Supplemental material for

"Understanding Innovation in European Mountain Product Value Chains: Empirical Typology, Patterns of Co-occurrence and Policy Implications", by Emilia Schmitt, Jonathan Hopkins, Gianna Lazzarini, Carmen Forrer, Gusztáv Nemes, Diana Surova, Carmen Maestre Diaz, Michele Moretti, and Dominique Barjolle, published in *Mountain Research and Development* 45(3), 2025. (See https://bioone.org/toc/mred/45/3)

APPENDIX S1 Detailed method

Data collection

Collaborators across a consortium of research organisations identified 455 value chains in the mountain regions of 21 European countries. These value chains were selected in 2021 based on their association with local territorial (social, economic and cultural) and natural capital. For each value chain, data was collected by a local research team through secondary data (e.g., company's websites, articles), and existing knowledge through case study work and/or short interviews. The compiled inventory (Moretti et al. 2021) contains qualitative and quantitative information, including detailed descriptions of value chains' characteristics. Among these, project partners also reported whether the value chains were innovative, whether in terms of new products, processes, marketing approaches or governance and writing short descriptions of the innovation. Key quantitative characteristics about the regions where the value chains are embedded were also collected by consulting local, national or European statistical repositories. All the data on the value chains and the corresponding regions were compiled in individual value chain forms in excel. The data used at the front of this study concern the typology of innovation (innovative or traditional, exogenous or endogenous, predefined categories such as "new products", "New technology", etc), the text description of the innovation, and the related quantitative data about the region in which the value chain has been found.

Defining attributes of innovation

To analyse the emergence of a typology of innovation, the whole set of value chains in the inventory were reviewed. Despite being categorised as "innovative", "innovative and traditional" or "traditional", 23 value chains classified as "traditional" were included in the "innovative" group. After eliminating some entries with missing information, the final sub-sample of MPVC analysed reached 275 value chains from 17 countries in the European Continent.

To determine the typology of innovation, an empirical and exploratory approach was used, iterated and confronted with literature. Using iterations, the innovation descriptions were summarised into key-words and then grouped in lists of possible innovation attributes that were again compared with the value chain descriptions. Then, the value chains' innovation's' descriptions were associated with up to four attributes each through reading by researchers. The frequency of appearance of each attribute was then calculated to shorten the list of attributes to the 12 with the highest frequencies (more than 20 occurrences) and enough differentiation. Attributes with lower counts of appearances were re-combined with others or removed. The final list of attributes was compared to the results of a prompt asking the AI tool Perplexity.ai to synthesis the full sample of innovation description text into 10 to 20 keywords. The generated AI attributes were closely related and similar in coverage and thus the 12 original attributes were kept. The 12 attributes are described in the results and illustrated with examples (table 1).

Analysis of co-occurence and clusters of innovation types

Several tests were conducted regarding clustering of the attributes among the MPVC handling and using data with R (R Core Team, 2024). First, to identify empirically distinct subgroups of value chains based on their innovation attributes, we employed Latent Class Analysis (LCA) with the R package poLCA (Linzer and Lewis 2011). LCA is a statistical method designed to uncover unobserved (latent) subgroups within a population using categorical observed variables (Sinha et al. 2021). This approach is particularly suitable for our study as it allows for the classification of value chains into mutually exclusive and exhaustive latent classes based on their patterns of innovation across the 12 attributes. LCA enables us to identify how these innovation attributes empirically group together, revealing underlying patterns that may not be immediately apparent through descriptive analysis alone and that go beyond a thematic regrouping of innovation types. Unlike traditional clustering methods, LCA provides a model-based approach with statistical criteria for determining the optimal number of classes, and it can handle the categorical nature of our innovation attributes without requiring assumptions of normality or linear relationships (Spurk et al. 2020). By applying LCA to our inventory of value chains, we aim to discern meaningful subgroups that share similar innovation profiles, thereby providing insights into the prevalent combinations and co-emergence of innovation types in our sample.

Risks of co-occurrence in specific geographies

To further identify the innovation attributes with a tendency to co-occur in the same mountain area, the geographical details of the reference mountain landscape and respective Local Administrative Unit (LAU) were extracted from the inventory for each MPVC and linked to spatial data. The vast majority of MPVC were located using single or multiple LAU1 geographies. However, 30 MPVC in Austria, France and Switzerland were represented using NUTS regions, and another 25 value chains were spatialised using district and other boundaries downloaded from OpenStreetMap, a documented global database of volunteered geographical information (e.g. Klinkhardt et al. 2021) which also contains open datasets from official publishers. All data handling and analysis used R (R Core Team, 2024) with use of the *sf* (Pebesma, 2018; Pebesma and Bivand, 2023) and *dplyr* (Wickham et al., 2023) packages for spatial analysis, and *osmdata* (Padgham et al., 2017) for querying and extracting OpenStreetMap data.

To identify the forms of innovation which tend to co-occur in the same spatial area, we draw on the concept of 'bundles' of ecosystem services: the positive spatial associations between diverse environmental characteristics (Raudsepp-Hearne et al. 2010). Analyses to identify the existence and the form of these bundles have often used bivariate correlation and multivariate cluster approaches (Saidi and Spray 2018). We apply these statistical techniques to gain understanding of innovation in MPVC. Firstly, the number of innovations occurring within MPVC at 182 locations were calculated and converted to a presence/absence matrix (i.e. variables with values of 1 or 0) for each attribute. Cross-tables of the presence/absence data were then produced for every unique pair of innovation attributes ($n = 132$ pairs, not including attributes cross-tabulated with themselves). Positive and negative correlations between attributes were calculated using relative risks, a measure of effect size which compares probabilities of events for two groups (Tenny and Hoffman 2024). Statistically significant associations between pairs of attributes were identified using Fisher's Exact Test, applying the null hypothesis that the odds ratio equals 1. The relative risks and significant ($p < .1$) associations were visualised using a form of correlation plot, identifying groups of strong pairwise associations between attributes.

Following this, we used hierarchical cluster analysis to identify groups of locations with similarities in their innovation 'profile', considering the mix of attributes present. Cluster analysis is an example of a more advanced technique that has been applied to better understand the diversity of rural areas, as the quantitative measurement of rurality has become more sophisticated over time (Nelson et al. 2021). Hierarchical clustering uses the 'distance' between cases in a dataset, calculated based on multiple measurements of these cases, to identify similar groups (Crawley 2013: 819–21). As innovations are measured in a presence/absence format for the 182 locations in the dataset, a binary distance matrix was calculated. A data-driven approach to identifying the most appropriate number of clusters for the dataset was applied, using recommendations from multiple metrics generated using the NbClust R package (Charrad et al., 2014). Cluster analysis specifying the Ward's method was run, and the locations were subsequently partitioned into cluster models. The two, five and six cluster solutions were investigated in more detail, and the two and six cluster models are described in detail, below. We investigated differences between these clusters using the relative frequency of different types of innovation - the percentage of regions within each cluster where each innovation was present - and assessed whether each type of innovation was significantly associated with the cluster typologies. The MPVC's localisations were then represented on maps per cluster with the two and six cluster models as a form of visualisation.

Finally, to further explore how innovation is spatially associated with challenges in mountain regions, we investigated the regional links between the multidimensional perspectives on innovation which emerged from this study and an established measure of innovation in Europe. The Regional Innovation Scoreboard is a sub-national dashboard measuring innovation through indicators representing dimensions of framework conditions, investments, innovation activities and impacts (European Commission 2023). This analysis defines a typology of regions (Innovation Leaders, Strong Innovators, Moderate Innovators and Emerging Innovators) based on a composite index of regional performance, expressed relative to the EU. This definition, broadly, situates innovation as a product of education and skills, scientific research and development, intellectual property and information technology, which align with regional characteristics considered during research on innovation (e.g. Rodríguez-Gulías et al. 2021). However, analysis of innovation among rural companies has found that 'internal' (firm-based) factors have a stronger effect on innovation than the regional context, although remoteness has a negative effect (García-Cortijo et al. 2019). The potential for rural innovation to occur despite environmental constraints in remoter areas (North and Smallbone 2000), and gaining a better understanding of the effects of constraints on innovation more broadly (see Acar et al. 2019) are particularly pertinent to mountain areas. In this analysis, we considered the intersection of combinations of MPVC innovations and the regional innovation context as understood using the Regional Innovation Scorecard's typology. To carry out this analysis, a spatial join between the centroids of each value chain and polygons of the NUTS2 boundaries (souce: Eurostat) was created. 180 regions were included in this analysis, with linkage at the NUTS1 level required in some cases.

Software used in analysis and mapping

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Secondary datasets used in analysis and mapping

- OpenStreetMap. Data © OpenStreetMap contributors, ODbL 1.0. https://www.openstreetmap.org/copyright
- Eurostat GISCO: Local administrative units (LAU) (2020, 2021) [files LAU_RG_01M_2020_4326.shp, LAU_RG_01M_2021_4326.shp]. © EuroGraphics for the administrative boundaries.
- Eurostat GISCO: Territorial units for statistics (NUTS) (2021) [file NUTS_RG_01M_2021_4326.shp]. © EuroGraphics for the administrative boundaries.
- Eurostat: LAU – NUTS 2016, EU-28 and EFTA / available candidate countries [file EU-28-LAU-2019-NUTS-2016.xlsx] Available at https://ec.europa.eu/eurostat/documents/345175/501971/EU-28-LAU-2019-NUTS-2016.xlsx.
- European Commission Directorate-General for Research and Innovation: Regional Innovation Scoreboard 2023 - Regional innovation indexes. Creative Commons Attribution 4.0 International (CC BY 4.0) licence http://creativecommons.org/licenses/by/4.0/. Available at https://research-and-innovation.ec.europa.eu/document/download/76fe7424-5aba-4617-a25f-d373080ff580_en?filename=ec_rtd_ris-2023-regional-indexes_0.xlsx

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APPENDIX S2 Supplementary results and figures

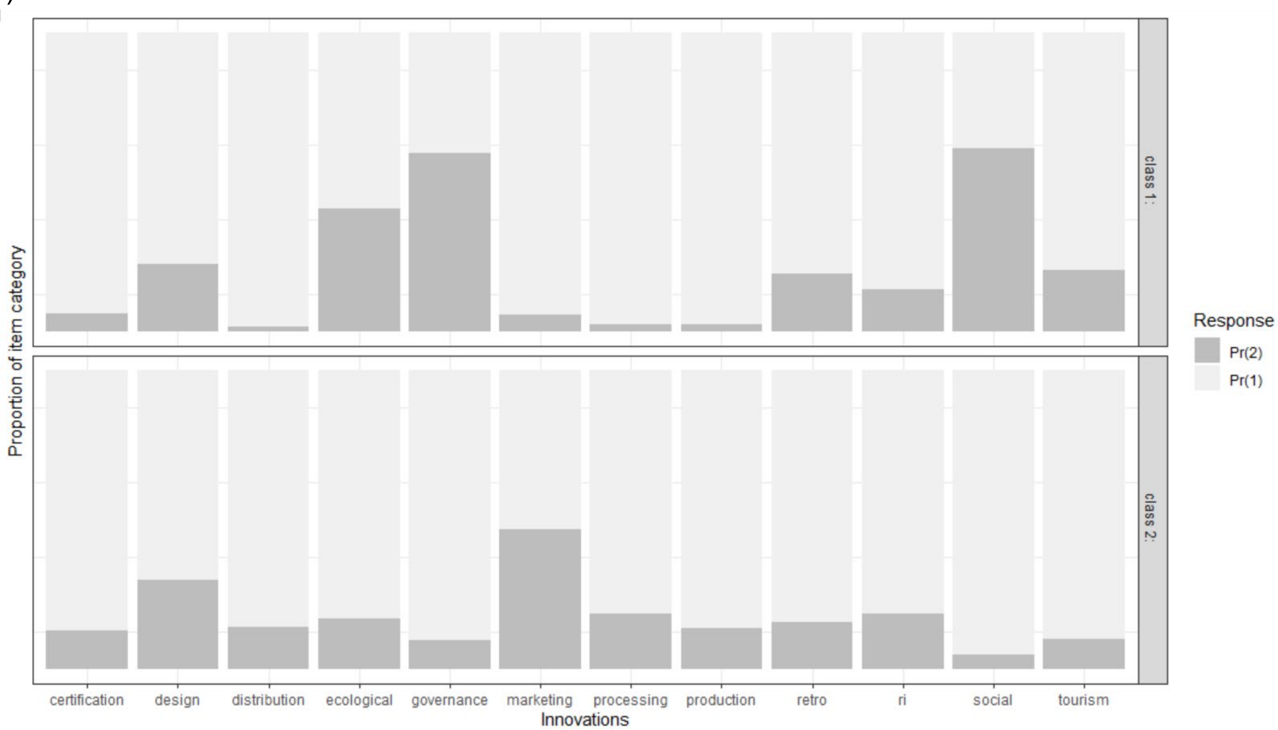
Results of the latent class analysis (LCA)

TABLE S1 Statistical indicators resulting of the Latent class analysis, calculated with poLCA R package (Linzer and Lewis 2011; see Appendix 1, “Software used in analysis and mapping”) tested for 1 to 6 classes in the inventory of MPVC.

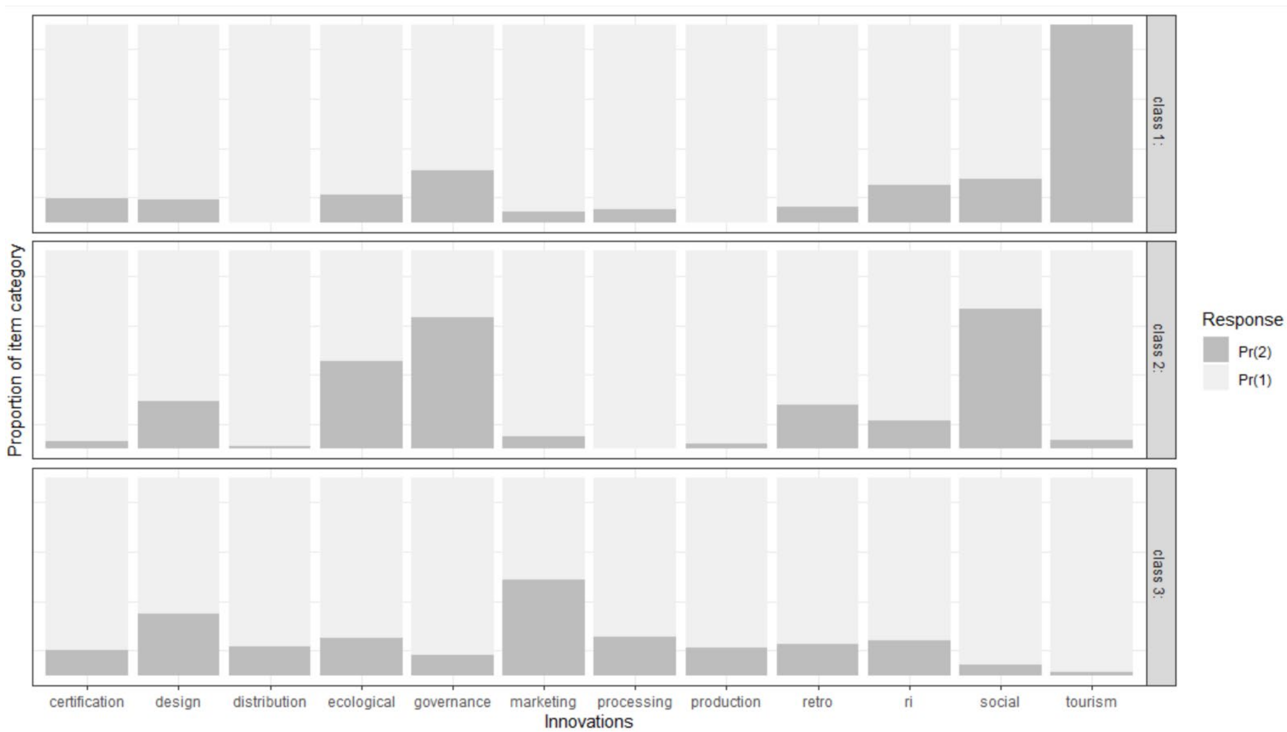
Model	log-likelihood	resid. df	BIC	aBIC	cAIC	likelihood-ratio	Entropy
Modell 1	-1532,5329	263	3132,46701	3094,41732	3144,46701	555,209902	-
Modell 2	-1482,1409	250	3104,70098	3025,4308	3129,70098	454,425849	0.613
Modell 3	-1456,7561	237	3126,94958	3006,4589	3164,94958	403,656421	0.723
Modell 4	-1443,8166	224	3174,08845	3012,37727	3225,08845	377,777264	0.776
Modell 5	-1431,276	211	3222,02525	3019,09358	3286,02525	352,696046	0.756
Modell 6	-1420,5213	198	3273,53402	3029,38185	3350,53402	331,186788	0.734

FIGURE S1 (A–D) Latent class analysis of the attributes of innovation in the inventory, results in two (A) to five (D) classes.

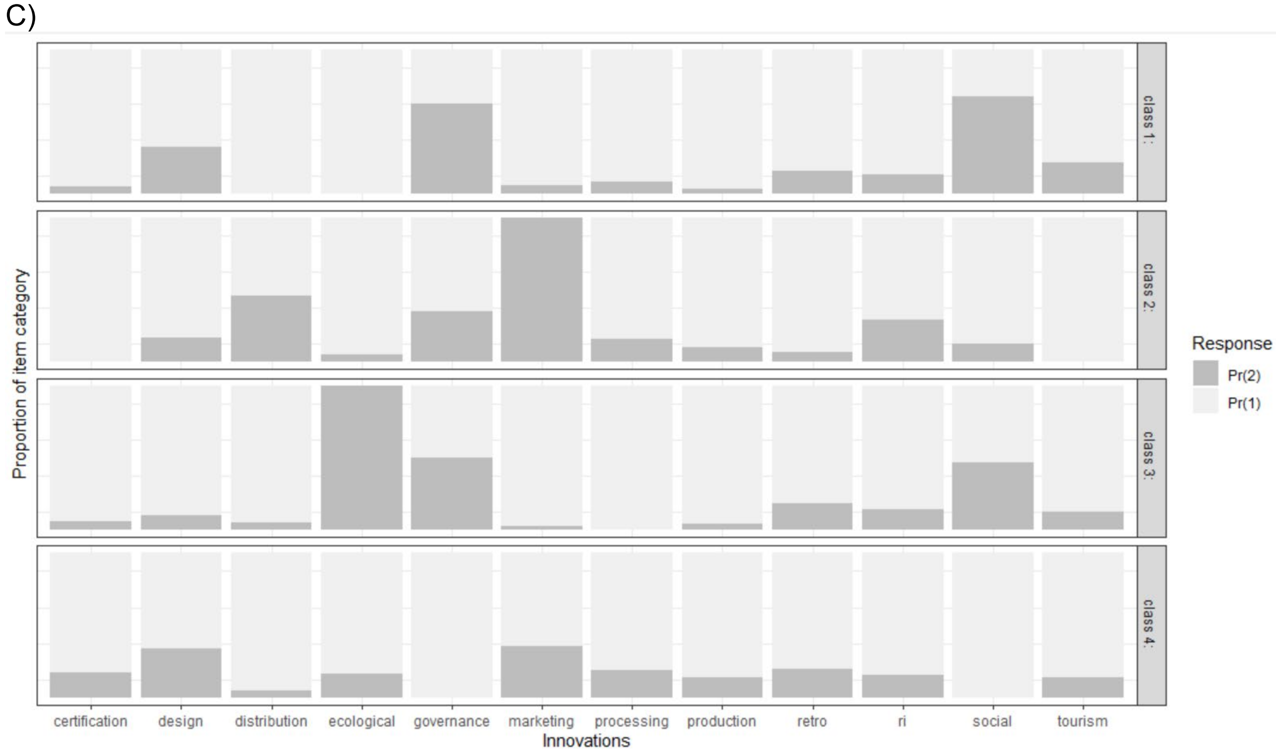
A)



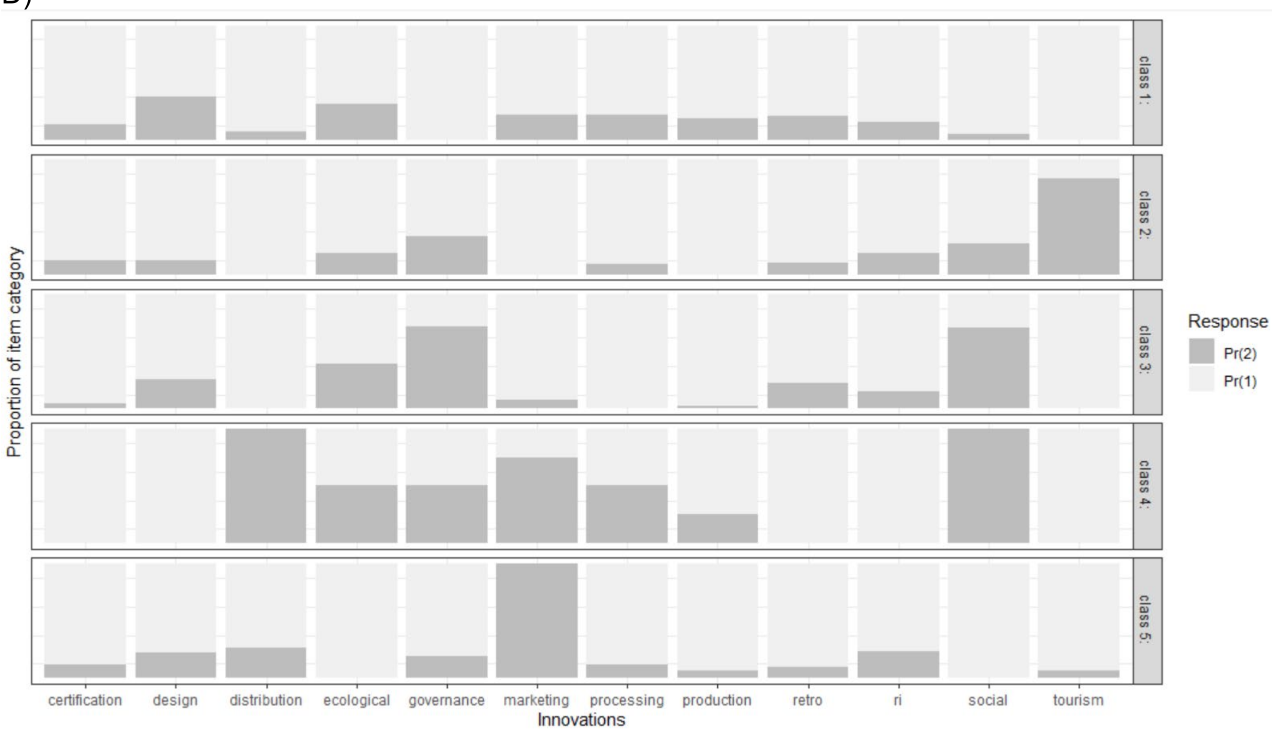
B)


class 1:
class 2:
class 3:
Proportion of item category
Response
Pr(2)
Pr(1)
certification
design
distribution
ecological
governance
marketing
processing
production
retro
ri
social
tourism
Innovations

C)


class 1:
class 2:
class 3:
class 4:
Proportion of item category
Response
Pr(2)
Pr(1)
certification
design
distribution
ecological
governance
marketing
processing
production
retro
ri
social
tourism
Innovations

D)

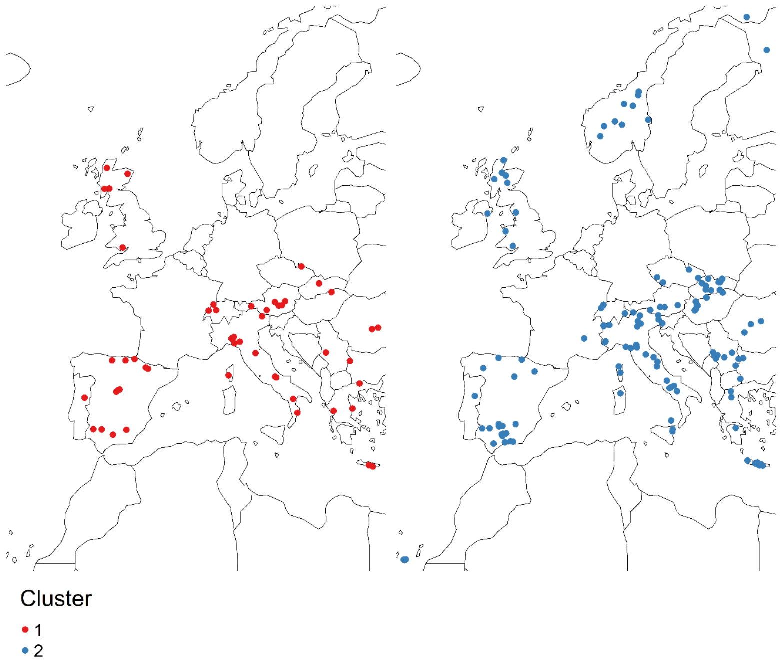

Proportion of item category
class 1:
class 2:
class 3:
class 4:
class 5:
Response
Pr(2)
Pr(1)
certification
design
distribution
ecological
governance
marketing
processing
production
retro
ri
social
tourism
Innovations

Supplementary results of the geographical clusters

TABLE S2 Count of the number of times an attribute was associated with a MPVC per country.

Attributes by country	Certification	Design	Distribution	Ecological	Governance	Marketing	Processing	Production	Retro-innovation	R&I	Social	Tourism
Austria	0	7	2	7	7	12	1	1	4	1	5	0
Czech Republic	0	5	0	1	0	1	1	3	1	1	1	0
France	1	10	1	10	9	4	1	3	3	4	9	1
Greece	0	10	2	3	6	7	3	6	3	6	6	3
Hungary	0	1	6	4	7	12	3	1	3	8	8	5
Switzerland	1	8	0	4	5	5	0	1	7	2	3	2
Spain	9	9	5	14	18	12	7	1	4	5	14	7
Portugal	0	1	1	2	0	0	1	0	1	1	0	0
Romania	0	4	1	1	2	0	2	0	0	0	1	1
Bulgaria	0	1	0	0	1	0	1	1	0	0	2	1
Italy	7	8	5	9	8	13	4	8	8	8	7	4
Serbia	7	5	3	4	3	10	2	1	5	3	3	2
Turkey	0	0	0	0	0	0	0	0	0	0	0	0
North Macedonia	0	0	0	0	0	0	5	0	0	3	1	0
Scotland	1	1	0	7	2	3	5	0	2	3	3	4
Scandinavia	3	3	0	0	2	9	0	0	3	2	2	5
Slovakia	0	2	1	2	2	3	0	1	2	0	0	2

FIGURE S2 Spatial distribution of innovation clusters: 2-cluster model.



Spatial data sources: 1) © EuroGeographics for the administrative boundaries, 2) © OpenStreetMap contributors, ODbL 1.0