Territorial typologies and environmental pressures: Evidence from Moldova's districts using Principal Component Analysis and Fuzzy C-Means

Területi tipológiák és környezeti terhelések: Bizonyítékok Moldova körzeteiből főkomponens-elemzés és fuzzy c-means klaszterezés alkalmazásával

DANIELA LUMINIȚA CONSTANTIN, IONUȚ NICA, CAMELIA DELCEA, BIANCA CIBU, ȘTEFAN IONESCU

Daniela Luminița CONSTANTIN: professor emeritus, Research Centre for Macroeconomic and Regional Forecasting, Faculty of Administration and Public Management, Bucharest University of Economic Studies; Piața Romană 6.; RO-010374 București, Romania; daniela.constantin@amp.ase.ro; https://orcid.org/0000-0002-6839-7396
Ionuț NICA: assistant professor, Department of Economic Informatics and Cybernetics, Faculty of Economic Cybernetics, Statistics and Informatics, Bucharest University of Economic Studies; Piața Romană 6.; RO-010374 București, Romania; ionut.nica@csie.ase.ro; https://orcid.org/0000-0003-2118-3654
Camelia DELCEA: professor Department of Economic Informatics and Cybernetics, Faculty of Economic Cybernetics, Statistics and Informatics, Bucharest University of Economic Studies; Piața Romană 6.; RO-010374 București, Romania; camelia.delcea@csie.ase.ro; https://orcid.org/0000-0003-3589-1969
Bianca CIBU: PhD candidate, Department of Economic Informatics and Cybernetics, Faculty of Economic Cybernetics, Statistics and Informatics, Bucharest University of Economic Studies; Piața Romană 6.; RO-010374 București, Romania; bianca.cibu@csie.ase.ro; https://orcid.org/0009-0003-8597-7514
Ștefan IONESCU: PhD candidate, Department of Economic Informatics and Cybernetics, Faculty of Economic Cybernetics, Statistics and Informatics, Bucharest University of Economic Studies; Piața Romană 6.; RO-010374 București, Romania; stefan.ionescu@csie.ase.ro; https://orcid.org/0000-0002-0469-3022

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ABSTRACT: Territorial development in the Republic of Moldova is spatially uneven, but district typologies based on absolute volumes risk reproducing differences in population size rather than identifying substantive territorial profiles. This study constructs a size-adjusted district-level typology linking socio-economic development intensity, infrastructure provision, environmental and service-related pressure, and environmental expenditure intensity. The analysis uses the latest available mixed-year cross-section data covering 34 territorial units, while Chișinău is examined separately because of its structurally exceptional profile. Population is used as a denominator and contextual variable rather than as an active clustering indicator. Absolute measures are converted into per-capita or rate-based indicators, positively skewed variables are logarithmically transformed, and all active indicators are standardized. Principal Component Analysis (PCA) is used to summarize the correlation structure, while Fuzzy C-Means (FCM) is applied to the first three

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descriptive component scores. A two-cluster resolution is reported as a binary benchmark, whereas three clusters are retained as the preferred substantive typology after jointly considering fuzzy validity, membership clarity, interpretability and robustness. The results distinguish between (i) development pressure intensive districts with higher environmental expenditure intensity; (ii) intermediate development districts with lower observed pressure; and (iii) peripheral lower-intensity districts with lower environmental expenditure. GIS mapping and fuzzy membership diagnostics show that several districts occupy transitional positions rather than belonging unambiguously to a single territorial type. The findings provide a size-adjusted account of Moldova's internal core–periphery structure and support differentiated, place-based territorial and environmental interventions. The mixed reference years and the proxy character of waste collection and environmental expenditure as indicators are explicitly acknowledged as limitations.

CONSTANTIN, Daniela Luminița: *professzor emeritus, Bukaresti Közgazdaságtudományi Egyetem, Közigazgatási és Közmenedzsment Kar, Makrogazdasági és Regionális Előrejelzési Kutatóközpont; RO-010374 București, Piața Romană 6., Románia; daniela.constantin@amp.ase.ro; https://orcid.org/0000-0002-6839-7396*

NICA, Ionuț: *egyetemi adjunktus, Bukaresti Közgazdaságtudományi Egyetem, Gazdasági Kibernetikai, Statisztikai és Informatikai Kar, Gazdaságinformatikai és Kibernetikai Tanszék; RO-010374 București, Piața Romană 6., Románia; ionut.nica@csie.ase.ro; https://orcid.org/0000-0003-2118-3654*

DELCEA, Camelia: *professzor, Bukaresti Közgazdaságtudományi Egyetem, Gazdasági Kibernetikai, Statisztikai és Informatikai Kar, Gazdaságinformatikai és Kibernetikai Tanszék; RO-010374 București, Piața Romană 6., Románia; camelia.delcea@csie.ase.ro; https://orcid.org/0000-0003-3589-1969*

CIBU, Bianca: *kandidátus, Bukaresti Közgazdaságtudományi Egyetem, Gazdasági Kibernetikai, Statisztikai és Informatikai Kar, Gazdaságinformatikai és Kibernetikai Tanszék; RO-010374 București, Piața Romană 6., Románia; bianca.cibu@csie.ase.ro; https://orcid.org/0009-0003-8597-7514*

IONESCU, Ștefan: *kandidátus, Bukaresti Közgazdaságtudományi Egyetem, Gazdasági Kibernetikai, Statisztikai és Informatikai Kar, Gazdaságinformatikai és Kibernetikai Tanszék; RO-010374 București, Piața Romană 6., Románia; stefan.ionescu@csie.ase.ro; https://orcid.org/0000-0002-0469-3022*

KULCSSZAVAK: területi tipológia; környezeti terhelés; főkomponens-elemzés; fuzzy c-means; helyalapú politika; GIS; Moldovai Köztársaság

ABSZTRAKT: A Moldovai Köztársaság területi fejlődése térben egyenlőtlen, de az abszolút volumeneken alapuló körzeti tipológiák azzal a kockázattal járnak, hogy inkább a népességszámbeli különbségeket, semmint a valódi területi profilokat tükrözik vissza. Ez a tanulmány méretre korrigált, körzeti szintű tipológiát dolgoz ki, amely összekapcsolja a társadalmi-gazdasági fejlettség intenzitását, az infrastrukturális ellátottságot, a környezeti és szolgáltatásokkal összefüggő terhelést, valamint a környezetvédelmi kiadások volumenét. Az elemzés a legfrissebb elérhető, vegyes évekből származó keresztmetszeti adatokat használja 34 területi egységre vonatkozóan, míg Chișinău – strukturálisan kivételes profilja miatt – külön vizsgálja. A népességet nevezőként és kontextuális változóként, nem pedig aktív klaszterezési mutatóként alkalmazza. Az abszolút mutatókat egy főre jutó vagy rátaalapú mutatókká alakítja, a jobbra ferde eloszlású változókat logaritmikusan transzformálja, és minden aktív mutatót standardizál. A korrelációs szerkezet összegzésére főkomponens-elemzést alkalmaz, míg az első három leíró komponens-pontszámra fuzzy c-means klaszterezést végez. Kétklaszteres megoldást közöl bináris viszonyítási alapként, míg – a fuzzy validitás, a tagsági egyértelműség, az értelmezhetőség és a robusztusság figyelembevétele alapján – a három klasztert tekinti preferált tartalmi tipológiának.

Az eredmények alapján a következő típusok különböztethetők meg: (i) fejlett és terhelésintenzív körzetek magasabb környezetvédelmi kiadásokkal; (ii) közepes fejlettségű körzetek alacsonyabb megfigyelt terheléssel; és (iii) periférikus, alacsonyabb intenzitású körzetek alacsony

környezetvédelmi kiadásokkal. A GIS-alapú térképezés és a fuzzy tagsági diagnosztika azt mutatja, hogy több körzet átmeneti pozíciót foglal el, nem sorolható egyértelműen egyetlen területi típusba. Az eredmények Moldova belső centrum–periféria szerkezetéről nyújtanak méretre korrigált képet, és differenciált, helyalapú területi és környezeti beavatkozásokat tesznek indokolttá. A vegyes referenciaévek, illetve a hulladékgyűjtési és környezetvédelmi kiadási mutatók proxy jellege a cikk korlátaiként említhetők.

Introduction

Differences between territories are not only visible on the map. They are felt in the pace of investment, in access to infrastructure, in the quality of jobs and in the pressures placed on local resources. In the Republic of Moldova, these contrasts are visible between municipalities and districts, but also between districts that, at first glance, seem comparable. Economic and urban development almost inevitably brings an increase in resource consumption and waste quantities, and the capacity of local authorities and actors to respond through environmental protection measures often remains uneven. In this context, it becomes important to understand not only who is performing better, but also what type of development is taking shape at local level and what environmental costs are associated with it. These issues get a special relevance in the context of the Growth Plan for Moldova adopted by the EU, aiming to accelerate the reforms and to boost the economy, so as to be better prepared for the EU membership.

The scientific literature frequently discusses the link between development and environmental pressures (Alyahya et al. 2022; Betts, Super, North 2018; Q. Wang, X. Wang, Li 2026), but many analyses remain at the aggregate national or regional level, missing the internal variation that is essential for targeted public policies. For a country with pronounced territorial disparities, such as the Republic of Moldova (Knott, Gobbat, Slav 2025; Penina 2022; Roşcovan, Russu, Guţu 2024), a district-level approach can provide a more realistic picture about the structure of the development: where investments and infrastructure are concentrated, where resource (especially water) use is intensified, where differences in waste management occur, and, last but not least, where there is a more consistent financial/managerial response to environmental challenges.

This study examines territorial heterogeneity in the Republic of Moldova through four analytically connected blocks: socio-economic development intensity, infrastructure and basic digital readiness, environmental and service-related pressures, and environmental expenditure intensity. Resident population is not treated as an active dimension of development because doing so would risk conflating territorial size with territorial performance. Instead, population is used as a denominator for converting volume indicators into per-capita or rate-based measures and is retained only as a contextual characteristic. The resulting framework therefore compares districts in terms of the intensity and

configuration of development, infrastructure, resource use, waste collection and recorded environmental expenditure rather than their absolute demographic or economic mass.

Methodologically, we use Principal Component Analysis (PCA) to reduce the number of dimensions and highlight the major axes that differentiate the districts, and then apply Fuzzy C-Means (FCM) to identify territorial typologies, allowing for gradual memberships, and thus offering a more sophisticated picture. This approach is suitable for a heterogeneous territorial context, where a district may partially resemble several profiles. The result is an interpretable classification, which can support more applied discussions about public policy priorities: where there is a need to strengthen the environmental response, where pressures are growing faster than the intervention capacity, and which types of territories require differentiated approaches.

In regional science, territorial development is understood as a spatially uneven process, shaped by the interaction between economy, infrastructure, demography, resources and local institutional capacity (Cuadrado-Roura, Kourtit, Nijkamp 2025; Rodríguez-Pose 2020; Sedita, Coenen, Kogler 2025; Torre 2025). From this perspective, it is not enough to observe differences between territories, but it becomes essential to identify patterns and mechanisms that explain why some areas concentrate investments and economic activity, while others lag behind or evolve with disproportionate environmental pressures. The present study follows this logic through a district-level analysis in the Republic of Moldova, combining socio-economic, infrastructural and environmental indicators to outline territorial typologies.

Against this background, the study addresses the following research questions:

RQ1: What dimensions structure inter-district differences in socio-economic development intensity, infrastructure provision, environmental and service-related pressure, and environmental expenditure intensity after controlling for territorial size?

RQ2: What fuzzy territorial profiles emerge from these size-adjusted indicators, and which districts display mixed or transitional membership?

RQ3: How do the resulting profiles contribute to the interpretation of core–periphery relationships and differentiated development paths within the Republic of Moldova?

The contribution of the study is threefold. First, it develops a size-adjusted territorial indicator system that reduces the risk of reproducing differences in district population through multivariate analysis. Second, it combines PCA and FCM to distinguish both dominant territorial dimensions and gradual membership in development–environment configurations. Third, it integrates statistical typology with GIS-based visualization, thereby showing how the identified profiles and transitional districts are distributed across Moldova's internal core–periphery

structure. The study not only classifies the districts, but also establishes a framework for interpreting differentiated territorial development paths and place-based policy needs.

Literature review

The relationship between economic development and environmental performance has become a central topic in the literature, particularly in the context of differences between developed and emerging economies. In this regard, a study by Betts, Super and North (2018) showed that the character of economy significantly influences the adoption of environmental practices, which in turn affect the environmental performance of organizations. Through their study, the authors demonstrate that companies in developing economies may exhibit a stronger relationship between the adoption of innovative environmental practices and institutional pressures than those in advanced economies. In fact, institutions play a significant role in development. (Alyahya et al. 2022) observed that these pressures are decisive factors when it comes to innovation and sustainable development. In turn, understanding the important role played by institutions in development, Rodríguez-Pose (2020) researched the progress of the literature, illustrating the gaps in the field and proposing ways to improve the integration of more beneficial development policies.

A complementary perspective is provided by the Environmental Kuznets Curve (EKC) hypothesis. It suggests that some forms of environmental degradation may initially increase with economic growth and later decline as higher income, technological progress, structural transformation and stronger environmental regulation facilitate cleaner production and greater environmental investment (Grossman, Krueger 1995; Stern 2004). However, this relationship is not universal across pollutants, countries, or territorial scales. The EKC should therefore be understood as a possible non-linear development–environment relationship rather than as an automatic trajectory followed by all territories (Stern 2004). The present study does not formally test the EKC, because its cross-sectional design does not estimate an income turning point; instead, the framework is used to interpret whether districts with different development intensities also display different combinations of environmental pressure and expenditure.

Institutional economics offers a complementary explanation for why similar levels of development may produce different territorial and environmental outcomes. Institutions shape incentives, investment decisions, coordination mechanisms, and the capacity to implement territorial and environmental policies (North 1990). At the regional level, institutional quality influences the capacity of territories to mobilize resources, attract investment, and translate development opportunities into sustainable outcomes (Rodríguez-Pose 2020).

Although these studies clarify the role of institutions in shaping environmental practices, most of them focus on firms or organizations rather than on territorial units. At the territorial level, economic activity, infrastructure, demographic concentration, and institutional resources are distributed unevenly, producing differentiated development paths and core–periphery relationships (Bański 2025). Consequently, similar levels of economic activity may coexist with different combinations of infrastructure provision, resource consumption, environmental pressure, and financial effort. This perspective is consistent with the approach of place-based development, which argues that territorial policy should respond to the specific constraints, resources, and institutional characteristics of each place rather than applying spatially uniform interventions (Barca, McCann, Rodríguez-Pose 2012). From this perspective, territorial typologies are useful not only for ranking regions, but also for identifying different configurations of development, infrastructure, environmental pressures, and financial capacity that may require differentiated policy instruments.

The relationship between development and environmental conditions can be organized through an adapted pressure–response logic. Socio-economic activity and infrastructural development act as territorial driving forces that may increase demand for water, construction, transport infrastructure, and waste management services. Water use and municipal waste collection provide partial indications of environmental and service-related pressure, while environmental financial flows reflect the intensity of recorded expenditure associated with environmental protection. But these dimensions should not be interpreted as a deterministic causal chain. Higher development intensity does not necessarily generate proportionally higher environmental pressure, because territorial outcomes also depend on economic structure, technological efficiency, public service coverage, and institutional arrangements. Similarly, higher environmental expenditure does not automatically indicate better policy performance, since it may also reflect higher underlying pressure, more costly infrastructure, or the concentration of environmentally intensive activities. The analytical framework is informed by the Driving Forces–Pressures–State–Impact–Response (DPSIR) logic (EEA 1999), but it does not represent a complete DPSIR application. Given the available district-level data, the study focuses on selected development drivers, environmental and service-related pressures, and recorded environmental financial intensity.

In territorial research, PCA is often used to summarize sets of correlated quantitative indicators and to identify the dominant dimensions along which territorial units differ (Greenacre et al. 2022). Its principal advantage is the reduction of redundancy while retaining a substantial proportion of the total variance. However, PCA does not demonstrate that the observed indicators are generated by theoretically defined latent factors: it provides a descriptive representation of the main dimensions of variation.

Regional applications have used PCA to summarize socio-economic, infrastructural and environmental information before constructing territorial

classifications (Pavone 2026). Delcea et al. (2025) and Rotaru et al. (2024) applied PCA to regional development and performance indicators, while Bezrukov (2020) combined PCA and clustering to identify differentiated regional structures in the Russian Federation. Environmental studies have similarly used PCA to construct multidimensional indices of environmental degradation and ecological carrying capacity (Khatun 2009; Liu et al. 2018).

FCM has also been increasingly applied in regional and environmental research (Cafaro et al. 2025; Nosov 2025), particularly when the analyzed units display mixed characteristics and cannot be assigned unambiguously to a single category. The method was initially formalized as a fuzzy objective function clustering approach by Bezdek (Bezdek 1981). Recent applications have demonstrated the usefulness of FCM in delimiting agricultural management areas (Zeraatpisheh et al. 2020), analyzing regional tourism typologies (Rahmanita et al. 2025), and evaluating energy and sustainability performance (Nica, Georgescu, Kinnunen 2026). In environmental studies, FCM has been applied to classify a large set of hydrochemical data, obtaining cluster centers with which the chemical and physical processes that produce variations in water chemistry can be observed, thus confirming its usefulness in identifying complex territorial patterns (Güler, Thyne 2004). The selection of the optimal number of clusters is usually performed based on validation indicators such as the Fuzzy Partition Coefficient, Partition Entropy, and the Xie–Beni index, which allow for the evaluation of the clarity and separation of the obtained solutions (Bezdek 1981; Xie, Beni 1991).

Several alternative methods could be used to construct territorial typologies. K-means provides a parsimonious hard partition but assigns each territorial unit exclusively to one cluster (Pant, Leigh, Fajardo Rueda 2025). Ward hierarchical clustering is useful for examining nested similarities and does not require an initial specification of cluster centers (Gao, Venkitasubramaniam, Choi 2026), but it also ultimately produces mutually exclusive groups. Model-based clustering offers probabilistic classifications, although it generally relies on stronger distributional assumptions. Multi-criteria methods may integrate heterogeneous indicators, but their results depend on externally established weights and preference rules (Libório et al. 2025). FCM was selected because territorial profiles are unlikely to have perfectly discrete boundaries. A district may simultaneously display characteristics associated with higher development intensity, moderate environmental pressure and limited environmental expenditure. FCM preserves this information through continuous membership degrees, whereas a hard clustering method would conceal such intermediate configurations. K-means and Ward clustering are nevertheless retained as robustness benchmarks in order to assess whether the main territorial allocation depends on the fuzzy algorithm.

The Republic of Moldova faces persistent challenges related to territorial governance and public administration, including urban–rural disparities,

demographic decline, large-scale emigration, uneven access to local public services, limited institutional capacity, territorial fragmentation, and low fiscal autonomy at the local level (Ionescu et al. 2026; Roşcovan, Russu, Guţu 2024). These problems are also reflected in widening spatial inequalities. Existing evidence indicates that regional inequality and welfare gap between urban and rural areas have increased, while territorial differences remain in educational attainment, infrastructure and access to essential services. Such disparities support the need for a district-level approach capable of distinguishing not only higher- and lower-performing territories, but also different combinations of development intensity, infrastructure provision and environmental pressures (WBG 2018). Environmental vulnerability further reinforces the connection between territorial development and resource management. Moldova's development and climate challenges are closely interconnected, mainly because infrastructure, water systems, economic vulnerability and institutional capacity differ considerably across territorial contexts (WBG 2024).

Hachi, Cujbă and Crăciun (2023) constructed a multidimensional human development index for northern Moldova using 12 indicators organized into four dimensions, identifying differences between rural and urban development trajectories. From a longer-term perspective, Ianos, Sirodoev and Pascariu (2012) showed that Moldova's territorial structures have also been shaped by privatization, institutional restructuring and the uneven implementation of environmental policies. These transformations contribute to spatially differentiated relationships between economic development, resource use and environmental protection.

Despite these contributions, the existing literature remains fragmented in three respects. First, studies on Moldova generally examine socio-economic disparities, administrative capacity or environmental challenges separately, rather than integrating them into a common district-level analytical framework. Second, territorial analyses frequently rely on absolute indicators, which may cause multivariate classifications to reproduce differences in population size instead of relative development and environmental profiles. Third, conventional hard classifications do not adequately represent districts with mixed or transitional characteristics.

The present study addresses these gaps by combining size-adjusted socio-economic, infrastructural, environmental pressure and environmental financial indicators with PCA, FCM and GIS visualization. PCA is used to identify the principal axes structuring territorial variation, while FCM retains gradual memberships and reveals districts located between the dominant profiles. The resulting typology contributes to the understanding of Moldova's internal core–periphery relationships and provides an empirical basis for place-based interventions.

Data and methodology

Data and variables

The empirical analysis covers 34 territorial units included in the baseline typology. Chișinău municipality is analyzed separately because its structurally exceptional demographic and economic profile would disproportionately influence the multivariate distance structure. Resident population is retained as a contextual variable and denominator, but it is not included as an active variable in PCA or clustering.

The empirical database was initially assembled from ten official district-level indicators published by the National Bureau of Statistics of the Republic of Moldova. Table 1 presents these source indicators in their original form, together with their conceptual relevance and their subsequent analytical treatment. The variables were not entered unchanged the baseline PCA–FCM model. With the exception of average gross monthly wage, they were used to construct the size-adjusted indicators reported in Table 2.

Resident population was retained as a denominator and contextual variable, whereas water abstraction was included only in the sensitivity analysis. Most of the source indicators presented in Table 1 are expressed as absolute territorial volumes. Their direct inclusion in a multivariate model would risk reproducing differences in district population rather than identifying substantively different development–environment configurations. A more populous district would generally be expected to record more employees, construction activity, entities with computers, urban streets, water use and collected waste, even in the absence of a higher relative development or environmental pressure intensity. To reduce this common scale effect, the baseline specification converted the relevant source indicators into per-capita or rate-based measures. Table 2 presents the eight indicators effectively included in the baseline PCA and FCM analyses, together with the population variable used for contextual purposes and the water abstraction indicator retained for sensitivity analysis.

The active indicator system consists of eight size-adjusted or already intensive indicators organized into four analytical blocks including socio-economic development intensity, infrastructure and digital readiness, environmental and service-related pressure, and environmental financial effort (Table 2). Absolute volume measures were converted into rates or per-capita values in order to reduce the common population-scale component identified in the original specification. Water abstraction per resident was retained only for sensitivity analysis because of its conceptual and empirical overlap with water use.

Table 1. Official district-level source indicators used to construct the analytical variables
Hivatalos, körzeti szintű forrásmutatók az elemzés változóinak megalkotásához

Indicator	*Acronym*	*Analytical block*	*Analytical treatment*	*Source*
Average resident population	NMPRO	Territorial context	Used as denominator and contextual variable; not included as an active PCA–FCM indicator.	National Bureau of Statistics of the Republic of Moldova
Number of employees	NSAL	Socio-economic development	Converted into employees per 1,000 residents.	National Bureau of Statistics of the Republic of Moldova
Average gross monthly wage	CSMLB	Socio-economic development	Retained as an already intensive indicator.	National Bureau of Statistics of the Republic of Moldova
Value of construction works	VLCR	Investment and built environment	Converted into construction works per resident.	National Bureau of Statistics of the Republic of Moldova
Legal entities with personal computers	PJCP	Digital readiness	Converted into entities with personal computers per 1,000 residents.	National Bureau of Statistics of the Republic of Moldova
Urban streets (total length)	SOPT	Infrastructure	Converted into urban street length per 10,000 residents.	National Bureau of Statistics of the Republic of Moldova
Water use (excluding reused water and water in closed circulation systems)	UA	Environmental pressure	Converted into water use per resident.	National Bureau of Statistics of the Republic of Moldova
Municipal waste collected from households, institutions and economic agents	DMCPIA	Environmental and service-related pressure	Converted into municipal waste collected per 1,000 residents.	National Bureau of Statistics of the Republic of Moldova
Current environmental protection expenditures and ecological payments	CCPME	Environmental financial effort	Converted into environmental financial flows per resident.	National Bureau of Statistics of the Republic of Moldova
Water abstraction (water intake)	CAPTR	Environmental pressure	Converted into water abstraction per resident and included only in sensitivity analysis.	National Bureau of Statistics of the Republic of Moldova

Source: authors' compilation

Table 2: Size-adjusted district indicators used in the empirical analysis
Méretre korrigált körzeti mutatók az empirikus elemzésben

Analytical block	*Revised indicator*	*Acronym*	*Construction*	*Reference year*	*Role*
Context	Resident population	POP	Official value	2024	Denominator / context only
Socio-economic development	Employees per 1,000 residents	EMP1000	$\frac{NSAL}{POP} \times 1{,}000$	2024	Active
Socio-economic development	Average gross monthly wage	WAGE	Official intensive indicator	2023	Active
Investment / built environment	Construction works per resident	CONSTR_PC	$\frac{VLCR \times 10^6}{POP}$	2024	Active
Digital readiness	Entities with personal computers per 1,000 residents	DIGITAL1000	$\frac{PJCP}{POP} \times 1{,}000$	2025	Active
Infrastructure	Urban street length per 10,000 residents	STREET10000	$\frac{SOPT}{POP} \times 10{,}000$	2024	Active
Environmental pressure	Water use per resident	WATER_USE_PC	$\frac{UA \times 10^6}{POP}$	2024	Active
Environmental / service pressure	Municipal waste collected per 1,000 residents	WASTE_INT	$\frac{DMCPIA}{POP} \times 1{,}000$	2018	Active
Environmental financial effort	Environmental financial flows per resident	ENVEXP_PC	$\frac{CCPME}{POP} \times 1{,}000$	2024	Active
Environmental pressure	Water abstraction per resident	WATER_ABS_PC	$\frac{CAPTR \times 10^6}{POP}$	2024	Sensitivity only

Source: authors' compilation based on data from the National Bureau of Statistics of the Republic of Moldova

Data preparation

Since the indicators have different scales and units, the data are processed before analysis in three steps: (i) cleaning and filling in missing values, (ii) z-score standardization, and (iii) outlier checking. Missing values are treated by an explicit rule (e.g. filling in from official sources or simple imputation, where justified), so that each district has available values for the set of variables used in the analysis. The dataset does not represent a fully harmonized 2024 cross-section. Municipal waste collection refers to 2018, average gross monthly wage to 2023, entities with personal computers to 2025, and the remaining indicators to 2024. The baseline specification is therefore described as a mixed-year cross-section based on the latest available data. The reference year is reported explicitly for every indicator, and a strict specification only using the data from 2024 is estimated as a sensitivity test.

Data preparation followed four stages. First, absolute indicators were converted into per-capita or rate-based measures using resident population as the denominator. Population itself was removed from the active PCA–FCM matrix. Second, positively skewed indicators were transformed using ln(1+x); average wage was retained in levels because its distribution was comparatively less skewed. Third, all active variables were standardized to zero mean and unit variance. Standardization places the indicators on a common statistical scale (Adachi 2020), whereas the preceding per-capita transformation addresses the substantive population size effect. Pearson coefficients are used as the main correlation measure because the active variables are quantitative and PCA is estimated from the linear correlation structure. Spearman coefficients are reported as a robustness check for possible rank-based or non-linear monotonic relationships. Multivariate atypicality was examined using Mahalanobis distance (Wang 2012). Chișinău obtained $d^2=25.28$, marginally exceeding the Bonferroni-adjusted threshold of 25.22. Its exclusion from the baseline model is therefore based both on this diagnosis and on substantive comparability, rather than on an assumption that the observation is erroneous. A sensitivity analysis including Chișinău is reported in the robustness section. No missing values were identified in the variables used for the baseline model.

Principal Component Analysis

To capture the common structure of the indicators and reduce the number of dimensions (Zeraatpisheh et al. 2020), PCA is applied to the standardized matrix. PCA identifies linear combinations of variables (principal components) that maximize the explained variability (Adachi 2020; Greenacre et al. 2022; Ji, Moore-Cherry, Kogler 2026).

Sampling adequacy was evaluated using the Kaiser–Meyer–Olkin statistic and Bartlett's test of sphericity. PCA was estimated only after confirming that the overall correlation structure was sufficiently different from an identity matrix.

To make the procedure explicit, let $X \in R^{n \times p}$ denote the standardized data matrix (districts × indicators), with columns centered and scaled to unit variance. PCA is obtained from the eigen-decomposition of the sample correlation matrix, according to relation (1):

$$R = \frac{1}{n-1} X^T X = V \Lambda V^T \quad (1)$$

In relation (1), Λ=diag(λ_1,...,λ_p) contains the eigenvalues ($\lambda_1 \geq \lambda_2 \geq ... \geq \lambda_p$), *and V = [v1, ... , v_p] the corresponding eigenvectors (loadings). The k-th princip*al component scores are calculated according to the relationship (2):

$$S_k = Xv_k \quad (2)$$

The proportion of variance explained by component k is computed according to relation (3) and (4):

$$PVE_k = \frac{\lambda_k}{\sum_{j=1}^{p} \lambda_j} \quad (3)$$

$$CVE_k = \sum_{k=1}^{K} PVE_k \quad (4)$$

In relation (4) CVE_k is the cumulative variance explained by the first k components. Component retention was evaluated using eigenvalues, cumulative explained variance, loading interpretability and Horn's parallel analysis. The first three components had eigenvalues above one and were retained as parsimonious descriptive coordinates for territorial profiling, explaining 68.23% of total variance. Parallel analysis identified PC1 as the strongest statistically supported dimension; PC2 and PC3 are therefore interpreted more cautiously as supplementary descriptive axes rather than definitive latent constructs.

Fuzzy C-Means clustering

Territorial typologies are constructed with Fuzzy C-Means (FCM), a clustering method that allows for gradual membership of observations in multiple clusters (Bezdek 1981; Hashemi, Gholian-Jouybari, Hajiaghaei-Keshteli 2023; Nica, Georgescu, Kinnunen 2026). This feature is relevant for territorial analysis, as some districts may have mixed profiles (e.g. high pressures but moderate development). K-means and Ward hierarchical clustering were considered as hard clustering alternatives. However, these methods assign every district exclusively to one group and therefore suppress the mixed territorial configurations that are central to the present research. FCM was selected as the

main method because it estimates continuous membership degrees, while K-means and Ward solutions are retained as robustness benchmarks.

Formally, let $Z=\{z_i\}_{i=}{}^{n}{}_{1}$, $z_i \in R^p$, denote the standardized feature vectors for the n districts. FCM estimates a set of c cluster centers $V = \{v_k\}_{k=1}^{c}$ and a membership matrix $U=[u_{ik}] \in [0,1]^{(n\times c)}$, where u_{ik} represents the degree to which district i belongs to cluster k. The method minimizes the objective function, according to relation (5):

$$J_m(U,V) = \sum_{i=1}^{n}\sum_{k=1}^{c} u_{ik}^{m} \left||z_i - v_k\right||^2, m > 1 \quad (5)$$

Subject to the constraints, according to relation (6):

$$\sum_{k=1}^{c} u_{ik} = 1\,, \forall i,\ 0 < u_{ik} < 1 \quad (6)$$

Given U, cluster centers are updated according to relation (7):

$$v_k = \frac{\sum_{i=1}^{n} u_{ik}^{m} z_i}{\sum_{i=1}^{n} u_{ik}^{m}},\ k = 1, \dots, c \quad (7)$$

And given V, memberships are updated according to relation (8):

$$u_{ik} = \left(\sum_{j=1}^{c} \left(\frac{||z_i - v_k||}{||z_i - v_j||} \right)^{\frac{2}{m-1}} \right)^{-1},\ i = 1, \dots, n,\ k = 1, \dots, c \quad (8)$$

The algorithm iterates relations (7) – (8) until convergence (e.g., negligible change in U or J_m). The fuzziness parameter is set to $m = 2$, a common choice in applied studies, and the algorithm was estimated using multiple random initializations in order to reduce sensitivity to local minimum. For reporting, each district is assigned a hard label via relation (9):

$$l_i = \arg\max_k u_{ik} \quad (9)$$

In relation (9), the maximum membership $\max_k u_{ik}$ is used as an indicator of classification clarity (high values indicate core districts, while lower values indicate borderline cases).

Selecting the number of clusters

The number of clusters was evaluated using both statistical validity and substantive typological criteria. A two-cluster resolution was first estimated as a benchmark. This provided a comparatively simple division dominated by the principal development intensity gradient. However, it absorbed several

intermediate and mixed territorial configurations into the two broad groups and was therefore considered insufficient for the main aim of constructing a differentiated territorial typology. Several candidate values are evaluated using validity indices specific to fuzzy clustering (Bezdek 1973): (i) Fuzzy Partition Coefficient (FPC) – higher preferred (clearer partition) (Verma, Tiwari, Thakur 2023), (ii) Partition Entropy (PE) – lower preferred (less uncertainty) (Verma, Tiwari, Thakur 2023), and (iii) Xie–Beni (XB) – lower preferred (compactness–separation trade-off) (Boral, Pal, Ghosh 2024; Rahmanita et al. 2025).

Let U = $[u_{ik}]$ denote the fuzzy membership matrix obtained for a given number of clusters c, where $u_{ik} \in [0,1]$ $\sum_{k=1}^{c} u_{ik} = 1$ and The FPC is computed according to relation (10):

$$FPC(c) = \frac{1}{n}\sum_{i=1}^{n}\sum_{k=1}^{c} u_{ik}^2 \tag{10}$$

The PE is calculated according to relation (11):

$$PE(c) = -\frac{1}{n}\sum_{i=1}^{n}\sum_{k=1}^{c} u_{ik}\log_a(u_{ik}) \tag{11}$$

The XB evaluated the compactness-separation trade-off (Xie, Beni 1991), according to relation (12):

$$XB(c) = \frac{\sum_{i=1}^{n}\sum_{k=1}^{c} u_{ik}^m \|z_i - v_k\|^2}{n \times min_{k \neq j}\|v_k - v_j\|^2} \tag{12}$$

In relation (12), m is the fuzziness parameter, z_i are the standardized observations, and v_k are the cluster centers.

In addition, membership diagnostics (the proportion of core observations with high membership and the proportion of borderline observations) were analyzed (Profiroiu et al. 2025). Three clusters were treated as the minimum substantively meaningful typological resolution in our study. Candidate solutions from $k = 3$ to $k = 8$ were compared using the Fuzzy Partition Coefficient, Partition Entropy, Xie–Beni index, Modified Partition Coefficient, normalized Partition Entropy, core membership share and borderline membership share. The final decision was not based on a single index, because conventional validity measures may mechanically favor solutions with fewer clusters. Relative to the binary benchmark, the three-cluster solution reduced the Xie–Beni index from 0.400 to 0.325 and normalized entropy from 0.675 to 0.658, while maintaining the same core share of 61.8%. More importantly, the third cluster isolated an intermediate territorial configuration that was largely absorbed into the higher-intensity group under $k = 2$. More clusters generated greater fragmentation and a larger proportion of ambiguous memberships. Accordingly, $k = 3$ is interpreted as the preferred substantive typology, rather than as an unconditional mathematical optimum.

Cluster profiling through composite scores

Cluster profiles were interpreted using three composite dimensions calculated as arithmetic means of standardized indicators:

- Development and infrastructural intensity: EMP1000, WAGE, CONSTR_PC, DIGITAL1000, and STREET10000;
- Environmental and service-related pressure: WATER_USE_PC, and WASTE_INT;
- Environmental expenditure intensity: ENVEXP_PC.

The third dimension should not be interpreted as a comprehensive measure of institutional or policy capacity. It reflects the relative intensity of recorded current environmental protection expenditure per resident. The cluster-level values are used descriptively to compare the configurations identified by FCM.

Robustness, stability assessment and diagnostic

Robustness was assessed by re-estimating the PCA–FCM pipeline under alternative analytical specifications: without logarithmic transformation, with water abstraction included, with the environmental financial indicator excluded, using only indicators referring to 2024, including Chișinău and using the original absolute indicators. Agreement between the hard maximum membership allocations and the baseline three-profile solution was evaluated using the Adjusted Rand Index.

The sensitivity of the typology to the number of PCA scores was examined by estimating additional FCM models using PC1 alone and PC1–PC2. K-means and Ward hierarchical clustering were also estimated for $k = 2$ and $k = 3$ as hard clustering benchmarks.

Conditional bootstrap stability was evaluated over 300 resamples of the three-dimensional PCA score matrix. FCM was re-estimated for each resample, cluster labels were aligned with the baseline solution, and district-level stability was calculated as the proportion of resamples in which a territorial unit retained its baseline profile assignment. Because the bootstrap is conditional on the estimated PCA representation, it assesses clustering stability rather than uncertainty in the entire data construction and PCA pipeline.

Agreement between alternative clustering solutions was assessed using the Adjusted Rand Index (ARI), a chance-corrected measure of similarity between two partitions. ARI evaluates whether pairs of territorial units are grouped together or separated consistently across two classifications. It takes the value 1 for identical partitions, is approximately 0 when agreement is comparable to that expected by chance and may take negative values when agreement is lower than expected by chance.

Since FCM generates continuous membership degrees, ARI was calculated using the hard profile assignments obtained through the maximum membership rule. Accordingly, ARI evaluates the stability of the induced hard partition and does not capture changes in the magnitude of fuzzy membership degrees. It is therefore interpreted jointly with maximum membership values, membership gaps and district-level bootstrap stability.

To examine the relative alignment between environmental and service-related pressure and recorded environmental expenditure, a standardized diagnostic gap was calculated for each territorial unit, according to relation (13):

$$G_i = P_i - E_i \tag{13}$$

In equation (13), P_i denotes the composite pressure score and E_i denotes environmental expenditure intensity. Positive values indicate that observed pressure is higher than expenditure intensity in sample-relative standardized terms, whereas negative values indicate that expenditure intensity is higher than measured pressure. Because both components are standardized scores, G_i is dimensionless. It should not be interpreted as an absolute budgetary deficit, a financing requirement, or a direct measure of policy effectiveness.

Results

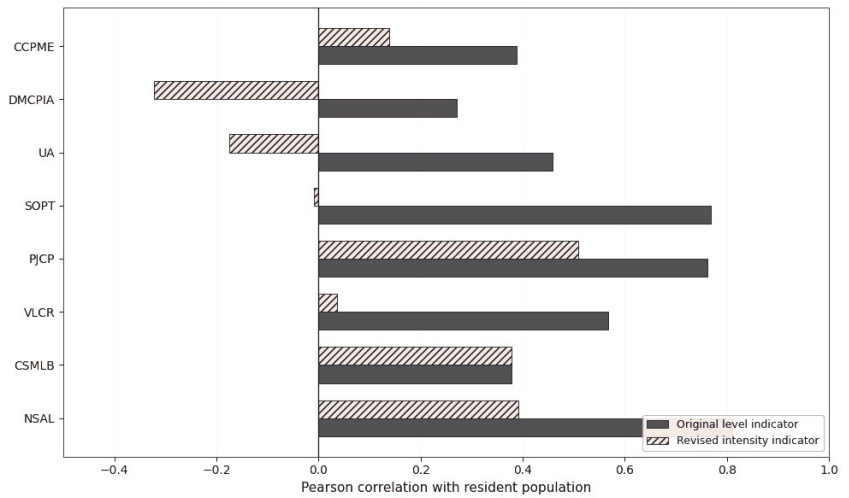
The baseline sample comprises 34 district-level territorial units: 32 raions, Bălți municipality and U.T.A. (Autonomous Territorial Unit) Găgăuzia. Chișinău municipality is examined separately and is not included in the baseline PCA–FCM model, as explained earlier. The results are presented in six stages: assessment of the population scale effect, analysis of the revised correlation structure, evaluation of the PCA solution, selection of the fuzzy territorial typology, and spatial interpretation of the profiles and robustness assessment.

Size adjustments and correlation structure

Figure 1 compares the Pearson correlations between resident population and the original source indicators with the corresponding correlations obtained after the construction of the revised intensity-based indicators. Across the eight active source–revised indicator pairs, including average wage, which was already an intensive measure and was therefore retained unchanged, the mean absolute correlation with population decreased from 0.551 to 0.245. The largest reductions were observed for urban street length, construction works and number of employees. The reduction was not uniform across all variables. In particular, municipal waste collection intensity changed the direction of its relationship with population and remained

moderately associated with territorial size. Consequently, the revised specification should be interpreted as substantially reducing, rather than completely eliminating, the population scale effect. The correlation between PC1 and logarithmic population also declined from 0.780 in the specification based on the original indicators to 0.410 in the revised model. The remaining association is not unexpected, because development intensity may itself be spatially concentrated in relatively more populous territorial units. Nevertheless, the considerable reduction confirms that the revised PCA is less strongly driven by district size.

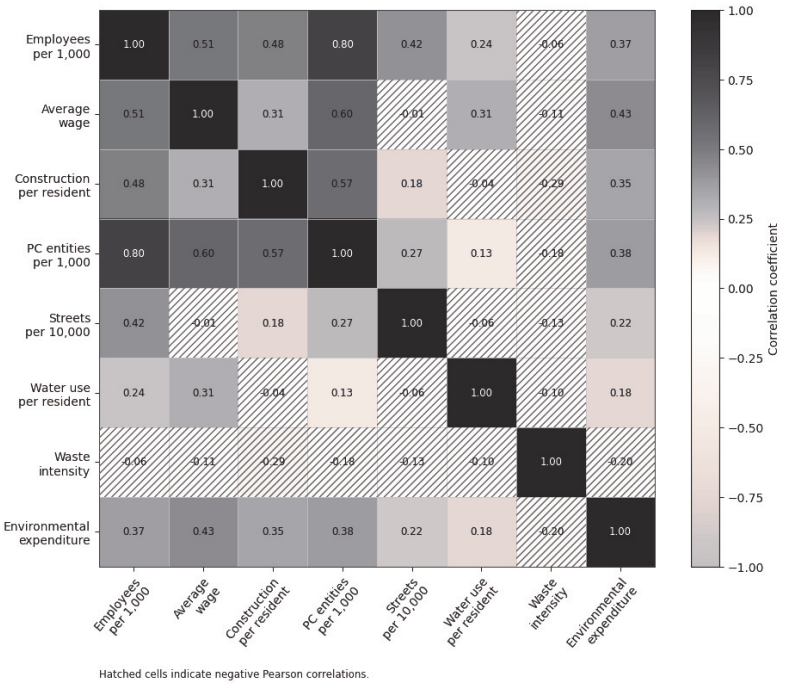
Figure 1: Population scale effect before and after normalization
Népességléptékbeli hatás a normalizálás előtt és után



Source: authors' compilation

Figure 2 presents the Pearson correlation matrix for the revised size-adjusted indicators. The strongest relationship is observed between employees per 1,000 residents and entities with personal computers per 1,000 residents (r = 0.795), indicating that employment intensity and basic organizational digitalization form part of a common development-related structure. Average gross monthly wage is also positively associated with digital intensity (r = 0.602). Municipal waste collection intensity is weakly or negatively related to most development indicators. This pattern is consistent with the fact that the indicator reflects not only the amount of waste generated, but also the coverage, organization and reporting of formal waste collection services. It should therefore not be interpreted as a direct measure of environmental degradation. Pearson and Spearman structures are broadly consistent, with a correlation of 0.954 between their off-diagonal elements. The Spearman matrix is reported in Appendix (Figure A.4.) as a robustness check.

Figure 2: Pearson correlation matrix
Pearson-féle korrelációs mátrix



Source: authors' compilation

PCA adequacy and component structure

According to Table 2, overall Kaiser–Meyer–Olkin value of 0.691 indicates adequate sampling suitability for an exploratory territorial analysis. Bartlett's test of sphericity is statistically significant (χ^2 (28) = 83.609, $p < 0.001$), rejecting the hypothesis that the correlation matrix is an identity matrix. PC1 has an eigenvalue of 3.204 and explains 40.06% of total variance. It is characterized by high positive loadings for digital intensity, employment intensity, average wage, construction intensity and environmental financial intensity. PC1 is therefore interpreted as a broad development and territorial intensity axis, rather than as a pure economic development measure. PC2 explains 15.40% of variance and primarily contrasts water use intensity, which has a positive loading, with urban street provision, which has a negative loading. Construction intensity contributes more weakly to this contrast and should not be presented as a defining PC2 variable. PC3 explains 12.77% and is dominated by municipal waste collection intensity. Together, PC1–PC3 explain 68.23% of the total variance.

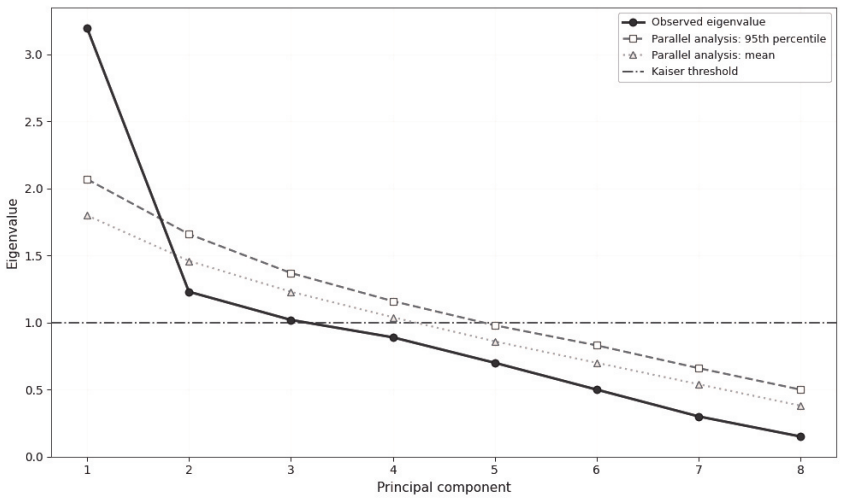
Table 3: PCA adequacy, eigen value and explained variance
PCA-megfelelőség, sajátérték és magyarázott variancia

Diagnostic / component	*Eigenvalue*	*Explained variance*	*Cumulative variance*	*Parallel-analysis 95th percentile*
KMO overall	0.691	-	-	-
Bartlett χ^2 (28)	83.609	-	-	-
Bartlett $p - value$	< 0.001			
PC1 explained variance	3.204	40.06%	40.06%	2.068
PC2 explained variance	1.232	15.40%	55.46%	1.655

Source: authors' compilation

The scree plot and Horn's parallel analysis are presented in Figure 3. At the 95th-percentile criterion, parallel analysis supports only PC1, whereas the Kaiser criterion identifies three components with eigenvalues above one.

Figure 3: Scree plot and Horn parallel analysis
Könyökgörbe (scree plot) és Horn-féle párhuzamos analízis



Source: authors' compilation

Accordingly, PC2 and PC3 are treated as supplementary descriptive coordinates rather than as independently validated latent factors. Their use is consistent with the exploratory and typological objective of the study, in which PCA serves as a low-dimensional representation of the territorial indicator matrix rather than as a psychometric latent factor model. An additional sensitivity analysis shows that FCM estimated using PC1–PC2 reproduces exactly the same hard three-profile allocation as the baseline PC1–PC3 model, with an Adjusted Rand Index of 1.000. By contrast, a model based only on PC1 produces moderate agreement with the baseline solution (ARI=0.644). These results indicate that the second component contributes to the territorial differentiation,

while the third component enriches the descriptive interpretation without determining the hard profile assignment.

According to Table 4, PC1 is a broad development intensity axis, with the strongest positive loadings for digital entities per 1,000 residents, employees per 1,000 residents, average wage, construction per resident and environmental expenditure per resident. PC2 contrasts water use intensity with street provision and construction intensity. PC3 is dominated by the load indicator of municipal waste collection/service.

Table 4: PCA loadings for the first three descriptive components
Főkomponens-súlyok (loadings) az első három leíró komponensre

Indicator	*PC1*	*PC2*	*PC3*
EMP1000	***0.850***	−0.045	0.333
WAGE	***0.711***	0.450	0.062
CONSTR_PC	***0.682***	−0.296	−0.172
DIGITAL1000	***0.878***	−0.039	0.174
STREET10000	0.396	−0.609	0.184
WATER_USE_PC	0.285	***0.725***	−0.130
WASTE_INT	−0.315	0.189	***0.870***

Note: Loadings with an absolute value of at least 0.50 are shown in bold. Component signs indicate the direction of the selected component orientation.
Source: authors' compilation

Selection of the typological solution

The two-cluster model is retained as a binary benchmark rather than as the final typology (Table 5). As expected, it produces sharper memberships and primarily separates territorial units along the dominant higher versus lower development intensity gradient. However, this broad division suppresses an intermediate territorial configuration that is substantively relevant to the research. Because FPC and unnormalized PE are sensitive to the number of clusters, the decision was not based on these indices alone. Compared with $k = 2$, the $k = 3$ solution lowers the Xie–Beni index from 0.400 to 0.325 and slightly lowers normalized entropy from 0.675 to 0.658, while maintaining the same core share of 61.8%.

The modified partition coefficient is also nearly unchanged, at 0.391 for $k = 2$ and 0.385 for $k = 3$. Although k=5 yields a marginally lower Xie–Beni index than $k = 3$ (0.318 compared with 0.325), this small compactness gain is accompanied by a substantial deterioration in membership clarity. The borderline share increases from 29.4% under $k = 3$ to 50.0% under k=5, while mean maximum membership decreases from 0.714 to 0.639. Solutions with more than three clusters therefore generate increasingly fragmented and diffuse partitions. The substantive contribution of the third profile is also demonstrated by the cross-classification of the $k = 2$ and $k = 3$ solutions.

Table 5: FCM validity indices
FCM-validitási indexek

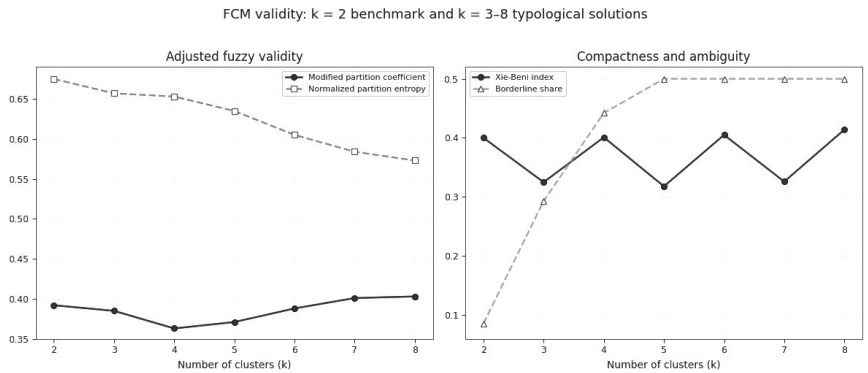
k	*FPC*	*PE*	*XB*	*MPC*	*NPE*	*Core share*	*Intermediate share*	*Borderline share*	*Mean max. membership*
2	0.695	0.468	0.400	0.391	0.675	0.618	0.294	0.088	0.784
3	0.590	0.723	0.325	0.385	0.658	0.618	0.088	0.294	0.714
4	0.522	0.907	0.402	0.363	0.654	0.412	0.147	0.441	0.655
5	0.497	1.023	0.318	0.372	0.636	0.412	0.088	0.500	0.639
6	0.489	1.086	0.407	0.387	0.606	0.412	0.088	0.500	0.632
7	0.487	1.135	0.327	0.401	0.583	0.412	0.088	0.500	0.623
8	0.479	1.193	0.415	0.405	0.574	0.382	0.118	0.500	0.615

Notes: FPC = Fuzzy Partition Coefficient; PE = Partition Entropy; XB = Xie–Beni index; MPC = Modified Partition Coefficient; NPE = normalized Partition Entropy. Core observations have u_max≥0.70; intermediate observations have 0.60≤ u_max<0.70; boarderline observations have u_max<0.60.
Source: authors' compilation

All six Profile A units and ten of the twelve Profile B units are absorbed into the broad higher-intensity group under $k = 2$, whereas all sixteen Profile C units and two Profile B units form the lower-intensity group. Thus, the binary solution largely suppresses the intermediate profile rather than demonstrating that only two meaningful territorial configurations exist. On this basis, $k = 3$ is retained as the preferred substantive territorial typology. It is not interpreted as an unconditional mathematical optimum, but as the minimum resolution that combines acceptable fuzzy validity, membership clarity, parsimony and policy-relevant differentiation.

According to Figure 4, relative to k=2, the k=3 solution lowers the Xie–Beni index from 0.400 to 0.325 and slightly lowers normalized entropy from 0.675 to 0.658. The modified partition coefficient is nearly unchanged (0.391 vs. 0.385), and the core share remains 61.8%.

Figure 4: FCM validity for the binary benchmark and candidate typological solutions
FCM-validitás a bináris viszonyítási alaphoz és a lehetséges tipológiai megoldásokhoz



Source: authors' compilation

Territorial profiles

Profile A contains Bălți municipality, Anenii Noi, Criuleni, Orhei, Rezina, and Cahul. It has the highest average development intensity, above-average environmental/service pressure and clearly above-average environmental expenditure intensity (Table 6). Profile A should not be interpreted as uniformly characterized by an effective environmental response. The financial indicator captures the relative intensity of recorded environmental expenditure or financial flows, not policy effectiveness or institutional quality. Moreover, the fuzzy memberships of Bălți and especially Rezina indicate mixed territorial configurations.

Profile B includes Edineț, Soroca, Călărași, Hîncești, Ialoveni, Strășeni, Ungheni, Basarabeasca, Căușeni, Cimișlia, Taraclia, and U.T.A. Găgăuzia. It combines

positive development intensity with lower average observed pressure and average environmental expenditure. This profile is precisely the configuration obscured by the binary benchmark.

Profile C embraces Briceni, Dondușeni, Drochia, Fălești, Florești, Glodeni, Ocnița, Rîșcani, Sîngerei, Dubăsari, Nisporeni, Șoldănești, Telenești, Cantemir, Leova, and Ștefan Vodă. It has lower development intensity and below-average environmental expenditure. Its average observed pressure is close to the sample mean, so the profile must not be described simply as low pressure. The term peripheral refers to the profile's relative position in the multidimensional development intensity space and does not necessarily imply geographical remoteness from the national capital.

Table 6: Profiles identified by the preferred FCM solution
A preferált FCM-megoldás által azonosított profilok

Profile	*A*	*B*	*C*
N	6	12	16
Development intensity	1.040	0.593	−0.835
Pressure	0.775	−0.469	0.062
Environmental expenditure	1.160	0.028	−0.456
Districts	Bălți, Anenii Noi, Criuleni, Orhei, Rezina, Cahul	Edineț, Soroca, Călărași, Hîncești, Ialoveni, Strășeni, Ungheni, Basarabeasca, Căușeni, Cimișlia, Taraclia, U.T.A. Găgăuzia	Briceni, Dondușeni, Drochia, Fălești, Florești, Glodeni, Ocnița, Rîșcani, Sîngerei, Dubăsari, Nisporeni, Șoldănești, Telenești, Cantemir, Leova, Ștefan Vodă
Interpretation	Development-pressure intensive, higher expenditure	Intermediate development, lower observed pressure	Peripheral lower-intensity, lower expenditure

Notes: Composite values are sample-relative standardized scores. Positive values indicate intensities above the mean of the 34-unit analytical sample, while negative values indicate intensities below the sample mean. Source: authors' compilation

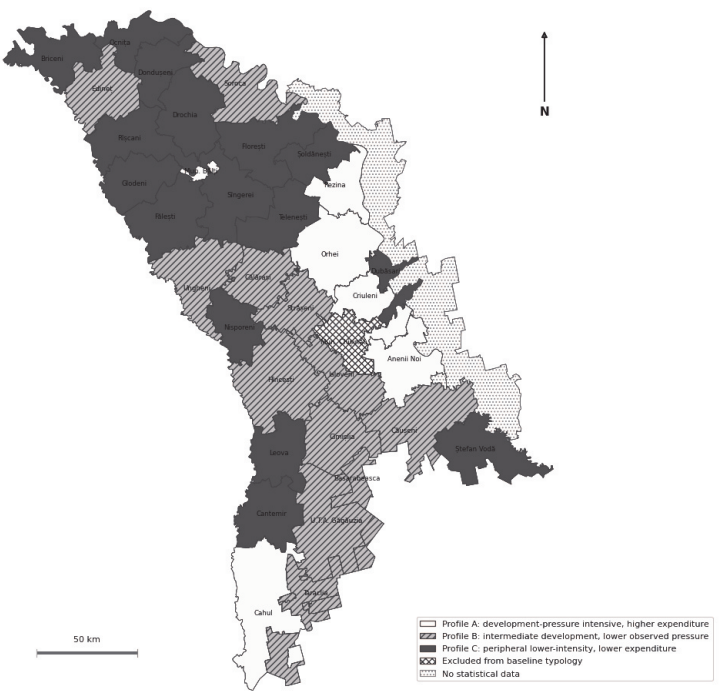
Fuzzy membership and spatial distribution

Using maximum membership degree, $u_{max,i} = \max_j (u_{ij})$, as an indicator of classification clarity, 21 of the 34 territorial units are classified as core cases, with $u_{max} \geq 0.70$. Three units have intermediate clarity, with maximum membership between 0.60 and 0.70, while ten units are classified as borderline cases, with $u_{max} < 0.60$. This distribution confirms that the three profiles are not separated

by rigid territorial boundaries and that a substantial group of districts occupies intermediate positions. Rezina is the clearest mixed case, with a maximum membership of 0.374 and a difference of only 0.012 between its two highest membership degrees. Dubăsari, Căușeni, Bălți, Șoldănești, and Ștefan Vodă also display comparatively diffuse memberships. These units should be interpreted as transitional or hybrid territorial configurations rather than as typical representatives of a single case.

The categorical map reveals a non-contiguous spatial distribution of the three profiles (Figure 5). Profile A appears in several distinct territorial poles, including Bălți in the north, Anenii Noi and Criuleni in the vicinity of Chișinău, Orhei and Rezina in the central-eastern part of the country, and Cahul in the south. Profile B is distributed across western, central and southern territorial units, while Profile C is more widely represented by northern and southwestern districts. These patterns are descriptive and should not be interpreted as statistically validated spatial clusters. Nevertheless, they show that the territorial differentiation of the units outside Chișinău is not reducible to a simple concentric capital–periphery gradient.

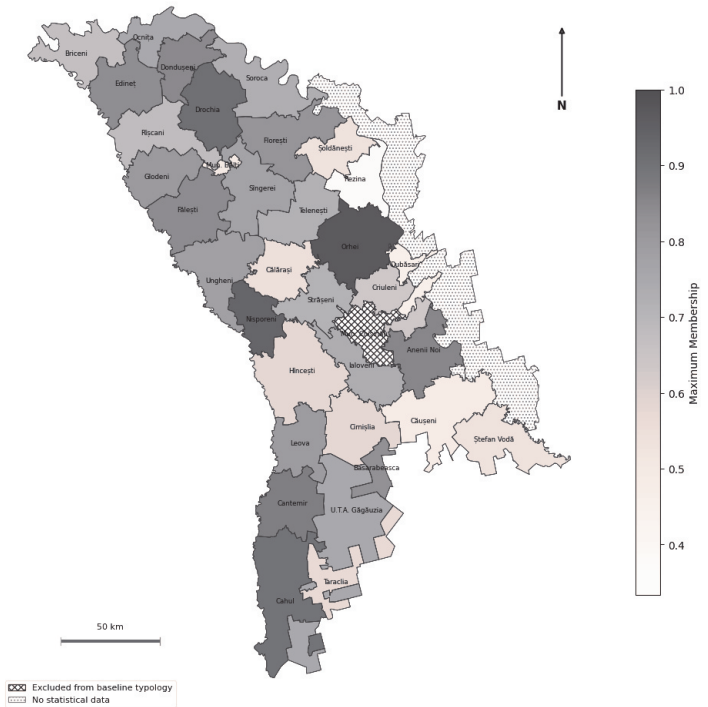
Figure 5: Territorial typology of Moldova's districts
Moldova körzeteinek területi tipológiája



Source: authors' compilation

The maximum membership map from Figure 6 complements the categorical typology by showing the degree of classification certainty. High values identify core districts, whereas lower values indicate transitional configurations. Rezina is the clearest borderline case, with a maximum membership of 0.374 and almost equal affiliation to Profiles A and B. Dubăsari, Bălți, Căușeni, Șoldănești, and Ștefan Vodă also display relatively diffuse memberships. These cases demonstrate the analytical advantage of FCM over a purely hard partition.

Figure 6: Maximum fuzzy membership by district
Legmagasabb fuzzy tagsági érték körzetenként



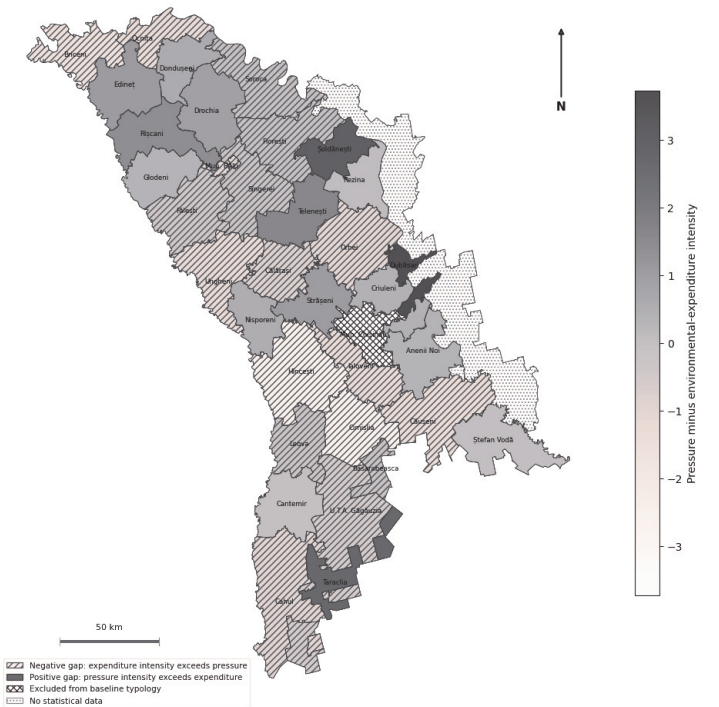
Source: authors' compilation

To complement the maximum membership classification, Figures A1–A3 in Appendix present the complete district-level fuzzy membership degrees associated with Profiles A, B and C. The maps use a common scale ranging from 0 to 1 and show that territorial affiliation is gradual rather than categorical. Profile A membership is concentrated in a limited number of territorial poles, Profile B displays a broader transitional distribution, while Profile C has the most extensive spatial coverage. This maps also confirm that several borderline districts retain non-negligible membership in more than one territorial profile.

Relative pressure – environmental expenditure intensity gap

Figure 7 maps the relative difference between environmental and service-related pressure and environmental expenditure intensity. The largest positive gaps are observed in Dubăsari (G = 3.725), Șoldănești (G = 3.047), Taraclia (G = 2.708), Telenești (G = 1.601), and Rîșcani (G = 1.409). In these territorial units, observed pressure or service-related load is comparatively high relative to the recorded intensity of environmental expenditure. These positive values identify territories that warrant further diagnostic attention, but they do not demonstrate policy failure or insufficient expenditure in an absolute sense. The observed gaps may also be affected by economic structure, waste collection coverage, reporting practices, the cost structure of environmental services and the mixed reference years of the indicators.

Figure 7. Relative pressure – environmental expenditure intensity gap
Relatív terhelés – környezetvédelmi kiadások intenzitásában mutatkozó különbségek



Source: authors' compilation

The largest negative gaps occur in Cimișlia (G = -2.596), Hîncești (G = -2.561), Briceni (G = -1.629), Căușeni (G = -1.408), Ocnița (G = -1.338), Ialoveni (G = -1.283), and Ungheni (G = -1.249). In these cases, recorded expenditure intensity exceeds

measured pressure relative to the sample mean. This may indicate stronger preventive or service-related financial effort, but it may also reflect unobserved environmental needs, higher operating costs or limitations of the pressure proxies.

The diagnosis also reveals a strong internal heterogeneity within Profile A. Orhei, Bălți, and Cahul display negative pressure–expenditure gaps, whereas Anenii Noi, Criuleni, and Rezina record positive gaps. Therefore, the average characteristics of Profile A should not be interpreted as describing a uniform relationship between pressure and expenditure across all its members.

Robustness checks and stability

According to Table 7, the preferred typology is highly robust to the inclusion of water abstraction and to the exclusion of the environmental financial indicator. Including Chișinău produces substantial agreement for the 34 territorial units common to both specifications. In contrast, the no-logarithm model and the original absolute-indicator specification produce only moderate agreement with the baseline. These findings indicate that both skewness treatment and adjustment for territorial size materially influence the empirical typology.

Table 7: Agreement between the baseline three-profile typology and alternative specifications
Egyezés az alapmodell szerinti háromprofilos tipológia és az alternatív specifikációk között

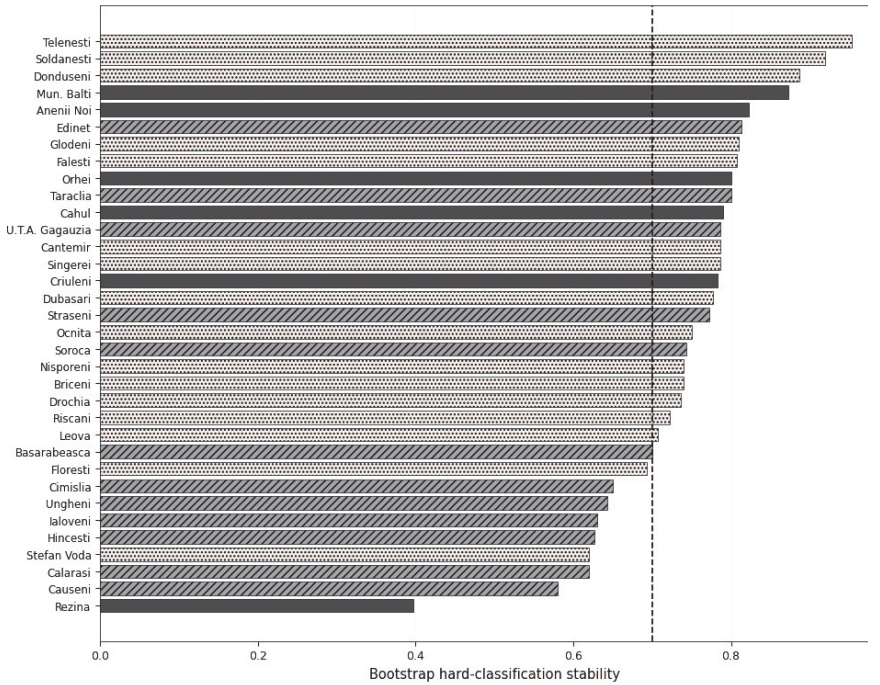
Robustness specification	*ARI versus baseline*	*Interpretation*
FCM using PC1 only	0.644	Moderate agreement; a single axis suppresses part of the typological differentiation.
FCM using PC1 – PC2	1.000	Identical hard assignment; PC3 does not determine the final allocation.
No logarithmic transformation	0.562	Skewness treatment materially affects the partition.
Water abstraction included	0.847	High agreement; results are robust to adding the second water indicator.
Environmental financial indicator excluded	0.817	High agreement; the typology is not driven exclusively by the financial indicator.
Strict 2024 – only specification	0.170	Very low agreement; temporal harmonization is a material limitation.
Chișinău included	0.733	Substantial agreement across the 34 common units.
Original absolute indicators	0.509	Size adjustment materially changes the territorial classification.

Source: authors' compilation

The strict 2024-only specification produces very low agreement with the baseline (ARI=0.170). This confirms that the mixed reference years are not merely a formal limitation but can affect the empirical partition. Accordingly, the baseline results should be interpreted as a mixed-year territorial typology based on the latest available data rather than as a fully harmonized single-year classification.

The maximum membership allocation from FCM is highly consistent with K-means for $k = 3$ (ARI=0.935), and moderately consistent with Ward hierarchical clustering (ARI=0.664). The corresponding silhouette coefficients are 0.305 for K-means and 0.312 for Ward clustering. These values indicate moderate rather than strong natural separation, reinforcing the appropriateness of a fuzzy interpretation.

Figure 8: District-level bootstrap stability of the preferred three-profiles classification
Körzeti szintű bootstrap-stabilitás a preferált háromprofilos besorolásnál



Source: authors' compilation

The conditional bootstrap analysis yields a median ARI of 0.641, a mean ARI of 0.626 and a mean district-level classification stability of 0.743 (Figure 8). The 5th-percentile ARI is 0.266, indicating that some resamples generate considerably different partitions. The three-profile solution should therefore be described as moderately stable rather than fully invariant. Membership ambiguity and bootstrap instability are related but not identical. Rezina combines a very low maximum membership (0.374), with low bootstrap stability (0.397). In contrast,

some units with diffuse fuzzy membership, such as Bălți and Șoldănești, retain comparatively stable hard assignments under resampling. Reporting both diagnostics is therefore preferable to treating maximum membership as the sole measure of classification reliability.

Discussion

The comparison between the original and revised specifications shows that adjustment for population size is a substantive methodological requirement in district-level territorial analysis. When absolute volumes are used, the dominant principal component largely reflects demographic and economic mass. After the indicators are converted into rates or per-capita measures, the association between PC1 and population is substantially reduced, and the resulting profiles reflect different combinations of development, resource use, service-related pressure and environmental financial intensity. The revised typology therefore moves from a classification of larger and smaller territorial units toward a classification of relative territorial configurations.

The spatial distribution of the profiles suggests that Moldova's internal core–periphery structure is neither strictly concentric nor reducible to a single capital versus rural periphery opposition. The higher-intensity profile appears in several non-contiguous territorial poles, while the intermediate profile includes districts with relatively positive development intensity but lower observed environmental and service-related pressure. The lower-intensity profile is spatially extensive but is not homogeneous in terms of pressure. These results support a relational interpretation of territorial peripherality, in which infrastructure, employment, digital readiness and environmental financial resources combine differently across space.

The results do not indicate a linear progression from development to environmental pressure and then to financial response. Profile A records relatively high values across all three dimensions, but individual districts differ in fuzzy membership and internal composition. Profile B demonstrates that positive development intensity may coexist with comparatively lower observed pressure, while Profile C shows that lower development intensity does not necessarily imply low environmental or service-related pressure. This finding is particularly important because municipal waste collection reflects service coverage as well as waste generation. Similarly, the environmental financial indicator should not be interpreted as a direct measure of governance effectiveness. Higher recorded financial flows may reflect stronger environmental effort, but they may also arise from greater underlying pressure, the presence of environmentally intensive activities or higher operating costs. The profiles should consequently be read as configurations of relative intensity rather than as rankings of policy performance.

The substantial number of intermediate and borderline observations confirms that territorial typologies are characterized by gradients rather than rigid boundaries. The fuzzy approach is therefore particularly useful for districts such as Rezina, Dubăsari, Căușeni, and Bălți, whose profiles combine characteristics associated with more than one group. From a place-based policy perspective, such districts should not automatically receive the same intervention package as the core members of their maximum membership profile.

At the same time, the robustness analysis requires a cautious interpretation. The typology is comparatively stable under several indicator specifications and is strongly aligned with K-means, but it is sensitive to temporal harmonization and moderately stable under bootstrap resampling. The profiles should therefore be used as an exploratory territorial diagnostic and policy-screening framework, not as immutable administrative categories.

The EU Growth Plan for Moldova provides a relevant policy context for interpreting the territorial profiles (EC 2024). The Plan supports competitiveness and SME development, transport and digital connectivity, energy security and efficiency, social capital, public administration reform and the green transition. Nevertheless, these interventions are not spatially neutral. Their territorial effects are likely to depend on existing levels of development, infrastructure, environmental pressure and administrative capacity. The profiles identified in this study should not be interpreted as predetermined beneficiaries of the Growth Plan, since the programme does not allocate resources according to the present classification. Rather, they indicate where particular reform and investment channels may be the most relevant and where accompanying environmental safeguards may be required.

Conclusion

This study developed a size-adjusted territorial typology of the Republic of Moldova by combining socio-economic development intensity, infrastructure provision, environmental and service-related pressure, and environmental expenditure intensity. The revised specification addresses a central methodological risk of territorial multivariate analysis: absolute indicators may reproduce population size rather than reveal substantively different territorial configurations. By using population primarily as a denominator and converting volume measures into per-capita or rate-based indicators, the analysis reduced the correlation between the dominant component and territorial population.

PCA identified one dominant development intensity dimension and two supplementary descriptive axes associated with water use, infrastructure and municipal waste collection. The first three components explained 68.23% of the total variation. FCM subsequently identified three substantively meaningful

profiles. Profile A combines higher development and pressure intensity with higher environmental expenditure; Profile B represents an intermediate and internally heterogeneous configuration with lower average observed pressure; and Profile C captures a peripheral lower-intensity configuration with lower environmental expenditure.

The spatial distribution of these profiles refines the interpretation of Moldova's internal core–periphery structure. Rather than identifying a single contiguous core and a uniform periphery, the results reveal selective development poles and corridors, transitional districts and an extensive group of lower-intensity peripheral territories. The fuzzy membership results further show that several districts occupy intermediate positions, confirming that territorial boundaries between development profiles are gradual rather than discrete.

From a policy perspective, the typology supports place-based interventions. Profile A requires attention to resource efficiency and the alignment of environmental expenditure with higher activity and pressure. Profile B requires district-specific diagnosis because intermediate average values conceal substantial internal variation. Profile C requires measures that strengthen development opportunities, infrastructure and the ability to finance environmental services without assuming that lower recorded activity automatically implies low environmental need. Profile C should not be interpreted as an ecological idyll. First, its average environmental and service-related pressure is close to the sample mean rather than being the lowest of the three profiles. Second, low recorded water use or municipal waste collection may result from lower economic activity, incomplete service coverage or weaker statistical reporting rather than from superior environmental quality. The profile is therefore more appropriately interpreted through the concept of a potential development trap. Low economic and infrastructural intensity may reduce immediate pressures, but limited environmental expenditure and administrative capacity may restrict the ability of these districts to extend basic environmental services, attract sustainable investment and respond to future pressure increases. Distinguishing an ecological advantage from a development trap would require additional indicators of environmental state and quality, including water quality, untreated wastewater, illegal waste disposal, air pollution, biodiversity condition and access to utility services.

Although Chișinău was excluded from the baseline typology, it remains central to the interpretation of the surrounding territorial structure. Anenii Noi and Criuleni are classified in Profile A, whereas Ialoveni, Strășeni, and Hîncești belong to Profile B. This variation suggests that proximity to the capital does not generate uniform territorial outcomes. Potential positive spillovers include access to employment, markets, specialized services, digital infrastructure and business networks. At the same time, suburbanization and metropolitan expansion may increase commuting, construction, land conversion, water demand, traffic and waste service pressure in the surrounding districts. These mechanisms provide a plausible interpretation of the profiles but are not directly tested in this study. Future

research should integrate commuting, travel time to Chișinău, firm location, residential construction and inter-district infrastructure networks.

Several limitations should be acknowledged. First, the baseline is provided by a latest-available mixed-year cross-section dataset rather than a fully harmonized single-year one. Second, municipal waste collected reflects both environmental load and service coverage, while environmental expenditure is a financial intensity proxy rather than a comprehensive measure of governance capacity or policy effectiveness. Third, the relatively small number of territorial units limits the strength of multivariate validation. Future research should construct a harmonized multi-year panel, incorporate indicators of environmental quality, utility service coverage and economic structure, and examine temporal transitions between territorial profiles.

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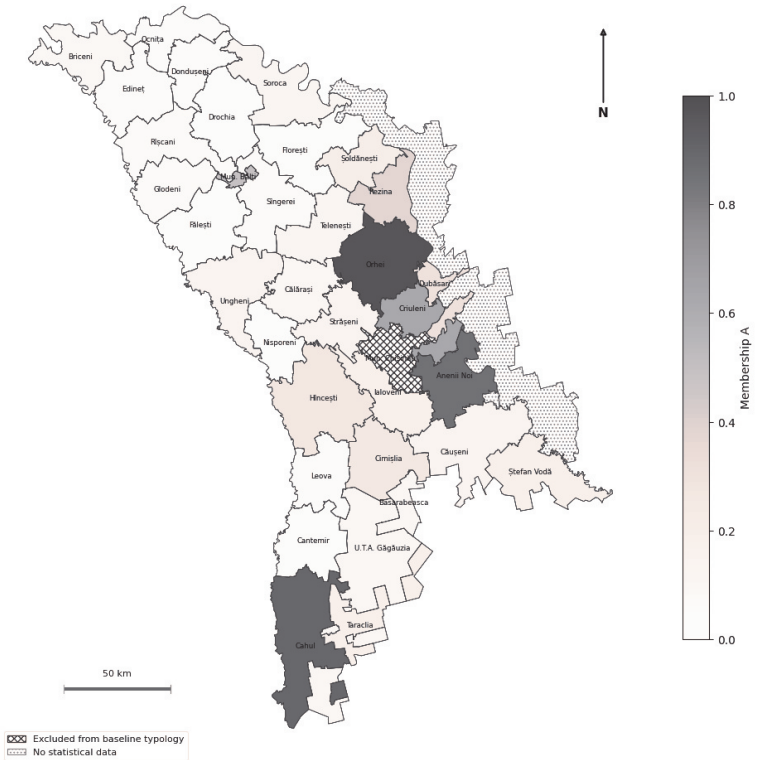
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Appendix

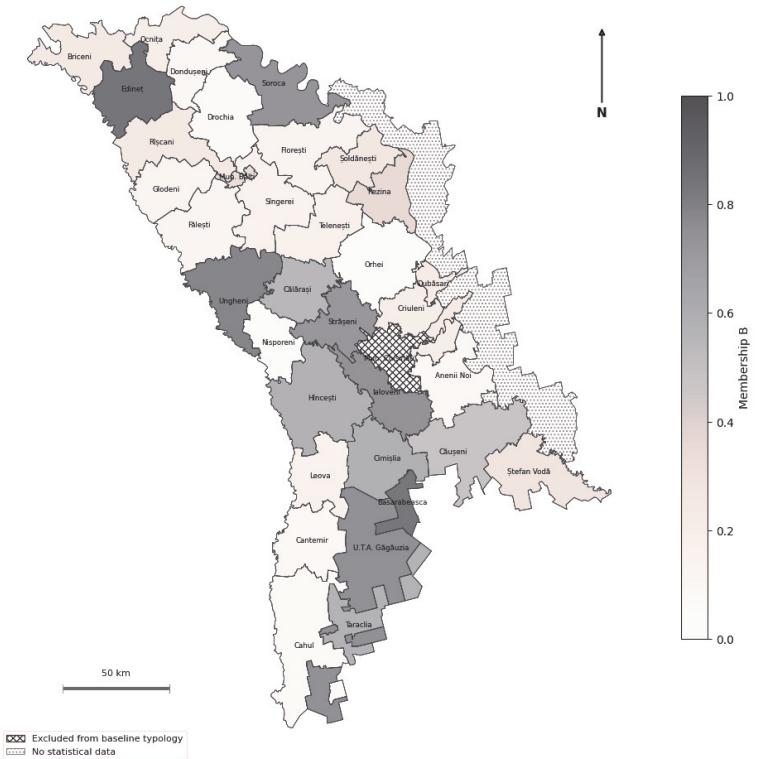
Figure A.1: District-level fuzzy membership degrees for Profile A: development pressure intensive territories with higher environmental expenditure intensity

Körzetszintű fuzzy tagsági értékek az A profilban: intenzív fejlődési terhelés alatt álló térségek magasabb környezeti kiadásintenzitással



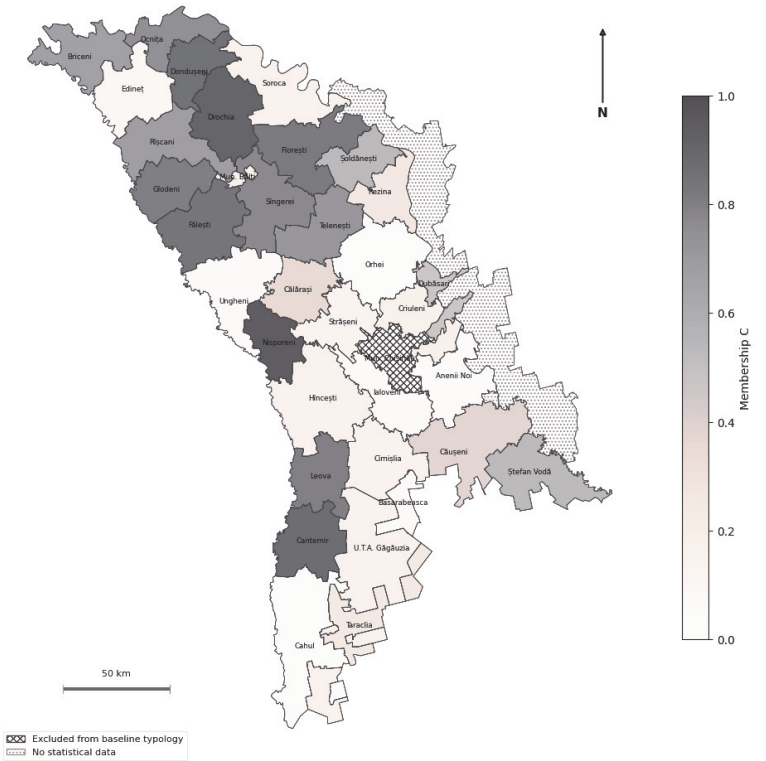
Source: authors' compilation

Figure A.2: District-level fuzzy membership degrees for Profile B: intermediate development territories with lower average observed environmental and service-related pressure
Körzetszintű fuzzy tagsági értékek a B profilban: közepesen fejlődő térségek alacsonyabb megfigyelt környezeti és szolgáltatásalapú terheléssel



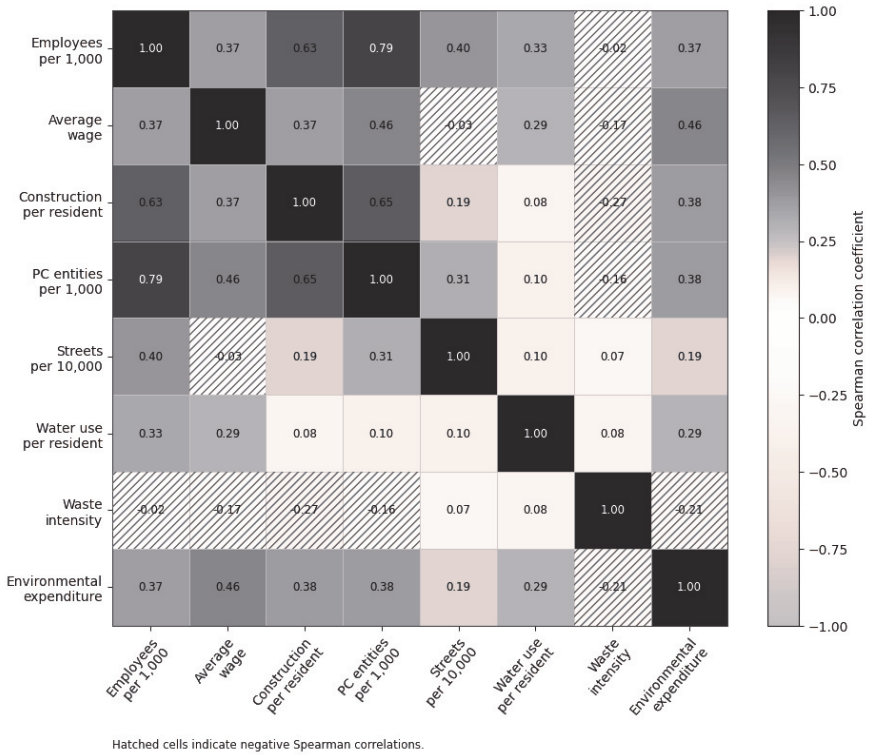
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Figure A.3: District-level fuzzy membership degrees for Profile C: peripheral lower-intensity territories with lower environmental expenditure intensity
Körzetszintű fuzzy tagsági érték a C profilban: perifériikus, kevésbé intenzív fejlődési terhelés alatt álló térségek alacsonyabb környezeti kiadásintenzitással



Source: authors' compilation

Figure A.4: Spearman correlation matrix
Spearman-féle korrelációs mátrix



Source: authors' compilation