides data about the amount of nitrogen, phosphorus, and potassium in mineral fertilizers. Thus, for nitrogen in mineral fertilizers, the AI_i value reported by RECAN code SE296 was used directly in expression (1).
5. It should be noted that the direct payments system applied in Spain in the period 2015-2022 still presented a strong link with historical payments, which implies large differences between farmers in direct payments per hectare.
6. The one-step approach is simply the estimation of the LPA model simultaneously including the covariates. However, using the one-step approach would mean the that farms would be classified not only according to their economic and environmental performance, which was the objective of our paper, but also their characteristics as defined by the covariates.
7. In order to increase the replicability of the analysis, the code used for modeling the LPA with the Syntax version of Latent GOLD 6.0 has been included in Appendix C (included as supplementary material).
8. Concerning the linear relationship between each pair of performance indicators, it is also worth pointing out that the LPA model we run can also provide the correlation coefficients between them for each profile. These correlation coefficients are shown In Appendix E (included as supplementary material).
9. The pseudo-R^2 in this LPA model is an estimation of the reduction of errors associated with the inclusion of covariates (Vermunt and Magidson 2016). Thus, the closer to 1 (i.e. 100% of the error reduced by the inclusion of covariates), the better. It does not indicate the percentage of variance explained, as the R^2 in ordinary least squares (OLS) regressions does.

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Supplementary information

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Data availability statement

The authors do not have permission to share the Spanish Farm Accountancy Data Network (RECAN) microdata provided by the Ministry of Agriculture, Fisheries, and Food (MAPA).

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