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D2.1 – Report on the analysis of the variety of bio-economies in participating local communities

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DISSEMINATION AND UPTAKE

The document is confidential only for members of the consortium (including the Commission Services). It shall be used by all partners within the project.

VERSIONS AND HISTORY OF CHANGES

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1. Introduction

The circular bioeconomy (CBE) is crucial for transforming our currently prevailing fossil-based economic system into a sustainable and bio-based system. So far, the existing literature on this subject mainly focuses on technological aspects, thereby neglecting the importance of adopting a comprehensive systemic perspective that also includes social aspects and regional specificities. Adopting a regional innovation systems perspective recognizes that innovation is dependent on, and connected to, the broader socio-economic context of a region (Lau and Lo 2015; Yam et al 2011; Cooke et al 1997) and allows for considering besides technological and economic aspects also social dimensions. In the context of transitioning from a fossil-based economy to a sustainable and bio-based system, adhering to the principles of the so-called triple bottom line (TBL) is essential. This means that economic, environmental, and social aspects must all be considered. The TBL originated in the late 20th century and evolved as a framework for evaluating organisational performance based on the three interconnected dimensions: economic, environmental, and social (Purvis et al. 2019; Elkington and Rowlands 1999). Nowadays, its application is diverse and not limited to the corporate context. In the context of the CBE, the TBL is crucial as it promotes sustainable practices by addressing not only economic profit but also environmental and social well-being, aligning with the CBE's goal of using biological resources in an environmentally and socially responsible manner. Furthermore, it is equally important to recognize that a successful transformation necessitates the active participation of all societal actors, which also includes a special focus on empowering and involving marginalised groups, which often are not addressed directly and implicitly run danger to be missing in transformation strategies.

This report contributes to the work envisaged in package 2 and supports the assessment of the needs and conditions of the BIOLOC regions. In this report we assess the heterogenous conditions of the BIOLOC regions regarding their bioeconomy strategy development and implementation and conduct a comparative analysis of the underlying innovation systems. For this aim, a cluster analysis has been performed to reveal relationships among the BIOLOC regions to highlight structural similarities as well as differences. This is a necessary exercise to avoid comparing apple with pears and mistakes from a simple transfer of knowledge and experiences. This approach allows to detect possibilities of knowledge transfer from highly developed regions to less developed regions and between regions in general and to also detect situations where this is not possible due to severe structural differences. The aim of this report is to reckon the heterogeneity across the BIOLOC regions and to investigate the correlations with local development and innovation trends to extrapolate knowledge and recommendations for BIOLOC activities in the participating regions. The twelve participating regions are (see also Figure 1): Plovdiv (Bulgaria), Moravian-Silesian Region (Czech Republic), Baden-Württemberg (Germany), Western Macedonia (Greece), Aragon (Spain), Adriatic Croatia (Croatia), Campania (Italy), North Hungary (Hungary), Apeldoorn (Netherlands), West Romania (Romania), Slovenia, Nitra (Slovakia). The cluster analysis provides insights that can foster collaboration and knowledge sharing and enable more precise development strategies across the twelve regions. The remainder of this report is organized as follows: Section 2 presents the research design, i.e., data collection, variable selection, and the methodological steps for conducting a cluster analysis. Section 3 summarizes and discusses the results on the different levels of analysis (global, economic, environmental, and social). And section 4, the conclusions and implications are presented.

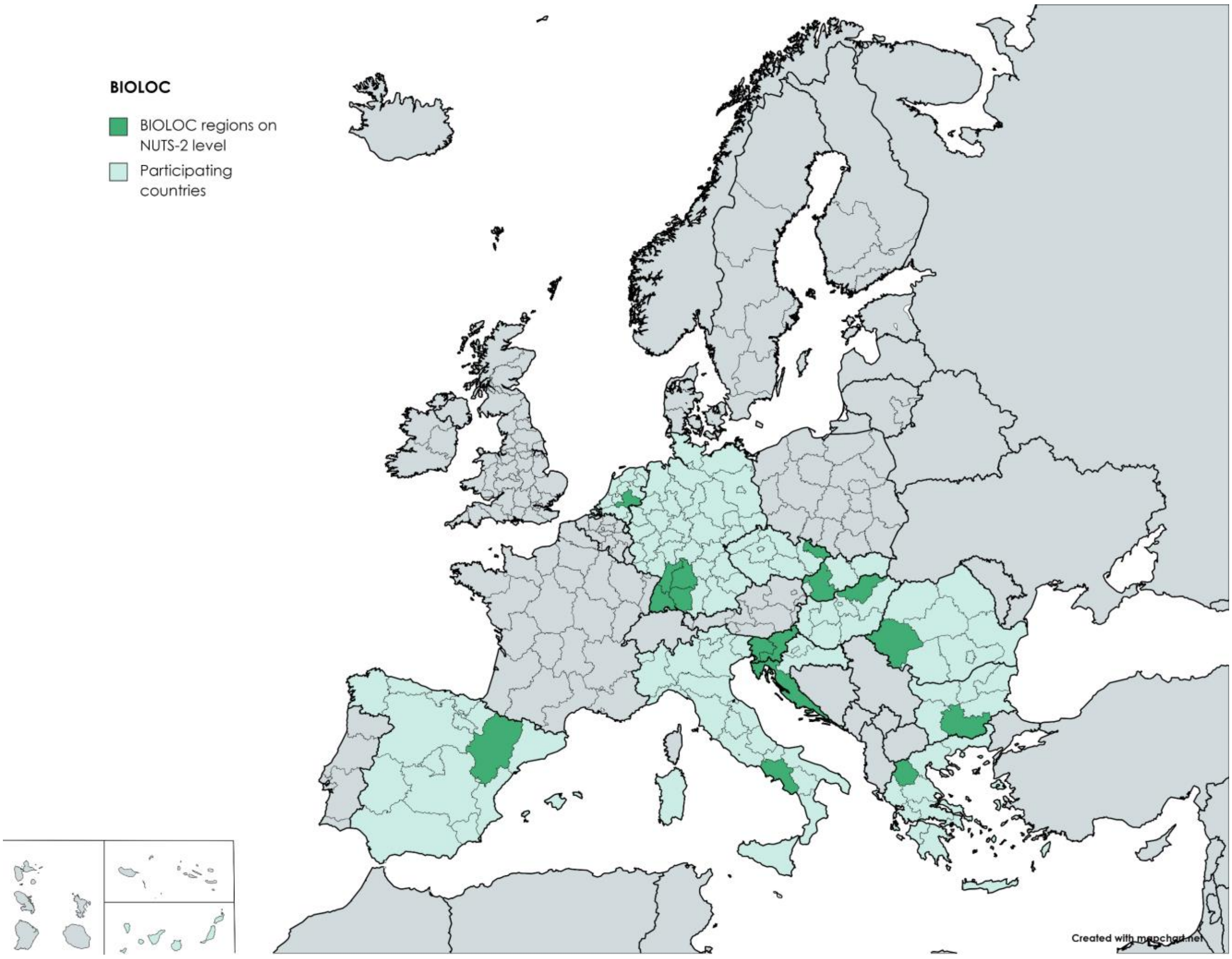

Figure 1: BIOLOC regions on NUTS-2 level

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2. Research Design

2.1 Data: Cases and Variables

The heterogeneity of the BIOLOC regions is already evident in the selection process of the region in the BIOLOC participating countries. For example, in the Netherlands the municipality of Apeldoorn was chosen as the BIOLOC region, whereas in Slovenia it is important to consider the whole country within the scope of the project. Therefore, the BIOLOC regions are already divers in terms of the area chosen. In order to be able to evaluate the regions through a cluster analysis, on a statistical level they have to be brought to a common level, which in this case is NUTS-2. To ensure that we are selecting the right NUTS-2 regions for the cluster analysis and to make sure that possible changes since the project proposal phase are taken into account, a selection of applicable NUTS-2 regions has been included in the survey that was conducted under the lead of the work package leaders 2, 3, and 4 (see annex to D2.2). The selected NUTS-2 regions are listed in table 1.

Table 1: BIOLOC regions and corresponding NUTS-2 regions

Case	Country	BIOLOC regions	Corresponding NUTS-2 regions	Code
1	Bulgaria	Plovidiv region	South Central Bulgaria (Yuzhen tsentralen)	BG42
2	Czech Republic	Moravian-Silesian region	Moravian Silesian (Moravskolezsko)	CZ08
3 4 5 6	Germany	Baden-Württemberg region	Stuttgart Karlsruhe Freiburg Tübingen	DE11 DE12 DE13 DE14
7	Greece	Western Macedonia region	Western Mazedonia (Dytiki Makedonia)	EL53
8	Spain	Aragon region	Aragón	ES24
9	Croatia	Adriatic region	Adriatic Croatia (Jadranska Hrvatska)	HR03
10	Italy	Campania region	Campania	ITF3
11	Hungary	Northern region	North Hungary (Észak-Magyarország)	HU31
12	Netherlands	Apeldoorn region	Gelderland	NL22
13	Romania	West region	Western Romania (Vest)	RO42
14 15	Slovenia	Whole country	Eastern Slovenia (Vzhodna Slovenija) Western Slovenia (Zahodna Slovenija)	SI03 SI04
16	Slovakia	Nitra region	Western Slovakia (Západné Slovensko)	SK02

The quality of the cluster analysis depends strongly on the number of variables and their quality. In order to represent the regions in an encompassing way, different statistical sources are to be used. A total of 26 variables[1] have been selected for the cluster analysis. The selection criteria of the variables are: the variable can be assigned to one of the TBL categories (economic, environmental, or social) and the data are available for all 16 NUTS-2 regions (representing the 12 BIOLOC regions). For this purpose, data from three different sources, namely EUROSTAT, the Regional Innovation Score (RIS), and the previously mentioned survey (see annex of D2.2) has been collected among the regional representatives in the environmental, social, and economic categories. Nevertheless, the availability of comprehensive data at NUTS-2 level for all the BIOLOC regions turns out to be limited, but sufficient for the desired analysis.

[1] In a cluster analysis, a variable refers to a specific characteristic or feature that is measured and used to group similar objects together.

Table 2: Overview variables

Category	Variable	Reference Year	Database
Economic	GDP per head (€/inhabitant)	2020	Eurostat
Economic	Employment rate total (%)	2021	Eurostat
Economic	Employment rate females (%)	2021	Eurostat
Economic	Employment rate males (%)	2021	Eurostat
Economic	Population	2021	Eurostat
Economic	Innovative capacity (Patent applications to EPO/million inhabitants)	2011	Eurostat
Economic	Income of households (€/inhabitant)	2020	Eurostat
Economic	International scientific co-publications	2021	RIS
Economic	SMEs introducing product innovations	2021	RIS
Economic	R&D expenditure (% of GDP)	2019	Eurostat
Environmental	Generation of municipal waste (kg per capita)	2019	Eurostat
Environmental	Utilised agricultural area (hectare)	2020	Eurostat
Environmental	Imports of waste for recovery and recycling (tonnes per capita)	2021	Eurostat
Environmental	Exports of waste for recovery and recycling (tonnes per capita)	2021	Eurostat
Environmental	Forest area (km²)	2018	Eurostat
Environmental	Water exploitation index (%)	2019	Eurostat
Environmental	Recycling facilities	2018	Eurostat
Environmental	Landfills	2018	Eurostat
Environmental	Bioeconomy Strategy (yes/no)	2023	Survey
Social	Persons at risk of poverty or social exclusion (%)	2019	Eurostat
Social	NEET (young person Not in Education, Employment, or Training) (%)	2019	Eurostat
Social	Early leavers from education and training (18-24 years) (%)	2019	Eurostat
Social	Education level 0-2 less than primary, primary and lower secondary (25 to 64 years) (%)	2020	Eurostat
Social	Education level 3-4 Upper secondary and post-secondary non-tertiary (25-64) (%)	2020	Eurostat
Social	Education level 5-8 Tertiary education (%)	2020	Eurostat
Social	Population involved in life-long learning (%)	2021	RIS

2.2 Method: Cluster analysis

Cluster analysis is a multivariate statistical technique[2] used to group objects based on their characteristics (Hair et al. 2010; Urmetzer and Pyka 2017). The cluster analysis is used in the project to group the BIOLOC regions according to their economic, social, and environmental characteristics. The goal of cluster analysis is

[2] Multivariate statistical techniques allow for looking at more than one thing at once and figuring out how they are related to each other.

to create clusters in which the objects within each cluster exhibit maximum homogeneity (i.e., the objects are similar to each other in their characteristics), while at the same time, maximizing heterogeneity (i.e., the clusters are different to each other) between different clusters to ensure that objects from different clusters are distinct. To do this, an agglomerative hierarchical clustering process is used. The underlying principle is to repeatedly combine similar objects into clusters, and then to merge these clusters into larger clusters, until a point is reached where the clusters have the highest possible diversity between them while maintaining homogeneity within each cluster (Urmetzer and Pyka 2017). This process is performed using the software tool SPSS (Statistical Package for the Social Sciences). The coherence of a cluster and the diversity between clusters are determined by calculating the Euclidean distance[3]. The average linkage method[4] is used to measure the similarity between clusters. The original data is standardised by converting the variables into standard scores[5] before clustering, because of the different scales of the variables. All variables are considered to be equally important. The generated output is presented as dendrograms (see Figure 2 r.h.s. for the dendrogram of the global analysis).

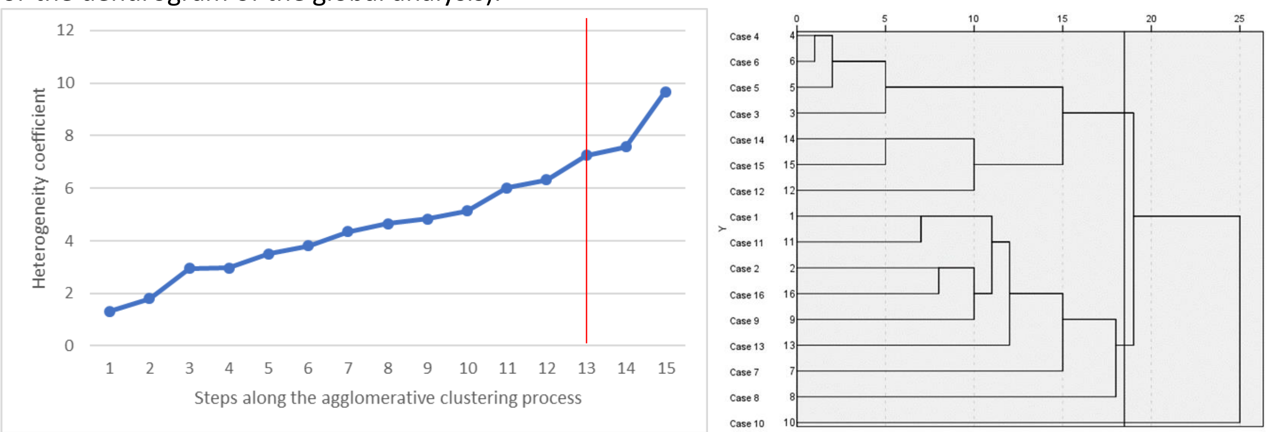

Figure 2: Elbow method (l.h.s.) and dendrogram (r.h.s.) of the global analysis

A dendrogram is a graphical illustration often used in hierarchical clustering. Hierarchical clustering algorithms create this tree-like structure to show how objects can be grouped together at various levels of detail (in our case the NUTS-2 regions "case 1-16"; see also table 1). By moving the vertical line in the dendrogram, one can control how finely or broadly the objects are clustered, which is useful for evaluating the data and choosing the most appropriate clustering solution based on the specific analysis needs (Davidson and Ravi, 2005). Therefore, the number of clusters is not known before the analysis is performed. To determine the accurate number of clusters c (i.e. to place the vertical line in the dendrogram), we use as a fist approximation the so-called *elbow method*. That is, we plot the heterogeneity coefficient against the number of steps taken along the agglomerative clustering process (see Figure 2 l.h.s.). The step, within which the line of the graph suddenly steepens is considered "too many" steps (see red line in Figure 2 l.h.s). The accurate number of clusters c is calculated as: $c = n - f$. n is the number of cases ($n = 16$) and f is the number of steps where the graph suddenly steepens (in Figure 2: $f = 13$). A plausibility check concerning the cluster allocation then is required, in order to avoid purely statistical artefacts. The data is evaluated at the global level and separately for each category (economic, environmental, social)[6].

[3] The Euclidean distance calculates the distance values between the objects based on their measured characteristics (variables).
[4] The average linkage method calculates the distance between clusters.
[5] Standardising data helps make things ready for comparison by putting them all on the same scale and showing how each measurement compares to the average.
[6] Illustrations of the elbow method and dendrograms of all analyses can be found in appendices a – d.

3. Results

3.1 Global Analysis

The results of the global analysis based on the economic, environmental and social variables (for a list of the included variables see table 2) lead to the formation of three clusters. The regions within each cluster share common characteristics in terms of economic, environmental, and social factors. When describing the clusters, we are not implying that one cluster is better than the other but simply highlighting the structural similarities and differences. At the same time, we focus on the comparison of regions within one cluster instead of comparing regions from different clusters or the relationship between clusters to avoid comparing regions that are so different from each other that they should not be compared directly. Comparing two dissimilar regions can be misleading because they may have distinct characteristics that make a meaningful comparison difficult. Cluster 1 includes the NUTS2 regions of Stuttgart, Karlsruhe, Freiburg, Tübingen, Eastern Slovenia, Western Slovenia, and Gelderland. The German regions within this cluster have established regional Bioeconomy strategies. In contrast, the other three regions lack such strategies on the regional level. The presence of Bioeconomy strategies in some regions and their absence in others suggests the potential for valuable knowledge exchange, allowing regions without strategies to benefit from the experiences and structural considerations of those that implemented strategies. The similarity of the regions given by the allocation in the same cluster suggests a potential benefit from such a strategy transfer. Cluster 2 includes the regions of South-Central Bulgaria, North Hungary, Moravian-Silesian region (Czech Republic), West Slovakia, Adriatic Croatia, West Romania, Western Macedonia, and Aragon. In this cluster, South-Central Bulgaria and Aragon have a Bioeconomy strategy, therefore, in this cluster the same rationale applies than in cluster 1, but of course for regions which cannot easily be compared with those in cluster 1. Regions without a strategy can benefit from the experiences and best practices of those that implemented strategies. Campania forms its own Cluster 3, indicating that it has distinct characteristics compared to the two other clusters. Campania stands out with the highest population (5,624,260) compared to the other regions, while at the same time having the lowest employment (total: 32.8%, female: 22.4%, male: 44%).

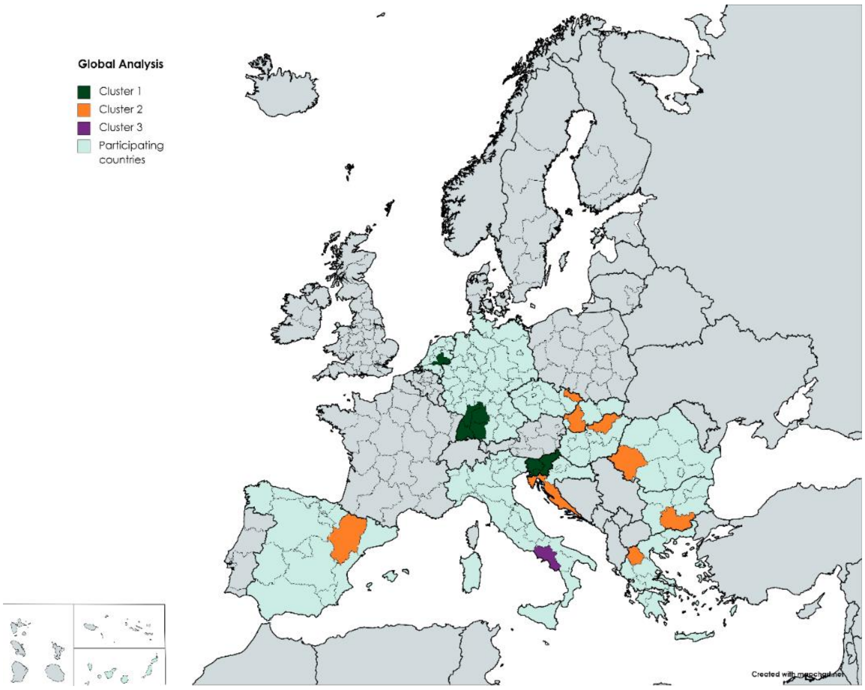

Figure 3: Map with clusters (global analysis)

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3.2 Economic Analysis

The results of the cluster analysis, which focuses exclusively on economic variables. As listed in table 2 above, economic variables encompass GDP per head, employment rates, population size, innovative capacity, income of households, international scientific co-publications, SMEs introducing product innovations, and R&D expenditure. This leads to the formation of two clusters among the BIOLOC regions. These clusters shed light on the economic similarities and differences between the regions but they do not imply that one cluster is better or worse than another cluster. For example, regions in cluster 1 have a lower GDP per head and lower R&D expenditures compared to regions in cluster 2. Cluster 1 includes South Central Bulgaria, Moravian-Silesian region in the Czech Republic, Western Macedonia in Greece, Aragon in Spain, Adriatic Croatia, Campania in Italy, Northern Hungary, Western Romania, Eastern Slovenia, and Western Slovakia. This suggests similarities between the regions. Cluster 2 includes Stuttgart, Karlsruhe, Tübingen, Freiburg (all located in Germany), Gelderland in the Netherlands and Western Slovenia. The regions in this cluster differ from the group of regions within Cluster 1 in terms of their economic characteristics. Comparing the regions within this cluster leads to the observation that the German regions and Gelderland have a higher income of households than Western Slovenia and makes the German regions and the Dutch region an interesting benchmark for Western Slovenia. Western Slovenia and Eastern Slovenia are not allocated to the same cluster, this could be for example due to the higher GDP per Head of Eastern Slovenia (26,500) compared to Western Slovenia (15,600) or due to the higher total employment rate in Eastern Slovenia (57.2%) compared to Western Slovenia (54.3%) and the complex combination of all economic variables together. The lower number of clusters identified for the economic variables indicates a higher degree of structural homogeneity among the participating regions concerning the economic composition compared to their overall homogeneity. The particular composition of the two clusters also indicates that the line of separation does not simply follow their status of old and new EU-membership. When looking at the single variables, it shows that Western Slovenia and Aragon have the same GDP per head, nonetheless, they are in separate clusters. This finding demonstrates that the clustering process is not merely examining individual variables, but considers a more complex combination of factors, challenging the assumption that similarities in one variable automatically place regions in the same cluster. For this reason, we should avoid an oversimplification in the comparison of regions – just having similar income per head levels is not enough for immediate comparisons.

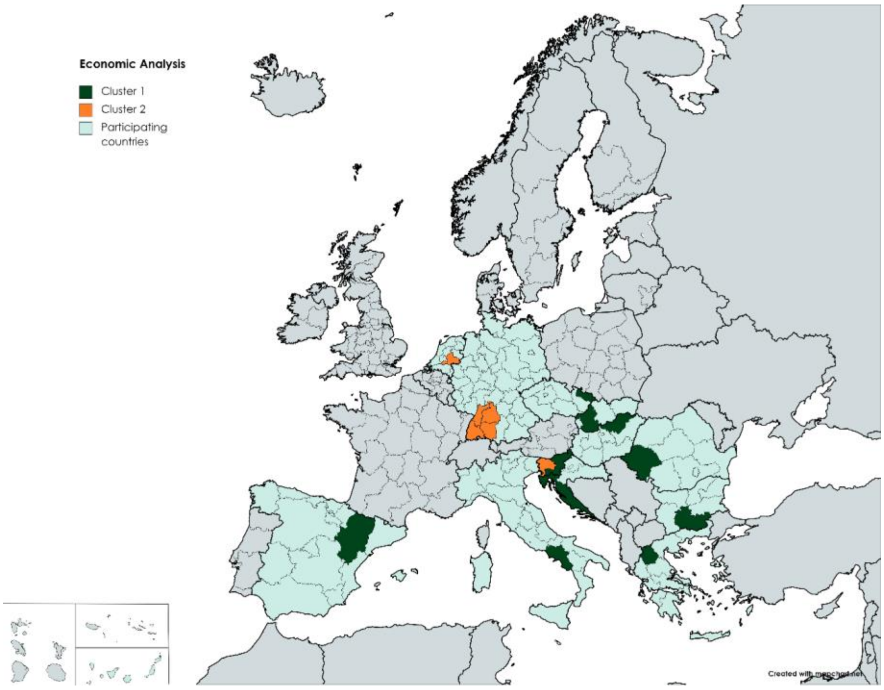

Figure 4: Map with clusters (economic analysis)

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3.3 Environmental Analysis

The results of the cluster analysis based solely on environmental variables lead to the formation of four clusters among the BIOLOC regions. As listed in table 2, environmental variable encompass generation of municipal waste, utilised agricultural area, imports and exports of waste, forest area, water exploitation index, recycling facilitie, landfills, and bioeconomy strategy. When describing the clusters, we are not implying that one cluster is better than the other but simply highlighting the structural similarities and differences. Regions in cluster 1 have significantly higher imports of waste for recovery and recycling than regions in the other clusters. Cluster 3 has significantly more utilised agricultural area and forest area compared to regions in the other clusters. Cluster 1 includes Eastern Slovenia, Western Slovenia, and Gelderland in the Netherlands. When comparing the regions within cluster 1, we observe that the Slovenian regions have higher imports of waste than exports of waste, while Gelderland has higher exports of waste than imports of waste. Cluster 2 includes South Central Bulgaria, the Moravian-Silesian region in the Czech Republic, Stuttgart, Karlsruhe, Freiburg, Tübingen, Western Macedonia in Greece, Adriatic Croatia, Northern Hungary, and Western Slovakia. Cluster 3 includes Aragon in Spain and Western Romania. Both regions have a high share of utilised agricultural area and forest area. Campania in Italy again forms its own Cluster 4, which was already visible in the global analysis. Campania stands out with the highest number of recycling facilities and the lowest number of landfills compared to the other regions. Regions within a cluster share common characteristics in terms of environmental variables. This analysis shows that geographical location obviously matters, but is not an exclusive clustering principle.

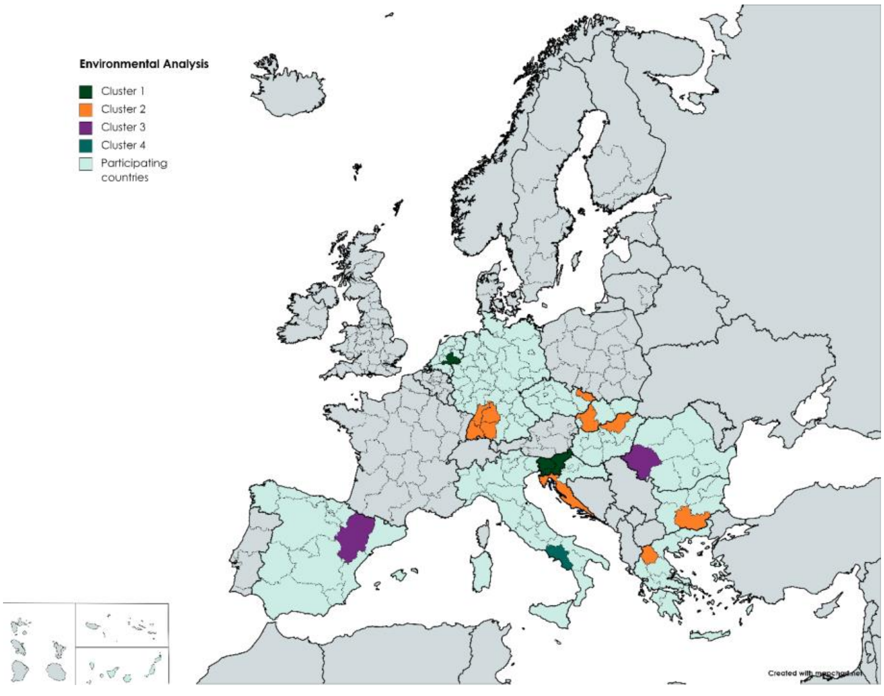

Figure 5: Map with clusters (environmental analysis)

3.4 Social Analysis

The results of the cluster analysis focusing solely on social variables lead to the formation of six clusters. As listed in table 2, social variables encompass persons at risk of poverty or social exclusion, NEET rates, education levels, and population involved in life-long learning. Cluster 1 combines Stuttgart, Karlsruhe, Freiburg, Tübingen (all in Germany), Gelderland in the Netherlands, Eastern Slovenia, and Western Slovenia. Cluster 2 includes the Moravian-Silesian region in the Czech Republic, Western Slovakia, Western Romania, and Adriatic Croatia. Cluster 3 includes South Central Bulgaria and Northern Hungary, which along with Campania (Cluster 6), stand out as the regions with high rates of "early leavers from education". On the other hand, Western Macedonia in Greece has the lowest rate of "early leavers from education" and forms its own Cluster 4. Aragon in Spain forms its own Cluster 5, characterized by specific educational patterns. Both, lower education and higher levels of education exceed that of middle education. And Campania in Italy once more forms its own Cluster 6. This region faces the highest amount of "persons at risk of poverty and exclusion" compared to regions in other clusters. The data reveals that 45.9% of the population has low education levels and has a relatively high rate of "early leavers from education". Social heterogeneity together with environmental heterogeneity, seems to be most characteristic for the selected regions in BIOLOC and consequently relevant for the number of different clusters in the overall analysis. Structural economic heterogeneity, surprisingly is less pronounced. Nevertheless, with this description of the clusters, we do not imply that one cluster is better or worse than the other but simply highlight the structural similarities and differences in social terms.

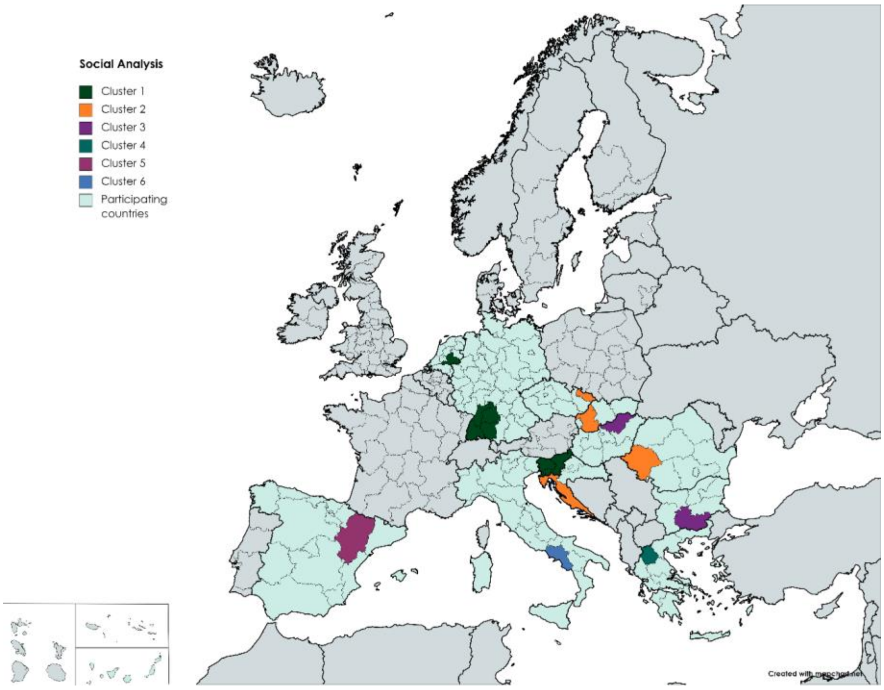

Figure 6: Map with clusters (social analysis)

4. Conclusions

The analysis of the regional innovation systems of BIOLOC regions by means of a cluster analysis highlights the embeddedness of bio-based innovations in the socio-economic context of each BIOLOC region and acknowledges structural heterogeneities among the selected regions. When designing tailored solutions, it is important to take into account the diversity and distinct characteristics of these regions and to avoid one-size-fits-all recommendations. On the contrary, each cluster and each region has different needs that BIOLOC wants to address in order to promote the revitalisation of local communities. Structural differences do not mean better or worse, but require a sound understanding of the different composition. Only within the different single clusters direct comparisons are possible which might include a support for catching-up of lower performing regions compared to higher performing reaching within this cluster (e.g. by applying benchmarking. For regions belonging to different clusters, a simple benchmarking most likely will fail to produce meaningful results. In this sense, clustering the regions and focusing on the comparison of regions within a single cluster helps avoiding comparisons that oversimplify complex situations.

Despite the heterogeneity of the BIOLOC regions, the results of the cluster analysis highlight opportunities for the regions. Regions within each cluster share structural similarities, suggesting the potential for mutual learning and collaboration. In addition, collaborative efforts among the regions can play a crucial role in fostering connections between them, facilitating the exchange of knowledge on how to involve marginalised groups or support the development of a bioeconomy and develop strategies. There is also the possibility of developing regional strategies together, such as the BIOLOC hub roadmaps. It may be of interest for the project partners and regional representatives to foster the exchange of ideas and good practices (compiled in Task 3.3) among the regions within their clusters. Furthermore, while BIOLOC workshops and activities put the focus on specific local communities, the cross-border and intra-regional exchange and knowledge transfer need to be kept in mind, as none of the regions can be seen as closed system.

Further, for developing recommendations in BIOLOC the social dimension seems to play an outstanding role for understanding the differences among the regions. To a lesser extent the heterogeneities between clusters in the environmental dimension matter. Structural differences in the economic dimension turned out to be less influential. Here, a benchmark analysis in the two identified clusters might allow to derive recommendations for less performing regions to learn and to transfer knowledge from those regions which are identified as leading. Before developing the portfolio of potential information and training offers in T5.4, the information and training needs of the BIOLOC regions must first be assessed. As far as the roadmaps of the BIOLOC hubs are concerned, different results and different roadmaps can be expected. And also, the dissemination activities might be different in the different BIOLOC regions. In order to identify the needs of each BIOLOC region, the active participation and involvement of different actors (societal, political, business, etc.) in events, workshops or bilateral conversations is required. In this way, regional and context-specific strategies can be developed.

In conclusion, analysing the varieties of bioeconomies in the participating local communities requires a comprehensive consideration of economic, environmental, and social indicators. This cluster analysis provides insights into the regional similarities and differences. The results have the potential to guide collaborative efforts, promote knowledge sharing, and ultimately contribute to more targeted and effective development strategies in the 12 BIOLOC regions. The recommendations are fine-grained to the specificities of the regions and avoid the problems of a potentially deteriorating oversimplification where all regions are lumped together.

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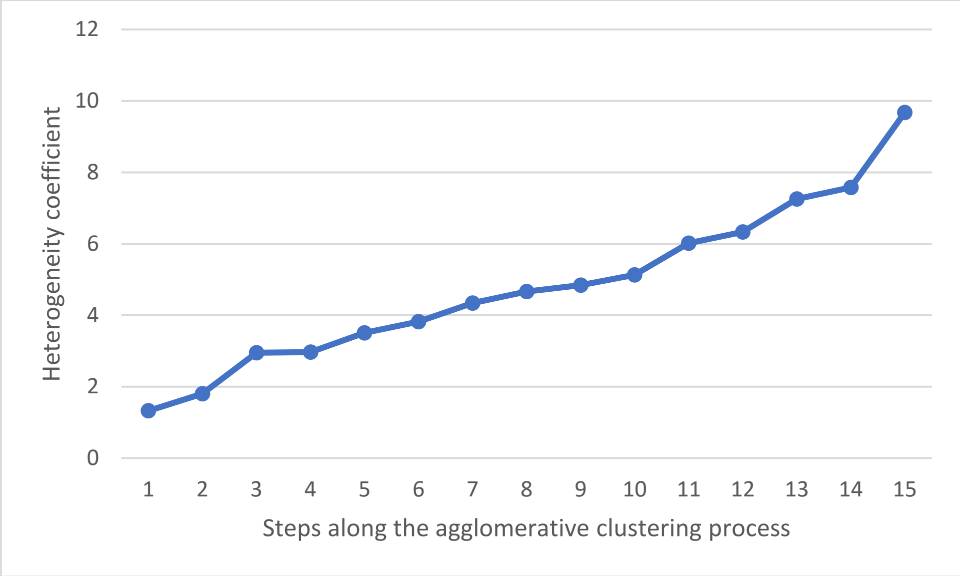
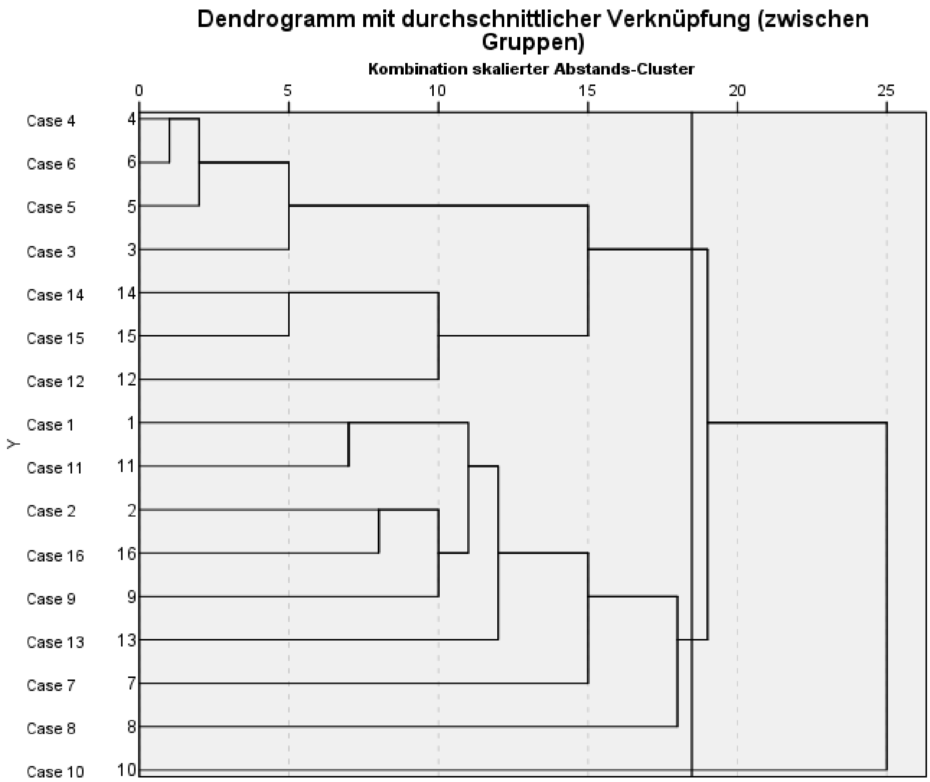
Appendix

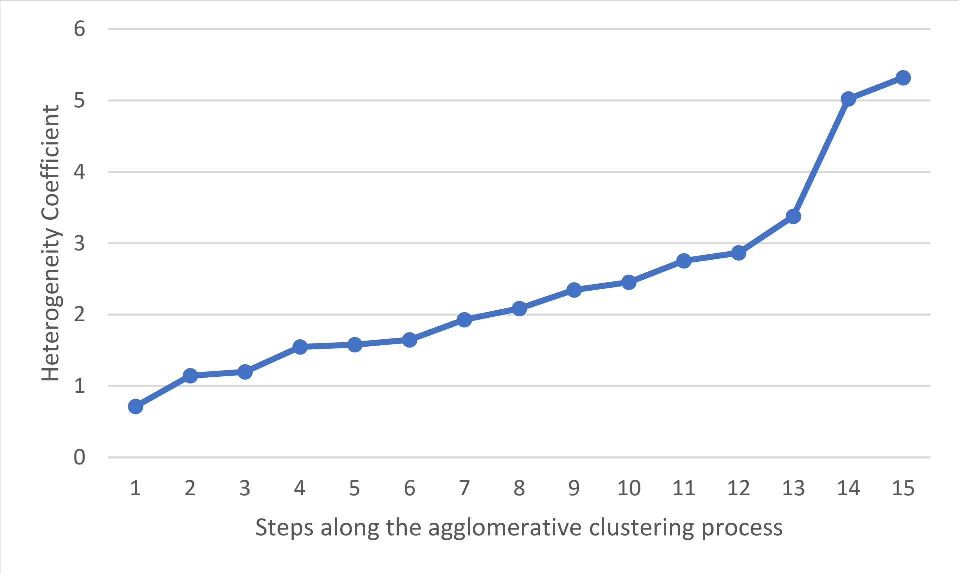
Appendix a: Global Analysis

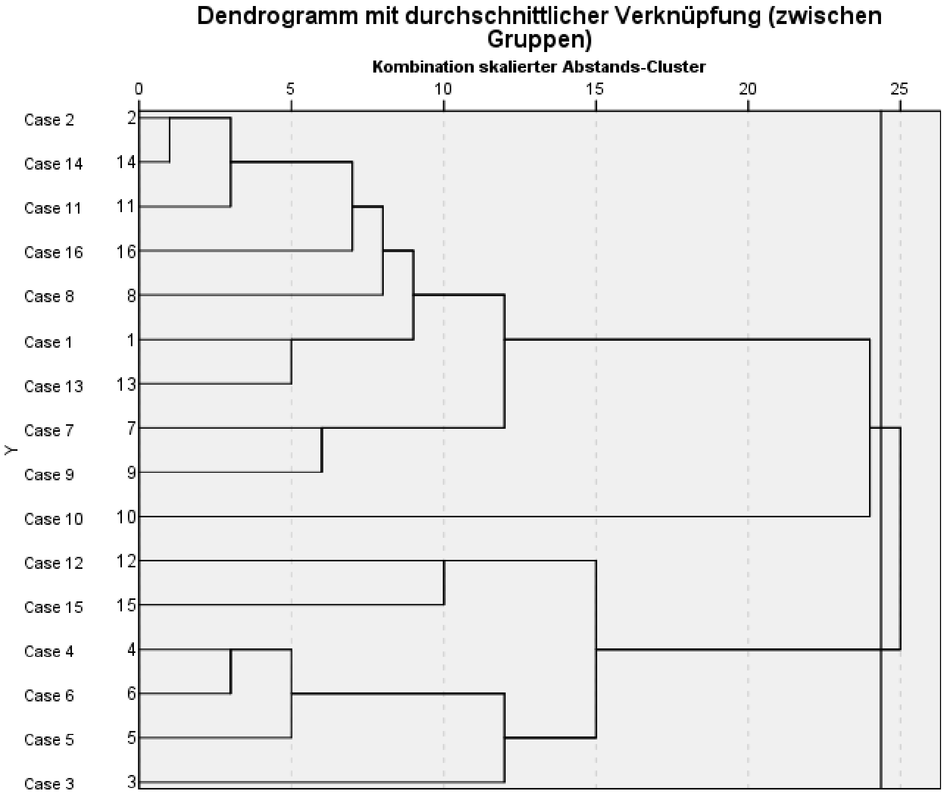




$c = n - f = 16 - 13 = 3$

Appendix b: Economic Analysis





$$c = n - f = 16 - 14 = 2$$

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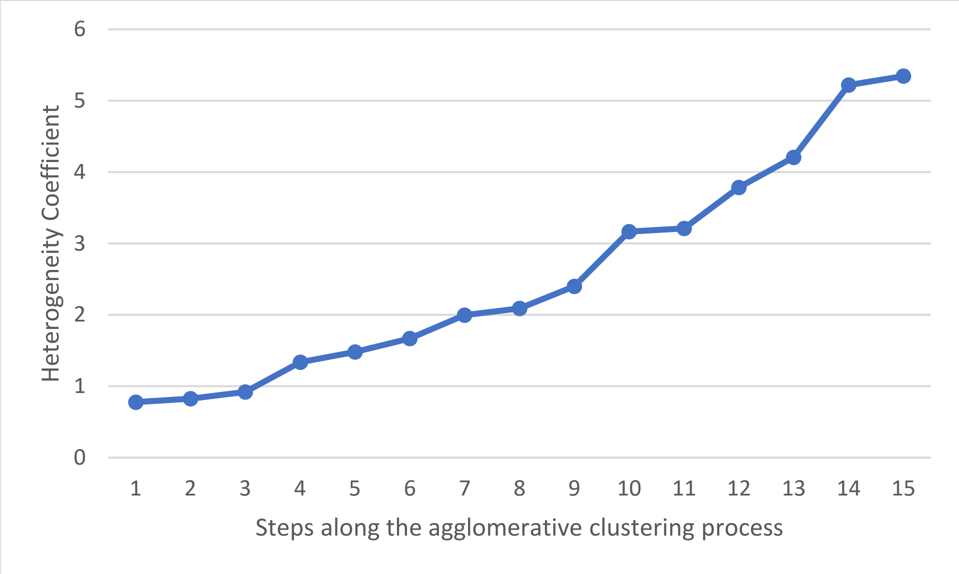
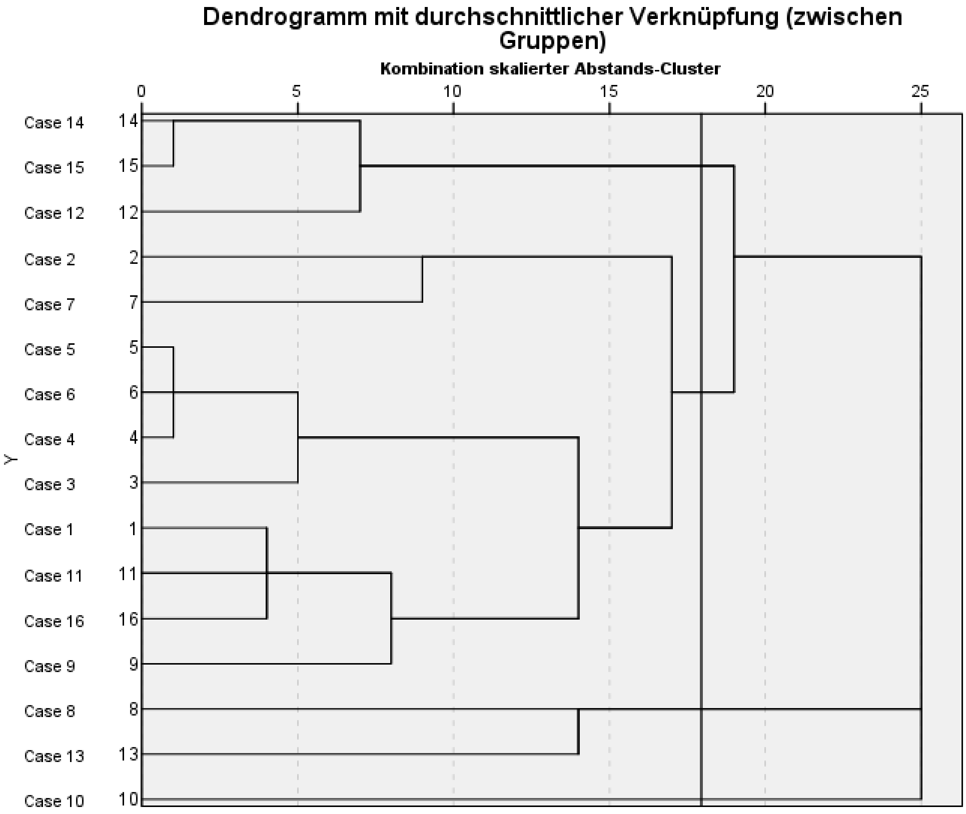
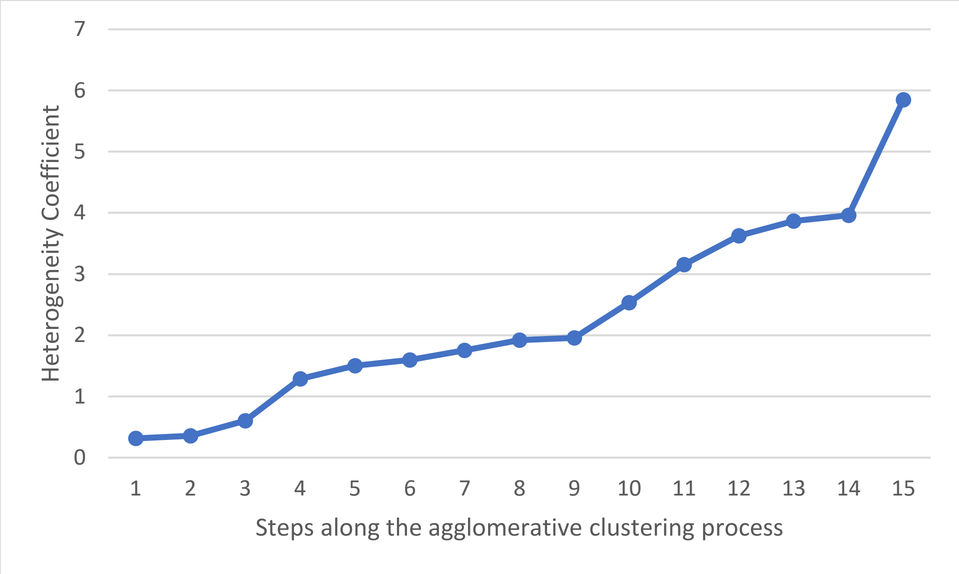
Appendix c: Environmental Analysis

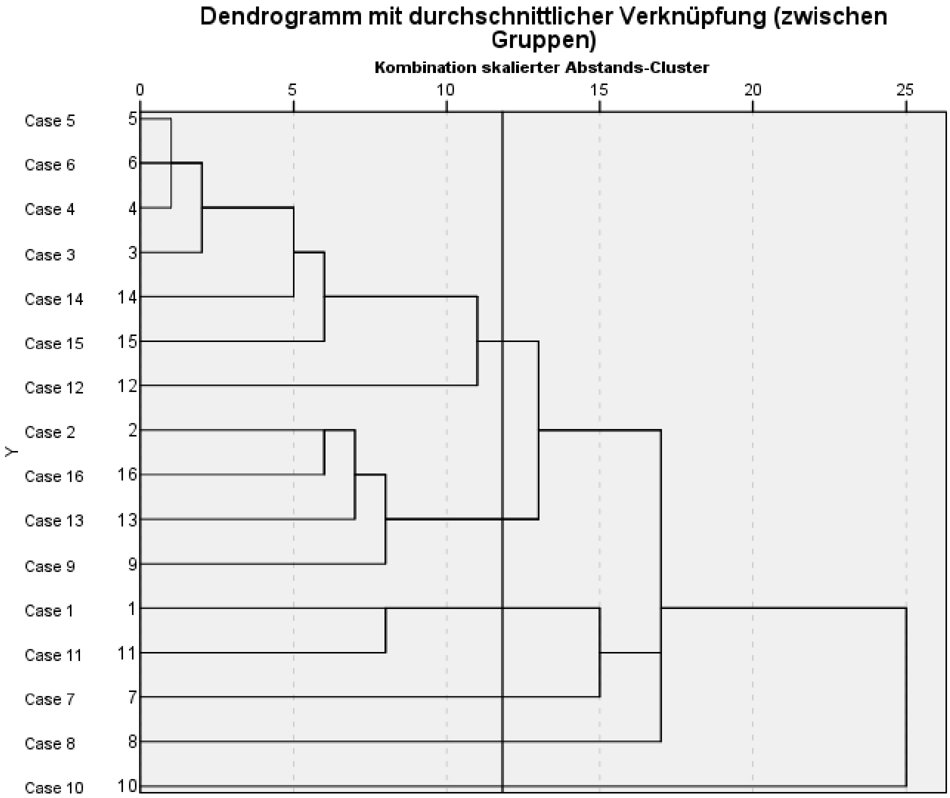




$$c = n - f = 16 - 12 = 4$$

Appendix d: Social Analysis





c = n – f = 16 - 10 =6

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Appendix e: Table on the data (1/2)

Region_GEO_Code_Eurostat	Population_Total_2021_NUTS2_Eurostat_Econ	NEETS_from15to29_2019_Eurostat_Soc	Persons_at_risk_2019_Eurostat_Soc	BEStrategy_2023_Survey_Env	GDP_perHead_2020_Econ	Population_Education_Level0to2_2020_Soc	Population_Education_Level3to4_2020_Soc	Population_Education_Level5to8_2020_Soc	Early_leavers_from_education_2019_Soc	Agricurltural_area_utilised_2020_env	Generation_municipal_waste_2019_env	Waste_recovery_imports_2021_env	Waste_recovery_exports_2021_env
BG42	1403991	19,40	37,70	1	6400	22,70	55,40	21,90	16,30	671270	442	0,096	0,246
CZ08	1192834	12,70	14,90	0	15700	6,30	72,60	21,10	9,80	208800	500	0,259	0,530
DE11	4151094	7,00	13,30	1	51900	15,40	49,90	34,70	11,10	463110	609	0,261	0,310
DE12	2807601	6,50	14,50	1	44000	14,80	50,80	34,50	8,30	202750	609	0,261	0,310
DE13	2276924	6,40	13,50	1	38100	14,50	51,90	33,60	8,20	316190	609	0,261	0,310
DE14	1867424	5,40	14,10	1	43300	16,00	51,80	32,20	7,90	426010	609	0,261	0,310
EL53	262052	26,60	34,80	0	12600	26,00	47,40	26,60	0,90	309130	524	0,196	0,126
ES24	1331133	11,60	21,10	1	26500	32,50	27,70	39,70	14,60	2217490	472	0,266	0,105
HR03	1369176	14,50	22,00	0	11500	9,40	64,20	26,40	1,70	443710	445	0,413	0,281
ITF3	5624260	34,30	49,70	1	18100	45,90	37,80	16,30	17,30	515540	503	0,208	0,078
HU31	1112263	19,50	23,90	0	9500	21,10	62,10	16,80	21,50	580040	387	0,210	0,297
NL22	2096603	5,00	14,70	0	39200	20,10	41,70	38,10	6,10	225770	508	1,021	1,097
RO42	1758582	17,70	21,90	0	11700	12,00	71,00	17,00	10,30	1514340	280	0,082	0,152
SI03	1105046	10,10	17,00	0	18500	10,80	58,50	30,80	4,70	342660	504	1,135	0,941
SI04	1003931	7,50	11,50	0	26500	8,60	49,80	41,60	4,40	140780	504	1,135	0,941
SK02	1819399	11,10	11,30	0	15600	6,60	71,10	22,40	6,30	815630	421	0,232	0,466

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Appendix f: Table on the data (2/2)

Region_GEO_Code_Eurostat	Forest_area_2018_env	Water_exploitation_index_2019_env	RD_expenditure_2019_econ	Employment_rate_total_2021_econ	Employment_rate_female_2021_econ	Employment_rate_male_2021_econ	Income_of_households_2020_econ	Patent_application_2021_econ	Popularion_Lifelonglearning_2021_soc	Internat_scientific_copub_2021_econ	SMEs_product_inno_2021_econ	Recycling_facilities_2018_env	Landfills_2018_env
BG42	22366	1,56	0,54	51,0	44,7	57,9	4000	2,665	14,141	50,148	66,812	162	17
CZ08	5430	12,07	1,09	55,4	48,3	62,9	10700	6,663	86,869	93,693	133,427	231	21
DE11	10556	2,57	7,40	61,6	56,1	67,2	33800	430,743	89,899	95,600	200,395	259	83
DE12	6917	2,57	5,29	59,7	54,3	65,3	31400	364,031	94,949	202,598	194,329	184	68
DE13	9355	2,57	2,87	61,6	57,0	66,4	31100	367,635	80,808	143,389	182,651	175	93
DE14	8917	2,57	5,17	62,5	58,5	66,6	32000	359,584	88,889	178,608	162,328	143	71
EL53	9462	13,27	0,42	38,7	31,3	46,3	10100	4,652	41,414	72,095	119,900	6	6
ES24	47722	8,10	0,94	52,0	47,0	57,2	17200	54,011	97,980	129,737	48,297	161	18
HR03	24705	0,17	0,59	44,8	39,6	50,4	7500	1,418	30,303	97,581	151,764	36	66
ITF3	13670	7,30	1,29	32,8	22,4	44,0	12300	9,741	45,455	56,040	68,496	532	2
HU31	13426	1,31	0,65	52,0	44,4	60,4	6200	2,981	53,535	118,543	127,228	63	18
NL22	5137	4,82	2,32	64,3	59,9	68,7	28300	96,666	194,949	205,876	120,011	41	6
RO42	32042	9,03	0,38	46,2	36,6	56,6	7100	3,326	20,202	63,743	5,376	10	6
SI03	12433	0,44	1,60	54,3	48,8	59,7	13900	34,778	105,051	85,194	147,628	239	11
SI04	7840	0,44	2,38	57,2	53,8	60,7	15000	62,181	121,212	199,629	171,987	173	5
SK02	14992	1,24	0,62	58,1	52,3	64,3	9800	6,965	26,263	73,677	50,408	203	39