CLASSIFICATION OF DISTRICTS IN SERBIA BASED ON THE AGRICULTURAL PRODUCTION DEVELOPMENT INDICATORS

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A R T I C L E I N F O

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A B S T R A C T

The purpose of this paper is to analyze regional differences in agricultural production development at district level in the Republic of Serbia. For the realization of defined objectives a multivariate statistical methodology was employed, based on the combined application of hierarchical and non-hierarchical cluster analysis methods, using following four indicators: employment in agriculture, average farm size, land productivity, and agricultural gross value added per farm. The research results indicate the existence of five distinct clusters of districts, which differ significantly in production structure, resource utilization, and economic efficiency. The findings confirm pronounced regional disparities and emphasize the need for differentiated agricultural development measures. The recommendations arising from results relate to the creation of targeted institutional and financial support tailored to the specific characteristics of individual clusters. This research contributes to the enrichment of existing literature and provides a suitable analytical basis for creation of future agricultural and rural development strategy.

Introduction

Agriculture is one of the key economic sectors of the Republic of Serbia (RS) and the backbone of national economy (Government of the RS, 2022). Although the agriculture, forestry, and fisheries sector accounts for only 4.4% of gross value added (GVA) in 2023, employing around 27,552 persons in domain-specific legal entities and 53,633 registered individual farmers (SORS, 2024; 2025) within the total of 2,360,588 employed

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persons in the RS it still retains strategic importance for the country. This is particularly evident in rural areas, where it often represents the dominant economic activity, thereby contributing to their economic growth, poverty reduction, improved living conditions, and the mitigation of rural-to-urban migration (Jankowska & Hlavsa, 2025). Besides its economic role, agriculture in the RS also has an important social role, as it relies heavily on small and family farms (nearly 508,325 recorded in 2023), which form the basis of the country's agrarian structure. Furthermore, based on the well-known fact that agricultural production plays a critical role in ensuring food security by supplying essential crops and livestock to feed the country's population, as well as in providing raw materials and foundation for related industries (i.e., food processing, manufacturing of agricultural machinery, and agrochemicals), and in creating jobs and income opportunities across the value chain (Jankowska & Hlavsa, 2025), it is not surprising that agriculture is perceived as strategically important for sustainable development of the country and its regions, and, to a larger extent, for its independence and self-sufficiency (Lubova et al., 2023). However, the development potential of agriculture in the RS faces numerous constraints, including low productivity levels, fragmented land holdings, insufficient technical and technological equipment, and pronounced regional differences in the intensity and structure of production. These challenges have also been recognized in the Agriculture and Rural Development Strategy of the RS for the period 2014–2024 (MAEP, 2014), which highlights enhancing competitiveness, sustainable resource management, and reducing regional disparities as key development priorities. In parallel, the process of European integration and alignment with the Common Agricultural Policy of the European Union imposes additional requirements aimed at improving the agricultural sector's productivity and efficiency, while emphasizing the need for differentiated development measures customized to the traits of individual regions (Rađenović et al., 2022).

The spatial differences in agricultural development, along with the necessity of creating targeted and more effective development support policies, create the need for analytical (mainly multivariate statistical) approaches that enable a deeper understanding of internal disparities and the grouping of territories according to their agricultural characteristics. In other words, the existence of regional disparities in agricultural structures and performance raises important questions not only for policymakers but also for researchers (Fanelli, 2019). Consequently, the relevant literature includes numerous studies analyzing various issues related to agricultural development across different level territorial units, defined by the Nomenclature of Territorial Units for Statistics (NUTS), within specific country or group of countries, such as: Fanelli (2019) analyzes the agricultural features of 228 NUTS 2 level areas across 28 EU countries; Némethová & Civáň (2017) examine regional differences in Slovakia, using selected agricultural production indicators at 79 districts (LAU I level territories); Harizanova-Metodieva (2024) develops a classification of 28 districts (NUTS 3 level territories) in Bulgaria based on the livestock sector development indicators; and Romantseva & Kolomeeva (2021) conduct a multivariate evaluation of agriculture competitiveness across 77 NUTS 2 regions in the Russian Federation.

Consequently, this paper analyzes regional agricultural production and development disparities at the NUTS 3 level territories (districts) in the RS, based on the selected agricultural production development indicators in 2023. In this context, the following objectives have been formulated: (1) a detailed and statistically valid demonstration of application possibilities of cluster analysis in the domain of regional agricultural production development researching; and (2) the creation of a statistically optimal and practically meaningful classification of districts in the RS into mutually exclusive, internally-similar and externally-dissimilar groups, based on the values of selected agricultural production development indicators. The research hypothesis is defined as follows: pronounced disparities still exist among the 25 districts in the RS, in terms of the intensity and structure of their agricultural production, measured by representative indicators.

The practical contribution of this research is reflected in providing a comprehensive snapshot of the spatial differentiation of agricultural production in terms of its structure, productivity, and intensity at the district level in the RS. The proposed categorization can offer valuable insights to policymakers in preparing future national agricultural and rural development strategies, specifically adapted to the identified agricultural characteristics of each cluster of districts. The originality of the conducted research lies in the fact that, to the best of the authors' knowledge, the applied combination of temporal-spatial data coverage, methodology used, and selected agricultural production development indicators has not been exploited in the existing literature so far. Therefore, addressing this research gap will undoubtedly contribute to the enrichment of the existing knowledge and literature, but also to the creation of a suitable analytical basis for the formulation of targeted agricultural development policies at the district level in the RS.

After the Introduction, the rest of the paper is structured as follows. A detailed elaboration of the applied methodological framework, along with a description of the selected variables, used sources and spatial–temporal coverage of data, is presented in section named *Materials and methods*. The obtained cluster analysis results are given in the next section (*Results*), followed by the interpretation and discussion of the proposed classification of districts. The final considerations, limitations of the study, and recommendations for future research, are stated in the last section.

Materials and methods

Starting from the defined research objectives and official (NUTS-based) territorial organization of the RS, secondary (latest available) data, used to calculate the values of selected four indicators of agricultural production (*Table 1*), were collected for 24 districts and Belgrade area (i.e. NUTS 3 level territories). All data were sourced from the complex publication of the Statistical Office of the RS (acronym, SORS), entitled *Municipalities and Regions in the RS* (SORS, 2024), and working document – *Regional gross domestic product* (SORS, 2025) and refer to 2023. Districts within the Autonomous Province of Kosovo and Metohija were not used as observation units, due to SORS's inability to conduct data collection in their territories since 1999.

Table 1. List of selected agricultural production development indicators

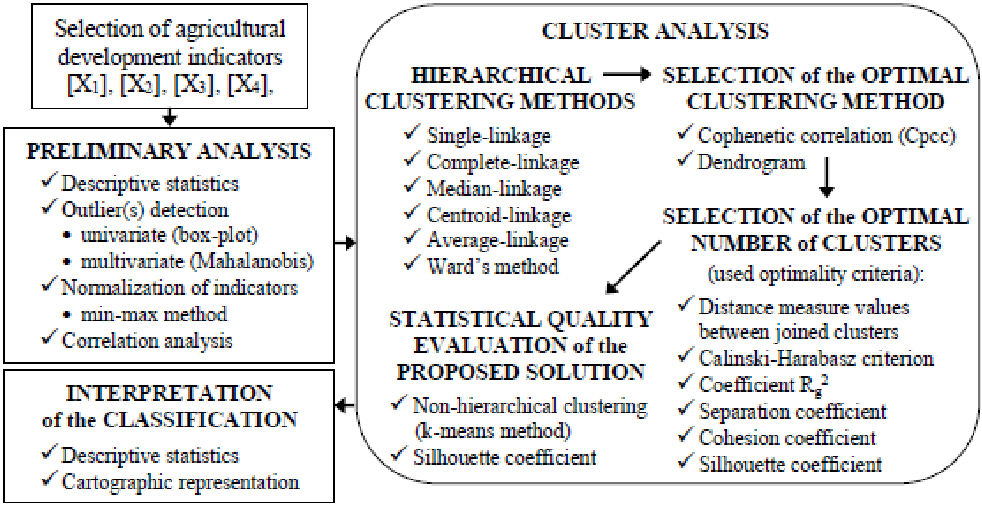
Symbol	Agricultural production development indicators	Measurement units
X_1	Employment in agriculture, forestry and fishing	% of total employment
X_2	Utilized agricultural area per agricultural farm	ha / farm
X_3	Productivity of agricultural land	thousands of RSD / ha
X_4	Agriculture, forestry & fishing, GVA per farm	millions of RSD / farm
Notes on calculating indicators' values: X_1 = (Number of employees in agriculture, forestry & fishing / Total number of employees) × 100 X_2 = (Utilized agricultural area (UAA) / Number of farms) X_3 = (Agriculture, forestry & fishing, GVA / UAA) / 1000 X_4 = (Agriculture, forestry & fishing, GVA / Number of farms)		

Source: Authors' representation

The construction of presented indicators was conditioned by the availability of data at district level in the RS and supported by the guidelines provided by the OECD (2001) and numerous authors in research studies of a similar nature. More precisely, listed as one of the most relevant indicators in the OECD comprehensive agricultural study (2001), the share of agricultural employment in overall employment has been used in research conducted by Špirkova et al. (2017), Némethová & Civáň (2017) and Fanelli (2019). Utilized agricultural area, expressed in hectares or as a percentage of a total land area, is also a frequently used indicator of agricultural production potential, in numerous studies (e.g. Soóki et al., 2024; Rakhmetova et al., 2020; OECD, 2001). On the other hand, Fanelli (2019) combined this variable with the number of farms in order to create a ratio indicator that provides information about the average farm size. His idea was applied in this research, in the form of X_2 indicator. Finally, based on its wide use in relevant literature (e.g. OECD, 2001; Apostolidou et al., 2014; Reiff et al., 2016; Špirkova et al., 2017; Rađenović et al., 2022; Lubova et al., 2023; Soóki et al., 2024), as a key indicator of the efficiency of harvesting the agricultural economic potential, gross value added (GVA) of the agricultural industry was used to calculate agricultural land and labor productivity indicators, following the approach presented by Grotkiewicz (2017), Romantseva & Kolomeeva (2021) and Bocean (2024).

A schematic representation of the methodological framework used, supplemented by detailed explanations of the applied statistical methods and their key determinations, is given in Figure 1. In the proposed methodological framework, a central analytical role is assigned to the cluster analysis (CA), as one of the most frequently used (non-parametric) multivariate statistical methods, intended and designed for simultaneous examination of interdependencies between a set of selected numerical variables. In fact, cluster analysis is a generic term used to describe a wide range of multivariate statistical procedures specifically designed to reveal "natural" structure, i.e. classification of observation units, within complex and heterogeneous data sets (Gore Jr., 2000). The common primary goal of these numerous procedures, mainly based on the principles of proximity concept, is to "divide" a given set of multivariate observations into a certain number (as a rule, a priori unknown and small) number of mutually exclusive and, to the greatest extent possible, internally–homogeneous and externally–heterogeneous, meaningful groups, so-called clusters (Stamenković, 2024).

Figure 1. Schematic representation of the applied research methodology framework



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Compared to the published studies of a similar research character and methodological approach, the application of CA in this research is distinguished by the following (threefold) methodological advantages. First, in contrast to the default application of Ward's method, primarily conditioned by the researcher's subjective assessment, the cophenetic-based approach for statistically objective evaluation of the individual clustering solutions' quality, obtained by six different CA methods and, consequently, selection of the optimal hierarchical clustering (HCA) method, was applied. Second, subjectivity in selecting the optimal number of clusters within the obtained HCA tree-classification structure was eliminated by comparing the calculated values of the entire spectrum of optimality criteria. The identification of the "optimal division" of observation units into groups was carried out on the basis of 6 different optimality criteria. Finally, since the non-hierarchical clustering procedure (Non-HCA) allows reallocation of observation units during the clustering process, a comparison and comprehensive evaluation of statistical quality of the obtained HCA and Non-HCA classifications was conducted based on the silhouette coefficient values, in order to identify the final classification of districts in the RS according to selected agricultural production development indicators (*Table 1*). Given the fact that agricultural indicators, used as CA input variables, are expressed in different measurement units, a modified *min–max* method of normalization of their original values was implemented, via the following expression (Stamenković, 2024: 24):

$$x_{ij}^{*} = 9 \times \frac{x_j - x_j^{\min}}{x_j^{\max} - x_j^{\min}} + 1 . \qquad (1)$$

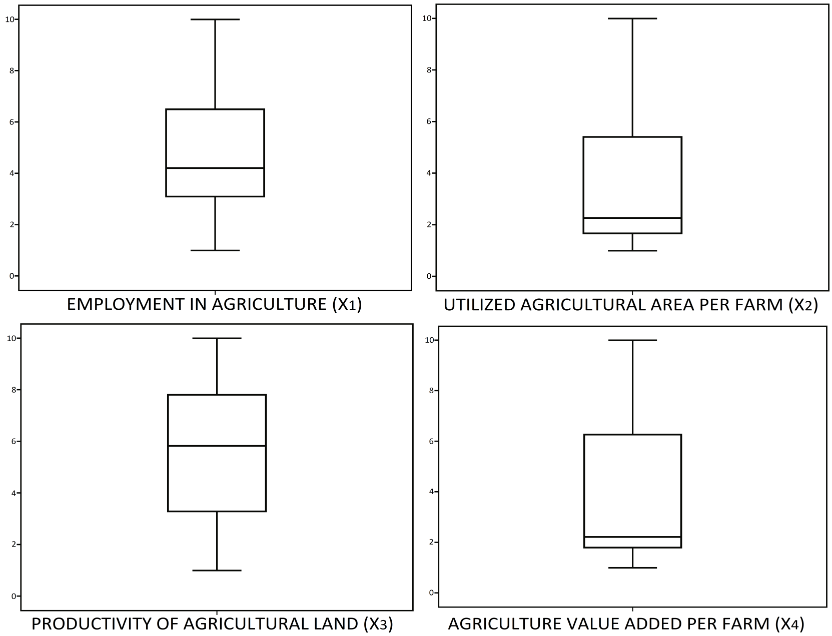
Within this expression, symbol x_{ij}^{*} denote normalized and x_{ij} original value of the j^{th} agricultural indicator for i^{th} district (for $i = 1, 2, ..., 25$, and $j = 1, 2, 3, 4$), while x_j^{max} and x_j^{min}

represent the largest and smallest original value of j^{th} indicator, respectively. The mentioned modification of the *min-max* method is reflected in the expansion of the initial range (i.e. from 0 to 1) to an interval ranging from 1 to 10, and was implemented primarily to create a more precise comparative basis. The analysis of collected data and all necessary statistical calculations were carried out using statistical software package *IBM-SPSS Statistics* version 21, and *Microsoft Office Excel*. The interpretation of the obtained research results was carried out using the adequate tabular, cartographic and graphical representations.

Results

Starting from the well-known sensitivity of CA results and distance measure used to the presence of univariate / multivariate outliers, multicollinearity, but also different measurement units of input variables, before conducting classification of 25 districts, as observation units, a preliminary analysis of four input variables was carried out. The analyzed indicators are not highly correlated, as the corresponding correlation coefficient values range from $r_{x3x4} = 0.165$ to $r_{x2x4} = 0.902$, with only one pair of variables (i.e. $X_2 \leftrightarrow X_4$) for which the value of this coefficient is greater than 0.80. Due to different measurement units in which they are expressed, the transformation of the indicators' original values to a comparable scale from 1 to 10 was carried out by the *min-max* normalization, using expression (1). Regardless of the observed differences between the arithmetic mean and median values (*Table 2*), especially present in the case of indicators X_1, X_2 and X_4, the box-plots constructed for each indicator (*Figure 2*), unequivocally confirmed the absence of one-dimensional outliers.

Figure 2. Box-plots for individual agricultural production development indicators



Source: Authors' representation

Apostrophized differences between central tendency measures, as a frequently used signal of atypical observations' presence, are evidently the result of high variability of the variables, taking into account the ranges between the minimum and maximum, but also individual values of the coefficient of variation, which are (for three out of four indicators) above 30%. In addition, by comparing the *Mahalanobis distance values* calculated for each district (ranging from 0.85 to 10.80), with the 97.5 percentile of Chi-square distribution ($\chi^2_{4;\,0.975} = 11.14$), as a threshold value, the presence of multivariate outliers was not detected.

Table 2. Descriptive statistics for agricultural production development indicators

Agricultural indicators	mean	median	min	max	coefficient of variation
X_1	5.21	4.74	0.54	12.30	56.15 %
X_2	7.10	4.87	2.76	17.77	63.76 %
X_3	103.37	107.15	61.95	146.13	22.74 %
X_4	0.71	0.48	0.28	1.75	63.71 %

Source: Authors' calculations

After the preprocessing phase, six different HCA methods were applied on the normalized values of agricultural indicators, using the squared Euclidean distance as an adequate proximity measure. In order to identify the HCA method that best fits empirical data, the cophenetic coefficient values (*Cpcc*), as a specific (but rarely used) statistical measure of the quality of individual clustering solutions, were calculated and presented in *Table 3*.

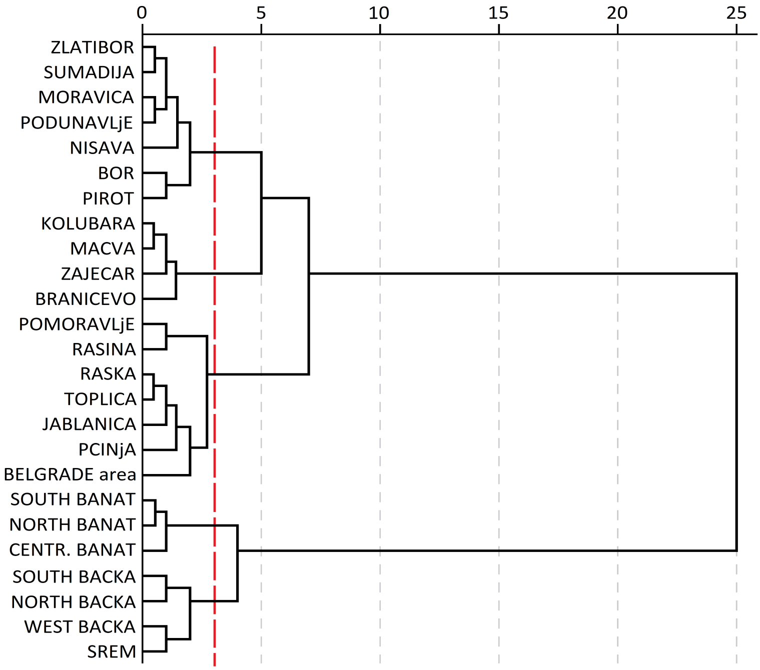
Table 3. Cophenetic correlation coefficient values for different HCA solutions

HCA methods →	Single-linkage	Complete-linkage	Median-linkage	Centroid-linkage	Average-linkage	Ward's method
***Cpcc* values**	0.785	0.779	0.821	0.838	0.852	0.853

Source: Authors' calculations

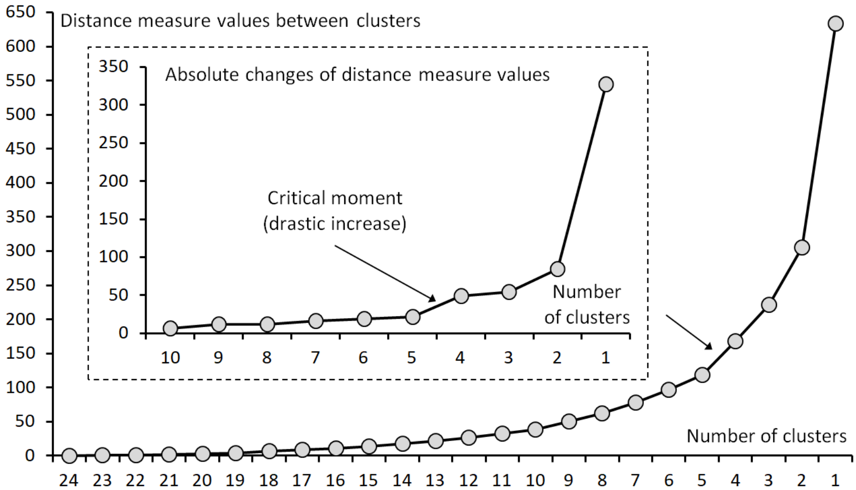
The highest *Cpcc* value (0.853), but also the most visually acceptable classification structure of the solution, singled out *Ward's method* as optimal. The complete tree-structure classification obtained as a solution to its application is given in *Figure 3*. The presented dendrogram contains 24 different clustering solutions (i.e. possible classifications), created in each step of the irreversible agglomeration process for 25 districts in the RS according to the used indicators of agricultural production. The decision regarding the selection of a specific classification solution that can be considered optimal in terms of the number of clusters within which the observed districts are allocated was made based on a thorough comparative analysis of the values of six different optimality criteria, as listed in the methodology framework. By analyzing the graphical representation in *Figure 4* and the series of optimality criteria given in *Table 4*, with a help of a trained "statistical eye", a sudden change in the values of all six criteria, which occurred at the moment of creating classification solution with four clusters, can be clearly noticed. The observed "drastic" change, occurred as a result of merging two very dissimilar (distant) clusters, unequivocally suggests the selection of a 5-cluster classification as the optimal solution, since it was created in the agglomeration step that immediately precedes it. From a graphical perspective, the moment of achieving the optimal HCA solution is marked on the dendrogram with a red dashed line.

Figure 3. Dendrogram



Source: Authors' representation

Figure 4. Changes of distance measure values between clusters for different CA solutions



Source: Authors' representation

Table 4. The optimality criteria values for different clustering solutions

Optimality criteria values	Number of clusters							
	9	**8**	**7**	**6**	**5**	**4**	**3**	**2**
Pseudo-F	23.21	22.33	21.19	21.00	21.71	19.42	20.42	24.62
Coefficient R_g^2	0.92	0.90	0.88	0.85	0.81	0.73	0.65	0.52
Separation coefficient	583.1	571.3	554.8	536.3	514.8	465.6	411.6	327.4
Cohesion coefficient	50.3	62.2	78.6	97.0	118.6	167.8	221.8	305.9
Silhouette coefficient	0.59	0.53	0.52	0.55	0.54	0.50	0.51	0.69

Source: Authors' calculations

Finally, the evaluation of statistical quality of the obtained HCA classification, but in terms of the structure of districts within the five formed clusters, was carried out based on a comparison with the Non-HCA reversible classification obtained by applying the *k-means* method for the same number of clusters. For this purpose, the silhouette coefficient values, calculated for both clustering alternatives, at the level of the overall solution as well as individual clusters, were used (*Table 5*).

Table 5. Silhouette coefficient values

Cluster codes	Number of districts		Silhouette values	
	HCA	**Non-HCA**	**HCA**	**Non-HCA**
C-1	4	3	0.403	0.537
C-2	3	4	0.899	0.675
C-3	4	3	0.475	0.684
C-4	7	9	0.488	0.516
C-5	7	6	0.417	0.542
Overall	**25**		**0.536**	**0.591**

Source: Authors' calculations

Based on the comparison of the silhouette values for the two clustering alternatives, it can be concluded that the resulting Non-HCA classification has higher quality, in terms of the structure of districts allocated within the extracted 5 clusters. The drawn conclusion is supported by the following facts: (1) higher overall silhouette value obtained for the complete Non-HCA classification (0.59); (2) due to the possibility of district reallocation during the clustering process, the Non-HCA solution contributed to an increase in the silhouette values of 4 groups and thus their internal-homogeneity and external heterogeneity, compared to the HCA alternative; and (3) negative values of the silhouette coefficient of individual districts, as indicators of their misallocation within a particular cluster, were not present in the proposed Non-HCA classification, in contrast to the HCA alternative in which 4 such cases were recorded.

Interpretation and Discussion

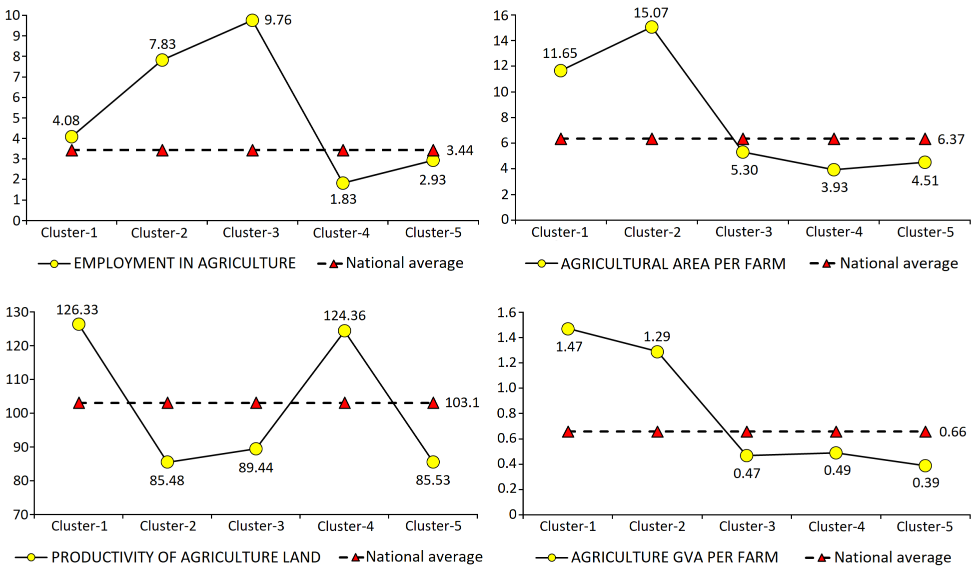
The Non-HCA results reveal pronounced district-level differences in the development of agriculture in the RS. The five identified distinct types of districts are characterized by specific combinations of the four agricultural production indicators used (*Figure 5*), reflecting diverse production structures, efficiency levels, and development potentials.

The discussion of results is enriched by additional indicators regarding the livestock fund and different types of land used (*Table 6*), which help confirm and specify the structural and development differences observed. The spatial distribution of clusters is illustrated in a cartographic representation (*Figure 6*), which provides a clear understanding of the geographical patterns of agricultural production in the RS.

Cluster C-1, labeled as "*Very high level of agricultural production development*"

This cluster, comprising three districts, represents the core of intensive agriculture in the RS. Although the average share of agricultural employment is only 4.08% of their total employment, the average farm size (11.65 ha) and productivity of agricultural land (126.33 thousand RSD/ha) are among the highest, resulting in the highest agricultural GVA per farm (1.47 million RSD), thus indicating not only productive but also economically efficient agricultural operations on their territories. It accounts for almost 20% of country's total agricultural employment, nearly one-fifth of utilized agricultural area (19.7%) and as much as 24% of arable land, indicating a strong dominance of crop farming in agricultural production. In addition to crop farming, specialized plant production is also developed → 6.7% of the country's orchards and more than 12% of vineyards are located within the districts belonging to this cluster. Livestock farming is strongly dominated by pig breeding (29% of country's pig stock) and poultry farming (18%), while a cattle breeding, with 14% of the national herd, plays a complementary role. These characteristics indicate an intensive and diversified production model characterized by strong commercial orientation, where large-scale farms and high productivity are the key drivers of competitiveness.

Figure 5. Graphical representations of agricultural indicators' averages per clusters



Source: Authors' representation

Cluster C-2, labeled as "*High level of agricultural production development*"

Although it comprises only four districts, this cluster occupies a highly significant position within the country's agricultural sector. Its relative importance derives from fact that it concentrates a disproportionately large share of agricultural employment and land resources, compared to the number of districts covered. It accounts for 19% of country's total agricultural employment, and 11.23% of agricultural farms, while encompassing as much as 26.56% of the UAA and 32.28% of arable land in the RS. The average UAA per farm is around 15.07 ha which is more than twice the national average (6.37 ha), and the highest among all clusters, indicating a strong consolidation of agricultural holdings. The substantial difference confirms the cluster's specialization in crop production, particularly cereals and industrial crops. Agricultural employment reaches 7.83% of total employment in these districts, considerably higher than in C-1, indicating that agriculture retains a stronger role in local labor markets and that diversification of economic activities is more limited. Despite its substantial land base, this cluster achieves relatively modest agricultural land productivity, below both the country's average and C-1. Nevertheless, agriculture GVA per farm reaches 1.29 million RSD, which is almost double the national average. This imbalance demonstrates that larger farm size compensates for lower land productivity, ensuring relatively high economic outcomes at the level of individual holdings while still underscoring the extensive nature of production systems. Agricultural production is predominantly land-oriented, while perennial crops play only a marginal role. The share of orchards and vineyards is the lowest among all clusters. Regarding livestock production, C-2 is characterized by highly developed poultry farming, constituting a leading area of this branch in the RS with more than ¼ of the national poultry stock.

Figure 6. Cartographic display of districts in the RS by agricultural production classification

Source: Authors' representation

Cluster C-3, labeled as "*Average level of agricultural production development*"

This cluster includes three districts, and with 9.76% of total employment engaged in agriculture, it stands markedly above the national average (3.44%) and higher than C-1 and C-2, indicating the considerable reliance of local economies on agriculture. At the same time, the average farm size remains below the national average and far smaller than in C-2 (*Figure 5*), revealing pronounced fragmentation of holdings. Land productivity also lags behind the national average, while agricultural GVA per farm is distinctly below both the national level and the leading clusters C-1 and C-2, which points to limited economic efficiency. Although it accounts for over one-fifth of national agricultural employment and 16% of farms, it uses only 13.3% of UAA and 12.9% of arable land, underscoring the imbalance between abundant labor and scarce land resources. Livestock production is a defining feature of C-3: it concentrates nearly ¼ of the national sheep stock, but also holds substantial shares of pigs (23%) and cattle (18.6%). Together, these branches form a diverse and relatively balanced livestock sector, in which mixed farming systems prevail. This cluster is an example of traditional, labor-intensive, but lower-profit agriculture.

Cluster C-4, labeled as "*Below average level of agricultural production development*"

This cluster represents a modal group, comprising 9 out of the 25 districts. Despite the small average farm size (3.93 ha), land productivity is exceptionally high due to production specialization. These districts dominate in fruit growing (46.1% of the country's orchards) and viticulture (50.6% of vineyards), confirming a clear orientation towards high value-added branches of agriculture. Nevertheless, agricultural GVA per farm remains low as a result of land fragmentation and limited scale of production. Livestock farming is well developed, with considerable shares of poultry (31.8%), cattle (29.4%) and sheep (29.1%) in the national livestock fund, which are the highest among all clusters. The average share of agricultural employment in these districts is very low (1.83%), mainly due to the inclusion of Belgrade area. However, this cluster still accounts for more than ¼ of national agriculture employment (28.1%), primarily as a result of its large territorial coverage and number of districts it encompasses. The dominance of perennial crops and livestock production points to labor-intensive systems, with limited economic efficiency due to land fragmentation.

Table 6. Additional agricultural indicators' values (as % in the country's total) per clusters

Additional indicators	Cluster codes				
	C-1	C-2	C-3	C-4	C-5
Number of employees in agriculture	19.8	19.0	20.4	28.1	12.7
Number of farms	10.8	11.2	16.0	37.6	24.4
Utilized agricultural area, UAA (ha)	19.7	26.6	13.3	23.1	17.3
Arable land and gardens (ha)	24.4	32.3	12.9	18.5	11.9
Fruit orchards (ha)	6.7	4.9	15.1	46.1	27.2
Vineyards (ha)	12.1	6.1	4.7	50.6	26.5
Cattle	14.2	17.5	18.6	29.4	20.3
Pigs	29.0	16.4	23.0	20.6	11.0
Sheep	7.5	10.7	24.7	29.1	28.0
Poultry	18.3	26.5	15.0	31.8	8.4

Source: Authors' calculations based on the data from SORS (2024)

Cluster C-5, labeled as "*Low level of agricultural production development*"

This cluster, composed of six districts, encompasses nearly ¼ of all farms in the country, yet accounts for only 12.7% of total agricultural employment. It consists of small, fragmented family agricultural farms, with an average size of 4.51 ha. Crop production is diversified, but with a more pronounced share of perennial plantations (orchards and vineyards), which account for over ¼ of national area under such crops, compared to approximately 12% of arable land. Since this cluster encompasses 41% of the national pastures, it is not surprising that sheep (28% of the national herd) and cattle farming (20.3%) constitute the dominant segment of livestock production. Despite relatively high shares in certain agricultural branches, C-5 shows low economic efficiency, as GVA per farm is the lowest among all clusters. This combination of perennial crops and livestock production reflects labor-intensive systems with relatively modest economic performance due to fragmentation and small production scale.

The analysis of the obtained five-cluster classification reveals pronounced agricultural production disparities, ranging from highly productive, market-oriented systems in clusters C-1 and C-2 to fragmented, labor-intensive, and economically less efficient production in other three, confirming the validity of formulated research hypothesis.

Conclusions

The results of the combined application of HCA and Non-HCA methods to the values of four selected agricultural production development indicators in 2023 unequivocally confirm that agriculture production at the district level in the RS is characterized by profound structural and spatial inequalities. These disparities are reflected in substantial differences in production orientation, farm size and structure, land productivity, and economic efficiency. The proposed classification, consisting of five groups, clearly reveals that districts with larger and more consolidated farms (clusters C-1 and C-2) exhibit higher levels of productivity and economic efficiency, while areas dominated by fragmented holdings and labor-intensive production systems remain at a disadvantage. These differences confirm the dual nature of agricultural production in the RS and the pronounced polarization between modernized, growth-oriented districts and those constrained by persistent structural limitations that hinder their development potential.

These findings underline the importance of formulating targeted and territorially differentiated agricultural policies that acknowledge the specific profiles of individual clusters of districts, shaped primarily by the geographical, natural, socio-economic, and other distinctive characteristics of rural areas. Instead of applying uniform measures, institutional and financial support should be specifically tailored, aimed at strengthening competitive districts while providing targeted support to less developed areas to help them overcome systemic limitations. Such an approach could contribute not only to a more effective allocation of available resources and the enhancement of competitiveness, but also to the reduction of regional inequalities in the agricultural sector and, consequently, to the development of the national economy as a whole.

Therefore, the methodological approach employed in this study may serve as a useful tool, while the obtained snapshot of spatial differentiation of agricultural production at the district level can provide valuable insights for policymakers in designing future strategy and support policies aimed at achieving balanced and sustainable agricultural development in the RS.

Some of the key limitations of this research include the absence of a time dimension in the analysis and the relatively limited possibility of direct comparability of the obtained results with previously published studies with similar objectives. Expanding the proposed analytical framework by incorporating additional statistical methods (e.g., panel data regression analysis or factor analysis) could represent an effective way to overcome the aforementioned limitations. Future research could also focus on including new agricultural input indicators and/or modifying the spatial and temporal scope of the analysis.

Conflict of interests

The authors declare no conflict of interest.

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