Analysis of Regional Imbalances in Italy Based on Cluster Analysis

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Abstract. In 2021 ISTAT presented the Report on Equitable and Sustainable Well-being (BES 2020), consisting of a system of indicators that follow the significant changes that have characterized the Italian society in the last 10 years. With the integration of new indicators, realized in coherence with the fundamental lines of the Next Generation EU, there has been an enrichment of information on the country system concerning health aspects, education and training, and economic well-being. The 20 Italian regions, the 2 autonomous provinces of Bolzano and Trento, the 3 territorial divisions North, Center, South and the total of Italy constituting a set of 26 territorial units, have been described each with a set of 36 numerical indicators, concerning the areas of Health, Education and Training, Economic Wellbeing. These areas are the most suitable for highlighting regional imbalances in Italy. In this paper has been analyzed the input data matrix, made up of 26 rows, one for each of the territorial units, and of 36 columns, the number of descriptors used for each territorial unit, by means of a factor analysis, using the principal components method, in order to construct a regional taxonomy characterized by those of the 36 indicators that are most correlated with each of the factors that have emerged. Moreover, starting from the coordinates calculated for each of the 26 territorial units in the factor space, a cluster analysis of the 26 territorial units was carried out, using the connected graph method, in order to highlight the territorial similarities and differences in Italy.

Keywords: Urban models · Factor analysis · Cluster analysis · Spatial data analysis · Spatial statistical model

1 Introduction

Equitable and Sustainable well-being indicators (Bes) have been introduced into the Italian legislative system (Article 14 of Law No. 163/2016 reforming the accounting law) as an economic planning tool. An ad hoc committee was appointed, chaired by the Minister of Economy and Finance, to select useful indicators for the assessment

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of well-being based on the experience gained at national and international level. Ten years after the start of the project, the proposed indicators show that there have been many changes in the profile of well-being in Italy, both in the direction of progress and in the persistence of critical areas. By effect of budget cuts carried out continuously throughout the decade, in our health system there are fewer beds, there are doctors of a higher average age, due to the blocking of turnover, with the result of greater inequality in access to care. There are still too few children enrolled in the nursery and young people who graduate, so the gap with Europe on education continues to widen. At the same time, the number of young people who don't study, don't work and aren't included in professional training programs (NEET) has increased. The quality of work in Italy is objectively critical, and the incidence of absolute poverty in 2019 showed, for the first time, a slight decline and then rose again in 2020. The Bes 2020 Report, presented by ISTAT at the end of 2020, highlights a complex and not merely emergency situation that is at the same time contradictory [3–5]. The extraordinary resources made available by the Next Generation EU Program represent an unprecedented opportunity to intervene substantially for economic recovery. The Bes is therefore a targeted, sensitive and reliable tool to guide decisions and to allow for the evaluation of results of the implemented policies. In this work, 15 variables of the Health area, 13 variables of the Education and Training Area and 8 variables of the Economic Wellbeing Area, as specified below, were assumed as indicators (descriptors) of the 26 territorial units considered.

1.1 Description of the Indicators

Health Area - Description of the 36 indicators of each of the 26 territorial units.

ID	Indicators
1	Life expectancy at birth
2	Healthy life expectancy at birth
3	Mental health index (SF36)
4	Avoidable mortality (0–74 years)
5	Multichronicity and severe limitations (75 years and over)
6	Child mortality
7	Mortality due to road accidents (15–34 years)
8	Mortality from cancer (20–64 years)
9	Mortality due to dementia and diseases of the nervous system
10	Unlimited life expectancy in activities at 65
11	Overweight
12	Smoking
13	Alcohol
14	Sedentary lifestyle
15	Adequate nutrition

Education and Training Area - Description of the 36 indicators of each of the 26 territorial units.

ID	Indicators
16	Attendance in kindergarten
17	People with at least a diploma (25–64 years)
18	Transition to the University
19	Young people who do not work and do not study (NEET)
20	Participation in continuing education
21	Inadequate literacy skills
22	Inadequate numerical competence
23	High digital skills
24	0–2 years old children enrolled in the nursery
25	Graduates in technical-scientific disciplines (STEM)
26	Cultural participation outside the home
27	Reading of books and newspapers
28	Usage of libraries

Economic Wellness Area - Description of the 36 indicators of each of the 26 territorial units.

ID	Indicators
29	Income available
30	Net income inequality (s80 / s20)
31	Risk of poverty
32	Severe material deprivation
33	Severe housing deprivation
34	Great difficulty to get to the end of the month
35	Low labor intensity
36	Overhead of the cost of housing

The corresponding values of the 36 indicators detected by ISTAT during 2020 were associated with each of the 26 territorial units, as listed in Table 1 [1, 2]. Only the data from the areas of health, education and training, economic well-being, of the twelve available, were used, because they were considered more discriminating for the purposes of an analysis of regional imbalances.

Health represents a central element of life and an indispensable condition for individual well-being and the prosperity of populations, as recalled, at European level, by the Lisbon strategy for Development and Work, declared by the European Commission in 2000 in response to the challenges of globalization and aging.

Health has consequences that impact on all dimensions of the life of each individual, being able to modify the living conditions, behaviors, social relationships, opportunities and perspectives of individuals and, often, of their families.

Table 1. .

ID	Territorial units
1	Piemonte
2	Valle d'Aosta/Vallèe d'Aoste
3	Liguria
4	Lombardia
5	Trentino-Alto Adige/Sudtirolo
6	Bolzano/Bozen
7	Trento
8	Veneto
9	Friuli-Venezia Giulia
10	Emilia-Romagna
11	Toscana
12	Umbria
13	Marche
14	Lazio
15	Abruzzo
16	Molise
17	Campania
18	Puglia
19	Basilicata
20	Calabria
21	Sicilia
22	Sardegna
23	Nord
24	Centro
25	Mezzogiorno
26	Italia

Education, training and skill levels influence people's well-being and open up opportunities for social growth that would otherwise be precluded.

Higher educated people have a higher standard of living and have more opportunities to find work, live longer and better, because they have healthier lifestyles and have more opportunities to find work in less risky environments.

Furthermore, a higher level of education usually corresponds to a higher level of access and enjoyment of cultural goods and services, and an active participation in the process of production of culture and creativity. Economic well-being is not considered a goal, but rather as a means by which an individual can have and sustain a certain standard of living.

Variables that contribute to economic well-being include income, wealth, spending on consumer goods, housing conditions, and ownership of durable goods [6–8].

Obviously, the judgment on the level of economic well-being of a society can vary if the same average overall income is equally distributed among citizens or is instead concentrated in the hands of a few wealthy people.

The peculiar characteristic that we call “value” is born in consumer products, a characteristic that can be defined as the ability of a product to excite in the individual the desire to have an exclusive use or at least a use for the total satisfaction of their needs. The 26 territorial units, each described by the 36 numerical variables concerning the three areas mentioned above, were considered as a matrix (input matrix X) of 26 “objects” in a 36-dimensional space [9–12]. We subjected the above matrix to a factor analysis, with the principal components (or Hotelling’s) method, in order to obtain a representation of the 26 territorial units projected in a space with only three-four dimensions (factor space) in order to use a simplified description of the 26 territorial units [13, 14]. This synthetic description, obtained from the factorial analysis, allows us to examine the distribution of the 26 territorial units, i.e. their possible mutual proximity in the space of the main components.

Furthermore, the 26 territorial units distributed in the space of the principal components were subjected to a cluster analysis in order to evaluate their similarities or their differences.

Since the factorial model is invariant (equivariance) with respect to changes in scale of the variables contained in the input matrix X, it’s possible to standardize the observed variables, in order to examine not the variance and covariance matrix, but the correlation matrix R [15, 16].

Below we briefly illustrate the results obtained with the factor analysis applied to the R correlation matrix of the 36 numerical indicators used for the description of the 26 territorial units.

The eigenvalues and corresponding eigenvectors of this matrix were calculated. The first four eigenvalues explained 77% of the total variance of the system.

Cumulative % of Eigenvalues.

.51	.62	.72	.77

After the rotation of the factor matrix, made up of the four eigenvectors corresponding to the first four eigenvalues, the 4 factor scores (coordinates in the factor space) were calculated for each of the 26 territorial units, with the significant (non-zero) weights (factor loading) of the input variables on each of the 4 factors.

1.2 Factor Analysis

For each factor, the following lists show the number of the variable, the weight of the variable on the factor and the description of each of the variables divided by area. Moreover, for each factor, the coordinates on the factor of the 26 territorial units are listed in an ordered manner. The weights of the variables and the coordinates on each main component are given below (Figs. 1, 2, 3 and 4):

Health Area – Factor loading 1st Main Component.

ID	Weights of variables	Indicators
2	0.57	Healthy life expectancy at birth
4	−0.81	Avoidable mortality (0–74 years)
5	−0.63	Multichronicity and severe limitations (75 years and over)
6	−0.54	Child mortality
8	−0.65	Mortality from cancer (20–64 years)
10	0.80	Unlimited life expectancy in activities at 65
11	−0.80	Overweight
13	0.61	Alcohol
14	−0.84	Sedentary lifestyle
15	0.70	Adequate nutrition

Education And Training Area - Factor loading 1st Main Component.

ID	Weights of variables	Indicators
17	0.90	People with at least a diploma (25–64 years)
19	−0.88	Young people who do not work and do not study (NEET)
20	0.64	Participation in continuing education
21	−0.78	Inadequate literacy skills
22	−0.84	Inadequate numerical competence

Economic Wellness Area - Factor loading 1st Main Component.

ID	Weights of variable	Indicators
29	0.75	Income available
30	−0.88	Net income inequality (s80 / s20)
31	−0.92	Risk of poverty
32	−0.84	Severe material deprivation
34	−0.76	Great difficulty to get to the end of the month
35	−0.91	Low labor intensity
36	−0.82	Overhead of the cost of housing

Coordinates of Territorial Units on the 1st Main Component.

Territorial units	Value
Trento	23.58
Trentino-AltoAdige	23.35
Bolzano/Bozen	17.34
Valle d'Aosta	16.36
Veneto	14.20
Friuli-Venezia Giulia	13.30
Emilia-Romagna	11.09
Toscana	8.81
Marche	7.18
Lombardia	6.94
Umbria	6.81
Piemonte	4.50
Liguria	4.48
Lazio	0.44
Abruzzo	−4.73
Sardegna	−9.43
Molise	−10.96
Basilicata	−12.73
Puglia	−15.53
Calabria	−21.18
Sicilia	−33.70
Campania	−34.87

Health Area – Factor loading 2nd Main Component.

ID	Weights of variables	Indicators
3	0.52	Mental health index (SF36)
7	0.58	Mortality due to road accidents (15–34 years)
12	−0.40	Smoking

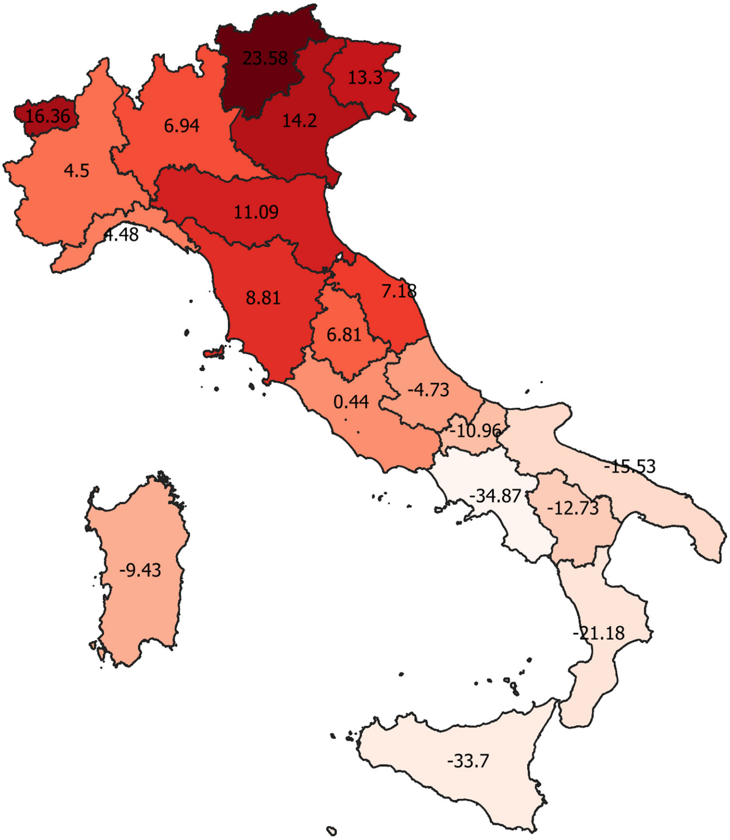

Fig. 1. Coordinates of territorial units on the 1st main component

Education and Training Area - Factor loading 2nd Main Component.

ID	Weights of variables	Indicators
18	−0.83	Transition to the University

Coordinates of Territorial Units on the 2nd Main Component.

Territorial units	Value
Bolzano/Bozen	13.49
Trentino-Alto Adige	9.01
Friuli-Venezia Giulia	1.69
Trento	1.68

(*continued*)

(*continued*)

Territorial units	Value
Veneto	1.66
Lazio	1.02
Puglia	0.74
Calabria	0.55
Sicilia	−0.39
Emilia-Romagna	−0.99
Valle d'Aosta	−1.04
Liguria	−1.17
Abruzzo	−1.41
Umbria	−1.50
Basilicata	−1.58
Lombardia	−1.88
Toscana	−2.10
Campania	−2.14
Sardegna	−2.35
Marche	−3.07
Piemonte	−3.28
Molise	−3.30

Education and Training Area - Factor loading 3rd Main Component.

ID	Weights of variables	Indicators
16	0.94	Attendance in kindergarten
23	0.81	High digital skills
24	0.62	0–2 years old children enrolled in the nursery
26	0.66	Cultural participation outside the home
27	0.66	Reading of books and newspapers.

Coordinates of Territorial Units on the 3rd Main Component.

Territorial units	Value
Trento	8.73
Valle d'Aosta	8.03
Trentino-Alto Adige	5.31
Friuli-Venezia Giulia	4.45

(*continued*)

(*continued*)

Territorial units	Value
Veneto	4.17
Emilia-Romagna	3.92
Bolzano/Bozen	3.89
Toscana	3.63
Lombardia	2.50
Liguria	1.86
Piemonte	1.80
Marche	1.50
Umbria	1.09
Sardegna	0.77
Abruzzo	−1.32
Molise	−2.61
Puglia	−2.77
Basilicata	−3.09
Calabria	−5.10
Sicilia	−9.04
Campania	−9.09
Lazio	−16.81

Health Area – Factor loading 4th Main Component.

ID	Weights of variables	Indicators
1	0.54	Life expectancy at birth
9	−0.72	Mortality due to dementia and diseases of the nervous system

Education and Training Area - Factor loading 4th Main Component.

ID	Weights of variables	Indicators
25	0.64	Graduates in technical-scientific disciplines (STEM)
28	−0.67	Usage of libraries

Economic Wellness Area - Factor loading 4th Main Component.

ID	Weights of variable	Indicators
33	0.51	Severe housing deprivation

Coordinates of Territorial Units on the 4th Main Component.

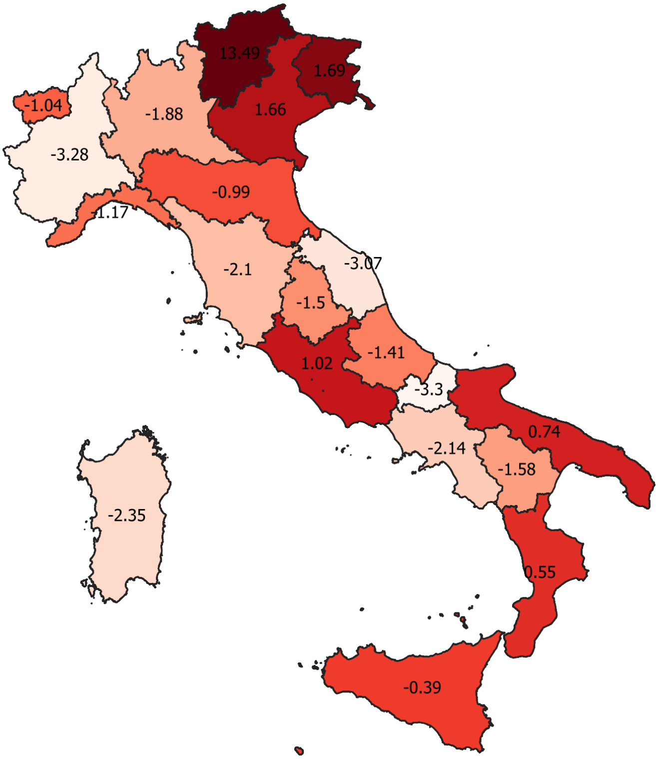

Fig. 2. Coordinates of territorial units on the 2nd main component

Territorial units	Value
Campania	12.84
Calabria	11.62
Sicilia	10.51
Basilicata	8.96
Molise	8.06
Abruzzo	6.76
Puglia	6.68
Lazio	3.40
Umbria	2.60
Sardegna	1.35
Marche	−0.05
Liguria	−2.43
Toscana	−2.76

(*continued*)

(*continued*)

Territorial units	Value
Piemonte	−3.88
Emilia-Romagna	−4.68
Friuli-Venezia Giulia	−4.72
Veneto	−4.80
Lombardia	−4.97
Trento	−10.36
Valle d'Aosta	−12.49
Bolzano/Bozen	−13.82
Trentino-Alto Adige	−14.08

2 Territorial Cluster Analysis

The new coordinates in factor space had been assigned to the 26 territorial units considered, it was possible to search for their proximity (similarity). It seems appropriate to clarify what is meant by similarity between regions. To this end, we introduce a similarity coefficient Si, j between two regions Ri and Rj in such a way that for each pair (i, j), with i,j = 1, 2,…, N we have:

$$0 <= \mathbf{S}i, j <= 1.$$

with

$$\mathbf{S}i, j = 1.$$

only if (1).

$$\mathbf{R}i = \mathbf{R}j.$$

with.

$$\mathbf{S}i, j = \mathbf{S}j, i.$$

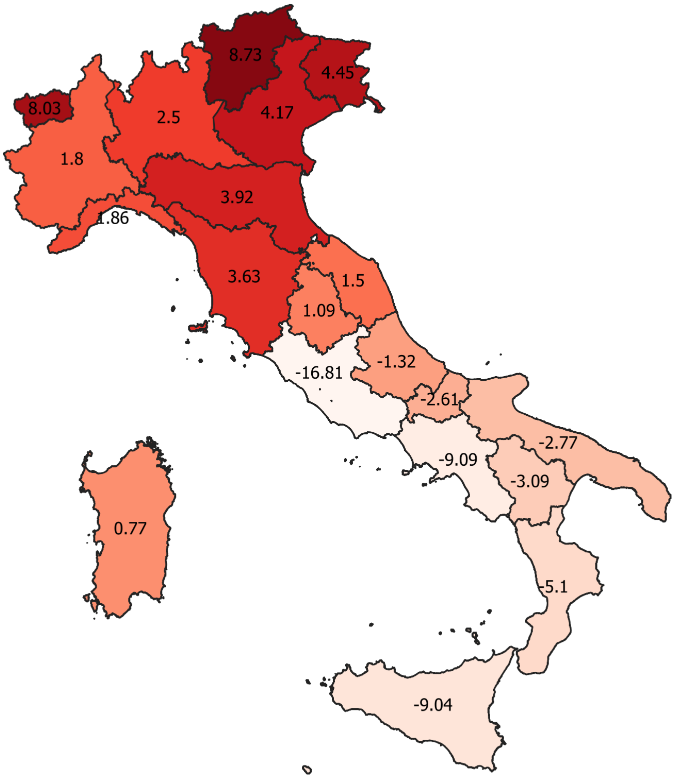

Fig. 3. Coordinates of territorial units on the 3rd main component

(symmetry property). If we denote by Di the modulus of the description vector of the spatial unit Ri where Di, k is the k-th component of the vector Di, the similarity coefficient Si, j can be defined as the addition k of the proportion [18].

$$(\mathbf{D}i,\ k\ *\mathbf{D}j,\ k)\ /\ (\mathbf{D}i\ *\mathbf{D}j)$$

which, as can easily be verified, satisfies the relations given in (1). The square matrix of order N constructed with the coefficients Si,j is called similarity matrix **S**. It is usually transformed into a Boolean matrix B by introducing a threshold t, with $0 < t < 1$, and setting bi,j = 1 if **S**i,j > t and setting bi,j = 0 otherwise [17, 23].

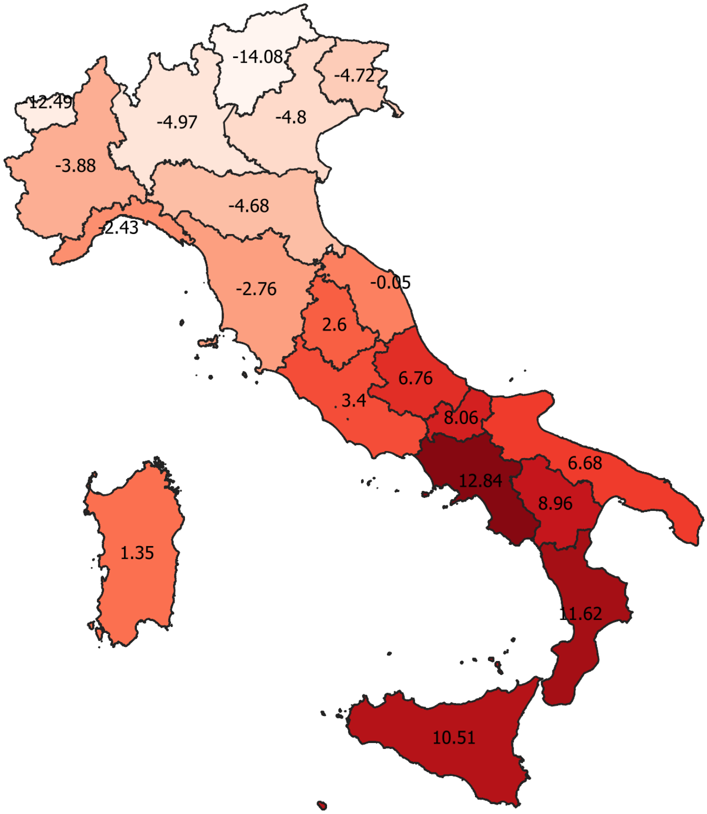

Fig. 4. Coordinates of territorial units on the 4th main component

The similarity matrix S can be interpreted as the adjacency matrix associated with a digraph. Since we are in the presence of a symmetrical matrix, if an arc **S**i,j exists between any pair (i,j) of nodes, the arc **S**j,i with the same ends but directed in the opposite direction will also exist [21]. One can then disregard the direction on the arcs and simply consider undirected graphs [20]. The existence of an arc between two nodes indicates that there is a similarity between corresponding regions that exceeds the threshold t adopted. The search for the connected components of a graph can be carried out by introducing the concept of a complete tree associated with each of the components. It is to be noted that a tree is a graph such that between any two nodes of it there is one and only one path; this implies that within a tree there are no cycles and that, if N is the number of nodes, the tree itself consists of exactly N-1 arcs [19, 22].

Considering the problem of the research of homogeneous clusters of our territorial units, having calculated the similarity matrix S, the classes have been identified through an algorithm of research of the connected components of the digraph associated to the Boolean matrix of the adjacencies, as deduced from the similarity matrix S, having imposed the threshold value t = 0.960. The results obtained are shown in the Table 2 below (Fig. 5):

Table 2. .

Cluster	Territorial Units
Cluster 1	Piemonte
Cluster 2	Trentino - Alto Adige
	Bolzano/Bozen
Cluster 3	Valle d'Aosta
	Liguria
	Lombardia
	Trento
	Veneto
	Friuli - Venezia Giulia
	Emilia - Romagna
	Toscana
	Nord Italia
Cluster 4	Umbria
Cluster 5	Lazio
Cluster 6	Abruzzo
Cluster 7	Marche
	Centro Italia
Cluster 8	Molise
	Campania
	Puglia
	Basilicata
	Calabria
	Sicilia
	Sardegna
	Mezzogiorno Italy

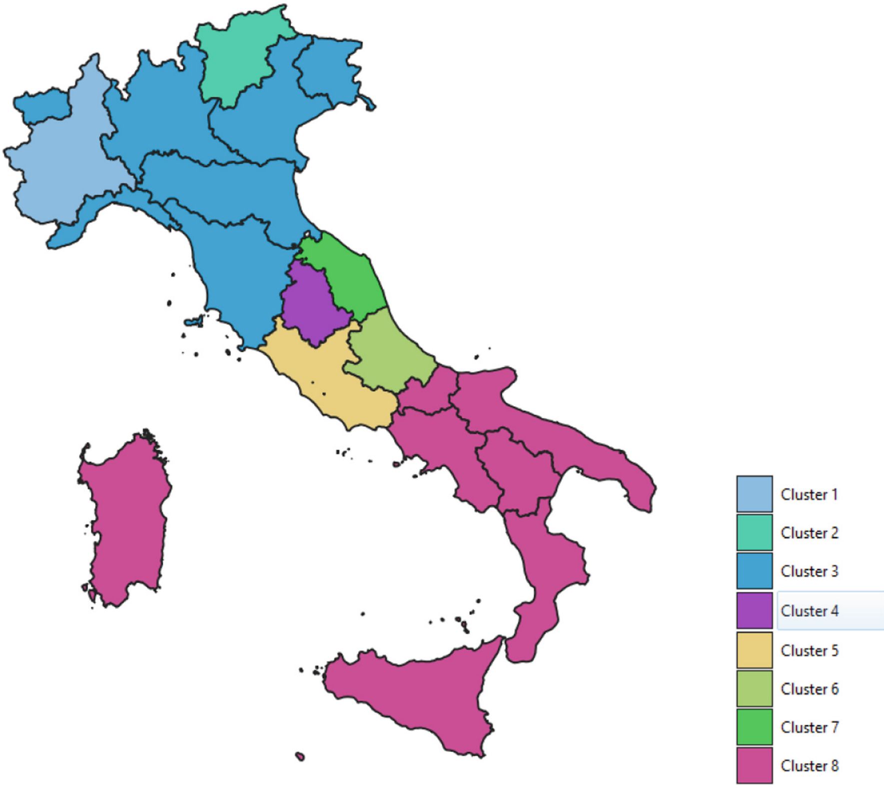

Fig. 5. Cluster of the territorial division

3 Conclusion

From the results obtained, considering the adoption of a highly discriminating value, close to unity, of the t threshold, it can be deduced that Piemonte, as well as Umbria, Lazio, Abruzzo and Marche present specific and peculiar regional profiles, in relation to the 36 descriptive variables used. It should also be noted, however, that the Marche Region has a profile that is most similar to the territorial distribution of Central Italy (cluster n. 7). Cluster n. 2 is formed by the Trentino respectively: the Autonomous Province of Bolzano while the Autonomous Province of Trento, which on the first principal component has assumed the greatest distance (23.58) from the origin of the factorial axes, near which the Lazio region is located, has been included in cluster n. 3 to which all the other regions of the Northern Italy territorial Breakdown also belong.

Finally, a special reflection should be made on cluster no. 8 that includes the seven southern regions, the territorial distribution Mezzogiorno and total Italy. It should be noted that the seven southern regions, Molise, Campania, Puglia, Basilicata, Calabria, Sicilia and Sardegna, described by their respective scores on the four factorial axes, all have negative coordinates on the first and third main components. It is left to the reader to read and easily interpret the weights of the variables on factors I and III, as they emerge from the factor analysis, in order to highlight the shortcomings, and therefore the regional imbalances, in the areas of health, education and training, and economic well-being.

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