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Strategic approach to the territorial distribution of EAFRD projects

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Abstract
Background: The implementation of the Common Agricultural Policy of the European Union aims at a balanced territorial development and economic convergence of the rural areas. However, in some cases, EU rural funding didn't manage to reduce the gaps between regions, but quite the contrary, the wealthiest regions attracted most of the resources.
Purpose: The main objective of the paper was to assess whether EAFRD funding reached the most vulnerable areas. This is a measure of the contribution of CAP to economic convergence.
Study design/methodology/approach: Cluster analysis was performed on Galaţi County in Romania. The analysis was performed at LAU level, considering four variables: population, poverty, agricultural area and the value of implemented EAFRD projects.
Findings/conclusions: The analysis concluded five clusters, with poorer areas receiving less funding, calling for better development strategies, focused on the central, northern and north-eastern parts of the county, where these areas are concentrated. Also, territorial reorganization of rural areas may be necessary in some cases, in order to address the uneven development and poverty.
Limitations/future research: The present research focused only on EAFRD funding related to agricultural exploitations. For more precise conclusions and recommendations, further research will also need to include other EAFRD submeasures.

Keywords
EAFRD, agriculture, rural development, uneven territorial distribution, cluster analysis, rural poverty, economic convergence

Introduction

Homogeneous development of rural areas is one of the objectives of the Common Agricultural Policy of the European Union (CAP), and economic convergence represents the most important contribution to the achievement of this objective. On the other hand, the persistence and deepening of development gaps between regions, counties and localities, is one of the drawback factors and increase internal migration.

As an important part of the CAP, the Second Pillar, implemented through the European Agricultural Fund for Rural Development (EAFRD), aims at a balanced territorial development of rural economies and communities. The Second Pillar focuses on rural development and had an allocated budget of approx. 95.6 billion euros for the 2014-2020 timeframe. Its implementation contributes positively to resilience, risk prevention, climate change adaptation and economic convergence (Tijanic & Korent, 2019).

A more detailed analysis, at Local Administrative Unit (LAU) level, can reveal potential territorial differences within the same county, regarding the distribution of EU funds. Cluster analysis has proven its usefulness in identifying and contextualizing these differences, by considering other aspects as well, such as poverty, population or agricultural potential. Thus, this study aimed to analyse, considering the above variables, the territorial distribution in the absorption of EU funds for rural development, at the level of local communities in Galați County in Romania.

1. Literature review

Disparities in rural development have been observed in rural areas all over the world and economic convergence in target areas needs prioritization of underdeveloped communities (Singh & Kumar, 2022).

Previous studies highlighted important differences between countries and development regions regarding absorption of EU rural development funds, with most funding being absorbed by the most developed areas (Cárdenas Alonso & Nieto Masot, 2017; Sin, Nowak & Burlacu, 2020; Beluhova-Uzunova & Hristov, 2020; Kiryluk-Dryjska, Beba & Poczta, 2020; Dax, Machold & Roberts, 2022).

In many cases, even if Pillar II contributed to economic development of rural areas, implementation of EAFRD projects failed to achieve all of CAP's goals, most importantly economic convergence, and support the engagement of small farms in market activities in a relevant manner (Sin, 2014; Popescu, 2018; Sodano & Gorgitano, 2021). Beside an overall low absorption rate (Marin, 2019), the extremely unequal territorial distribution across the Romanian business environment (Chivu, 2019) played a part in this outcome as well.

Creating jobs in rural areas proved to be a good driver of rural development, EU funding having a positive effect on a significant number of cases (Loizou, Karelakis, Galanopoulos & Mattas, 2019; Unay-Gailhard & Bojnec, 2019; Castaño, Blanco & Martinez, 2019). Thus, some countries prioritized measures targeting non-agricultural activities, but for most cases, funding targeted the farmers, limiting the effect on reducing economic disparities, while high administrative requirements for small farmers reduced the effectiveness of the programme (Schuh, Brkanovic, Gaugitsch et al., 2021; Balodis & Pilvere, 2021; Grodzicki & Jankiewicz, 2022). Also, in some cases, the employment increased in non-agricultural industries and services at the expense of agricultural labour (Zawalińska, 2019).

The impact of EU funding on diversification towards non-agricultural activities and labour structure in rural areas proved to be questionable (Garrone, Emmers, Olper & Swinnen, 2019; Galluzzo, 2020; Lillemets, Fertő & Viira, 2022). However, in assessing that issue, local structure of rural economy needs to be taken into consideration. Funding non-agricultural activities in areas where agriculture is predominant did not generate the desired growth, but the same approached worked well where the importance of agriculture was relatively low (Hyytiä, 2014).

Cluster analysis has proven to be an effective tool in assessing the level of socio-economic development of rural areas in general and for analysing the results of CAP's implementation in particular (Popescu, Dragomir, Popescu, Horablaga & Chis, 2016; D'Urso, Manca, Waters & Girone, 2019; Shcherbak, et al., 2020; Okereke & Wojciechowska, 2022). From the scientific point of view, cluster analysis is an exploratory method based on an unsupervised classification of data into groups. The characteristics of these groups are not determined in advance, but are an expression of the natural positioning of the analysed data. The formed groups contain objects (instances) with a maximum degree of similarity between them and a maximum degree of dissimilarity to the objects belonging to the other groups. This analysis, however, focuses more on group homogeneity than on differences between groups (Hennig, Meila, Murtagh & Rocci, 2015). Cluster analysis is useful for identifying patterns, to provide insights into the underlying structure of data, and studying significant relationships between data (Rotariu, Culic, Bădescu, Mezei & Mureșan, 2006; Kim, Kim & Cho, 2020).

In partition cluster analysis, the similarity between two objects is defined by their distance, which can be measured as Euclidean distance. The partition divides the analysed objects (instances) into k groups. The most widely used method for partitioning cluster analysis is the k-means method (Lucke & Forster, 2019). The advantages of this method are the ability to process large volumes of data and the flexibility of the analysis regarding the belonging of objects to groups (Govender & Sivakumar, 2020).

2. Materials and method

The efficiency of evaluation methods for CAP implementation are still being discussed, but they should focus on evidence-based policy-making and good governance (Thoyer & Préget, 2019). The tools for analysing if the implemented policies generated the expected outcomes should be orientated more towards development actors and the people living within the target area, and less towards academics (Cagliero, Licciardo & Legnini, 2021). For this study, data expressing the potential, development state and financial aid for the target areas was used: population, relative poverty rate, available agricultural area and EAFRD spending.

K-means clustering method was used to analyse data corresponding to all LAUs in Galați County, Romania. The aim was to relevantly partition the 65 LAUs into clusters, based on four variables.

For a more accurate identification of the optimal number of clusters, three methods were used: Elbow, Silhouette and Dunn.

The Elbow method uses the sum of squares (WCSS) as a function of the number of clusters. The internal mean sum of squares is defined as the average distance between points within a cluster:

$$WCSS_k = \sum_{r=1}^{k} \frac{1}{n_r} D_r$$

where k is the number of clusters, n_r the number of points in cluster r and Dr the sum of distances between all points in cluster r. As the number of clusters increases, the score decreases. This is because the points will be closer to the centroids they are assigned to. The Elbow method aims to identify the k value, for which the score drops the fastest, before the graphic representation (the curve) reaches a plateau. Increasing the number of clusters beyond this value will not further improve the analysis and will not lead to further relevant conclusions (David & Vassilvitskii, 2007).

The Silhouette method is based on cluster quality analysis. This is measured by calculating the degree of objects' membership to the clusters that contain them. A high value of the Silhouette index indicates good agglomeration. Thus, the optimal number of clusters (k) is the one that maximizes the indicator over a range of possible values for k (Kaufman & Rousseeuw, 2005).

The global Silhouette index is defined as:

$$S = \frac{1}{n} \sum_{i=1}^{n} S_i$$

Where Si represents the Silhouette index of one point:

$$s(i) = \frac{b(i) - a(i)}{\max(a(i), b(i))}$$

Whereas a(i) is the average distance between point i and all other points belonging to the same cluster and b(i) is the average distance between point i and all other points belonging to the nearest cluster.

The "Dunn" method aims to identify clustering solutions that provide compact and well-separated clusters. Clusters must be far enough apart but with little variation between points belonging to the same cluster. The Dunn index is defined by:

$$DI_m = \frac{\min\limits_{1 \le i < j \le m} \delta(C_i, C_j)}{\max\limits_{1 \le k \le m} \Delta_k}$$

where δ(Ci,Cj) is the distance between clusters i and j (measured as the distance between their closest points), Δk is the distance within the cluster (measured as the distance between the most distant points within the cluster) and m is the number of clusters. The higher the Dunn index value, the better the clustering, so the number of clusters that maximize the Dunn index is considered as the optimal number of clusters (Dunn, 1974).

The k-means algorithm uses a list of d-dimensional points as input values, performing data grouping in order to minimize the objective function, considering the Euclidean distance in d-dimensional space and being defined as:

$$J(X, S) = \sum_{k=1}^{K} \sum_{x \in S_k} dist(x, m_k)$$

The centres are first randomly initiated and are subject to change, with new centres being assigned, until the membership function doesn't change anymore (Aggarwal & Reddy, 2013).

2. Research and results

Collected data for all 65 LAUs in Galați County was analysed by k-means clustering. Analysed data referred to four variables: total population by residence (A), relative poverty rate (B), agricultural area per population (C) and total value of implemented EU agricultural projects per population (D), as represented in Table 1.

Table 1 Analysed dataset for Galați county, Romania

#	LAU	A	B	C	D
1	GALAȚI	306.617	8.9	0.04	20
2	ȘENDRENI	5.215	14.5	0.75	0
3	VÂNĂTORI	6.445	23.1	0.59	246
4	TECUCI	45.917	10.1	0.16	82
5	DRĂGĂNEȘTI	6.694	46.9	0.80	109
6	MUNTENI	7.641	30.6	1.09	724
7	BEREȘTI	3.131	63.4	1.00	99
8	BEREȘTI-MERIA	3.480	47.9	2.39	29
9	TÂRGU BUJOR	7.171	23.5	0.91	185
10	BARCEA	6.470	29.3	0.76	110
11	BĂLĂBĂNEȘTI	1.928	55.5	2.06	194
12	BĂLĂȘEȘTI	2.205	61.5	2.38	0
13	BĂLENI	2.245	48.2	2.77	18
14	BĂNEASA	2.050	63.9	2.65	51
15	BRANIȘTEA	4.386	47.2	1.12	133
16	BRĂHĂȘEȘTI	10.074	41.4	0.30	12
17	BUCIUMENI	2.429	51.0	1.11	6
18	CAVADINEȘTI	2.845	58.8	3.09	47
19	CERȚEȘTI	2.311	37.8	2.37	35
20	COROD	7.459	47.3	1.30	166
21	CORNI	2.109	67.0	2.35	109
22	COSMEȘTI	6,568	44.8	0.46	120
23	COSTACHE NEGRI	2,716	45.5	0.95	139
24	CUCA	2.085	41.1	1.79	7
25	CUDALBI	7.346	60.8	1.87	60
26	DRĂGUȘENI	5.682	41.8	1.06	8
27	FÂRȚĂNEȘTI	5.048	24.4	1.38	20
28	FOLTEȘTI	3.162	50.1	1.83	441
29	FRUMUȘIȚA	5.378	24.2	1.77	131
30	FUNDENI	3.765	39.0	0.85	20
31	GHIDIGENI	6.924	24.4	0.78	311
32	GOHOR	3.245	43.8	1.33	173
33	GRIVIȚA	3.730	62.6	1.01	83
34	INDEPENDENȚA	4.614	31.8	1.20	0
35	IVEȘTI	10.114	19.8	0.68	21
36	JORĂȘTI	1.772	21.3	2.64	0
37	LIEȘTI	10.856	46.3	0.67	34
38	MATCA	12.300	28.7	0.65	680
39	MĂSTĂCANI	4.683	55.5	1.10	78
40	MOVILENI	3.358	40.0	0.63	78
41	NĂMOLOASA	2.038	21.0	2.87	257
42	NICOREȘTI	3.997	22.6	1.22	132
43	OANCEA	1.667	56.2	2.60	0
44	PECHEA	11.092	24.6	0.97	31
45	PISCU	4.747	31.4	1.06	126
46	PRIPONEȘTI	2.097	39.9	2.33	14
47	REDIU	2.016	36.5	1.71	763
48	SCÂNTEIEȘTI	2.392	40.6	1.79	170
49	SCHELA	3.839	49.8	1.06	230
50	SLOBOZIA CONACHI	4.163	64.0	1.36	0
51	SMÂRDAN	5.849	26.9	2.29	3
52	SMULȚI	1.370	38.0	3.54	47
53	SUCEVENI	1.607	45.9	3.21	19
54	TUDOR VLADIMIRESCU	5.068	20.1	0.86	8
55	TULUCEȘTI	7.578	61.6	0.78	2
56	ȚEPU	2.372	43.8	1.29	344
57	UMBRĂREȘTI	7.057	28.5	0.80	299
58	VALEA MĂRULUI	3.593	44.1	1.35	155
59	VÂRLEZI	1.971	60.3	3.97	264
60	VLĂDEȘTI	2.561	41.9	1.85	81
61	RĂDEȘTI	1.447	37.1	1.95	0
62	NEGRILEȘTI	2.583	43.3	1.40	416
63	POIANA	1.726	58.8	1.09	0
64	CUZA VODĂ	2.681	29.9	0.74	72

Source: own calculations, based on INS, INCE and AFIR data

For three of the variables, calculations were made based on the latest available data: population by residence on 01.07.2020 and available agricultural area, both sourced from the Romanian National Institute of Statistics (INS, 2022), and total value of implemented EU rural development projects on 27.06.2022, sourced from the Agency for Financing Rural Investments (AFIR, 2022).

Total value of implemented EU agricultural projects referred to all EAFRD projects implemented for agricultural exploitations, in all agricultural areas: cultivation of cereals, legumes and oilseeds plants, vegetables, melons, grapes and fruit trees and bushes, as well as pigs, cattle, sheep, goats, birds and other animals farming (EAFRD submeasures 4.1, 4.1A, 6.1, and 6.3)

One of the objectives of the research was to find out if rural funding was properly directed to where it was needed the most, i.e. poorer areas. Thus, when including the variable referring to the relative poverty rate, the situation at the beginning of the implementation of the 2014-2020 CAP was considered most relevant, more specifically data corresponding to the year 2016, when actual financing the 2014-2020 EAFRD projects began. Data was sourced from the results of SIPOCA4 research project (INCE, 2019).

The dataset was standardized based on the mean and standard deviation results (Table 2).

Table 2 Standardized dataset

#	LAU	z-scores			
		A	B	C	D
1	GALAȚI	7.91	-2.14	-1.70	-0.64
2	ȘENDRENI	-0.12	-1.76	-0.86	-0.76
3	VÂNĂTORI	-0.09	-1.17	-1.05	0.71
4	TECUCI	0.96	-2.06	-1.56	-0.27
5	DRĂGĂNEȘTI	-0.08	0.45	-0.80	-0.11
6	MUNTENI	-0.05	-0.66	-0.46	3.56
7	BEREȘTI	-0.17	1.58	-0.57	-0.17
8	BEREȘTI-MERIA	-0.17	0.53	1.09	-0.58
9	TÂRGU BUJOR	-0.07	-1.15	-0.67	0.34
10	BARCEA	-0.09	-0.75	-0.85	-0.10
11	BĂLĂBĂNEȘTI	-0.21	1.04	0.69	0.40
12	BĂLĂȘEȘTI	-0.20	1.45	1.07	-0.76
13	BĂLENI	-0.20	0.54	1.53	-0.65
14	BĂNEASA	-0.20	1.61	1.38	-0.45
15	BRANIȘTEA	-0.14	0.47	-0.42	0.04
16	BRĂHĂȘEȘTI	0.01	0.08	-1.39	-0.68
17	BUCIUMENI	-0.19	0.74	-0.43	-0.72
18	CAVADINEȘTI	-0.18	1.27	1.92	-0.47
19	CERȚEȘTI	-0.20	-0.17	1.05	-0.55
20	COROD	-0.06	0.48	-0.21	0.23
21	CORNI	-0.20	1.83	1.03	-0.11
22	COSMEȘTI	-0.08	0.31	-1.20	-0.04
23	COSTACHE NEGRI	-0.19	0.36	-0.62	0.07
24	CUCA	-0.20	0.06	0.37	-0.71
25	CUDALBI	-0.06	1.40	0.47	-0.40
26	DRĂGUȘENI	-0.11	0.11	-0.49	-0.71
27	FÂRȚĂNEȘTI	-0.12	-1.09	-0.11	-0.64
28	FOLTEȘTI	-0.17	0.67	0.42	1.87
29	FRUMUȘIȚA	-0.11	-1.10	0.35	0.03
30	FUNDENI	-0.16	-0.09	-0.74	-0.64
31	GHIDIGENI	-0.07	-1.08	-0.82	1.09
32	GOHOR	-0.17	0.24	-0.17	0.27
33	GRIVIȚA	-0.16	1.52	-0.56	-0.26
34	INDEPENDENȚA	-0.13	-0.58	-0.33	-0.76
35	IVEȘTI	0.01	-1.40	-0.95	-0.63
36	JORĂȘTI	-0.21	-1.30	1.37	-0.76
37	LIEȘTI	0.03	0.41	-0.95	-0.55
38	MATCA	0.07	-0.79	-0.97	3.30
39	MĂSTĂCANI	-0.13	1.04	-0.45	-0.29
40	MOVILENI	-0.17	-0.02	-1.00	-0.29
41	NĂMOLOASA	-0.20	-1.31	1.65	0.78
42	NICOREȘTI	-0.15	-1.21	-0.30	0.03
43	OANCEA	-0.21	1.09	1.33	-0.76
44	PECHEA	0.04	-1.07	-0.60	-0.57
45	PISCU	-0.13	-0.60	-0.50	0.00
46	PRIPONEȘTI	-0.20	-0.02	1.01	-0.67
47	REDIU	-0.20	-0.26	0.27	3.79
48	SCÂNTEIEȘTI	-0.19	0.02	0.37	0.26
49	SCHELA	-0.16	0.65	-0.50	0.61
50	SLOBOZIA CONACHI	-0.15	1.63	-0.13	-0.76
51	SMÂRDAN	-0.10	-0.91	0.97	-0.74
52	SMULȚI	-0.22	-0.16	2.44	-0.47
53	SUCEVENI	-0.21	0.38	2.06	-0.65
54	TUDOR VLADIMIRESCU	-0.12	-1.38	-0.73	-0.71
55	TULUCEȘTI	-0.06	1.46	-0.82	-0.75
56	ȚEPU	-0.19	0.24	-0.22	1.30
57	UMBRĂREȘTI	-0.07	-0.81	-0.80	1.03
58	VALEA MĂRULUI	-0.16	0.26	-0.15	0.17
59	VÂRLEZI	-0.21	1.37	2.95	0.82
60	VLĂDEȘTI	-0.19	0.11	0.45	-0.28
61	RĂDEȘTI	-0.22	-0.21	0.56	-0.76
62	NEGRILEȘTI	-0.19	0.21	-0.09	1.72
63	POIANA	-0.21	1.27	-0.46	-0.76
64	CUZA VODĂ	-0.19	-0.71	-0.87	-0.33
65	SUHURLUI	-0.22	-0.94	-0.33	-0.50

Source: own calculations

Elbow, Silhouette and Dunn analysis were performed, in order to identify the optimal number of clusters. Data was processed using Jupyter application on Phyton platform.

Results were conclusive, as all three methods identified an optimum number of five clusters (Fig.1, Fig.2 and Fig.3). Thus, a number of five clusters were chosen for further analysis.

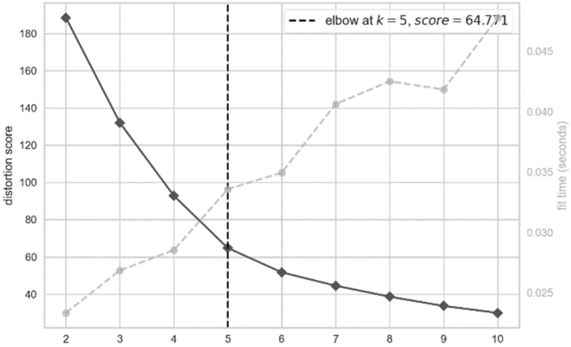

Figure 1 The Silhouette score graph results
Source: own calculations

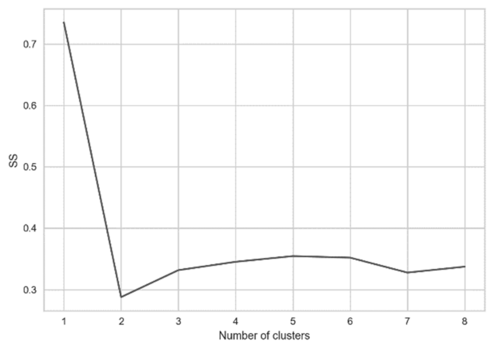

Figure 2 The Davies–Bouldin method graph results
Source: own calculations

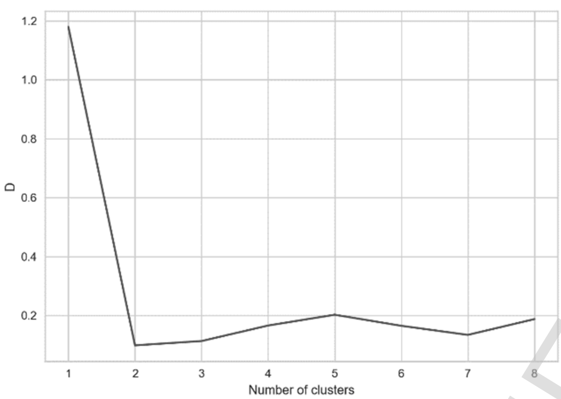

Figure 3 The Dunn method graph results
Source: own calculations

The algorithm started with five random observations and was replayed until no further improvement was possible and the best clustering solution was reached, based on the minimum total value of distances between observations and centres (Table 3).

Table 3 Clustering solution (Sol.) based on the minimum total distances

#	1	2	3	4	5	Min.	Sol.
1	79.99	84.70	68.16	73.67	0.00	0.00	5
2	9.04	20.02	1.23	5.81	65.26	1.23	3
3	9.10	8.74	1.02	3.55	67.04	1.02	3
4	15.10	18.89	3.65	9.06	48.34	3.65	3
5	3.79	14.84	3.03	0.17	71.58	0.17	4
6	21.00	0.00	12.81	13.73	84.70	0.00	2
7	4.03	19.00	7.91	1.30	80.67	1.30	4
8	0.00	21.00	5.31	2.65	79.99	0.00	1
9	6.77	10.64	0.25	2.79	66.55	0.25	3
10	5.60	13.56	0.53	1.70	66.81	0.53	3
11	1.39	14.24	6.19	1.69	82.70	1.39	1
12	0.89	25.49	9.60	3.82	86.28	0.89	1
13	0.21	23.17	6.89	4.29	83.28	0.21	1
14	1.29	24.70	11.05	4.80	89.37	1.29	1
15	2.65	13.73	2.84	0.00	73.67	0.00	4
16	6.36	19.44	3.37	1.63	67.36	1.63	4
17	2.37	20.32	4.37	0.65	75.48	0.65	4
18	1.25	25.67	11.32	6.35	90.11	1.25	1
19	0.49	19.46	3.26	2.93	77.09	0.49	1
20	2.36	12.44	2.91	0.09	73.27	0.09	4
21	1.93	21.94	11.05	3.98	89.23	1.93	1
22	5.57	14.48	3.12	0.64	70.44	0.64	4
23	3.37	13.29	2.56	0.06	73.38	0.06	4
24	0.75	19.51	2.61	1.37	74.85	0.75	1
25	1.19	20.81	7.61	1.85	80.79	1.19	1
26	2.69	18.84	2.32	0.70	70.70	0.70	4
27	4.03	17.95	0.50	2.98	68.10	0.50	3
28	6.49	5.43	7.47	4.12	83.98	4.12	4
29	3.56	13.35	0.44	3.08	70.04	0.44	3
30	3.71	18.05	1.89	0.87	70.15	0.87	4
31	9.05	6.39	1.43	3.71	68.55	1.43	3
32	2.40	11.72	2.19	0.17	74.08	0.17	4
33	3.80	19.43	7.62	1.21	79.91	1.21	4
34	3.25	18.68	1.02	1.74	68.98	1.02	3
35	7.86	18.36	0.91	4.24	63.43	0.91	3
36	3.43	22.42	3.44	6.98	76.02	3.43	1
37	4.20	18.34	3.42	0.66	69.10	0.66	4
38	21.10	0.37	11.37	12.59	79.25	0.37	2
39	2.70	17.74	5.18	0.43	76.43	0.43	4
40	4.74	15.58	2.01	0.69	70.30	0.69	4
41	5.56	12.62	4.38	8.02	79.61	4.38	3
42	5.31	12.81	0.00	2.84	68.16	0.00	3
43	0.41	24.94	8.57	4.07	85.52	0.41	1
44	5.41	17.27	0.50	2.81	64.27	0.50	3
45	4.11	12.72	0.40	1.17	68.80	0.40	3
46	0.31	20.52	3.64	2.80	77.57	0.31	1
47	20.42	0.77	15.39	15.12	92.79	0.77	2
48	1.48	12.09	2.02	0.88	75.34	0.88	4
49	3.95	10.44	3.84	0.37	75.79	0.37	4
50	2.72	24.01	8.68	2.04	81.50	2.04	4
51	2.11	20.61	2.30	4.45	72.73	2.11	1
52	2.32	24.97	8.90	8.84	87.13	2.32	1
53	0.97	25.15	8.57	6.61	86.40	0.97	1
54	6.94	18.84	0.76	4.08	65.98	0.76	3
55	4.54	23.19	8.00	1.75	77.15	1.75	4
56	5.31	6.04	3.73	1.68	77.23	1.68	4
57	7.94	6.57	1.41	2.77	68.95	1.41	3
58	2.15	12.50	2.21	0.14	73.92	0.14	4
59	6.17	23.33	17.89	12.80	101.8	6.17	1
60	0.67	16.18	2.41	0.98	75.35	0.67	1
61	0.85	19.92	2.36	2.07	74.84	0.85	1
62	6.81	4.29	4.92	3.02	79.17	3.02	4
63	2.96	22.40	6.77	1.27	79.06	1.27	4
64	5.41	15.31	0.69	1.73	68.31	0.69	3
65	4.16	16.63	0.36	2.31	69.37	0.36	3

Source: own calculations

Corresponding to the best clustering solution, the six resulting clusters included the following LAUs:

- Cluster 1: Berești-Meria, Bălăbănești, Bălășești, Băleni, Băneasa, Cavadinești, Cerțești, Corni, Cuca, Cudalbi, Jorăști, Oancea, Priponești, Rădești, Smârdan, Smulți, Suceveni, Vârlezi and Vlădești.
- Cluster 2: Munteni, Matca and Rediu.

- Cluster 3: Șendreni, Vânători, Tecuci, Târgu Bujor, Barcea, Fârțănești, Frumușița, Ghidigeni, Independența, Ivești, Nămoloasa, Nicorești, Pechea, Piscu, Tudor Vladimirescu, Umbrărești, Cuza Vodă and Suhurlui.
- Cluster 4: Drăgănești, Berești, Braniștea, Brăhășești, Buciumeni, Corod, Cosmești, Costache Negri, Drăgușeni, Foltești, Fundeni, Gohor, Grivița, Liești, Măstăcani, Movileni, Negrilești, Poiana, Scânteiești, Schela, Slobozia Conachi, Tulucești, Țepu and Valea Mărului.
- Cluster 5: Galați.

Average values for each cluster were calculated (Table 4).

Table 4 Clusters characteristics

#	No. of LAUs	A	B	C	D
Cluster 1	19	2.576	48	2.53	51.44
Cluster 2	3	7.319	32	1.15	722.44
Cluster 3	18	7.854	24	1.04	115.24
Cluster 4	24	4.591	49	1.07	125.69
Cluster 5	1	306.617	9	0.04	20.25

Source: own calculations

As it can be noticed, Galați city formed a cluster of its own. As the largest urban area in the county, it has the largest population and being so much different from all other LAUs, it stands as proof for the gap between urban and rural areas, having by far the lowest relative poverty rate, compared to the other LAUs in the county. Thus, we'll focus on comparing the other four clusters, more similar, between themselves.

The first cluster contains 19 LAUs, has low population and a low value of implemented projects. This cluster has the highest agricultural area per population, but also shares, together with the fourth cluster, the highest values of relative poverty rate.

The second cluster has a medium relative poverty rate, large population and highest value of implemented projects per population. It includes only three LAUs.

The third cluster contains 18 LAUs, has the largest population, lowest relative poverty rate and a medium value of implemented projects.

The fourth cluster has a medium to low population, highest relative poverty rate and medium value of implemented projects. This cluster is the largest, containing 24 LAUs.

The third and fourth clusters also share some of the lowest values regarding agricultural area per population.

Focusing on the areas with the highest values of relative poverty rate, clusters one and four, we can notice some differences. Even if cluster one has the largest agricultural area per population, it attracted the lowest value of EAFRD funding, less than half of the next lowest value. Cluster four performed better, attracting almost 2.5 times more funding, even with a much smaller agricultural area per population, almost 2.5 times smaller, in fact.

These two clusters, having the highest relative poverty rate and lowest populations, count for 66% of all the LAUs in the county being a cause for concern.

Cluster two is the obvious success story, attracting more than 5.5 times more funding than the next best situated cluster. As seen, the second cluster contains only three LAUs of the total of 65, making it an exception for the county.

Distribution-wise, a high concentration of clusters one and four LAUs can be noticed in the centre, North and North-East parts of the county, making those areas hotspots for high poverty incidence (Fig.4).

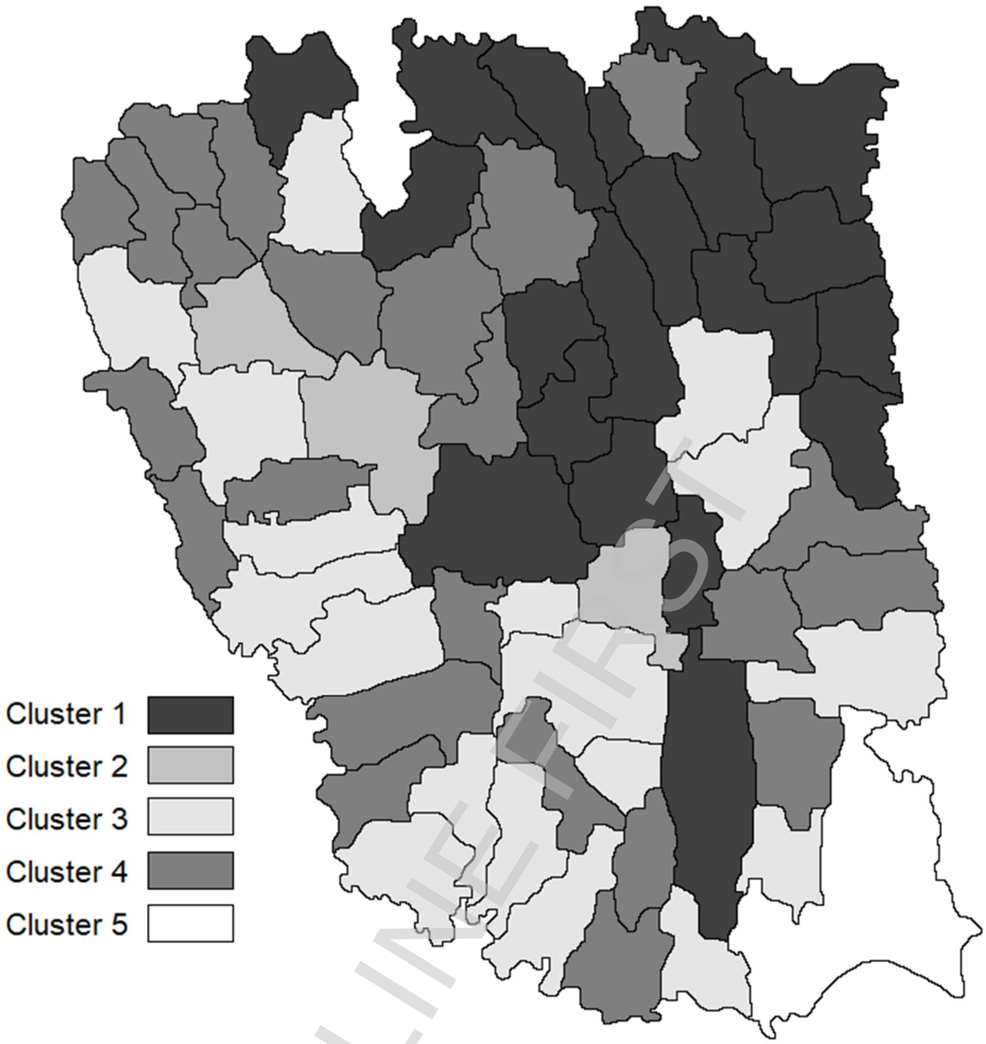

Figure 4 Spatial distribution of clusters within Galați County
Source: the authors

Conclusions

In Romania's case, reaching the proposed objectives was somewhat limited for the 2014-2020 National Rural Development Programme (Paul, 2020). Moreover, previous studies highlighted a tendency for the distribution of funds towards already developed areas, on the expense of less developed ones.

For Galați county, in Romania, a k-means cluster analysis on LAU level, considering four variables (total population, relative poverty rate, agricultural area per population and total value of EAFRD agricultural projects per population), reached an optimum number of five clusters. Cluster analysis proved to be a useful tool for rural development because it allows identifying patterns and grouping within data sets and helps in identifying similar communities or regions, by using different factors. It can be used to inform the design and implementation of targeted rural development programs and policies.

One cluster is composed by only one LAU, the large city of Galați, as a proof for the wide gap between urban and rural areas.

The two largest clusters by number of composing LAUs are also the poorest, representing together 66% of the county's LAUs. One of those clusters, even if having the most important agricultural potential per population, attracted by far the lowest value of EU funding. This cluster also presents the lowest population per LAU.

Generally, LAUs with larger population performed better in terms of population income, having the lowest relative poverty rate. Among them, the LAUs of cluster two performed exceptionally well at attracting EU funding. This represents the opposite pole compared with cluster one, with the lowest population and lowest attracted EU funds, bringing up the case for the small LAUs administration inefficiency and necessity of territorial reorganization. Like other areas in Romania, Galați County has been affected by emigration, as many people have moved to urban areas or other countries in search of better economic opportunities. This has led to a decline in population and economic activity in some rural areas, further exacerbating the uneven development. Communities with low population performed poorly in attracting EU funds. Territorial reorganization can address these issues by consolidating smaller LAUs into larger ones, creating new LAUs, or merging rural LAUs with neighbouring urban areas. This can help create more efficient and effective governance structures, and make it easier for residents to access services and markets. Additionally, it can also reduce administrative costs and improve the delivery of public services.

LAUs of cluster two represent success stories to be followed, especially by LAUs of clusters one and four. Know-how exchange can be beneficial in this regards and Local Action Groups (LAGs) can play an important role in this approach.

Rural development in Romania, including Galați County, has been uneven. Some rural areas have seen significant economic growth and modernization, while others have been left behind. This is due to a variety of factors, including differences in access to resources, population and EU funding.

For economic convergence at county level, development strategies need to focus on underdeveloped hotspot areas, like the central, northern and north-eastern parts of the county. Dedicated actions need to be designed especially for these areas, considering the specific problems they are facing. Further analysis of the differences compared to the others clusters might give an important insight on this matter. A bottom-up approach would also include relevant LAGs in this process.

Current research focused only on EAFRD funding towards agricultural exploitations. For a more detailed approach, further research is necessary in order to highlight other relevant differences between communities in different clusters, including consideration of other EAFRD submeasures, like economic diversification, processing agricultural products or infrastructure investments.

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