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Exploring Farm Diversity in Italian Commercial Chestnut Farms: Economic Intensity, Specialization, and Structural Maturity

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Abstract

Italy is among the world's leading producers and exporters of chestnut. Over the past two decades, however, the sector has undergone significant structural changes driven by phytosanitary shocks and evolving market conditions. This study examines the structural and economic heterogeneity of Italian commercial chestnut farms over the period 2019–2023, aiming to identify recurrent production configurations and assess their economic performance and territorial distribution within the Farm Sustainability Data Network (FSDN) field of observation. The analysis is based on a balanced panel of 96 farms, from which a subsample of 77 inliers was identified through robust multivariate diagnostic tests. Farm-level indicators were aggregated over five years to capture medium-term positioning. Principal Component Analysis (PCA) was used to identify the main latent dimensions of variability, and fuzzy k-means clustering was subsequently performed on the resulting component scores. A five-cluster configuration was selected on the basis of internal validity indices, bootstrap stability, fuzzifier sensitivity and leave-one-variable-out robustness checks. The results reveal pronounced multidimensional differentiation within the observed sample. High economic intensity does not necessarily translate into greater margin stability, the effects of structural maturity vary according to cost exposure and labor organization. Territorial differentiation is statistically significant but not deterministic. Overall, the analysis provides an empirical characterization of structural profiles and their associated trade-offs within the observed commercial segment, offering insights into differentiated policy responses for perennial Mediterranean farming systems.

Keywords: chestnut cultivation; chestnut farming profile; gross margin analysis; Farm Sustainability Data Network; principal component analysis; fuzzy clustering; spatial analysis

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1. Introduction

Italy is one of the leading countries in the global chestnut market and is among the world's major producers and exporters of chestnuts [1–3]. According to the Food and Agriculture Organization Corporate Statistical Database [4], Italy accounted for 25.3% of global chestnut export value in 2024, making it the world's leading exporter in value terms, ahead of China (23.7%), Spain (13.3%), Portugal (8.1%) and Türkiye (5.8%). In volume terms, however, China dominated the market with more than 42% of total exports, whereas Italy ranked second with a share of 13.1%. In the same year, Italy produced more than 64,000 tonnes of chestnuts, ranking fourth globally and third in Europe, behind Spain and Türkiye.

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Beyond its economic importance, chestnut cultivation has long been a defining feature of many Mediterranean rural areas, particularly in mountainous and marginal regions, where it contributes not only to farm incomes but also to ecosystem services, landscape conservation and the vitality of local communities [5–7]. Over the past two decades, however, the sector has undergone profound changes. The spread of the chestnut gall wasp (*Dryocosmus kuriphilus*), evolving consumption patterns and increasing competition from emerging producing countries have altered production dynamics and reshaped the organization of the sector.

The introduction of the chestnut gall wasp in 2002 [8,9] marked a turning point for Italian chestnut production. The pest caused a sharp decline in domestic output and led to wider structural changes across the sector [10]. Before the crisis (2000–2006), Italy maintained a stable trade surplus averaging around 15,000 tonnes annually. As production declined, this surplus gradually eroded and disappeared entirely by 2012 [11,12]. Italy consequently shifted from being a net exporter to a net importer, relying increasingly on foreign supply to satisfy domestic demand and support processing activities.

In recent years, the phytosanitary emergency has been substantially mitigated through a series of biological control programs promoted by the Italian Ministry of Agriculture, Food Sovereignty and Forestry (MASAF), with the BIOINFOCAST project [13] playing a central role. Production has gradually recovered and the trade balance has improved, with Italy returning to a net export position in 2024 for the first time since the crisis, recording a surplus of 2117 tonnes. Nevertheless, Italy remains one of the world's leading importers of chestnuts, reflecting the growing integration of the chestnut value chain within international markets.

The effects of these transformations remain clearly visible at farm level. Evidence from the 7th General Census of Agriculture [14] points to a long-term contraction in Italian chestnut farming. Between 2010 and 2020 [14,15], the number of chestnut-growing farms fell by 48.9%, while the cultivated area declined by 36.9% [16,17]. At the same time, the farms that remained in business became increasingly diverse. The proportion of young farmers rose from 11% to 16%, educational attainment improved and diversification activities, including agritourism and on-farm processing, became more widespread. Taken together, these developments suggest that Italian chestnut farming can no longer be regarded as a homogeneous production system, but rather as a collection of distinct organizational and economic models coexisting within the same sector.

Despite these developments, relatively little is known about the structural and economic diversity of market-oriented chestnut farms. Existing studies have primarily focused on phytosanitary issues, varietal improvement and pest management, whereas economic research has concentrated on trade patterns, supply chains, market organization and territorial development or specific regional experiences [11,12,18]. Much less attention has been devoted to understanding how production intensity, specialization, structural maturity and income stability interact at farm level and shape different development trajectories within the market-oriented sector. Consequently, quantitative evidence capable of capturing this diversity remains limited.

Against this background, the study investigates the heterogeneity of Italian market-oriented chestnut farms over the period 2019–2023. Using microdata from the Farm Sustainability Data Network (FSDN), it combines Principal Component Analysis (PCA) with fuzzy clustering to identify recurrent structural configurations and explore their economic characteristics. The aim is not merely to classify farms into homogeneous groups, but to gain a deeper understanding of the development paths currently observed within the sector.

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This study contributes to the literature in three main ways. First, to the best of our knowledge, it provides a quantitative typology of Italian commercial chestnut farms based on FSDN microdata, an aspect that has received limited attention in previous studies. Second, it extends the application of fuzzy clustering to Mediterranean perennial farming systems, showing that this approach is well suited to capturing gradual and overlapping differences that are often overlooked by conventional classifications [19–21]. Finally, it offers a policy-oriented interpretation of farm heterogeneity, highlighting how different structural profiles may require differentiated support measures within the framework of the Common Agricultural Policy (CAP) Strategic Plan [22] and the forthcoming National Chestnut Sector Plan.

2. Materials and Methods

2.1. Analytical Framework

The analysis was designed to identify recurrent farm profiles among Italian chestnut farms and to relate them to performance dynamics and territorial distribution. Given the coexistence of overlapping production models, heterogeneous orchard age structures, mixed labor regimes and varying degrees of specialization, a multivariate framework was considered more appropriate than single-indicator comparisons or threshold-based classifications.

The empirical strategy was developed in sequential stages. First, a harmonized and balanced farm-level panel was constructed using the FSDN data. Structural and economic indicators were then defined at farm level and transformed to ensure comparability across farms and over time. PCA was adopted as an exploratory dimensionality-reduction technique because the selected variables capture closely related aspects of farm structure and performance, including output intensity, gross margin, variable costs, labor input, machinery use, specialization and margin variability. Several of these indicators are inherently correlated in commercial farming systems. PCA [23] was therefore used to reduce redundancy among variables, derive orthogonal latent dimensions and limit the effects of multicollinearity on the subsequent clustering stage. The resulting component scores were subsequently used as inputs for fuzzy k-means clustering (FKM), corresponding to the classical fuzzy c-means (FCM) framework [24].

The combination of PCA and FKM was chosen to reflect the organizational characteristics of chestnut farming systems. PCA and clustering were not treated as alternative procedures, but as complementary steps. PCA was used to summarize the main linear gradients of variability in a reduced and interpretable space, while FKM was used to identify recurrent production configurations within that space. Other dimensional reduction techniques were not adopted because the objective was not predictive classification or the detection of complex nonlinear manifolds, but the construction of an interpretable farm typology directly linked to observed economic and structural indicators. In this context, PCA offered a transparent solution, since the retained components could be interpreted in terms of economic intensity, specialization, structural maturity, scale and margin stability. FKM was preferred to a hard clustering procedure because farm types in perennial Mediterranean crops rarely exhibit sharp boundaries. Production models tend to overlap, and intermediate profiles are common. FKM allows farms to be associated with clusters, assigning membership values between zero and one.

The analytical design followed a progressive refinement strategy. The first stage aimed to characterize the overall structure of the FSDN sample without imposing ex ante restrictions. A second diagnostic stage was introduced to assess the potential influence of extreme multivariate configurations on the typological structure. This sequential approach makes it possible to identify patterns that broadly characterize the observed commercial farm population and to assess whether these patterns remain stable after controlling for influential observations. Internal validity indices, bootstrap resampling procedures, sensitivity analysis with respect to the fuzzifier parameter and spatial association tests were employed to evaluate the coherence and robustness of the identified configurations.

The suitability of the PCA-FKM sequence was therefore assessed using multiple criteria rather than being assumed a priori. The adequacy of PCA was evaluated based on the correlation structure of the variables, eigenvalues, cumulative explained variance, scree plot inspection, and the economic interpretability of component loadings. The aim was not to assume strong correlations among all variables, but rather to verify whether the selected indicators shared a sufficient linear structure to justify dimensionality reduction into interpretable components. The clustering solution was then assessed using standardized and orthogonal PCA scores rather than the original variables, thereby reducing the influence of scale differences and multicollinearity. In addition, robust multivariate diagnostics were used to identify influential observations before refitting the clustering procedure, thereby limiting the effect of extreme cases on the resulting partition. The final solution was evaluated through complementary internal validity indices, bootstrap stability, sensitivity to the fuzzifier parameter and comparison with a probabilistic mixture-model benchmark.

The methodological framework consists of three main sequential phases—data preparation, robust clustering, and empirical assessment—as summarized in Figure 1.

Figure 1. Methodological framework of the study.

2.2. Sample Selection and Variable Construction

The empirical analysis focuses on six Italian regions where chestnut cultivation is most concentrated: Calabria, Campania, Lazio, Tuscany, Emilia-Romagna and Piedmont. The dataset is drawn from the Italian FSDN, whose field of observation consists of market-oriented farms as defined under European regulations. In the Italian implementation, agricultural holdings are included in the survey if they exceed a minimum economic size threshold of 8000 euros of Standard Output (SO) at whole-farm level. This threshold is embedded in the sampling design and ensures that the FSDN population comprises market-oriented agricultural holdings rather than subsistence farms. It should be noted that the Italian FSDN sample was not designed for sector-specific inferential analysis. The survey was structured to represent commercial farms at the national and regional levels according to economic size classes and farming types, rather than to provide statistically representative subsamples for individual crops. Therefore, the results presented in this study refer to the structural and economic diversity observed among commercially oriented chestnut farms included in the FSDN and should not be interpreted as representative of the entire national population of chestnut holdings.

Farms were selected if they reported a positive chestnut area devoted to fruit production in their land-use records. No minimum specialization threshold in chestnut production was imposed at the sampling stage; instead, the relative importance of chestnut activity within each farm was captured through structural and economic indicators included in the multivariate analysis. The final balanced panel consists of 96 farms observed continuously over the accounting years 2019 to 2023, corresponding to 480 farm-year observations. Each farm is present in all five years, allowing the construction of multi-year averages and variability measures while avoiding distortions associated with entry or exit dynamics within the observation window.

Structural and economic variables were constructed at the farm level to capture production intensity, cost structure, labor organization, specialization, and income stability, which represent the main dimensions through which structural and economic heterogeneity shapes farm positioning and performance.

Variable selection was guided by both the analytical objectives of the study and the information structure of the Italian FSDN. It was therefore defined before the clustering stage and reflected the economic, structural and organizational dimensions considered relevant for interpreting farm heterogeneity within the commercial chestnut segment. In line with farm typology studies based on structural and economic variables and with applications using FADN microdata for farm classification [20,25,26], the selected indicators were intended to capture the main dimensions of farm heterogeneity while remaining available, consistently measured and comparable across farms and years at the level of chestnut production activity or farm structure. Within this empirical framework, variables were chosen to describe the dimensions through which structural and economic heterogeneity can affect farm positioning and performance in perennial crop systems: economic performance, production and cost intensity, physical structure, specialization, labor and machinery organization, and income stability. Economic and labor intensity indicators were expressed per hectare of chestnut area to ensure comparability across farms of different sizes, while multi-year averages were used to reduce the influence of short-term annual fluctuations and to capture medium-term farm positioning over the 2019–2023 period.

The gross margin (GM_ha) was defined as the gross output (GO_ha) minus the variable costs (VC_ha) attributable to chestnut production, in accordance with FSDN accounting principles. VC_ha includes direct operating inputs such as fertilizers, plant protection products, energy, irrigation, contracted services and other current expenditures directly linked to chestnut cultivation. GM_ha is calculated before depreciation, labor remuneration and other fixed costs; therefore, it reflects the ability of the activity to cover fixed production factors and remunerate entrepreneurial effort. Although GM_ha and VC_ha are mechanically related, as variable costs enter directly into the gross margin calculation, both variables were retained because they capture different analytical dimensions: net economic return and cost intensity.

Output and variable costs refer to the chestnut production activity as recorded in FSDN and were therefore used to construct crop-specific performance indicators rather than whole-farm aggregates. Yield was calculated as chestnut production per hectare of chestnut area and was included to capture the productive intensity of the crop activity.

Structural endowment was described through chestnut area (CH_area) and orchard age (AgePlant), measured in 2023, which captures orchard maturity and indirectly reflects past investment cycles. Specialization was captured through the Chestnut Specialization Ratio (CSR), defined as the share of chestnut output in total farm output, thus situating chestnut activity within a broader farm economic structure. Human labor per hectare (Lh_ha), including both hired and family labor as recorded in the FSDN, and machinery use per hectare (Mh_ha), capturing mechanization intensity, were included as input intensity measures and expressed in hours per hectare of chestnut area. Income stability over time was captured through the coefficient of variation in gross margin (GM_cv), computed over the five-year period to quantify the relative dispersion of annual margins around the farm-specific mean.

Overall, the variable set was designed to balance analytical completeness with parsimony. GM_ha, GO_ha, VC_ha and Yield capture the economic and productive intensity of chestnut activity; CH_area and AgePlant describe physical structure and plantation maturity; CSR measures the role of chestnut production within the broader farm economy; Lh_ha and Mh_ha account for the organization of labor and mechanization; and GM_cv introduces a temporal stability dimension that is not captured by average performance levels alone. This combination allows the typology to reflect both the level and the stability of economic performance, while also accounting for structural and organizational characteristics relevant to perennial farming systems.

All variables included in the multivariate stage were standardized to zero mean and unit variance prior to PCA, ensuring comparability across heterogeneous measurement units and preventing variables with larger scale from dominating the extraction of latent components (Table 1). The suitability of the variable set for PCA was subsequently examined through the correlation structure of the indicators, eigenvalues, cumulative explained variance, scree plot inspection and component loadings, as reported in Sections 2.3 and 3.2. To further assess the robustness of variable selection, a leave-one-variable-out sensitivity analysis was conducted on the refitted sample, as described in Section 2.6 and reported in Section 3.6.

Table 1. Descriptive statistics of farm-level variables included in the multivariate analysis (five-year averages, 2019–2023).

	Variable	Unit	Mean	Std. Dev.	Min	Max
Performance	GM_ha	€/ha	3520	2609	193	15,111
	GO_ha	€/ha	4356	4466	322	37,910
	VC_ha	€/ha	837	2728	4	25,730
	GM_cv	-	0.44	0.32	0.01	1.54
	CH_area	ha	5.45	9.76	0.02	65.00
	Yield	q/ha	23.32	22.28	0.57	160.00
Structure	CSR	-	0.12	0.11	0.00	0.49
	AgePlant	years	36.83	16.74	6.50	93.00
Labor	Lh_ha	hours/ha	172.39	175.44	14.43	1093
	Mh_ha	hours/ha	43.14	58.40	0.00	320.00

Notes: GM_ha = gross margin per hectare; GO_ha = gross output per hectare; VC_ha = variable costs per hectare; GM_cv = coefficient of variation in gross margin; CH_area = chestnut area; Yield = chestnut yield per hectare; CSR = chestnut specialization ratio; AgePlant = orchard age; Lh_ha = total human labor per hectare; Mh_ha = machinery use per hectare.

2.3. Principal Component Analysis Procedure

The standardized farm-level variables were subjected to PCA to reduce multicollinearity and identify the main structural and economic gradients underlying farm heterogeneity.

PCA was performed in R software (version 4.5.1; R Foundation for Statistical Computing, Vienna, Austria) using the FactoMineR package (version 2.12).

In the full-sample specification comprising 96 farms, five principal components were retained based on scree plot inspection, cumulative explained variance and economic interpretability of the retained dimensions. While the first four components displayed eigenvalues greater than unity, the fifth component was retained to ensure adequate representation of structural heterogeneity, bringing the cumulative explained variance to 84.55 percent (Table 2). Retaining five components provided a balance between dimensional parsimony and adequate representation of structural and economic variability, as additional components beyond the fifth contribute only marginal increments in explained variance and lack clear economic interpretability.

Table 2. Eigenvalues and explained variance of retained principal components, full sample (96 farms).

Component	Eigenvalue	Variance (%)	Cumulative (%)
PC1	3.95	39.45	39.45
PC2	1.53	15.29	54.75
PC3	1.18	11.78	66.53
PC4	1.05	10.46	76.99
PC5	0.76	7.56	84.55

The first principal component (PC1) captured the per-hectare intensity and performance dimensions. It is strongly associated with gross output per hectare (GO_ha), yield, variable costs per hectare (VC_ha), and gross margin per hectare (GM_ha), but shows no substantive association with margin variability (GM_cv). Farms with high PC1 scores are characterized by higher production intensity and stronger per-hectare economic performance. The second component (PC2) reflects differences in specialization and farm structure. Positive loadings were observed for the Chestnut Specialization Ratio (CSR), human labor per hectare (Lh_ha), machine use per hectare (Mh_ha), and orchard age (AgePlant), whereas negative loadings were associated with GO_ha, yield and GM_ha. PC2 thus contrasts more specialized and labor-intensive farms with mature orchards against farms characterized by higher per-hectare output and margins but lower specialization.

The third component (PC3) was largely driven by the variability indicator GM_cv. Because of the sign convention adopted for the component, higher PC3 scores correspond to lower margin variability and, therefore, greater income stability over time. PCs 4 and 5 reflect additional aspects of farm heterogeneity related to orchard age, chestnut area (CH_area), and cost configuration. The loading pattern indicates that PC1 mainly reflects production intensity and economic performance, whereas PC2 captures differences in specialization and labor organization. PC3 is primarily associated with margin variability and income stability (Table 3).

Table 3. Loadings of the first five principal components, full sample (96 farms).

Variable	PC1	PC2	PC3	PC4	PC5
GM_ha	0.73	−0.34	0.18	−0.14	0.22
GO_ha	0.91	−0.33	−0.01	0.05	−0.08
VC_ha	0.80	−0.22	−0.19	0.22	−0.35

Table 3. *Cont.*

Variable	PC1	PC2	PC3	PC4	PC5
GM_cv	0.11	0.17	−0.87	0.23	0.26
CH_area	−0.18	−0.52	0.22	0.54	0.55
CSR	0.48	0.54	0.20	−0.39	0.41
AgePlant	−0.13	0.49	0.33	0.64	−0.17
Yield	0.87	−0.19	0.16	−0.02	−0.07
Lh_ha	0.61	0.50	0.26	0.19	0.03
Mh_ha	0.74	0.38	−0.24	0.16	0.12

Notes: GM_ha = gross margin per hectare; GO_ha = gross output per hectare; VC_ha = variable costs per hectare; GM_cv = coefficient of variation of gross margin; CH_area = chestnut area; Yield = chestnut yield per hectare; CSR = chestnut specialization ratio; AgePlant = orchard age; Lh_ha = total human labor per hectare; Mh_ha = machinery use per hectare.

The scores associated with PC1 to PC5 provided an orthogonal and reduced representation of farm heterogeneity. These uncorrelated component scores were subsequently used as inputs for the clustering stage, ensuring that the grouping procedure was not affected by multicollinearity among the original variables, allowing each retained dimension to contribute independently to the identification of farm profiles.

2.4. Fuzzy K-Means Clustering (FKM)

To identify groups of farms with similar structural and economic profiles, fuzzy k-means clustering was applied to the principal component scores obtained from PCA [27]. Clustering was performed on the first five components, which captured the main latent gradients of farm heterogeneity while ensuring orthogonality of the input space. Because the principal components are uncorrelated and standardized, Euclidean distance provides a coherent and scale-consistent measure of similarity across farms.

The fuzzy k-means algorithm was implemented using the R package fclust (version 2.1.2). The fuzzifier parameter was set to m = 2, a commonly used value in agricultural typology studies that balances cluster sharpness and overlap. To reduce sensitivity to initialization and avoid convergence to local optima, each configuration was estimated using 50 random starts, retaining the solution that minimized the objective function. The convergence criteria were monitored to ensure numerical stability of the partition.

As an exploratory baseline, alternative numbers of clusters were examined for the full sample of 96 farms. Solutions with k = 4, 5, and 6 were estimated to assess different levels of typological granularity. The partition quality was evaluated using complementary internal validity indices capturing compactness, separation and fuzziness of the resulting partitions. This baseline stage provides a descriptive mapping of structural diversity within the FSDN subsample and establishes a reference configuration before applying robust multivariate diagnostics.

2.5. Robust Multivariate Diagnostics and Refitted Specification

Following the exploratory baseline stage, a robust multivariate diagnostic analysis was conducted to assess the influence of extreme observations on the clustering structure. Given the multivariate nature of the procedure, such configurations may exert disproportionate influence on partition structure. The dispersion observed in the descriptive statistics reported in Section 2.2 (Table 1) motivated the adoption of a robust multivariate outlier detection procedure on the PC1–PC5 scores.

Robust Mahalanobis distances were computed using the Minimum Covariance Determinant estimator [28], which provides high-breakdown resistance to leverage points. Observations exceeding the chi-square cutoff at $\alpha = 0.99$ and five degrees of freedom were classified as multivariate outliers. The corresponding threshold was 15.086. Nineteen farms were identified as influential configurations under this criterion, yielding a refitted sample of 77.

PCA was then re-estimated for the refitted sample. In this specification, five principal components were retained based on scree plot inspection, cumulative explained variance and economic interpretability of the latent dimensions. Although only the first three components had eigenvalues greater than one, the inclusion of PC4 and PC5 ensured adequate representation of structural heterogeneity, bringing the cumulative explained variance to 83.74 percent (Table 4). The refitted PCA scores were then used as inputs to fuzzy k-means clustering.

Table 4. Eigenvalues and explained variance of retained principal components, refitted sample (77 farms).

Component	Eigenvalue	Variance (%)	Cumulative (%)
PC1	3.35	33.51	33.51
PC2	2.14	21.39	54.90
PC3	1.44	14.37	69.27
PC4	0.78	7.77	77.05
PC5	0.67	6.69	83.74

Clustering was re-estimated on the 77 inliers for alternative values of k. Based on the composite validity criteria described below and the economic interpretability of the resulting profiles, the configuration with k = 5 was selected as the primary specification. The selection of k = 5 reflects an improved balance between within-cluster cohesion and between-cluster separation in the refitted sample.

To quantify the structural difference between the baseline full-sample solution and the refitted specification, the Adjusted Rand Index was computed for the 77 farms common to both configurations. The index was 0.518, indicating a moderate reorganization of cluster assignments following the removal of influential observations. This restructuring reflects the elimination of multivariate leverage effects rather than an arbitrary modification of the typology.

2.6. Validation and Robustness Assessment

Cluster validity was assessed using a set of internal validity indices computed on the PC1-PC5 scores. Silhouette coefficients were computed using the cluster package (version 2.1.8.1), while the remaining internal validity indices were computed using the clusterCrit package (version 1.3.0). The indices include Silhouette coefficient [27], Dunn index [29], Davies–Bouldin index [30], Xie-Beni index [31], and fuzzy partition measures such as the Partition Coefficient and Classification Entropy [32]. As some indices increase with partition quality whereas others decrease, directionality was aligned by inverting those minimized under better partitions. All indices were standardized and aggregated with equal weight to obtain a composite score allowing direct comparison across alternative values of k.

Cluster stability was further evaluated through 200 bootstrap resamples [33]. Cluster solutions were re-estimated across repeated resamples of the data, and stability metrics were computed at both the cluster and farm levels. This approach helps identify both stable clusters and potentially fragile partitions.

Sensitivity to the fuzzifier parameter was examined by varying m between 1.5 and 2.5 in the selected k = 5 configuration. Concordance across solutions was evaluated using partition agreement measures to ensure that the typology was not driven by a specific fuzziness assumption.

The robustness of the active-variable set was further examined through a leave-one-variable-out sensitivity analysis. The objective was to determine whether the five-cluster solution depended excessively on any single variable. Rather than revisiting the conceptual rationale underlying variable selection (Section 2.2), this analysis provided an empirical assessment of the contribution of each active variable to the final typology. Starting from the refitted sample of 77 inlier farms, each active variable was removed in turn. For every reduced model, PCA was re-estimated on the remaining nine standardized variables and the first five principal components were retained. Fuzzy k-means clustering was then repeated using the same number of clusters and fuzzifier parameter as in the main specification, namely k = 5 and m = 2. The MCD-based trimming stage was intentionally not repeated, ensuring that all runs were performed on the same set of 77 farms and that any observed differences could be attributed solely to variable removal rather than changes in sample composition. The hard partitions obtained from maximum membership assignment were compared with the main refitted k = 5 partition using the Adjusted Rand Index. Mean silhouette values and cluster sizes were also inspected to verify whether any reduced specification generated a collapse of the partition structure or highly unbalanced groups.

Gaussian mixture models were estimated using the principal component scores as an external probabilistic benchmark. Model selection based on the Bayesian Information Criterion was examined for coherence with the fuzzy partition. However, given the moderate sample size and the exploratory nature of the typology objective of this study, the final model selection remained grounded in the internal validity structure of fuzzy clustering and its economic interpretability.

Finally, the relationship between cluster membership and territorial classification was examined using Fisher's exact tests with Monte Carlo simulation at the macro-area and regional levels. The strength of association was measured using Cramer's V. These tests assess whether the identified structural configurations display non-random geographical concentration.

2.7. Spatial Analysis

To investigate whether the identified farm profiles display systematic geographical patterns, cluster membership was cross-tabulated with both administrative region and macro-area classification. Each farm was assigned to its administrative region and then grouped into four macro-areas, South, Center, North-West and North-East. As the empirical sample covers only six regions, comparisons at the macro-area level should be interpreted as broad geographical groupings, rather than as fully independent territorial units.

The analysis was conducted on the refitted k = 5 solution, which represents the primary analytical specification. For this purpose, fuzzy memberships were hardened by assigning each farm to the cluster with the maximum membership degree. Contingency tables were constructed at both regional and macro-area level. Relationships between cluster membership and geographical location were examined using contingency tables and Pearson chi-squared tests. When expected cell frequencies were too small, Fisher's exact test was applied using Monte Carlo simulation with 5000 replicates. The strength of association was quantified using Cramer's V, providing an indication of the strength of geographical clustering beyond statistical significance.

In addition to global association measures, adjusted standardized residuals were also calculated to identify specific region-cluster combinations contributing most strongly to the observed association patterns. These residuals provide insight into localized over- or under-representation of structural profiles within specific geographical contexts. Taken together, these analyses complement the multivariate typology by showing whether particular farm profiles are disproportionately concentrated in specific geographical areas.

3. Results

3.1. Preliminary Note

All results presented in this section refer to the refitted sample of 77 farms obtained after robust multivariate outlier detection. The procedure was based on Mahalanobis distances computed on PC1-PC5 scores using the Minimum Covariance Determinant estimator and a chi-square threshold ($\alpha = 0.99$; df = 5). Nineteen farms were identified as multivariate outliers and excluded from the main analytical specification. The exploratory noRefit configuration based on the full sample of 96 farms is retained only as a baseline reference and is discussed in Section 3.6. Unless otherwise stated, all quantitative results, cluster assignments and spatial analyses refer to the refitted k = 5 specification.

The segmentation is based on farm-level averages computed across the 2019–2023 period and should therefore be interpreted as reflecting medium-term structural positioning, rather than short-term annual fluctuations. The empirical domain corresponds to the FSDN field of observation and therefore includes sampled farms above the minimum economic threshold defined by the sampling framework. The structural and spatial patterns described below must be interpreted as evidence of internal differentiation within this population. They do not represent the entire universe of Italian chestnut holdings and do not carry inferential claims beyond the observed population.

3.2. Principal Component Analysis Results

The PCA estimated on the refitted sample of 77 inliers identifies five principal dimensions that capture the main economic and structural gradients observed among sampled chestnut farms. Although the overall dimensional architecture remains broadly consistent with the exploratory full-sample solution, the refitted specification provides a more robust representation of the latent relationships among production intensity, specialization, structural maturity, scale and margin variability.

PC1 defines a clear economic intensity gradient. High positive loadings on GM_ha and GO_ha, both equal to 0.89, combined with Yield (0.78) and CSR (0.70), indicate that this component captures per-hectare performance and specialization intensity (Table 5). The positive contribution of Lh_ha (0.56) and Mh_ha (0.42) suggests that economic intensity in this sector is structurally embedded in labor organization rather than driven solely by scale expansion. PC1 therefore differentiates farms according to their combined productivity and specialization profile.

Table 5. Loadings of the first five principal components, refitted sample (77 farms).

Variable	PC1	PC2	PC3	PC4	PC5
GM_ha	0.89	−0.18	0.21	0.26	−0.03
GO_ha	0.89	−0.33	0.15	0.17	−0.01
VC_ha	0.33	−0.69	−0.15	−0.30	0.08
GM_cv	−0.17	−0.45	−0.54	0.39	0.56
CH_area	−0.02	−0.04	0.81	−0.24	0.48
Yield	0.78	−0.17	0.19	−0.04	−0.01
CSR	0.70	0.45	−0.22	0.18	−0.06
AgePlant	−0.21	0.66	0.34	0.39	0.16
Lh_ha	0.56	0.61	−0.17	−0.09	0.16
Mh_ha	0.42	0.53	−0.41	−0.43	0.26

Notes: GM_ha = gross margin per hectare; GO_ha = gross output per hectare; VC_ha = variable costs per hectare; GM_cv = coefficient of variation of gross margin; CH_area = chestnut area; Yield = chestnut yield per hectare; CSR = chestnut specialization ratio; AgePlant = orchard age; Lh_ha = total human labor per hectare; Mh_ha = machinery use per hectare.

PC2 reflects structural maturity and labor commitment. Strong positive loadings on AgePlant (0.66), Lh_ha (0.61) and Mh_ha (0.53) contrast with a pronounced negative loading on VC_ha (−0.69) and a negative association with GM_cv (−0.45). This axis separates farms characterized by older orchards and higher labor engagement from more cost-intensive and economically volatile structures. The negative sign on GM_cv suggests that structural maturity may contribute to greater margin stability within the commercial segment.

PC3 is dominated by CH_area (0.81) and negatively related to GM_cv (−0.54), capturing a scale-related dimension associated with reduced margin variability. PC4 and PC5, although explaining smaller shares of variance, remain structurally meaningful. PC4 reflects contrasting contributions of Mh_ha (−0.43) and GM_cv (0.39), while PC5 is strongly associated with GM_cv (0.56). The presence of GM_cv across several components suggests that margin variability is an intrinsic dimension of farm heterogeneity rather than a residual source of variation.

The PC1-PC2 projection illustrates the joint economic and farm diversity underpinning the clustering stage. The five-dimensional PCA space provides an interpretable representation of economic intensity, specialization, maturity, scale and margin stability within the refitted commercial sample and forms the basis for the subsequent clustering stage.

3.3. Cluster Validity and Selection

Cluster selection was conducted on the five-dimensional PCA scores of the refitted sample using fuzzy k-means and evaluated for k = 4, 5 and 6. The profile of internal validity indices supports k = 5 as the main specification (Table 6).

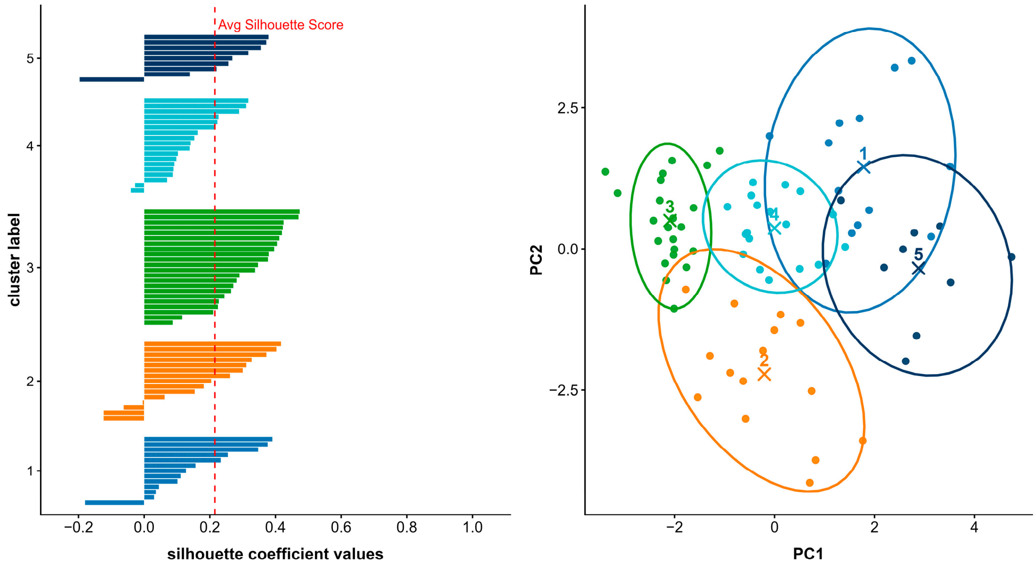
Table 6. Internal validity indices and composite score for alternative fuzzy clustering solutions (k = 4–6) in the refitted sample (77 farms).

k	Xie-Beni	Partition Coefficient	Classification Entropy	Mean Silhouette	Dunn	Davies–Bouldin	Composite Score
4	0.875	0.389	1.139	0.193	0.110	1.682	−0.385
5	0.490	0.362	1.280	0.215	0.066	1.400	1.841
6	0.772	0.319	1.434	0.188	0.146	1.353	−1.457

Note: Indices are computed on PC1-PC5 scores. For the composite score, validity criteria were standardized across candidate k values using z-scores. Criteria to be minimized (Xie-Beni, Classification Entropy, Davies–Bouldin) were sign-adjusted prior to aggregation. The composite score corresponds to the unweighted sum of standardized criteria.

The Xie-Beni index attains its minimum value at 0.490 for k = 5, compared with 0.875 for k = 4 and 0.772 for k = 6, indicating a more favorable balance between within-cluster compactness and between-cluster separation. The mean silhouette coefficient likewise reaches its highest value at 0.215 for k = 5, whereas the composite score equals 1.841 under this specification and turns negative for both alternative solutions. Taken together, these criteria consistently support k = 5 as the solution that best balances cohesion, separation and structural differentiation within the refitted sample. Although certain indices such as Dunn and Davies–Bouldin show marginal improvements at k = 6, these variations must be interpreted jointly rather than in isolation. The composite score, which aggregates normalized validity criteria, clearly favors k = 5. The decrease in the Partition Coefficient and the increase in entropy observed when moving from k = 4 to k = 5 should not be interpreted as deterioration. Rather, they reflect a more articulated membership structure consistent with the intrinsic heterogeneity of the commercial chestnut sector. In a fuzzy framework, higher entropy may reflect a more realistic representation of gradual structural transitions rather than excessive fragmentation.

The joint inspection of the silhouette profile and the PC1-PC2 projection, together with the extent and partial overlap of the 90% confidence regions, further corroborates the selection of the five-cluster solution (Figure 2). Partial overlap among clusters is consistent with the fuzzy nature of the algorithm, which allows farms to share degrees of membership across adjacent structural profiles. Most observations exhibit positive silhouette values, indicating that farms are, on average, closer to members of their assigned configuration than to alternative groups. The mean silhouette value indicates moderate separation, a pattern that is consistent with the fuzzy structure of the partition and with the presence of transitional profiles within the sector. Clusters 2 and 3 display both high silhouette concentration and strong geometric compactness in the factor plane. Cluster 5 occupies the positive side of the PC1 intensity gradient, with limited internal dispersion. Cluster 4 shows a broader silhouette distribution, including several values close to zero, reflecting intermediate structural positions within the multidimensional space. Cluster 1 shows comparatively lower cohesion, consistent with its more heterogeneous configuration.



(**a**) (**b**)

Figure 2. (**a**) Silhouette distribution; (**b**) Projection of farms on the PC1-PC2 plane for the refitted fuzzy k-means solution (k = 5). Note: The dashed vertical line represents the mean silhouette coefficient. Ellipses represent 90% confidence regions computed under a bivariate normal approximation in the PC1-PC2 space. Dots represent individual farms, while colors and numeric labels identify the five clusters.

Bootstrap resampling further supports the robustness of the five-cluster configuration. Mean Jaccard similarity equals 1.00 for Clusters 2 and 3, 0.86 for Cluster 5 and 0.70 for Cluster 4, while Cluster 1 records 0.60. According to conventional thresholds, three clusters are classified as stable, one as acceptable and one as comparatively less stable. At the farm level, 28.6 percent of observations are core members and 71.4 percent are borderline (Figure 3). Within a fuzzy framework, this distribution reflects gradual structural transitions and the presence of shared structural characteristics across adjacent groups, rather than statistical instability.

The comparison between noRefit and Refit partitions across the 77 common farms yields an Adjusted Rand Index equal to 0.518. This level of agreement indicates that more than half of pairwise farm relationships are preserved across specifications, while the remaining reassignments reflect structural reorganization induced by robust trimming. The moderate ARI should therefore be interpreted as evidence that the refitting stage meaningfully reshapes cluster boundaries without generating instability.

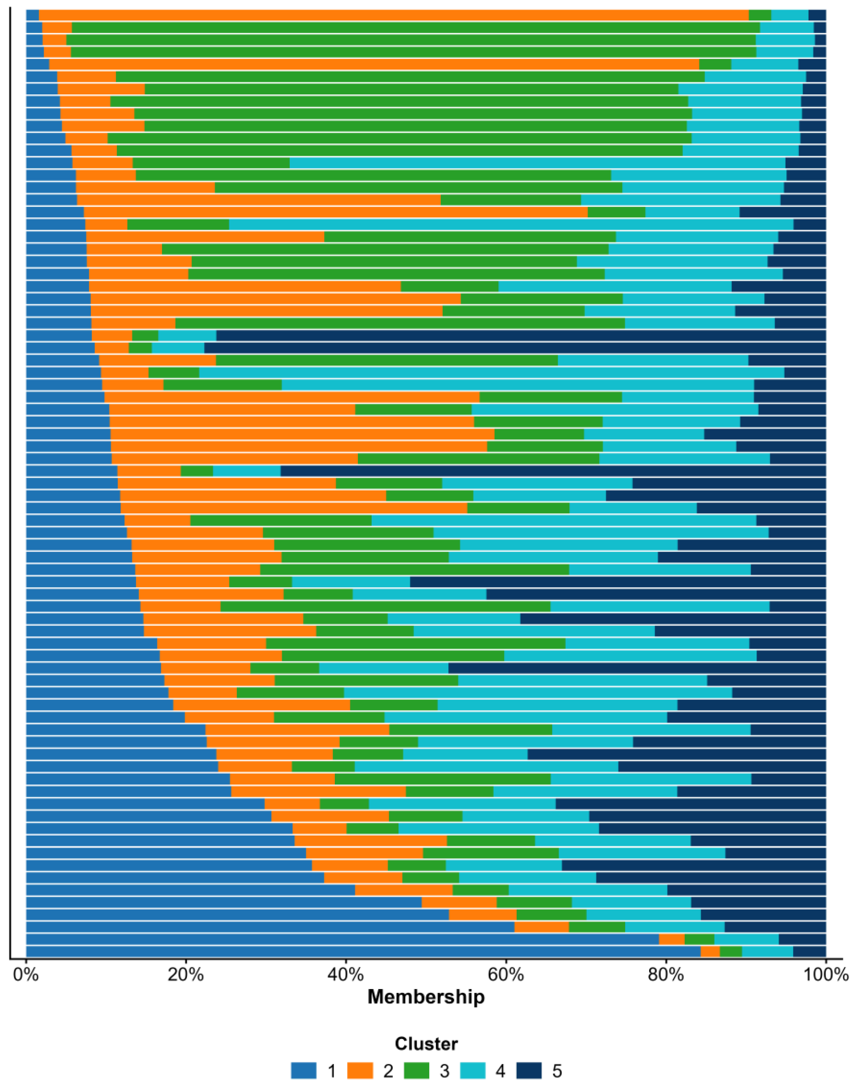


Figure 3. Distribution of fuzzy membership degrees across farms in the refitted k = 5 solution.

The fuzzy algorithm operates on a redefined distance structure in which influential observations no longer distort local density patterns, resulting in a partition that is internally more coherent according to both validity indices and resampling diagnostics.

The emergence of k = 5 as the preferred solution is closely linked to the refitting procedure. In the noRefit configuration, the presence of 19 multivariate influential farms affected the geometry of the PCA space by stretching distances along specific directions. Such distortions may generate masking effects, whereby structurally distinct but numerically limited configurations are absorbed into broader clusters. The robust MCD-based trimming stabilizes the covariance structure underlying Mahalanobis distance and redefines the relative positioning of farms in the reduced space. By rebalancing inter-farm distances, the refitted geometry allows the identification of a fifth structurally coherent cluster that was partially compressed under the full-sample specification. Within this stabilized configuration, positioning along PC1 and PC2 remains consistent with the economic gradients discussed in Section 3.2, confirming that the additional cluster reflects substantive structural differentiation rather than statistical artifact.

3.4. Economic Characterization of Clusters

The economic characterization of the five clusters is based on cluster-specific mean values of structural and performance variables in the refitted sample (Table 7). The k = 5 solution identifies groups of 13, 15, 22, 18 and 9 farms, respectively, for a total of 77 farms. Comparison with the sample means allows a consistent interpretation of relative positioning along the economic intensity, cost structure and stability dimensions. The differentiation is not reducible to farm size alone, as scale, specialization, labor intensity and margin variability load on distinct components and interact differently across clusters.

Table 7. Economic and structural characteristics of the five clusters in the refitted sample (mean values by cluster).

Cluster	n	GM_ha (€/ha)	GO_ha (€/ha)	VC_ha (€/ha)	GM_cv	CH_area (ha)	Yield (q/ha)	CSR	AgePlant (Years)	Lh_ha (hours/ha)	Mh_ha (hours/ha)
1	13	3758	4194	436.67	0.33	1.98	25.28	0.26	37.38	318.13	65.97
2	15	3102	4032	929.90	0.63	3.04	23.17	0.05	17.38	44.96	14.54
3	22	1168	1286	117.91	0.32	3.53	6.52	0.05	44.45	82.79	20.80
4	18	3440	3665	225.36	0.35	4.09	18.91	0.13	43.39	143.95	26.65
5	9	6251	6733	481.71	0.21	5.38	47.84	0.18	32.59	217.31	31.29
Sample	77	3544	3982	438.31	0.37	3.60	24.34	0.13	35.04	161.43	31.85

Notes: GM_ha = gross margin per hectare; GO_ha = gross output per hectare; VC_ha = variable costs per hectare; GM_cv = coefficient of variation of gross margin; CH_area = chestnut area; Yield = chestnut yield per hectare; CSR = chestnut specialization ratio; AgePlant = orchard age; Lh_ha = total human labor per hectare; Mh_ha = machinery use per hectare.

Cluster 1 "Intensive Specialized High-Margin Farms" combines above-average economic intensity with strong production specialization. GO_ha is 4194 €/ha, exceeding the sample mean of 3982 €/ha, and GM_ha is 3758 €/ha, also above the overall average of 3544 €/ha. The distinctive feature is specialization, with CSR equal to 0.26 compared with 0.13 in the full sample. Labor input and machine use are particularly high, with Lh_ha and Mh_ha equal to 318.13 and 65.97 h per hectare, respectively, approximately twice the sample averages. Margin variability, measured by GM_cv, is moderate at 0.33, slightly below the overall mean of 0.37. This combination indicates systems where high performance is supported by organizational intensity and specialization rather than by expansion of physical scale, since CH_area is 1.98 ha, below the sample mean. Overall, this cluster represents economically intensive and structurally specialized farms capable of translating labor engagement into stable margins.

Cluster 2 "Cost-Pressured and Volatile Commercial Farms" displays output levels close to the sample mean, with GO_ha equal to 4032 €/ha, yet its structural vulnerability emerges from cost and volatility indicators. VC_ha reaches 929.90 €/ha, more than twice the sample average of 438.31 €/ha, and GM_cv is highest at 0.63 among all clusters. Despite moderate gross margins of 3102 €/ha, high cost exposure compresses profitability relative to output levels. Orchard age is 17.38 years, well below the sample mean of 35.04, suggesting less consolidated production systems. Specialization is minimal, with CSR equal to 0.05. These farms remain commercially active but their economic performance appears particularly sensitive to cost fluctuations and market conditions, justifying the interpretation as cost-pressured and volatile commercial farms.

Cluster 3 "Low-Intensity Aging Systems" represents the lowest intensity profile. GO_ha equals 1286 €/ha and GM_ha equals 1168 €/ha, roughly one third of the sample means. Yield at 6.52 q/ha confirms limited productive intensity. However, orchard age is the highest among clusters (44.45 years), indicating mature but low-performing systems. Variable costs are low at 117.91 €/ha, consistent with limited input intensity. Margin variability is 0.32, remaining moderate and below the sample average. The organizational pattern suggests that these farms operate with aging orchards and low economic dynamism rather than acute instability. This cluster comprises farms characterized by structural maturity and limited productive renewal.

Cluster 4 "Mature and Structurally Balanced Farms" occupies an intermediate but structurally stable position. GO_ha is 3665 €/ha and GM_ha is 3440 €/ha, both close to sample averages, while VC_ha is 225.36 €/ha, substantially lower than the overall mean. Orchard age is high (43.39 years), and CH_area is 4.09 ha, exceeding the sample average, indicating relatively consolidated scale. Margin variability is 0.35, close to the overall value. Compared with Cluster 3, these farms combine maturity with significantly higher productivity and margin levels. Compared with Cluster 1, they operate with lower specialization and labor intensity but maintain balanced cost structures. Taken together, these characteristics suggest mature and structurally balanced commercial farms.

Cluster 5 "High-Performance Large-Scale Stable Systems" stands out clearly along all performance indicators. GO_ha reaches 6733 €/ha and GM_ha reaches 6251 €/ha, both far exceeding the sample means and reaching approximately twice the levels observed in most other clusters. Yield equals 47.84 q/ha, nearly twice the overall average of 24.34 q/ha. Structural scale is also the highest, with CH_area equal to 5.38 ha. Despite elevated output and margin levels, GM_cv is 0.21, the lowest among clusters, indicating superior stability. Labor input remains high at 217.31 h per hectare. This configuration reflects economically dynamic and relatively large-scale systems that combine high productivity with low volatility. It represents the group with the strongest combination of productivity, scale and margin stability within the analyzed population of market-oriented FSDN farms.

Overall, the five-cluster solution reveals pronounced stratification in economic intensity, cost exposure and structural maturity. Gross margins range from 1168 €/ha in Cluster 3 to 6251 €/ha in Cluster 5, while margin variability ranges from 0.21 to 0.63. The differences are not marginal but structural, reflecting distinct production strategies and organizational models within the FSDN commercial field of observation. The interpretative labels introduced here will be used consistently in the spatial differentiation and robustness sections to maintain analytical coherence.

3.5. Spatial Differentiation

The five farm profiles identified in the refitted k = 5 solution display a statistically significant territorial articulation. Fisher's exact tests with Monte Carlo simulation reject the hypothesis of independence between cluster membership and territorial location at the macro-area and regional levels, with $p = 0.0002$ in both cases. Cramer's V equals 0.545 at the macro-area level and 0.527 at the regional level, indicating a substantial association between structural configuration and territorial context rather than a marginal dependency. Territorial differentiation therefore emerges as an important dimension of variation within commercial chestnut farming. Macro-area aggregation serves descriptive purposes within the restricted regional subset and does not constitute an independent inferential geographical layer.

The adjusted standardized residuals clarify which cluster-territorial combinations drive this association (Figure 4). Cells exceeding an absolute value of 1.96 indicate statistically significant deviations from independence. At the macro-area level, Intensive Specialized High-Margin Farms (Cluster 1) and High-Performance Large-Scale Stable Systems (Cluster 5) are disproportionately represented in northern territories. In contrast, Cost-Pressured and Volatile Commercial Farms (Cluster 2) display significant positive deviations in southern macro-areas, indicating a more marked territorial concentration in those areas. At the regional level, the residual structure indicates that the observed association is driven by a limited number of cluster-region combinations.

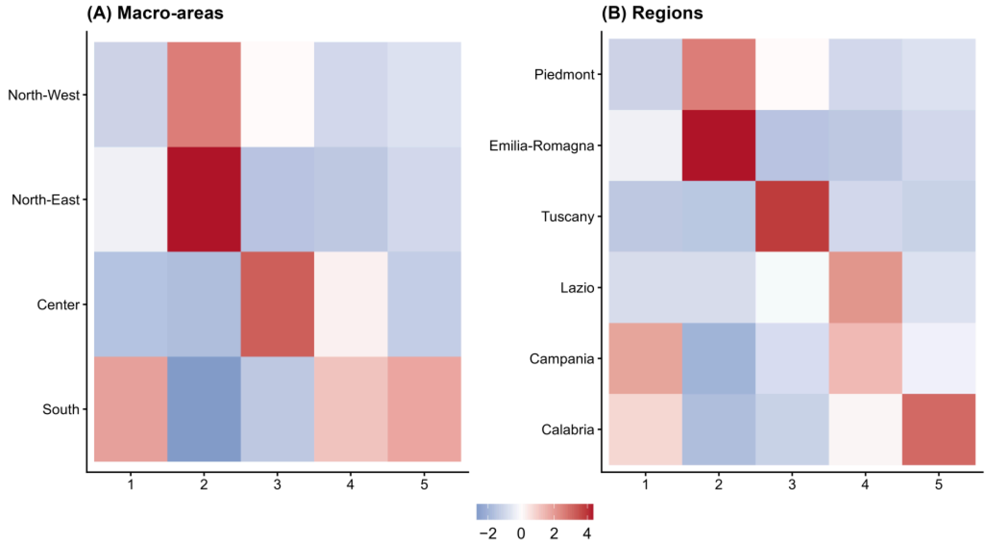


Figure 4. Adjusted standardized residuals for the association between clusters and territorial levels.

The distribution of row percentages provides a complementary descriptive representation of these patterns (Figure 5). At the macro-area level, Cluster 1 and Cluster 5 are relatively more prevalent in northern macro-areas, reflecting the stronger incidence of economically intensive configurations in these territories. Cluster 2 displays greater relative presence in southern macro-areas, consistent with higher cost exposure and volatility documented in Section 3.4. Low-Intensity Aging Systems (Cluster 3) are more frequent in central territories, while Mature and Structurally Balanced Farms (Cluster 4) appear more evenly distributed across macro-areas, suggesting structural adaptability rather than geographical concentration.

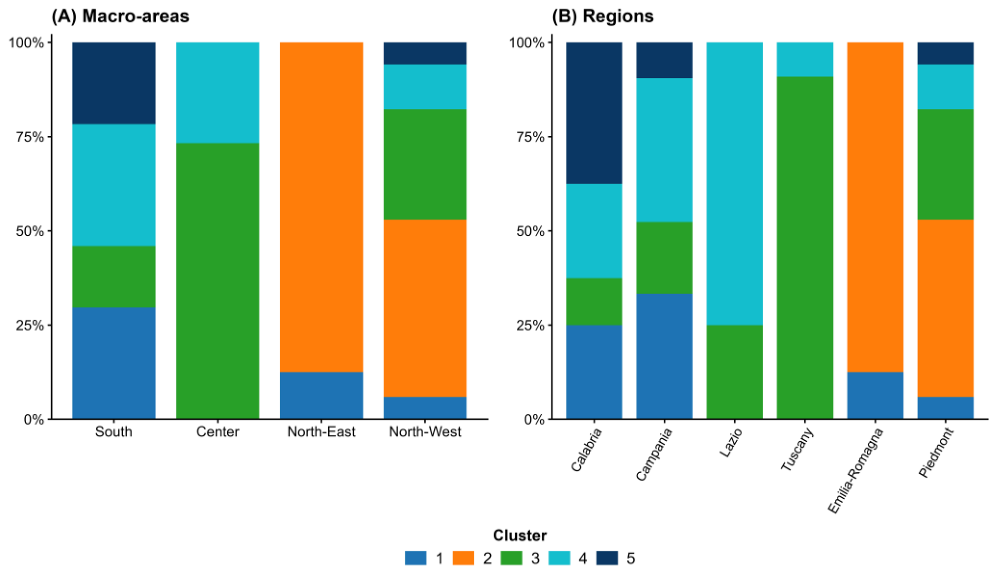


Figure 5. Territorial distribution of clusters by macro-area and region (row percentages).

At the regional scale, the territorial structure appears more clearly differentiated. Emilia-Romagna and Piedmont account for a disproportionate share of farms classified in Cluster 1 and Cluster 5, thereby consolidating the empirical association between northern regions and high-intensity, structurally consolidated configurations. In contrast, Calabria and Campania present more composite southern patterns: while Cluster 2 is more strongly represented, signaling greater cost pressure and volatility, there is also a selective presence of more intensive profiles. This combination suggests differentiated adjustment trajectories within southern regions, rather than a uniform structural model. Tuscany is more strongly associated with Cluster 3, consistent with the prevalence of aging orchards and lower productivity levels. Lazio does not display statistically dominant configurations, suggesting greater internal heterogeneity across structural types.

It should be emphasized that the analysis is confined to the six chestnut-specialized regions included in the empirical sample. Within this perimeter, the North-East macro-area is represented solely by Emilia-Romagna, while the North-West corresponds exclusively to Piedmont. Macro-area results therefore represent descriptive aggregation of selected regions rather than an independent geographical scale. Moreover, the spatial patterns refer exclusively to the FSDN field of observation, which covers commercial farms above the economic threshold. They describe the territorial articulation of the commercially structured segment of the sector and should not be interpreted as a direct representation of the overall regional structure of Italian chestnut farming. Geography influences the relative prevalence of farm profiles, but multiple production patterns coexist within each territory and no deterministic spatial specialization emerges.

3.6. Robustness and Comparison with Baseline

The robustness of the refitted k = 5 configuration was evaluated through bootstrap resampling, membership diagnostics and sensitivity analysis with respect to the fuzzifier parameter m. These procedures assess whether the identified production profiles are stable under data perturbations and changes in model specification rather than being artifacts of one specific clustering run.

Bootstrap analysis indicates differentiated but overall satisfactory stability across clusters. Mean Jaccard similarity is 1.00 for Clusters 2 and 3, 0.86 for Cluster 5, 0.70 for Cluster 4 and 0.60 for Cluster 1. According to conventional interpretation thresholds, three clusters can be classified as stable, one as acceptable and one as comparatively fragile. Importantly, even the lowest value remains above levels typically associated with random partitioning, indicating that no cluster collapses under resampling. Stability is therefore heterogeneous across clusters, but the overall partition is not structurally compromised.

At the observation level, 28.6 percent of farms are classified as core members, while 71.4 percent are borderline. In a fuzzy framework, this distribution reflects gradual transitions between structural configurations rather than classification weakness. The presence of borderline memberships is consistent with the continuous gradients identified in the PCA and with the economic heterogeneity of the commercial chestnut sector. This result suggests that partial memberships correspond to transitional structural positions rather than instability of the clustering algorithm.

Sensitivity analysis with respect to the fuzzifier parameter m further supports the stability of the five-cluster solution. Across the tested range of m values, internal validity indices and cluster composition remain substantively coherent, and no alternative k specification systematically outperforms k = 5 in composite scoring. The absence of abrupt structural shifts under moderate variation in m indicates that the identified segmentation is not driven by arbitrary tuning of the fuzziness parameter.

The comparison between noRefit and Refit partitions provides an additional robustness check. The Adjusted Rand Index was 0.518, indicating moderate agreement between the two specifications. This magnitude reflects meaningful reorganization rather than instability. The refitting procedure removes 19 multivariate influential configurations that distorted the covariance structure of the PCA space. Once these observations are excluded, inter-farm distances are recalibrated, and cluster boundaries adjust accordingly. The moderate ARI therefore reflects the correction of previously masked configurations rather than random reassignment. In this sense, the refitting stage stabilizes the covariance structure of the reduced space without increasing cluster separation, as indicated by consistent bootstrap diagnostics.

The reliability of the active-variable set was further assessed through the leave-one-variable-out sensitivity analysis described in Section 2.6. The results are reported in Table 8. Across the ten reduced specifications, ARI values comparing each leave-one-variable-out partition with the main refitted k = 5 solution ranged from 0.730 to 0.914. This indicates that the five-cluster structure was not determined by any single active variable. The largest changes occurred when Mh_ha, CSR, Lh_ha and VC_ha were removed, with values equal to 0.730, 0.731, 0.741 and 0.750, respectively. These results suggest that machinery intensity, chestnut specialization, labor intensity and variable costs are among the most influential variables in shaping the final typology. At the same time, all ARI values remained above 0.70, indicating substantial agreement with the main partition. The removal of GM_ha produced the highest ARI value, equal to 0.914, suggesting that the typology is not driven by gross margin alone. The mean silhouette values of the reduced specifications ranged from 0.178 to 0.240, a range comparable to the main k = 5 solution. Cluster-size inspection further indicated that no leave-one-variable-out specification generated a collapse of the partition structure or highly unbalanced groups. Overall, the sensitivity analysis supports the robustness of the active-variable set and indicates that the selected typology emerges from the joint contribution of economic, structural and organizational dimensions rather than from the dominance of any single indicator.

Table 8. Leave-one-variable-out sensitivity analysis for active-variable selection.

Removed Variable	Explained Variance PC1-PC5 (%)	ARI vs. Main Partition	Mean Silhouette	Cluster Sizes
Mh_ha	86.59	0.730	0.217	14, 16, 10, 22, 15
CSR	85.66	0.731	0.208	22, 13, 9, 15, 18
Lh_ha	86.22	0.741	0.216	13, 22, 14, 17, 11
VC_ha	87.52	0.750	0.240	14, 14, 18, 21, 10
GM_cv	88.32	0.787	0.232	17, 12, 23, 10, 15
Yield	86.60	0.799	0.178	17, 22, 14, 10, 14
AgePlant	87.56	0.803	0.197	23, 12, 15, 11, 16
GO_ha	82.75	0.841	0.209	13, 16, 20, 18, 10
CH_area	88.01	0.867	0.213	22, 16, 11, 15, 13
GM_ha	83.27	0.914	0.184	17, 11, 13, 15, 21

Note: Each row reports the results obtained after removing one active variable from the refitted sample of 77 inlier farms. In each run, PCA was re-estimated on the remaining nine standardized variables and fuzzy k-means clustering was repeated with k = 5 and m = 2 using the first five principal components. ARI = Adjusted Rand Index comparing the leave-one-variable-out hard partition with the main refitted k = 5 partition. Cluster sizes refer to the five clusters obtained in each reduced specification and are reported only to assess balance in the resulting partitions.

As an additional benchmark, probabilistic mixture models were estimated to assess whether model-based clustering would yield substantively different partitions. While mixture models rely on parametric distributional assumptions and impose elliptical cluster shapes, the resulting segmentation is broadly consistent with the five-profile structure identified through fuzzy k-means. Differences in membership probabilities remain concentrated among transitional observations rather than redefining core structural groups. This comparison indicates that the refitted fuzzy partition captures economically meaningful heterogeneity while avoiding reliance on restrictive parametric assumptions.

Taken together, the robustness checks show that the five-cluster refitted specification remains stable under resampling procedures, displays only moderate sensitivity to borderline units, and does not exhibit structural fragility. Moreover, its internal coherence is supported by comparison with alternative modeling approaches. The segmentation therefore provides a defensible empirical basis for the economic and territorial interpretation developed in Sections 3.4 and 3.5.

3.7. Synthesis and Implications

The refitted k = 5 configuration reveals a structurally differentiated commercial segment characterized by heterogeneous production intensities, cost structures and degrees of structural maturity. The segmentation is not driven by marginal statistical variation but reflects economically meaningful gradients captured in the PCA and validated through robustness diagnostics. The coexistence of Intensive Specialized High-Margin Farms (Cluster 1), High-Performance Large-Scale Stable Systems (Cluster 5), Cost-Pressured and Volatile Commercial Farms (Cluster 2), Low-Intensity Aging Systems (Cluster 3) and Mature and Structurally Balanced Farms (Cluster 4) indicates that the commercial segment of Italian chestnut farming operates along multiple strategic trajectories rather than converging toward a single dominant model.

This interpretation is consistent with qualitative evidence from recent stakeholder-based analyses of the Italian chestnut sector, which likewise point to the coexistence of heterogeneous production models and differentiated structural constraints across territorial contexts [34].

The clustering framework aims to uncover structurally coherent configurations within the commercial segment, providing a typological representation of heterogeneity rather than a causal model of farm behavior. In this perspective, the main contribution of the segmentation is to make explicit a set of non-trivial trade-offs that remain partially hidden under single-indicator readings. First, economic intensity and margin stability are related but not collinear. The contrast between High-Performance Large-Scale Stable Systems and Cost-Pressured and Volatile Commercial Farms illustrates that high output levels can coexist either with low volatility or with pronounced exposure to cost dynamics and margin dispersion. Second, specialization is not equivalent to performance leadership. Intensive Specialized High-Margin Farms combine strong margins and specialization with high labor commitment and relatively limited scale, whereas other configurations achieve superior performance through distinct combinations of scale, yield and organizational intensity. Third, structural maturity does not map mechanically into economic stagnation. The coexistence of Low-Intensity Aging Systems and Mature and Structurally Balanced Farms indicates that orchard age and long-term investment cycles interact with cost containment and labor organization in shaping outcomes.

These trade-offs have direct relevance for the interpretation of policy leverage. The differentiated structural profiles identified in the typology also imply differentiated exposure to policy constraints and heterogeneous capacity to absorb support measures. This aspect is particularly relevant in the context of the CAP Strategic Plan 2023–2027 [22,35], where investment support, risk-management instruments, innovation measures and territorial interventions are expected to interact with structurally heterogeneous farming systems rather than with a homogeneous sectoral population.

From a policy perspective, the five configurations imply differentiated intervention priorities rather than uniform sector-wide support measures. The results suggest that the effectiveness of CAP and national sectoral instruments depends on the structural position of farms within the multidimensional configuration space.

Cluster 2 should be considered the primary target for risk-management and resilience-oriented measures. The combination of high variable costs and strong margin volatility indicates structural exposure to economic shocks. In this configuration, CAP instruments related to income stabilization, mutual funds, insurance schemes and collective input procurement are likely to generate greater effects than generic investment support alone. Cluster 3 presents a different challenge linked to structural inertia and limited productive renewal. In these systems, orchard renovation and generational renewal measures should be selectively targeted only where minimum economic and organizational viability conditions are present. In structurally marginal contexts, ecosystem service payments and maintenance-oriented support may be more realistic than intensive modernization strategies. Cluster 5 represents the segment with the highest capacity to absorb innovation and market-oriented support. These farms appear particularly suitable for export promotion policies, value-chain integration, quality certification schemes and advanced technological upgrading, given their combination of high productivity, scale and margin stability. Cluster 1 is instead characterized by strong labor dependence and organizational intensity. In this case, policy effectiveness is likely to depend on labor-saving innovation, mechanization adapted to mountain systems and producer cooperation aimed at reducing organizational pressure while preserving specialization advantages. Finally, Cluster 4 appears relatively resilient but potentially exposed to medium-term stagnation risks. For this configuration, selective modernization and incremental innovation measures may be more appropriate than radical restructuring interventions.

Taken together, these results suggest that policy targeting based exclusively on territorial location or farm size may overlook substantial structural heterogeneity within the commercial chestnut sector. The proposed typology therefore offers an operational framework for aligning CAP Strategic Plan measures and the National Chestnut Sector Plan with differentiated structural conditions observed at farm level.

4. Discussion

The results indicate that the Italian commercial chestnut sector exhibits marked multidimensional heterogeneity rather than a single dominant production model. This type of differentiation is not specific to chestnut farming. Similar patterns have been observed in other Mediterranean perennial crops, where farms often differ in scale, labor organization, market orientation and capacity to renew long-term investments. In these sectors, production models rarely appear as clearly separated categories, since intensive farms, more vulnerable holdings and intermediate multifunctional systems often coexist within the same productive context. Similar coexistence between intensive commercial farms, structurally vulnerable holdings and multifunctional intermediate systems has been well documented in olive-growing, viticulture and other Mediterranean tree crop sectors [36,37].

The five-cluster solution identified in the refitted specification shows that economic performance depends on the interaction among production intensity, cost exposure, labor organization, orchard maturity and specialization. The identified typology should therefore be interpreted as an empirical representation of farm diversity within the FSDN field of observation rather than as a deterministic classification of the national chestnut sector. More broadly, the results suggest that commercial chestnut farming evolves through differentiated development trajectories rather than through a linear modernization pathway.

Compared with previous studies on the chestnut sector, which have mainly focused on production trends [1–3], phytosanitary crises [8,9,16,17], market organization and territorial development [11,12,18], the present analysis highlights the importance of farm-level diversity. In relation to existing farm typology studies based on multivariate classification approaches [20,25,26], the results are consistent with the use of PCA and clustering for representing farm heterogeneity, but also show that the commercial chestnut segment has a specific internal structure. The PCA and clustering results indicate that heterogeneity within this segment is not explained only by productive scale, production recovery or average economic performance. Instead, the five profiles emerge from the combined contribution of economic intensity, specialization, labor and machinery organization, cost exposure, orchard maturity and margin stability. This finding adds to previous research by showing that post-crisis adjustment in Italian chestnut farming has not produced a single professionalization pathway, but a set of differentiated configurations, including high-performance stable systems, cost-pressured volatile farms, mature balanced farms and low-intensity aging systems.

A first important result concerns the relationship between economic intensity and resilience. The comparison between High-Performance Large-Scale Stable Systems (Cluster 5) and Cost-Pressured and Volatile Commercial Farms (Cluster 2) shows that higher output levels do not systematically correspond to lower income volatility. While both groups display relatively strong market orientation, Cluster 2 combines output levels close to the sample average with the highest cost incidence and gross margin variability. This suggests that, within part of the sector, commercial intensity is not necessarily associated with greater economic stability. In this cluster, output levels close to the sample average are accompanied by a heavier cost structure and greater gross margin variability, pointing to a form of intensity that remains vulnerable to input prices, labor requirements and market shocks.

This result is also relevant in relation to the recent debate on agricultural resilience [38,39], where productivity and resilience are increasingly treated as distinct dimensions. In the present analysis, this distinction is visible in the contrast between the two commercially oriented profiles: both are market-oriented, but only one combines this orientation with lower economic volatility. The other profile illustrates how strong output performance can coexist with greater exposure to costs and external shocks.

A second important result concerns the role of orchard maturity. The findings do not support a linear interpretation of orchard age as a proxy for economic stagnation. Mature and Structurally Balanced Farms (Cluster 4) and Low-Intensity Aging Systems (Cluster 3) are both characterized by relatively old orchards, yet they differ substantially in terms of productivity, cost configuration and margin performance. Orchard maturity appears to interact with labor organization, productive renewal and cost containment rather than exerting a uniform effect on economic outcomes. In perennial systems such as chestnut cultivation, long investment cycles and limited reversibility of orchard renewal likely reinforce these differentiated trajectories.

Labor organization emerged as another important dimension of differentiation. In Intensive Specialized High-Margin Farms (Cluster 1), high gross margins are associated with strong labor engagement rather than large physical scale alone. This suggests that professional chestnut farming in Italy often relies on organizational capacity and specialized labor allocation rather than exclusively on scale expansion. This aspect is particularly important in Mediterranean perennial crops, where harvesting, orchard maintenance and quality-oriented practices still depend heavily on labor.

The result can also be read in relation to the literature on diversification and multi-functionality [40–42]. In Mediterranean farming, specialization and diversification often coexist, rather than appearing as alternative or sequential strategies. In perennial systems, competitiveness may arise not only from scale expansion, but also from organizational adaptation, labor allocation and integration with territorial value chains. The coexistence of highly specialized farms and structurally diversified configurations within the commercial chestnut sector is consistent with this broader interpretation.

Spatial analysis complements this interpretation. Territorial differentiation is statistically significant but does not imply fixed geographical specialization. High-intensity profiles were relatively more frequent in northern regions, whereas more volatile configurations appeared more concentrated in southern areas. However, multiple structural profiles coexist within each territory. Geography influences the relative prevalence of farm profiles without mechanically determining farm positioning. This result is particularly relevant because it suggests that territorially uniform policy approaches may fail to capture substantial within-region heterogeneity.

From a policy perspective, the results indicate that different farm profiles are likely to respond differently to CAP instruments and sectoral policy measures. The effectiveness of public support depends not only on farm size or territorial location, but also on the interaction between productivity, cost exposure, labor organization, specialization and structural maturity. The empirical evidence presented in this study suggests that policy priorities should be aligned with the specific characteristics of farms, as the identified configurations differ markedly in terms of vulnerability, adaptive capacity and their ability to benefit from innovation and public support measures.

Cluster 2 emerges as the profile most exposed to economic instability and should therefore represent a priority target for risk-management and resilience-oriented measures. The combination of high variable costs and strong margin volatility suggests that CAP instruments linked to income stabilization, mutual funds, insurance schemes and collective input procurement may generate greater structural effects than generic investment support alone. Cluster 3 presents a different structural challenge associated with aging orchards, low productive dynamism and limited renewal capacity. In these systems, orchard renovation and generational renewal measures should be selectively targeted only where minimum economic and organizational viability conditions are present. In structurally marginal contexts, ecosystem service payments and support for the maintenance of existing orchards may be more appropriate than measures aimed at intensive modernization. Cluster 5 points to a different policy need. These farms combine high productivity, larger operational scale and lower margin variability, and therefore seem better placed to use innovation and market-oriented support, including value-chain integration, quality schemes and technological upgrading. Cluster 1 represents another distinct policy profile. These farms combine strong economic performance with very high labor intensity and strong specialization. Their main vulnerability is linked less to productive inefficiency than to labor organization and management intensity. In this case, labor-saving innovation, mechanization adapted to mountain systems and producer cooperation may be particularly relevant for sustaining competitiveness. Cluster 4 requires a more cautious reading. These farms occupy a relatively balanced position, but their older structural base may become a constraint if renewal remains limited. For this group, support measures should therefore avoid assuming either fragility or high innovation capacity, and should focus on gradual renewal, targeted innovation and maintenance of the existing productive balance.

Taken together, the results suggest that policy targeting based exclusively on territorial criteria or farm size may overlook substantial structural heterogeneity within the commercial chestnut sector. The proposed typology therefore provides an operational framework for aligning current CAP Strategic Plan measures with the diverse conditions observed at farm level, while also offering empirical insights to inform the forthcoming National Chestnut Sector Plan (Table 9).

These findings also qualify the idea of modernization in perennial Mediterranean agriculture. In the chestnut sector, commercial farms do not appear to move along a single path. Some rely mainly on scale and productivity, whereas others rely primarily on labor intensity or production balance, while another group remains more exposed to costs and income volatility. This matters especially in perennial systems, where orchard renewal is slow, investment decisions are difficult to reverse and farm strategies remain strongly linked to local production conditions, market access and territorial resources.

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Table 9. Policy implications associated with the identified farm profiles.

Cluster	Farm Profile	Main Vulnerability	Policy Priority	Possible Policy Instruments
1	Intensive specialized high-margin farms	Dependence on labor-intensive management and specialized production systems	Sustain competitiveness and innovation uptake	Investment support for technological upgrading, producer cooperation, market integration and innovation advisory services
2	Cost-pressured and volatile commercial farms	High cost exposure and income volatility	Strengthen economic resilience and reduce vulnerability to shocks	Risk-management instruments, cost-efficiency support, technical advisory services, collective input procurement
3	Low-intensity aging systems	Low productivity, aging orchards and limited renewal capacity	Facilitate structural renewal where economically viable	Orchard renovation support, targeted technical assistance and gradual modernization measures adapted to farm-specific constraints
4	Mature and structurally balanced farms	Risk of medium-term stagnation in the absence of productive renewal	Preserve productive balance while supporting selective modernization	Selective investment support, maintenance of orchard quality and innovation incentives compatible with existing farm conditions
5	High-performance large-scale stable systems	Exposure to market concentration and long-term competitive pressure	Consolidate competitive positioning and support strategic upgrading	Market development measures, support for value-chain integration, export promotion and advanced innovation investments

In this sense, the Italian chestnut sector can be read as one expression of the wider diversity observed in Mediterranean tree crop agriculture. Its internal diversity is not limited to farm size or location, but also involves cost exposure, labor use, orchard maturity and economic stability. The relevance of these results is not limited to chestnut farming, since they also add empirical evidence to the wider discussion on farm heterogeneity, resilience and differentiated adjustment paths in perennial agriculture.

To facilitate the interpretation of these findings from a policy perspective, Table 9 summarizes the main structural vulnerabilities identified for each cluster and links them to the corresponding policy priorities and possible intervention instruments. In operational terms, these recommendations are primarily addressed to national and regional authorities responsible for the CAP Strategic Plan and sectoral programming, advisory services, producer organizations and value-chain actors involved in innovation, marketing and coordination along the chestnut supply chain. Public authorities can use the typology to improve the targeting of investment, risk-management and orchard-renewal measures, while advisory services and producer organizations can support the translation of these measures into farm-specific technical and organizational strategies.

Limitations and Future Research

This study has several limitations that should be considered when interpreting the results. First, the empirical domain is restricted to the FSDN field of observation and therefore refers exclusively to commercially oriented farms above the economic threshold established by the sampling design. Consequently, the identified typology should not be considered representative of the entire population of Italian chestnut holdings, which also includes smaller and more marginal farms not covered by the survey. This limitation has direct implications for the interpretation of policy recommendations. The proposed typology is suitable for differentiating interventions within the commercial segment of the sector, but it cannot be used to define policy needs for small-scale, subsistence-oriented or primarily landscape-maintenance holdings. These farms may face different constraints, including limited market integration, lower investment capacity, greater reliance on household labor and a more pronounced role in landscape stewardship and local ecosystem service provision.

Second, the analysis is based on five-year averages, which provide a robust representation of medium-term farm characteristics but do not capture potential transitions of individual farms between different production configurations over time. The identified clusters should therefore be interpreted as prevailing farm profiles rather than fixed or permanent categories.

Third, the analytical framework focuses primarily on economic and farm-level variables, while environmental and social dimensions of sustainability are not directly incorporated. Chestnut cultivation provides a wide range of ecosystem services and plays an important role in the socio-economic fabric of many mountainous and marginal areas. Consequently, their omission limits a more comprehensive assessment of farm performance and resilience. For this reason, the results should be interpreted as an economic typology of farm profiles, rather than as a full sustainability assessment of chestnut farming systems.

Future research could address these limitations in several directions. Longitudinal analyses would make it possible to investigate whether farms move across different farm profiles and under which economic, environmental or institutional conditions such transitions occur. Moreover, the ongoing evolution of the FSDN framework offers the opportunity to integrate environmental and social indicators, making it possible to explore the relationships between economic intensity, income stability, ecological performance and ecosystem service provision.

Future studies could also extend the comparative perspective beyond the Italian case by investigating whether similar farm typologies emerge in other Mediterranean regions where chestnut cultivation is practiced. Such research would contribute to a more comprehensive understanding of resilience, structural diversity and the different development pathways that characterize Mediterranean perennial agriculture.

5. Conclusions

The analysis of Italian market-oriented chestnut farms over the period 2019–2023 identified five coherent farm profiles through a multivariate framework combining principal component analysis, robust multivariate diagnostics and fuzzy clustering. The refitted specification provides an empirically grounded typology of commercial chestnut farms included in the FSDN field of observation.

The results show that the chestnut sector is characterized by substantial multidimensional heterogeneity. Economic performance is not reducible to farm size alone, nor does higher production intensity systematically correspond to greater margin stability. Cost exposure, labor organization, specialization, and orchard maturity interact to produce distinct economic outcomes. The coexistence of high-performing stable systems, cost-pressured volatile farms, mature balanced profiles, and low-intensity aging systems confirms that the observed farm population operates along multiple strategic trajectories rather than converging toward a single dominant model.

Territorial differentiation is statistically significant but not deterministic. Regional context influences the relative prevalence of farm profiles, yet multiple configurations coexist within the same territorial setting. The results support the interpretation of geography as a conditioning factor rather than a prescriptive determinant of farm performance.

From a methodological perspective, the study also shows that robust trimming combined with fuzzy clustering improves the interpretability of farm typologies in moderately sized agricultural datasets. Robustness checks indicate that the five-cluster solution captures stable multidimensional patterns rather than a partition driven by specific model settings or influential observations. From a policy perspective, the main implication is that uniform support schemes may generate heterogeneous effects across structurally differentiated farms. The typology proposed here does not imply fixed intervention categories but provides an operational framework for interpreting how farms with different characteristics may respond differently to investment support, orchard renewal measures, risk-management instruments, and innovation-oriented policies.

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Abbreviations

The following abbreviations are used in this manuscript:

ARI	Adjusted Rand Index
CAP	Common Agricultural Policy
CH_area	Chestnut area
CSR	Chestnut Specialization Ratio
FCM	Fuzzy C-means
FKM	Fuzzy k-means
FSDN	Farm Sustainability Data Network
GM	Gross margin
GM_cv	Coefficient of variation in gross margin
GM_ha	Gross margin per hectare
GO_ha	Gross output per hectare
ISTAT	Italian National Institute of Statistics
Lh	Human labor
Lh_ha	Total human labor per hectare
MASAF	Italian Ministry of Agriculture, Food Sovereignty and Forestry
MCD	Minimum Covariance Determinant
Mh	Machinery use
Mh_ha	Machinery use per hectare
PCA	Principal Component Analysis
PC	Principal Component
VC	Variable costs
VC_ha	Variable costs per hectare

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