Measuring Attractiveness with FLAIR

French Localities Attractiveness IndicatoR

A Composite Indicator of Real Attractiveness for All French Municipalities: Construction and Spatial Patterns

Abstract

This paper introduces the French Localities Attractiveness IndicatoR (FLAIR), a composite indicator covering all 34,827 municipalities of hexagonal France and Corsica, designed to address the lack of attractiveness measures at the local scale. Conceptualizing attractiveness as the set of territorial assets that enable residents to emancipate and flourish, rather than competitive advantages designed to attract outsiders, the FLAIR aggregates 54 indicators from various French open data into five dimensions: Health and Education, Social Life, Economy, Housing, and Risk and Climate Exposure. The construction follows mainly the OECD Handbook on Constructing Composite Indicators, with spatial smoothing calibrated to urban-rural typology, min-max normalization, equal weighting within dimensions, and geometric mean aggregation to ensure partial non-compensability across dimensions. The findings show that attractiveness, measured this way, is organised primarily by functional centrality and so intermediate Urban centres outperform the largest metropolises. Attractiveness is spatially autocorrelated, indicating that habitability is sometimes built at the scale of living areas rather than isolated municipalities, and it is modestly linked to lower poverty. A territory-profile analysis further shows that there is no universal driver of attractiveness: the dimension that sustains the strongest municipalities differs from the one that holds back the weakest within the same territorial type, pointing toward differentiated, context-specific territorial policy.

Introduction

Territorial attractiveness has become a structuring concept in spatial planning policies across Europe and beyond. In France, the shift from redistributive spatial Keynesianism toward competitive territorial governance, institutionally marked by the reorientation of national planning agencies in the early 2000s, has elevated attractiveness to a central policy objective at all administrative levels (Pinson, 2020; Houllier-Guibert, 2022). The term, however, remains loosely defined and is deployed across contexts as varied as inter-municipal competition for investment, regional marketing campaigns, and national depopulation strategies.

Yet the spread of attractiveness discourse raises an immediate and often neglected question: attractiveness for whom, and to what end? Traditional attractiveness policies typically target a restricted profile of desirable arrivals (investors, tourists, young graduates, or affluent newcomers) on the assumption that capturing mobile and high-value populations is the primary goal of territorial development (Kirszbaum, 2012; Miot, 2015; Houllier-Guibert, 2019). This competitive framing has been widely criticized. Bouba-Olga and Grossetti (2018) argue that it has served primarily to concentrate public resources in already-advantaged territories while structurally neglecting others. More fundamentally, places endowed with attractive characteristics (good services, natural amenities, low risk exposure, strong social cohesion) tend to become progressively inaccessible to the populations who might most benefit from them (Alivon, 2016). Attractiveness, left unexamined, can deepen the territorial inequalities it claims to address (Berroir et al., 2019).

This critique is all the more valid given France's demographic trajectory. The share of residents aged 60 and over has risen across all territorial types over the past two decades, while the share of young adults has declined in numerous rural and peri-urban areas (DITEP, 2025). As Paumelle (2024) demonstrates, ageing has been systematically misread in local policy as a symptom of territorial fragility when in reality older residents can constitute a genuine social and economic resource, particularly in the rural towns and small municipalities where retiree in-migration sustains local demand and presential activity. This misreading is rooted in the associations between population youth and territorial vitality, associations that are rarely interrogated but that shape resource allocation and policy priorities across all scales of government (Paumelle, 2024).

What do we measure?

Five theoretical frameworks, each addressing a distinct dimension of the problem, jointly support the conception of attractiveness developed here. New economic geography provides the starting point. Its central insight is that the spatial distribution of services, employment, and amenities follows systematic logics of centrality and polarization: increasing returns to scale, transport costs, and agglomeration externalities generate hierarchical urban systems in which central places concentrate a larger share of resources and opportunities (Boiscuvier, 2000; Talandier, 2023b). This framework explains why local territorial assets create self-reinforcing comparative advantages. However, reducing attractiveness to competitiveness and metropolitan concentration, as a strictly New Economic Geography reading would suggest, calls for additional frameworks to assess the multidimensionality of territorial development (Friboulet, 2010).

The right to the city, as theorized by Henri Lefebvre and taken up by Harvey (2011), introduces a justice dimension that competitive attractiveness frameworks systematically occlude. It holds that it is those who produce and inhabit space through daily life who hold the legitimate claim to shape it: a territory is not primarily a product to be positioned on a competitive market for mobile populations, but an environment co-constructed by its current inhabitants, whose collective needs and uses define its qualities. This has a direct empirical implication: a territory's competitive attractiveness ranking on flow-based metrics and its capacity to support the daily lives of its resident population may diverge substantially. Conventional attractiveness policies tend to target a restricted profile of desirable arrivals, whether investors, graduates, or affluent newcomers, at the risk of engendering gentrification and treating lower-income or less mobile residents as a social burden (Pinson, 2020; Miot, 2015). Articulating the right to the city within an attractiveness framework affirms that territorial assets should first benefit those already in place, support social mix rather than producing exclusion.

The notion of environmental hospitability (Stavo-Debauge, 2020) complements the right-to-the-city perspective by addressing the qualitative and relational dimension of territorial reception. Hospitability is understood here as a property of environments rather than an interpersonal virtue: a territory is hospitable when its material arrangements, spatial organization, and social institutions actively make room for those who inhabit it, including newcomers, while preserving the living conditions of existing residents. This includes the accessibility of public spaces, the physical and social conditions of coexistence, and the degree to which territorial organization supports rather than constrains the daily activities of a diverse population (Stavo-Debauge, 2020).

The capability approach, developed by Amartya Sen and applied to territorial analysis by Friboulet (2010), recentres the question of attractiveness on individual human development. A territory is attractive insofar as it functions as a provider of capabilities: the real freedoms that enable residents to live in ways they have reason to value. Under this framework, what matters is not the volume of flows a territory generates but the range of territorial assets, in services, economic opportunity, housing, social infrastructure, and environmental quality, that it places at the disposal of those who inhabit it. In the construction of FLAIR, this justifies measuring these assets directly rather than capturing attractiveness through its demographic or economic outcomes (Djamen Kouptoudji, 2022).

Habitability, finally, envelops all four preceding frameworks by situating territorial development within ecological limits. The value of a place depends, at the most fundamental level, on its capacity to offer the environmental conditions that make life sustainable over the long run. At a time of intensifying climate change, this condition is not residual but structurally binding: the interdependence between human prosperity and the preservation of living environments makes ecological integrity a prerequisite for any other form of attractiveness, not an additional criterion to be traded off against others (Barrioz & Laslaz, 2025; Bouba-Olga et al., 2026).

Taken together, these five frameworks converge on a conception of territorial attractiveness as the capacity of a place to support the lives of those who inhabit it: defined by what it concretely offers residents across economic, residential, social, health-related, and environmental dimensions, and only secondarily by its ability to attract new populations (Miot, 2015; Berroir et al., 2019).

How do we measure it?

Despite the proliferation of attractiveness discourse, measurement tools remain inadequate at the local level. Two limitations characterize existing approaches. First, most territorial attractiveness indices operate at larger spatial scales, regions, provinces, or nations, obscuring the fine-grained variations that matter for local policy (Édouard & Mainet, 2021; OECD, 2022). At the international and national scale, attractiveness and competitiveness are captured by a dense ecosystem of composite indices ranking countries on competitiveness, talent, or investment appeal (OECD, 2022), few descend below the regional level (Musolino & Kotosz, 2024). Sub-national French initiatives, by contrast, remain confined to single agglomerations and oriented toward territorial well-being rather than attractiveness as such (Le Roy & Ottaviani, 2022 ; Delahais et al., 2023 ; Édouard & Mainet, 2021). There have been recent methodological advancements in evaluating local attractiveness in other European countries, such as the Spanish Municipal Attractiveness Index (Bonilla et al., 2025) and various municipal-level competitiveness and administrative quality indices in Italy (Musolino & Volgger, 2020; Scaccabarozzi et al., 2024; Musolino & Kotosz, 2024). For France, comprehensive coverage of all municipalities with an asset-based approach remains absent: existing regional and metropolitan indices use too few indicators, bring together territorial assets with the flows they generate, counting migration or investment flows as components of attractiveness rather than as its outcomes, or are limited to partial territorial coverage (Alexandre et al., 2010). Second, many studies measure attractiveness through its consequences, migration flows, business location decisions, or population growth, rather than through the territorial assets. The closest precedent to a pure asset-based approach is Bonilla et al. (2025), yet their index incorporates demographic dynamics and migration flows as a direct component of attractiveness. This compromises their conclusion that low attractiveness is associated with population decline: since depopulation is embedded in the measure by construction, the relationship cannot be interpreted as an empirical finding.

This article presents the French Localities Attractiveness IndicatoR (FLAIR), a composite indicator covering all 34,827 municipalities of hexagonal France and Corsica. The FLAIR makes three cumulative contributions. First, it achieves unprecedented spatial completeness at the municipal scale. Second, it operationalizes attractiveness as *real attractiveness* (Musolino & Volgger, 2020): a direct measure of territorial assets rather than observed flows, breaking the circular logic of most existing indices. Third, it incorporates a spatial smoothing methodology based on inter-communal distance differentiated by urban-rural typology, reflecting the reality that residents access services and amenities across administrative boundaries.

The remainder of the article is structured as follows. Section 1 presents the conceptual framework. Section 2 describes the data, indicator selection, and methodological steps, including robustness and sensitivity analyses. Section 3 reports the empirical results and discusses the findings.

1. Conceptual Framework

1.1 Defining Territorial Attractiveness

The notion of territorial attractiveness is ambiguous (Chaze, 2017). In French, the term conflates two semantically distinct ideas. The first is *attraction*: the dynamic capacity of a territory to draw and retain mobile resources, whether populations, firms, or investment flows. The second is *attrait*: the intrinsic or constructed qualities that make a territory desirable, whether defined objectively through measurable characteristics or subjectively through residents' and outsiders' perceptions. The English word "attractiveness" maps more naturally onto the second meaning, designating the quality of being pleasant, and the French Dictionary of synonyms associates it primarily with the term *avantages* (advantages). Yet most empirical work and policy frameworks default to the former sense, measuring attractiveness through its observable consequences: migration balances, firm relocations, investment volumes, tourist arrivals.

Musolino and Volgger (2020) formalize this distinction by identifying three analytically separate approaches to studying attractiveness. *Revealed attractiveness* corresponds to the attraction sense: it rests on the analysis of measurable flows, including migration balances and population change, firm creation and relocation, direct investment flows, and tourist arrivals. *Perceived attractiveness* addresses the subjective dimension of territorial appeal: the image projected by the territory, the perception of amenities by different publics, and the reach of territorial identity. *Real attractiveness* aims to objectify the intrinsic assets of territories: the measurable characteristics that constitute genuine appeal independently of the flows they may or may not generate at any given moment. The present study focuses exclusively on real attractiveness. This choice reflects two aims. The first is methodological: by restricting the measure to territorial assets, the index avoids the circular logic of flow-based approaches, in which migration balances or investment volumes function simultaneously as evidence of attractiveness and as components of its measurement. The second is operational: local authorities have limited leverage over macroeconomic flows or investor decisions, but can act directly on territorial assets: service provision, housing quality, environmental management, local governance. An asset-based index therefore functions as a diagnostic tool identifying the dimensions on which public action can realistically act on.What constitutes the real attractiveness of a municipality? The literature and local policy frameworks converge on a broad set of asset categories. Housing quality, access to education and healthcare, employment opportunities, local commercial activity, transport connectivity, public safety, and the provision of cultural and sports infrastructure are consistently identified as the primary components of residential attractiveness (Alexandre et al., 2010; Sauvin, 2015; Sueur, 2023). Each of these represents a dimension of what makes a place pleasant and functional to inhabit. The FLAIR operationalizes real attractiveness by assembling these components into a structured indicator covering five dimensions, defined in Section 1.3, that together capture a large range of territorial assets. Identifying these assets makes it possible to map the strengths and weaknesses of each territory and to support the design of differentiated improvement strategies adapted to each municipality's specific profile.

1.2 The Case for Composite Indicators

Territorial attractiveness is a concept mobilized across a wide range of public policies, from economic development strategies seeking to attract businesses and skilled workers to planning instruments oriented toward improving residents' living conditions and habitability. Despite these varied policy uses, the concept shares a common feature: it is inherently multidimensional. No single indicator, whether migration balance, employment rate, or housing affordability, captures what makes a territory attractive, because the relevant conditions span health and education access, economic opportunity, social life, housing, and environmental quality simultaneously. A composite indicator addresses this by organizing base indicators into theoretically motivated dimensions, each capturing a distinct facet of attractiveness, and aggregating them into a synthetic score that preserves both global comparability and the possibility of dimensional decomposition, answering not only how attractive a territory is but through which specific assets or deficits (OECD, 2008; Mazziotta & Pareto, 2013).

1.3 Attractiveness as a Formative Measurement Model

The construction of any composite indicator rests on an implicit assumption about the relationship between the indicators and the concept they describe. This assumption, however, is rarely made explicit: the OECD Handbook on Constructing Composite Indicators (2008), the most widely cited methodological reference in the field, makes no reference to the measurement model, a silence that has been identified as a source of widespread misspecification in practice (Mazziotta & Pareto, 2025). The handbook by Mazziotta and Pareto (2025) addresses this gap directly, introducing the distinction between two measurement approaches whose implications for construction and validation differ substantially. Two measurement models are conventionally distinguished. In a reflective model, the concept exists independently of its indicators and causes them: the indicators are interchangeable manifestations of a single latent construct and are expected to correlate strongly, since a common underlying cause moves them together. In a formative model the causal direction is reversed. The indicators define and constitute the concept, which has no existence prior to them. Removing an indicator does not reduce the precision of the measure but changes the definition of the construct itself, and the indicators are neither required nor expected to be correlated.

The FLAIR follows a formative measurement model. Territorial attractiveness, understood here as the set of assets that make a territory habitable, is not a latent property that radiates into housing, employment, service, economic, and environmental conditions as so many manifestations. It is the joint configuration of these conditions. A municipality can offer a strong labour market and a weak housing supply, or abundant services and high exposure to natural risk: these dimensions are conceptually independent, and it is precisely their combination that constitutes attractiveness. The Human Development Index follows the same logic, combining health, education, and income into a construct that none of its components could replace and that does not presuppose any correlation among them.

This measurement model carries three consequences for the construction and validation of the FLAIR. First, low correlation between dimensions is expected rather than problematic. If the dimensions were strongly intercorrelated, they would be measuring the same underlying gradient, and a single indicator would suffice. Second, internal consistency measures designed for reflective models are not the appropriate validation criterion. Cronbach's alpha and confirmatory factor analysis presuppose an intercorrelation among indicators that a formative construct does not require, and a low coefficient indicates only that the indicators capture different facets of the concept, not that the instrument is poorly built. For the same reason, principal component analysis is not used here as a weighting or validation device, since its weights derive from inter-indicator correlations, a property that carries no interpretive value in a formative model (Mazziotta & Pareto, 2025). Third, the formative model supports the choice of a partially non-compensatory aggregation. Because the dimensions are not substitutable expressions of a common cause but distinct constituents of attractiveness, a severe deficit in one cannot be fully offset by strength in another. The geometric mean operationalises this view by penalising imbalance while still rewarding dimensional strengths, consistent with treating each dimension as a necessary condition for attractiveness rather than an interchangeable one.

1.4 Dimensions of Territorial Attractiveness

The five dimensions of the FLAIR are not an administrative checklist but a theoretically motivated partition of what it means for a territory to be habitable. Each dimension captures a distinct and partially non-substitutable facet of territorial attractiveness: distinct, in that each dimension constitutes a separate facet of the construct rather than a proxy for another; non-substitutable, in that a deep deficit in one cannot be made irrelevant by strength in another without violating the habitability logic. Consistent with the formative model set out above, this distinctness does not presuppose any particular pattern of inter-dimensional correlation. The dimensional structure emerges from a combined reading of the attractiveness literature (Alexandre et al., 2010 ; Sauvin, 2015 ; Chaze, 2017; Bourdeau-Lepage et al., 2015; Musolino & Volgger, 2020) and partially in the territorial well-being literature (Le Roy & Ottaviani, 2022; Leroy, 2013).

Health and Education captures access to the functional services that constitute the basic infrastructure of a good life: medical and social care, early childhood and education facilities, and the healthcare provision that enables residents to sustain their health independently of their economic resources. It is consistently ranked among the primary concerns of residents (Bourdeau-Lepage et al., 2015; INSEE, 2026). The capability approach treats health as a foundational capability whose absence forecloses all others (Poirot & Gérardin, 2010).

Social Life captures the quality of the social and cultural environment through connectivity infrastructure, cultural and associative offerings, sports facilities, and social cohesion. This dimension reflects both material infrastructure and the intangible social capital that Stavo-Debauge (2020) places at the heart of environmental hospitability. Connectivity, both physical and digital, is increasingly recognized as a foundational determinant of territorial participation (Leroy, 2013). Social cohesion captures the capacity of communities to sustain shared institutions and maintain trust across social groups.

Economy captures economic dynamism through employment, business creation (Alexandre et al., 2010), and the local authority fiscal capacity that funds service provision (El Harchaoui, 2014). It reads local economic vitality not only through the productive base but through residential and presential activity: the retail density, business creation, and local authority investment capacity that sustain employment and services at the local level (Talandier, 2023b). Tourism is treated as a sub-dimension of Economy: tourist assets (accommodation capacity, cultural heritage, quality-labelled establishments) contribute to local economic resilience, particularly in territories where productive activity is limited (PUCA, 2007).

Housing captures residential conditions through affordability, supply and quality of dwellings, energy performance, and social housing availability. Housing occupies a distinctive position in a hospitality-oriented indicator: it mediates access to all other territorial assets. A municipality with excellent services but severely unaffordable housing is inaccessible to a large share of potential residents; a municipality with poor housing quality imposes genuine capability constraints on those who inhabit it regardless of other assets (Alivon, 2016).

Risk and Climate Exposure captures the negative externalities that reduce territorial quality: technological and industrial risks, natural hazards (flooding, wildfire, drought, seismic activity), and climate vulnerability (Bourdeau-Lepage et al., 2015; Feldmeyer et al., 2020). This dimension operationalizes an emerging dimension of hospitability: the degree to which a territory's environmental conditions threaten or protect the capacities of its residents (Buclet & Donsimoni, 2020). Climate change intensifies the relevance of this dimension for all territorial policy planning. Its inclusion as a full dimension, rather than a set of deductions from other scores, reflects the genuine non-compensability of severe risk exposure.

2. Data and Methods

2.1 Study Area : French Municipalities

France's territorial organisation is exceptionally fragmented by European standards, comprising approximately 34,900 municipalities in hexagonal France and Corsica. This fragmentation reflects a history of settlement stretching back to the pre-industrial era: two centuries ago, population was relatively evenly distributed, with nearly two-thirds of inhabitants living in municipalities of fewer than 2,000 residents. Since then, successive waves of industrialization and metropolitanization have profoundly restructured the spatial distribution of population and economic activity, concentrating weight in large urban areas while leaving extensive rural and peri-urban zones in demographic fragility (Talandier, 2023b).

The choice of the municipal scale for the analysis of territorial attractiveness is justified by several converging considerations. Attractiveness has become a widely shared strategic objective among French local authorities, and the policy instruments through which it is pursued, including city contracts (contrats de ville) and urban renewal programmes, operate precisely at this scale (PUCA, 2007). The municipality is also the last tier of political decisionmaking with the capacity to directly affect territorial actors and residents: it is where planning decisions are made, where local services are organized, and where the conditions of daily life are most directly shaped by public action. Finally, the municipal scale benefits from an exceptional statistical infrastructure in France: the availability of administrative and census data at the municipality level is among the richest in Europe, a reflection of France's advanced open data ecosystem, ranked among the most mature on the continent by the European Commission's Open Data Maturity assessment (European Commission, 2025). This data richness enables the construction of meaningful and comprehensive indicators across a broad range of dimensions at fine spatial resolution.

The indicator is computed for 34,827 municipalities after the following exclusions: French overseas territories (DROM), whose fundamentally different attractiveness dynamics would require dedicated benchmarking; six villages morts pour la France, destroyed during the First World War and containing no resident population; and municipalities with more than seven missing values across the indicator set, primarily newly merged municipalities and isolated islands.

2.2 Data Sources and Variable Selection

Indicators were retained when they met three criteria: exhaustive coverage at the municipal scale, conceptual correspondence to one of the five dimensions, and stability across the reference period. The full list of indicators, their sources, reference years, and dimensional assignment is provided in the supplementary material.

The indicator selection process was iterative, combining academic input and practitioner knowledge made possible by the CIFRE research framework, which embedded the research within La Poste, an organisation with direct operational knowledge of territorial conditions across all French municipalities.

The final set comprises 54 base indicators grouped into five dimensions and 14 sub-dimensions (Table 1).

Dimension	Sub-dimensions	Number of indicators
Health & Education	Medical-social, Early childhood & education	11
Social Life	Connectivity, Cultural/associative/sports offering, Social cohesion	10
Economy	Employment, Enterprises, Local authorities, Tourism	13
Housing	Housing supply & quality, Social housing	7
Risk & Climate Exposure	Natural risks, Technological & health risks, Climate	13
Total	**14 sub-dimensions**	54

Table 1. Dimensional structure of the FLAIR, dimensions, sub-dimensions, and approximate indicator counts.

2.3 Spatial Smoothing

A distinctive methodological feature of the FLAIR is the application of spatial smoothing to all base indicators prior to normalization and aggregation. This procedure reflects a fundamental characteristic of territorial attractiveness as habitability: municipalities do not function as isolated units, and residents routinely cross administrative boundaries to access services, employment, and amenities. A municipality without a hospital within its boundaries is not characterised by absent healthcare if one is reachable within a short distance. Treating it as such would systematically overstate service deprivation for small municipalities adjacent to larger service centres, generating a bias that is both statistically incorrect and analytically misleading. The importance of accounting for spatial structure in composite indicators is increasingly recognised in the methodological literature (Palma et al., 2024; Fusco et al., 2024). The FLAIR addresses this concern at the measurement level: by smoothing each indicator before any aggregation, spatial structure is incorporated prior to, and independently of, the aggregation procedure.

The objective of spatial smoothing in the FLAIR is to capture the geographic space within which residents realistically use services located in neighbouring municipalities.

The smoothing bandwidth was calibrated empirically using the Enquête Mobilité des Personnes 2019. The median inter-communal travel distance was computed for two mobility contexts separately and by urban-rural typology category: daily service mobility (shopping, healthcare, administrative errands, and local leisure) and commuting mobility (home-to-work trips). This distinction reflects the different spatial logics governing service access and labour market reach, with commuting distances generally exceeding daily service distances.

For each indicator, the smoothing bandwidth h is set to the median distance observed in the relevant mobility context and urban-rural category, and determines the shape of the weighting function. The outer inclusion radius is set to the 80th percentile of the same distribution: only municipalities within that distance of the focal municipality enter the smoothing window. The weight assigned to a neighbouring municipality at distance d is:

$$\mathrm{w}(d) = \exp\left(\frac{-d^2}{2h^2}\right)$$

Two aggregation methods are applied depending on the nature of each indicator. The mean method applies to indicators representing resources distributed across municipalities: a municipality with a high concentration of social housing, for instance, effectively shares that provision with its neighbours, and the weighted average reflects how that supply is spread across the broader area. The maximum method applies to indicators where a good score in one municipality benefits surrounding municipalities without diminishing the original: a municipality hosting a polluted site retains its score while neighbouring municipalities are penalised by proximity to it. The max captures this propagation, ensuring that a local hazard depresses the assessed conditions of the surrounding area without being attenuated by cleaner neighbours.

2.4 Construction and Validation of the Index

2.4.1 Construction procedure

Outlier treatment

A winsorisation procedure was applied selectively to municipalities with fewer than 500 inhabitants, where extreme indicator values frequently reflect small-sample artefacts rather than genuine territorial characteristics: a single firm creation, for instance, can produce a business creation rate far above any plausible benchmark in a very small municipality. The procedure replaces values whose z-score exceeds ±3 standard deviations with the corresponding threshold value, thereby retaining 99.7% of the distribution untouched while correcting only the most extreme observations.

Missing data

Missing values are minimal, not exceeding 1% per indicator after exclusions. Residual missing values were addressed through k-nearest neighbours imputation applied to the full indicator matrix. A comparison of imputation methods, including Random Forest multiple imputation, confirmed that results are insensitive to this choice at such low rates of missingness.

Normalisation

All indicators were normalised to a [1, 100] scale using min-max rescaling:

$$X_{\text{norm}} = 1 + 99 \times \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

where $X_{\min}$ and $X_{\max}$ are the observed minimum and maximum values. Min-max rescaling preserves relative distances between municipalities, ensures cross-indicator comparability regardless of original scale, and produces a bounded range compatible with subsequent geometric aggregation.

Weighting

Equal weights were applied both within dimensions and across dimensions. In the absence of theoretical consensus on the relative importance of dimensions, equal weighting avoids the false precision of subjective differentiation while remaining transparent and fully reproducible.

Aggregation

Both within-dimension sub-indices and the overall FLAIR score are computed using a geometric mean:

$$\text{CI} = \left(\prod_{i=1}^{n} X_i\right)^{\frac{1}{n}}$$

Geometric aggregation is partially non-compensatory: a municipality's weight on a given dimension increases as its score on that dimension decreases, so that severe weakness in one dimension cannot be fully offset by excellence in another.

2.4.2 Validation: sensitivity and uncertainty analysis

Section 1.3 established that the instruments conventionally used to validate composite indicators, namely Cronbach's alpha, confirmatory factor analysis and principal component analysis, presuppose an intercorrelation among indicators that a formative construct neither requires nor expects. We use here only uncertainty and sensitivity analysis to assess the variability: the index is regenerated under alternative specifications and the variance of the resulting rankings is decomposed across the decisions that produced it (Saisana et al., 2005; Bas et al., 2016). Three factors were varied: winsorisation, in 23 configurations; normalisation, min-max against z-standardisation; and aggregation, four functions spanning the continuum of compensability, with the geometric mean falling between them. The response variable is the mean absolute rank displacement from the nominal index (Saisana et al., 2005). Appendix A sets out the design, the estimation procedure and the complete results; the analysis was conducted with COINr (Becker et al., 2022).

FLAIR proves robust to the choices that are properly technical. Winsorisation accounts for 5.6 per cent of the variance in rank displacement even under deliberately aggressive settings, k-nearest neighbours and Random Forest imputation perform equivalently, and no single indicator drives the ranking, the removal of any one of the 54 leaving a median rank correlation of 0.998 with the nominal classification.

The index is sensitive to the choice of aggregation function, and above all to the way that choice interacts with normalisation. Neither factor exercises a discernible effect of its own, both first-order Sobol indices having confidence intervals that contain zero, whereas their total-order indices reach 0.80 and 0.54; a factorial decomposition attributes 50.8 per cent of the variance to their joint effect. Min-max preserves a within-municipality dispersion across dimensions that z-standardisation compresses, the median coefficient of variation falling from 0.394 to 0.029, and power means diverge only to the extent that the values they combine differ. Substituting one aggregation function for another accordingly displaces municipalities by 6,062 ranks on average under min-max, against 1,548 under z-standardisation. Removing an entire dimension of FLAIR displaces municipalities less, at a minimum rank correlation of 0.902, than changing the aggregation function, at 0.689.

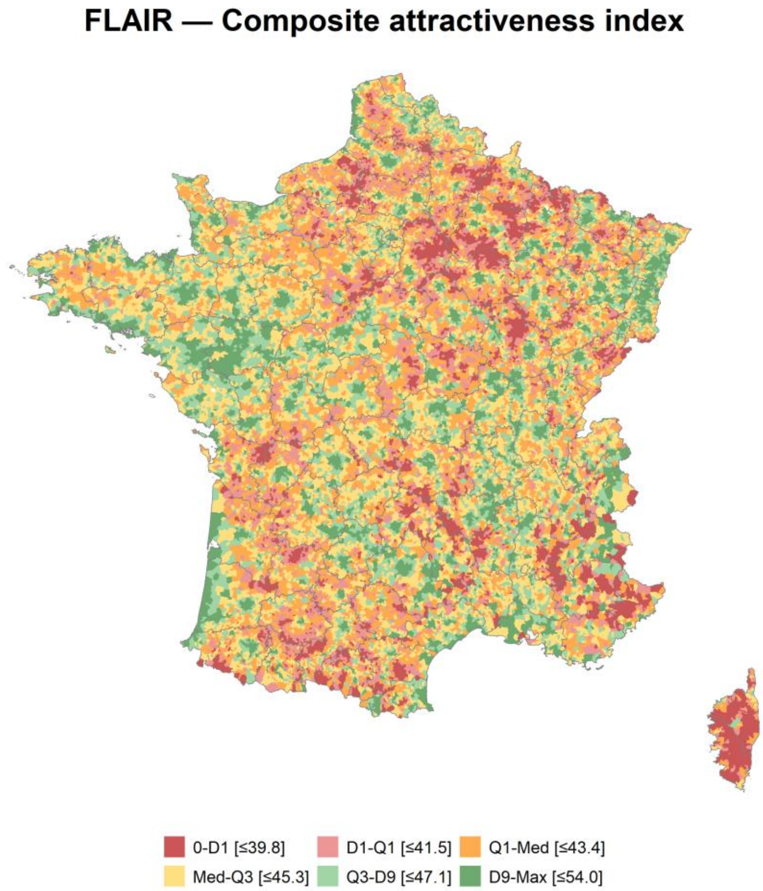
Individual positions are correspondingly uncertain. Depending on the specification, a municipality's rank varies over a range of 11,616 positions for the median municipality, that is a third of the classification. The range narrows to 2,569 positions among the first thousand municipalities. These intervals are wide because scores are densely packed in the middle of the distribution, where a minimal change displaces a municipality by thousands of positions. The ordering is more stable than they suggest, since a change of specification displaces neighbouring municipalities together: two of them may have overlapping intervals and still be ordered identically throughout. Among pairs drawn from distinct regions of the ranking, 48 per cent have overlapping intervals but only 28 per cent are ever ordered differently, and 6 per cent beyond thirty thousand ranks of separation. FLAIR is accordingly to be read as an instrument of territorial typology rather than as a detailed hierarchical classification.

This sensitivity is not a defect. The aggregation function encodes the degree of compensability admitted between dimensions, and as established in Section 1.3 that degree belongs to what the index defines rather than to how it estimates. The harmonic mean treats a deficit as barely compensable, the geometric mean penalises imbalance while allowing partial substitution, the arithmetic mean lets a strength fully offset a weakness, and the generalised mean with $p = 2$ rewards specialisation. These are four definitions of what makes a municipality attractive, not four estimators of a single quantity, and it would be suspect if the ranking were indifferent to the choice. Min-max is retained because attractiveness is a matter of choice among the places that exist, so the pertinent reference is the range of observed situations rather than the distance to a national mean, and because it preserves the variation on which the compensability assumption acts. The apparent robustness of the z-score is the attenuation of the very effect that choice is meant to produce.

Two features should be borne in mind. The first-order Sobol indices are imprecisely estimated, so only their ordering is established; the conclusion rests on the total-order indices and the factorial decomposition, which concur. And indicators on which many municipalities score zero weigh more heavily than the others: min-max assigns them the bottom of the scale, and geometric aggregation treats a bottom score as a severe penalty. Municipalities are penalised there for the shape of the indicator's distribution as much as for their own performance (Appendix A).

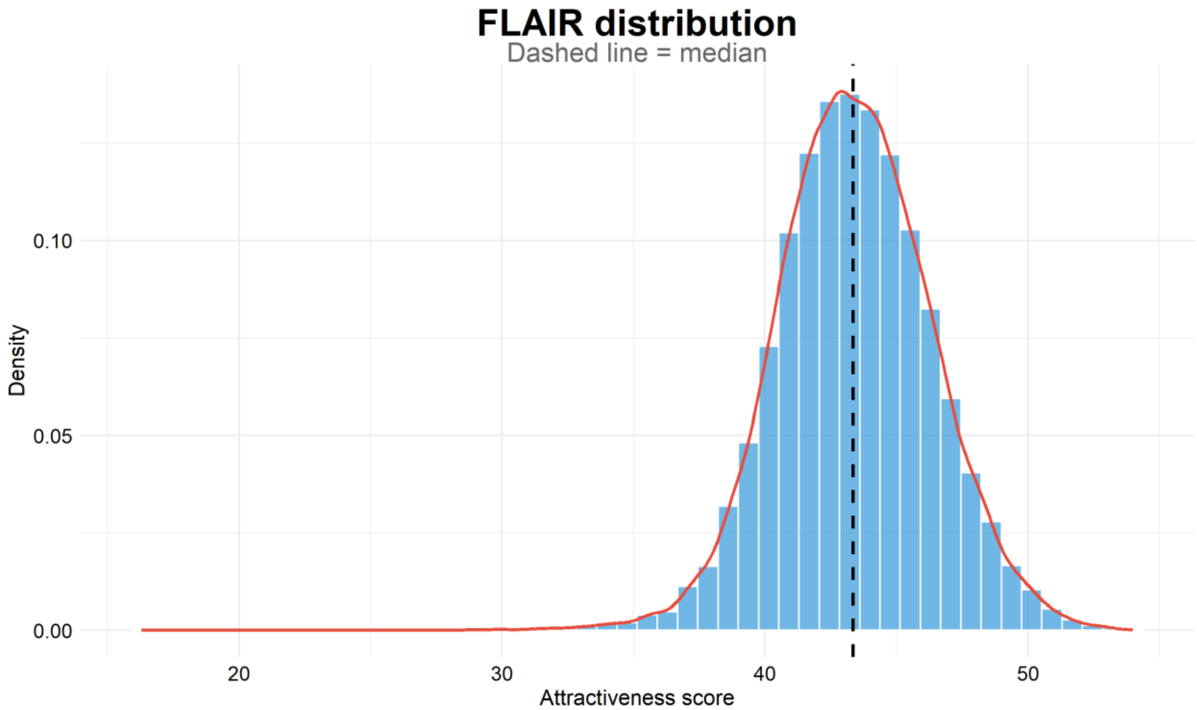
3. Results and Discussion

This section presents the empirical results and discusses them as it proceeds. It opens with the global distribution of the index, then establishes its central finding that FLAIR behaves largely as a measure of functional centrality, before examining the structurally independent Risk and Climate dimension, the spatial organisation of attractiveness, its relation to social inequality, and finally the differentiated profiles of territorial advantage and disadvantage.

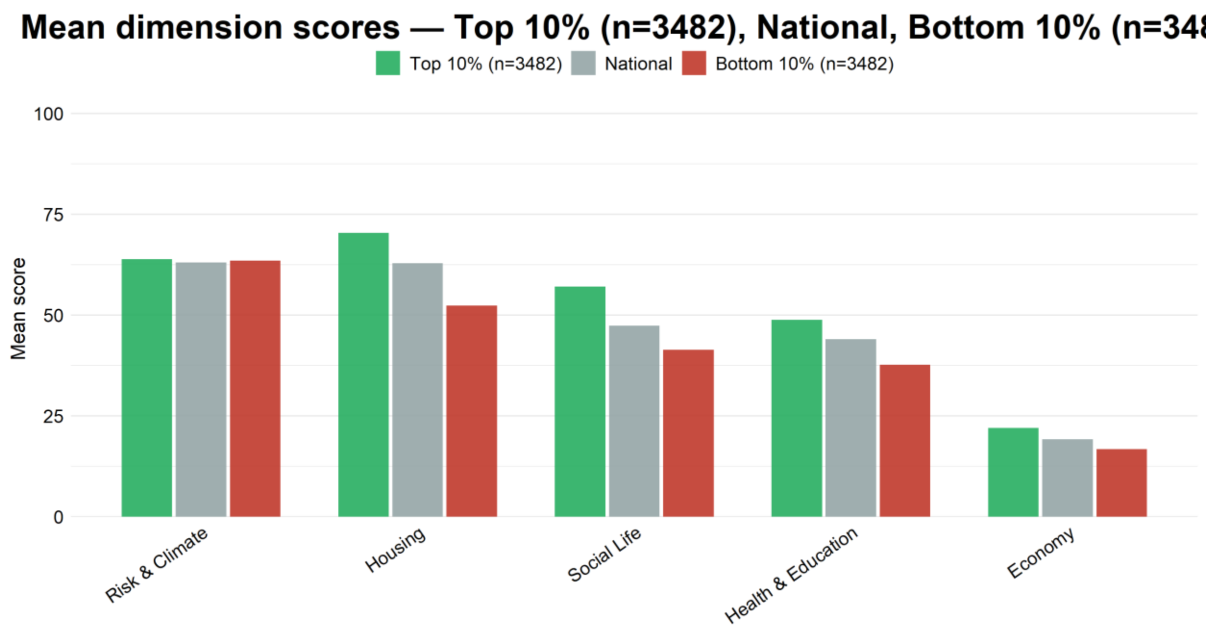


3.1 The global distribution of attractiveness

The composite index is distributed in a narrow band around a national mean of 43.4 (IQR = 3.84). The distribution is slightly left-skewed, which means that extreme scores are more common at the bottom than at the top: there are no outstanding winners, but a tail of municipalities that accumulate deficits across multiple dimensions simultaneously. This is the signature not of a competitive ranking but of a measure of territorial assets whose lower bound reflects cumulative deprivation.



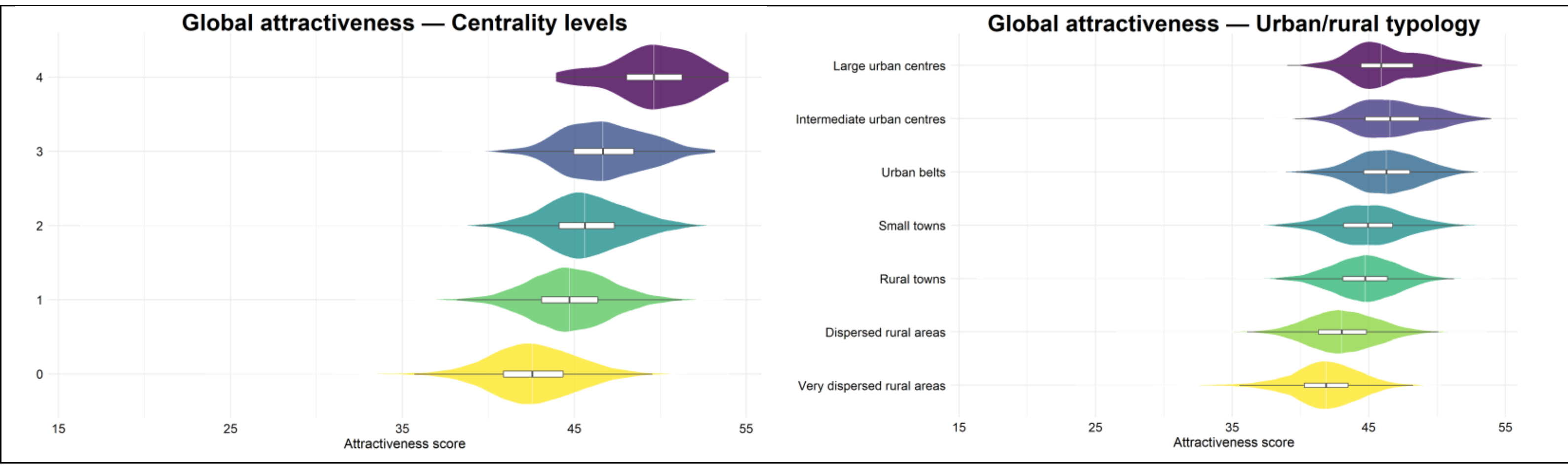
The lower decile makes this structure explicit. Municipalities at the bottom record simultaneous deficits across four dimensions: Social Life (-12.6%), Housing (-16.7%), Health and Education (-14.4%) and Economy (-13.0%), with one notable exception: Risk and Climate remains almost stable between the top and bottom deciles (Δ = 0.6%). Low attractiveness is therefore a cumulative condition rather than a failure on any single dimension, and the dimension that least follows the gradient is precisely the one least correlated with the others, a point developed in 3.3.



3.2 FLAIR as a centrality index: functional position over urban-rural type

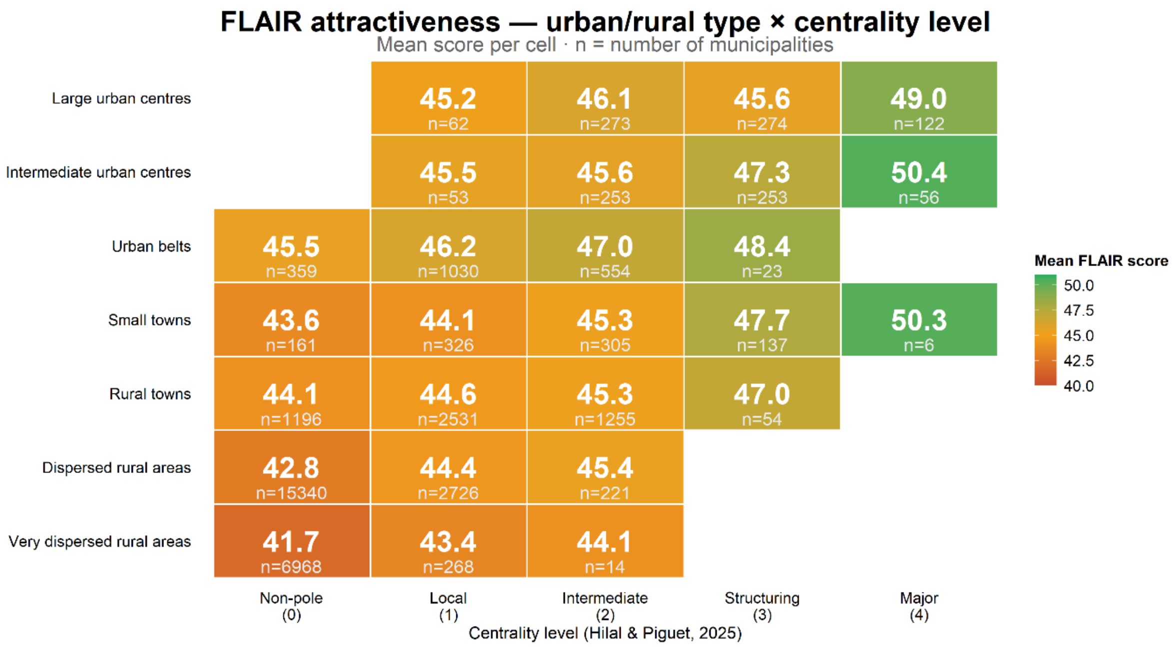
The most structuring result of the analysis is that FLAIR behaves largely as an index of functional centrality. Three independent angles converge on this conclusion.

The centrality classification used here is drawn from Hilal and Piguet (2025), who rank French municipalities by the range and diversity of the retail and public services they host, measured from the Base Permanente des Équipements. A mixed statistical classification applied to the full equipment matrix, without any exogenous threshold, separates municipalities that concentrate services and act as centres for a surrounding area from those that do not. The procedure yields five groups: non-pole municipalities (level 0), which host few or no services, and four ascending classes of service centres, local (level 1), intermediate (level 2), structuring (level 3), and major (level 4), whose service provision rises steadily with rank. Because the hierarchy rests on services rather than on population or employment, it captures the functional role of a municipality within its territorial system independently of its demographic weight.

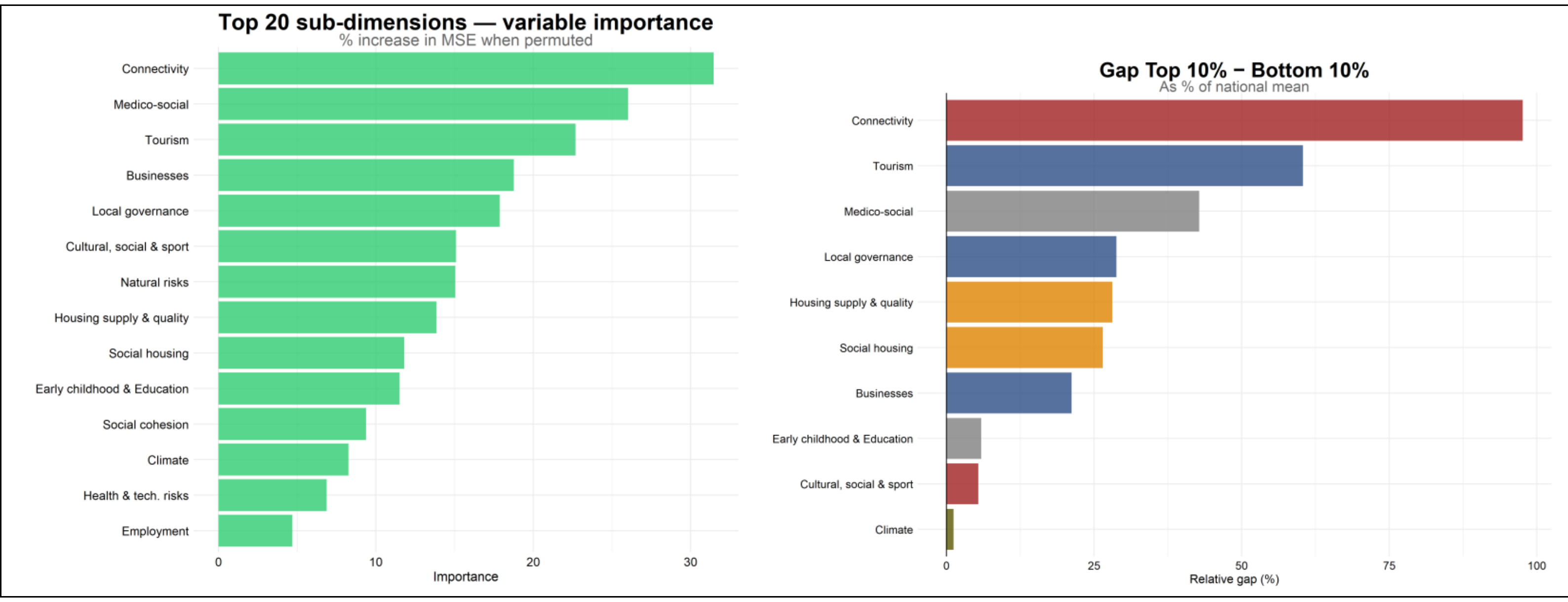


First, functional centrality predicts attractiveness as well as the urban-rural category. The two effect sizes are effectively equal, $eta^2 = 0.198$ for centrality against $eta^2 = 0.209$ for the urban-rural typology, and the gradient is monotonic and clear on both. This suggests that FLAIR captures less an urban character as such than access to collective resources, what the literature calls functional centrality (Hilal and Piguet, 2025).

Second, the two typologies combined are more explanatory still. The three highest mean scores are all at the top of the centrality hierarchy: intermediate urban centres at centrality 4 (50.4), small towns at centrality 4 (50.3) and large cities at centrality 4 (49.0). Centrality prevails over the type of city. Intermediate urban centres at maximum centrality slightly outperform large cities, pointing to an optimal combination of service concentration and diversity without the negative externalities that accumulate in the largest agglomerations. At equal centrality, urban belts also perform slightly above the average for their tier, suggesting a similar logic: high service access with lower urban density costs. There is therefore an optimal size and concentration of services beyond which additional urban mass yields diminishing returns in habitability.



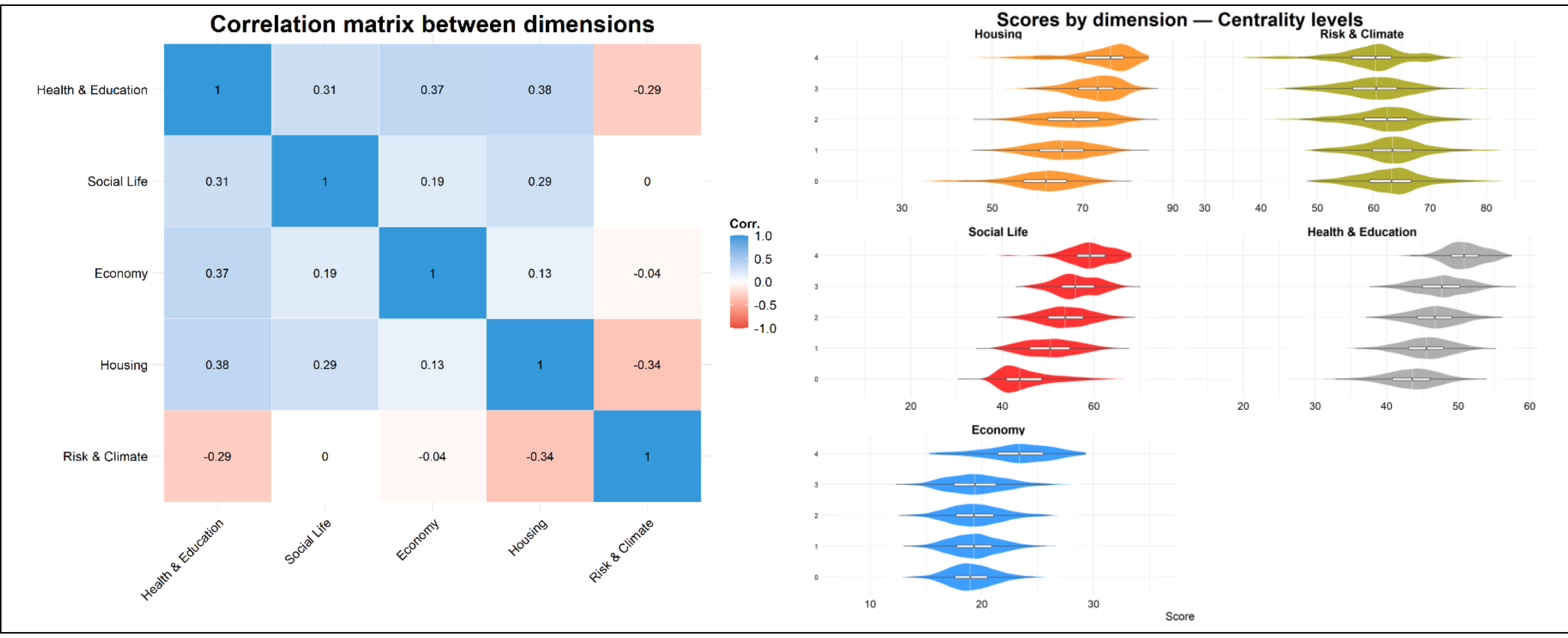
Third, connectivity operates as the underlying mechanism. A central municipality is by definition well connected to the others. Connectivity is the most discriminating sub-dimension between the top and bottom deciles (a gap of 97.6 points) and the most important variable when predicting FLAIR by its sub-dimensions with a random forest (PercIncMSE = 31.5). Centrality and connectivity measure distinct things, one a position within a system of places, the other a stock of infrastructure assets, but their effects converge within FLAIR.



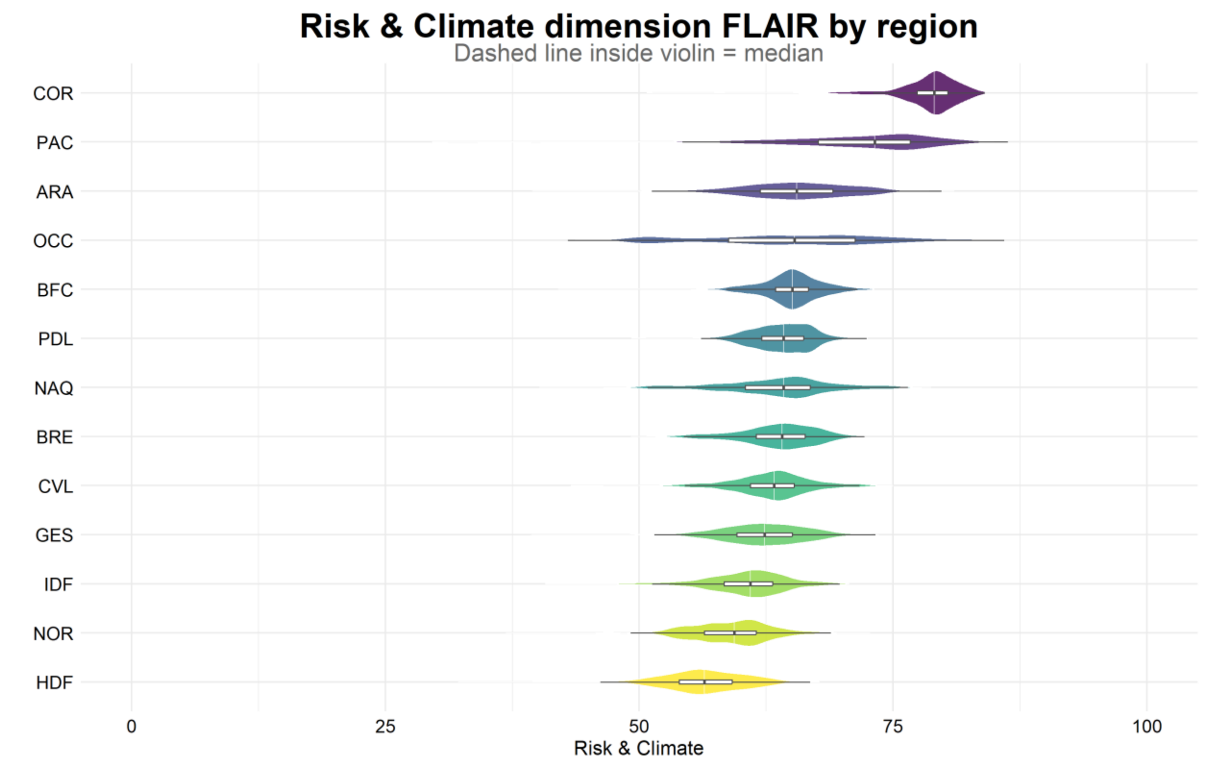
A corollary follows from the centrality result. Large cities (mean 46.32) score slightly below intermediate centres (46.75), but this gap dissolves once centrality is controlled for. What the data show is not a uniform metropolitan penalty but strong internal heterogeneity: Small towns at centrality 0 average 43.6 against 50.3 at centrality 4. The size of a city says little about its attractiveness until one knows the functional role it plays.

3.3 Risk and Climate as a structurally independent dimension

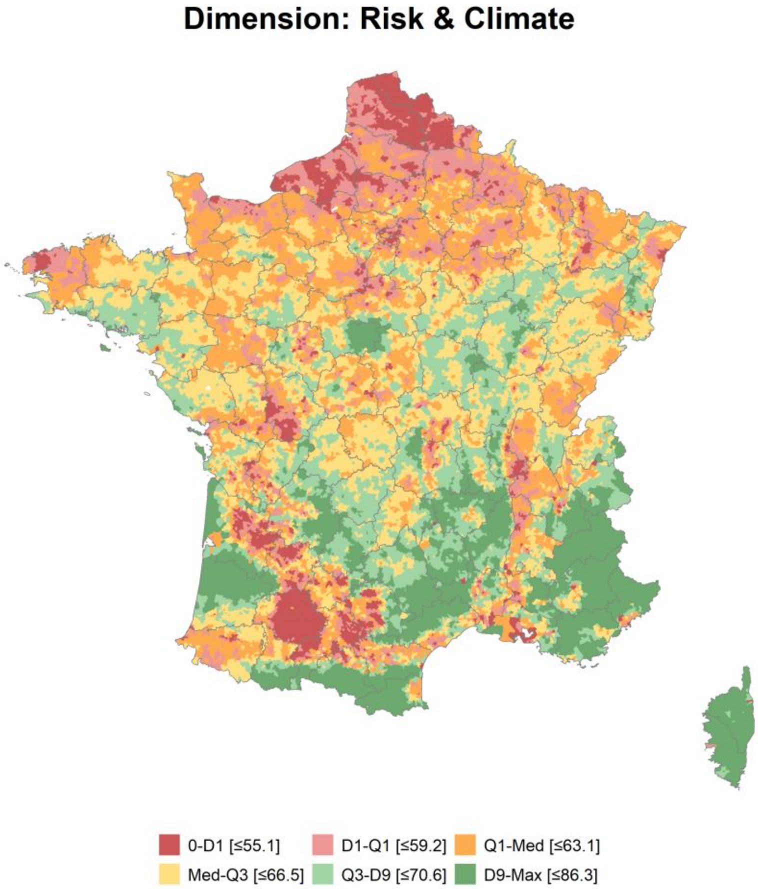
The Risk and Climate dimension is close to orthogonal to all the others. Its correlations reach at most -0.343 with Housing and are near zero with Social Life and Economy, and it correlates with the composite index at only 0.038. Yet it accounts for 21.7% of the variance of the index. This is directly relevant to the design of the index: a dimension can be substantially constitutive of attractiveness without being statistically redundant with the others, consistent with the formative model (Mazziotta & Pareto, 2025).



Geographically, Risk and Climate is the variable that best explains regional differences (eta² = 0.315 in the regional decomposition), notably for Corsica (38.04, SD = 4.02) and the Mediterranean coast.



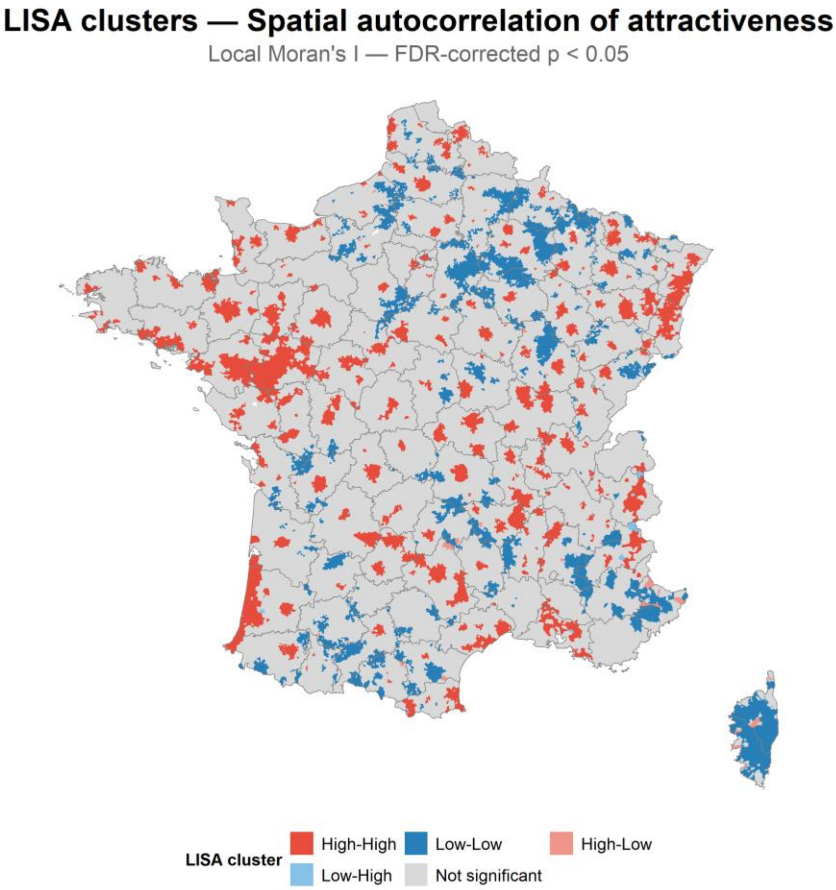
A dimension that is almost uncorrelated with the others can therefore dominate the between-region variance, which is the formative logic made spatially visible: Risk and Climate is structurally present but not substitutable. Unlike the service or housing dimensions, which are directly actionable through public investment, Risk and Climate is more resistant to policy intervention: while flood management infrastructure and wildfire prevention can reduce exposure at the margin, the underlying hazard geography changes slowly. This introduces a distinction between attractiveness that can be improved through policy and attractiveness that is structurally constrained by physical geography, a distinction that a compensatory index would erase by allowing strong service assets to offset high exposure to risk.



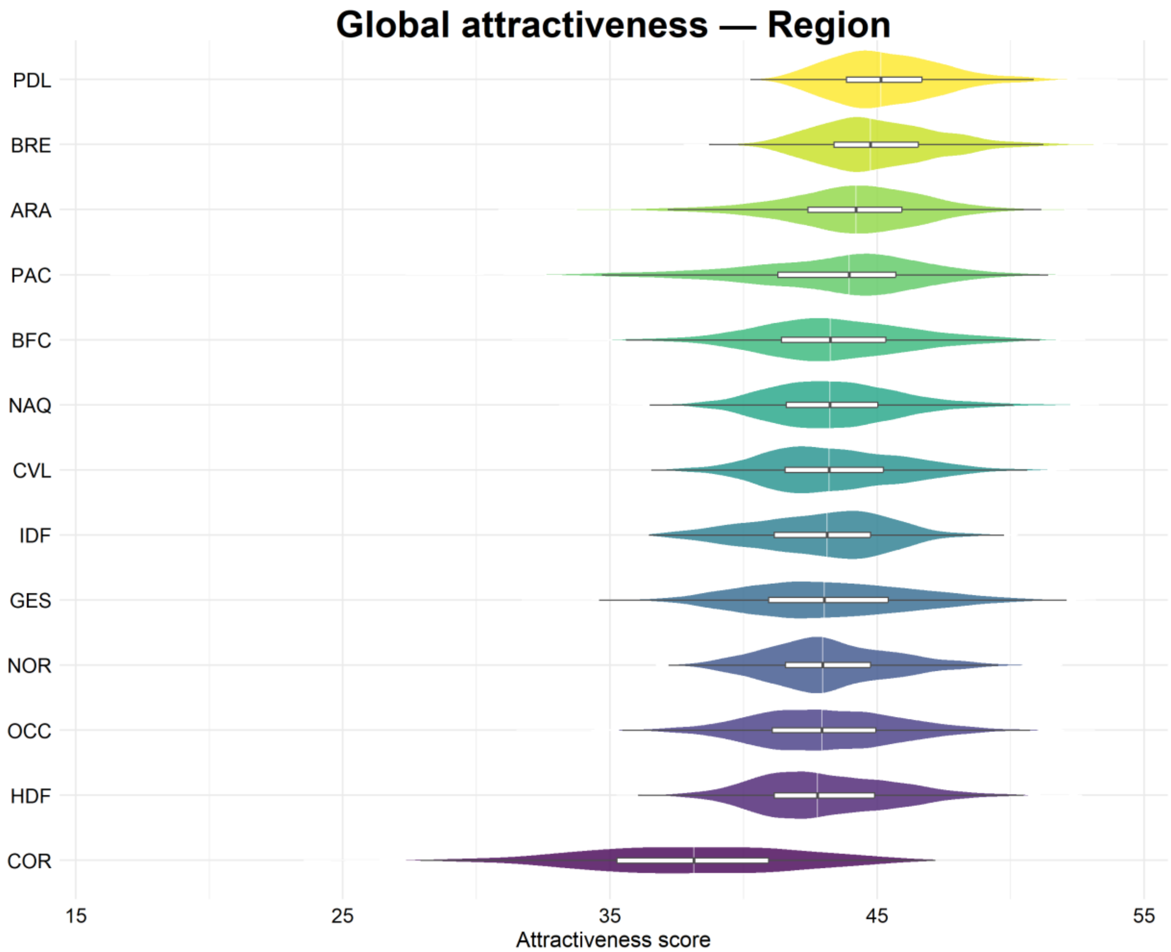
3.4 Spatial structure: strong autocorrelation and the limits of regional analysis

Attractiveness is strongly spatially structured: Moran's I = 0.711, highly significant. The LISA clusters identify 9.7% of municipalities as High-High and 8.8% as Low-Low, with fewer than 0.2% spatial outliers. Two policy readings follow, in opposite directions.

On one side, the scarcity of spatial outliers and the density of High-High clusters argue for intercommunal strategies. A weakly attractive municipality surrounded by attractive ones is statistically very rare: attractiveness is collective, built within a living area rather than municipality by municipality (Talandier, 2023b).

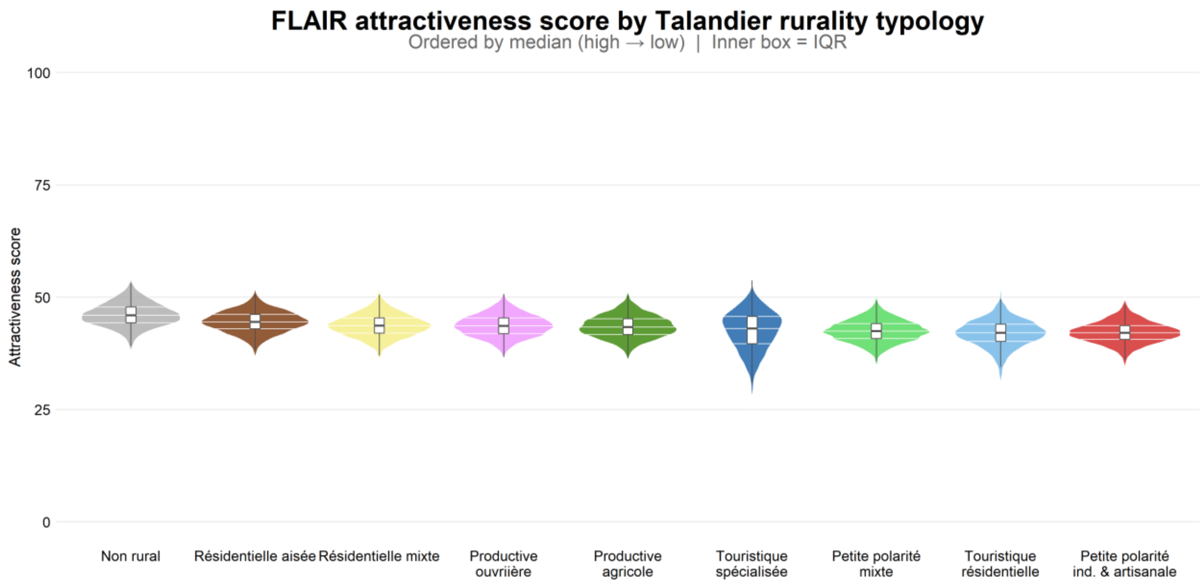


On the other side, the regional scale masks the most significant disparities which operate within rather than between regions. The region accounts for only $eta^2 = 0.072$ of the variance. Corsica scores well on Risk and Climate, benefiting from low industrial density and a relatively preserved natural environment, but this strength does not compensate for the weak service access of its many dispersed municipalities, far from any functional centre. Also, unlike mainland municipalities, dispersed municipalities on the island cannot benefit from the spatial smoothing effect of distant centralities beyond the sea. Its overall underperformance reflects a dimension that cannot be offset by another, precisely because of geometric aggregation. An attractiveness policy built on the regional level therefore risks missing most of the intra-regional inequalities that matter.

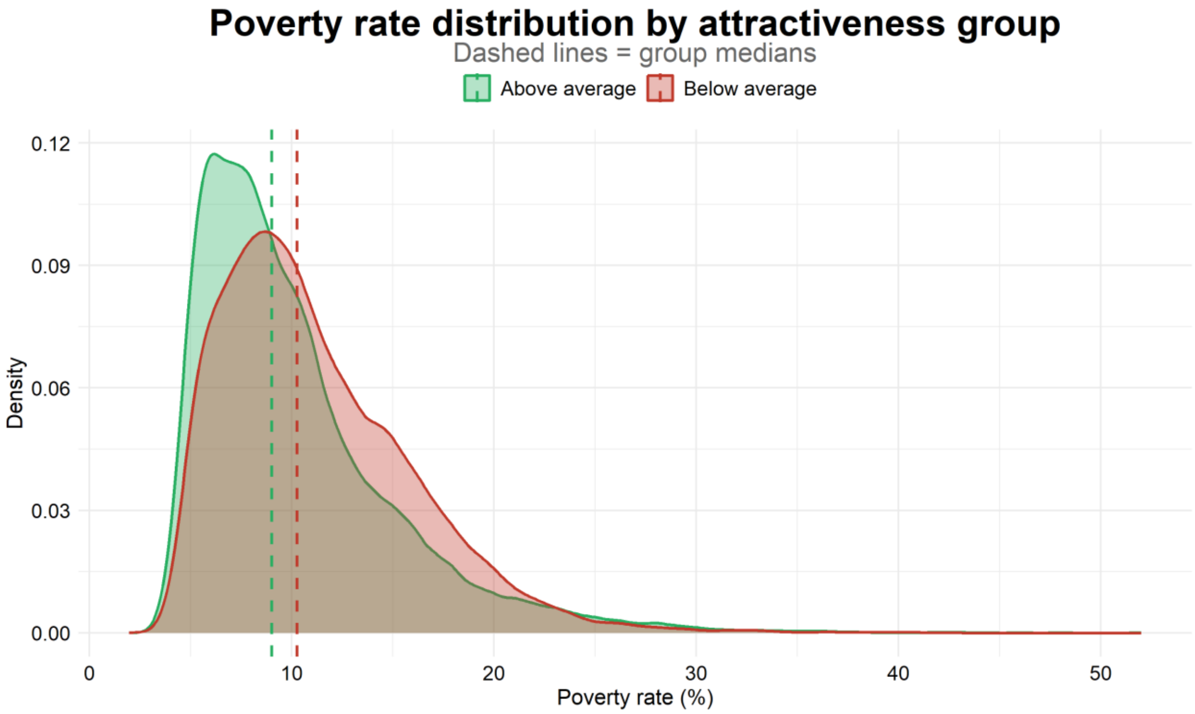


3.5 Inequality and poverty: attractiveness is not socially neutral

Two results concern the link between attractiveness and poverty. The first concerns specifically rural areas. Among the ANCT rural typologies (Talandier, 2023a), affluent residential rurality (44.54) leads all other rural categories. The municipalities where wealthier households preferentially settle also display stronger measured attractiveness assets.



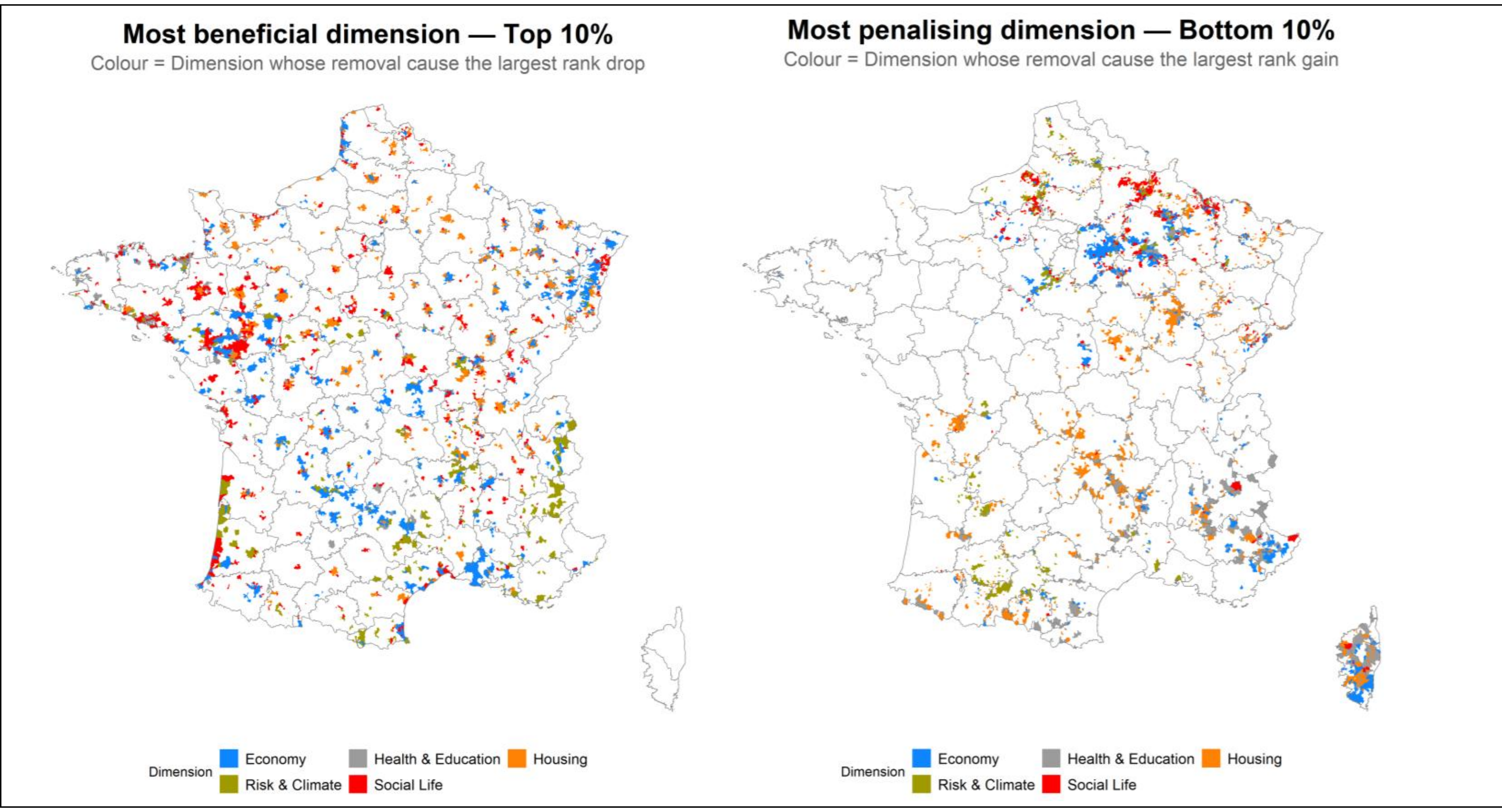
The second concerns the poverty in all municipalities. Across all municipalities, more attractive territories tend to have lower poverty rates: those above the national mean have an average poverty rate of 10.21% against 11.26% below, a modest but consistent gap that holds when the Attractiveness Areas of Paris, Lyon and Marseille are excluded (10.29% against 11.54%) (INSEE, 2021).



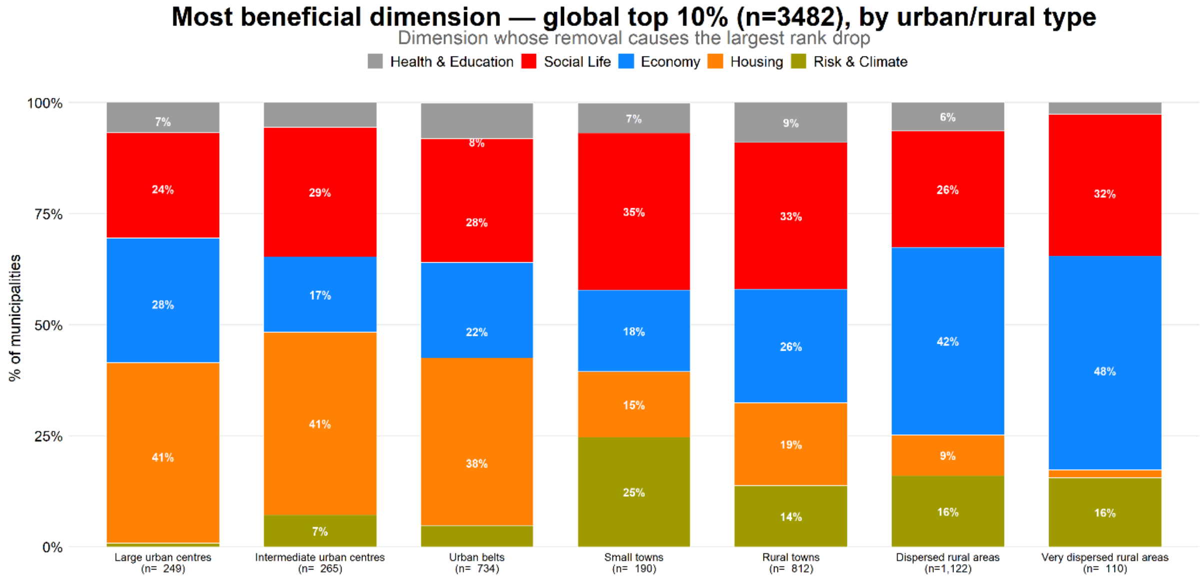
Residential attractiveness in the sense of FLAIR is not socially neutral. Because the index contains no socio-economic variable, this association is not imposed by construction. Its interpretation remains open: it is consistent both with a selection effect, whereby affluent households sort into already well-endowed territories, and with a resource effect, whereby their presence sustains local provision (Guison, 2024).

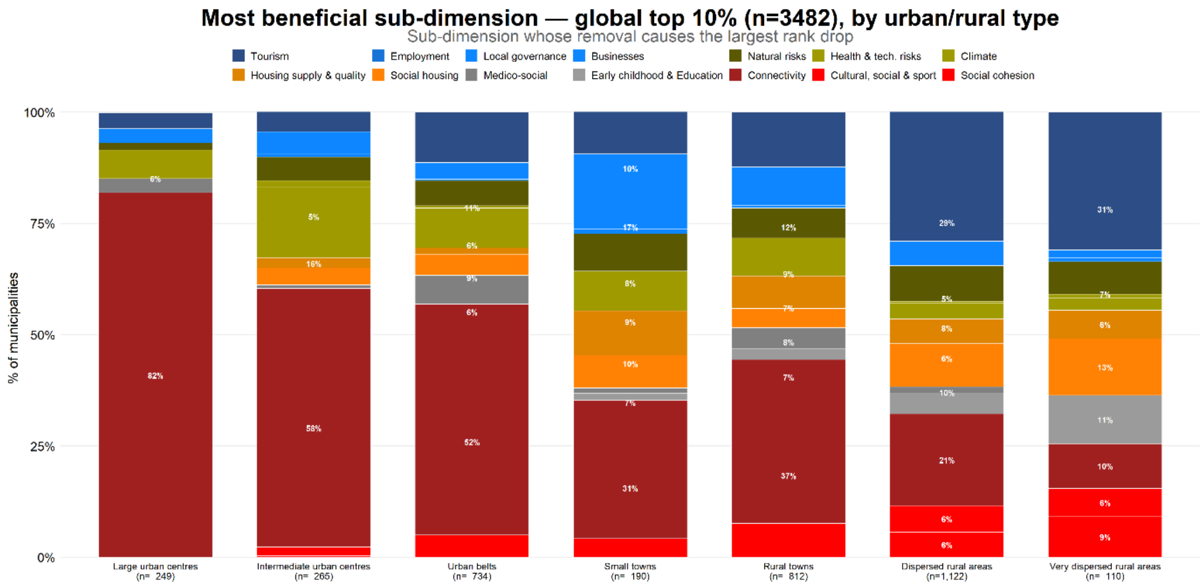
3.6 Territorial profiles: why municipalities lead or lag depends on context

The remove-elements analysis identifies, for each municipality, the dimension whose removal would cause the largest rank shift. Applied to the global top and bottom deciles and broken down by urban/rural category, it reveals something that aggregate scores cannot: there is no single recipe for territorial excellence or underperformance. The dimension that makes the difference depends fundamentally on territorial context. This result is not merely descriptive. It is a direct argument against one-size-fits-all attractiveness policy, and a demonstration that the FLAIR's multidimensional structure captures distinct facets of territorial quality rather than a single latent gradient.

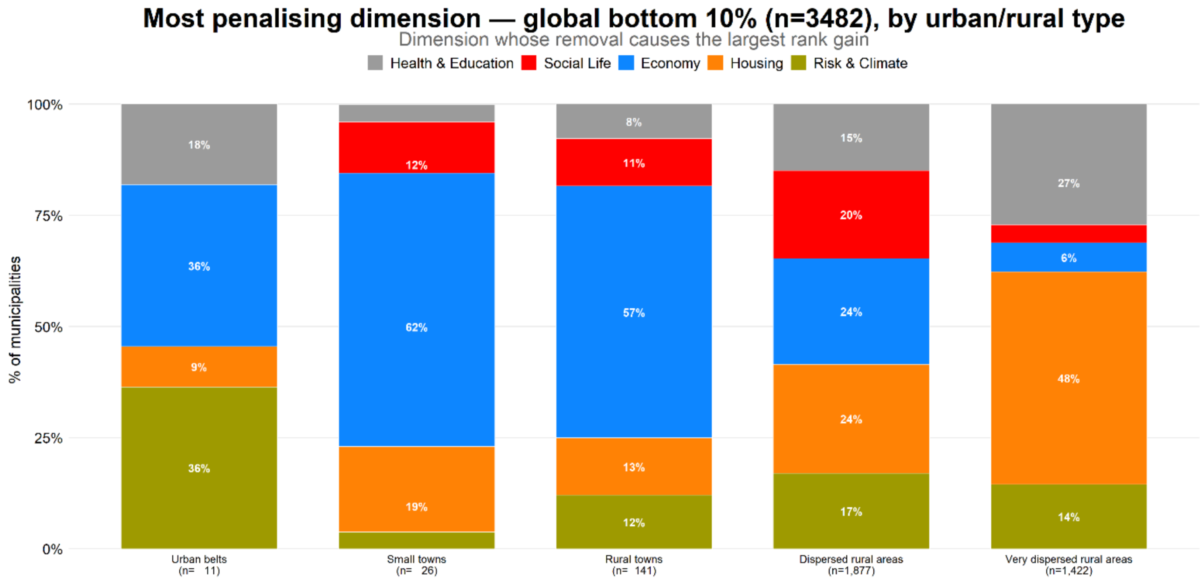


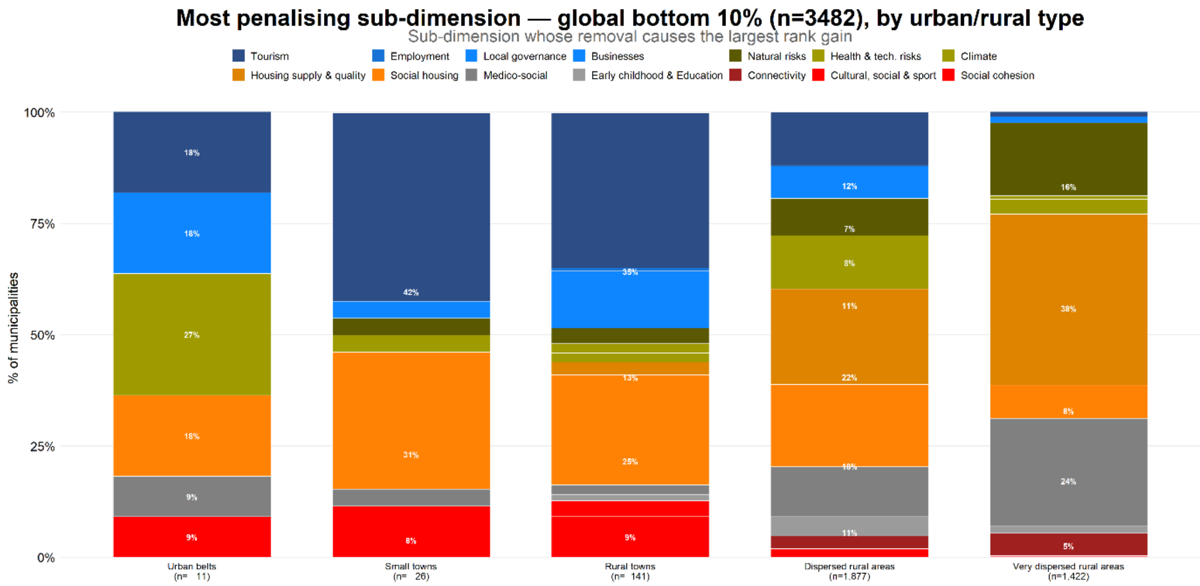
Among the global top decile, the most striking finding is the dominance of Connectivity across all urban categories: 81.9% of the strongest large urban centres, 58.1% of intermediate centres, and 51.9% of urban belts owe their lead primarily to this sub-dimension. This does not mean that connectivity causes their high score in a general sense; it means that connectivity is the asset that most differentiates them from the rest of their category. Removing it would cause the largest rank drop. This result connects directly to the centrality finding established in section 3.2: connectivity is both the operational expression of centrality in the index and its most discriminating measurement. For the other categories of the urban/rural gradient, the pattern diversifies. In small towns and rural towns, no single dimension dominates: Housing, Social Life, Tourism and Connectivity each account for 10 to 35% of the leading municipalities, and the mix shifts from one category to the next. Excellence here is assembled from multiple assets simultaneously, which is both a structural feature of these territories and a measurement artefact of the formative model: the geometric mean rewards breadth, and the most attractive rural municipalities tend to combine a relative tourism advantage with above-average connectivity and social infrastructure. In very dispersed rural areas, Tourism alone accounts for 30.9% and Connectivity for 10.0%, confirming that even the most isolated high performers are distinguished by economic assets and functional reach rather than by service provision alone.





The global bottom decile tells a symmetrical but distinct story. Among dispersed and very dispersed rural areas, the penalising dimension is not Economy or connectivity but Housing. In very dispersed rural areas, Housing supply and quality alone penalises 38.4% of the weakest municipalities, with Medico-social services a close second (24.1%). This is the inverse of the top decile picture: where the best rural municipalities stand out through tourism and connectivity assets, the worst are held back by residential and care deficits. Social housing is a secondary but consistent constraint across all rural bottom categories (7.5 to 30.8%), reinforcing the idea that access to affordable and quality housing is a binding constraint for habitability at the bottom of the rural distribution. Two further results deserve attention. First, Tourism appears as a penalising dimension for rural towns and small towns in the bottom decile (34.8% and 42.3% respectively), which may seem paradoxical given its role as a beneficial dimension in the top decile. The logic is consistent: tourism is a highly differentiating sub-dimension across rural municipalities, which means it lifts the best and penalises those who lack it relative to their peers. Its absence, more than any structural deficit, is what holds back many rural bottom performers. Second, Health and Education penalises 27.1% of the weakest very dispersed rural municipalities, confirming that service deserts remain a defining feature of the lowest-attractiveness rural municipalities.





What follows from these profiles is not simply that attractiveness policy cannot be uniform, but that the relevant policy lever differs in nature, not just in degree, across territorial contexts (Bouba-Olga et al., 2026). In urban areas, the marginal attractiveness gain comes from connectivity and economic dynamism; in rural areas, from housing quality, care access, and tourism development. And within any given territorial type, what holds back the weakest municipalities is not the absence of what makes the strongest excel: rural bottom performers lack decent housing and health services, not tourism assets. This asymmetry between the drivers of excellence and the sources of underperformance within the same territorial category is perhaps the most practically useful result of the analysis. It implies that policy strategies within a territory type must be designed around different diagnoses (Bonilla et al., 2025).

4. Conclusion

Measuring attractiveness as habitability rather than as competitive capture changes what the indicator sees, and the map it produces is not the one that competitive frameworks lead us to expect. The territories that rank highest are not the largest metropolises but the intermediate centres that pair service access with liveable density, and the asset that most distinguishes them is connectivity, the concrete capacity to reach what one needs across municipal boundaries, rather than economic mass. Risk and Climate, statistically independent of the other dimensions, weighs as heavily as any of them in the structure of attractiveness, which signals that ecological exposure is becoming a condition of where life remains sustainable rather than a separate policy file. And because attractiveness is built at the scale of living areas rather than isolated municipalities, and is modestly but systematically tied to lower poverty, the FLAIR brings into view a question that competitive measures cannot pose: whether well-provided territories are well-provided because the affluent selected them, or because public action made them liveable. The distinction matters for policy. If attractiveness simply tracks where wealth has already concentrated, territorial inequality is self-reinforcing and redistribution is the only lever; if it tracks the provision of assets that public action can build, then the geography of habitability is not fixed, and the role of policy is to extend liveability rather than to compete for residents.

Several limitations should be noted. The analysis is cross-sectional and cannot capture territorial trajectories; the data reflect conditions between 2019 and 2024 with some temporal asynchrony across sources. Subjective dimensions, such as residential preferences, social capital and institutional quality, are not captured and would require survey-based complementary work. Overseas territories are excluded by construction.

More than a ranking, the FLAIR offers public actors at every scale a structured diagnostic of what makes a territory habitable, for all its residents, including the growing share of older, less mobile and economically constrained people that competitive attractiveness frameworks tend to treat as a burden rather than a population to be served. Its central practical lesson is that there is no universal lever: the dimension that lifts one metropolis can be different for another and again different for a remote rural municipality, and effective policy must read each territory through its own profile rather than a national template. Comparative applications to other European municipal systems would test whether the dimensional structure and spatial patterns reported here reflect something general about how habitability is distributed across space, or a specifically French geography.

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Appendix A. Uncertainty and sensitivity analysis

A.1 Purpose and method

This appendix documents the uncertainty and sensitivity analysis summarised in Section 2.4.2. Variance-based sensitivity analysis treats the construction of the index as a function Y = f(X), where X is the vector of methodological choices and Y the resulting ranking (Sobol, 2001; Saltelli et al., 2008). The variance of Y is decomposed into fractions attributable to each choice taken separately and to interactions between choices. The first-order index Si measures the share of variance explained by a factor alone, averaged over all variations of the others; the total-order index STi measures the share attributable to that factor including all of its interactions. A gap between the two indicates that a factor operates in combination with others rather than on its own, and the sum of the STi exceeds unity whenever the model is not purely additive.

The indices are estimated by quasi-Monte Carlo sampling. Two independent samples of N points are drawn in the space of methodological choices, and d further samples are constructed by substituting one factor at a time, requiring N(d+2) evaluations of the model, where d is the number of factors. Each evaluation is a complete regeneration of FLAIR: winsorisation, imputation, normalisation and aggregation are replayed on the 54 indicators for the 34,827 municipalities. With N = 300 and two factors, the decomposition reported in Table A1 rests on 1,200 regenerations. Confidence intervals are obtained by bootstrap with 5,000 resamples of these regenerations; the bootstrap quantifies the precision of the estimator without requiring additional model runs, so that only an increase in N narrows the intervals themselves.

The uncertainty analysis follows a different logic. Rather than attributing variance to factors, it draws 500 specifications at random and describes, for each municipality, the dispersion of the ranks it obtains across them. A specification is a complete combination of methodological choices, one level per factor; since both factors are discrete, the space they define contains eight distinct combinations, and the intervals reported below describe the dispersion of each municipality across these eight rankings.

A.2 Design of the experiment

A sensitivity analysis is only informative if the alternatives it tests are ones a practitioner would genuinely entertain. Enumerating every technically available method guarantees large discrepancies without teaching anything, since some of those methods contradict the assumptions of the theoretical model in the first place. The design was therefore restricted to specifications that are defensible in themselves and consistent with the formative measurement model adopted here.

Two decisions were arbitrated separately and then held fixed. Imputation was assessed outside the sensitivity design, by introducing 15 per cent artificial missingness into three variables with contrasting distributions (mean rent, travel time to hospital, tourist accommodation capacity) and comparing k-nearest neighbours against Random Forest multiple imputation. Six kNN configurations were benchmarked, crossing the number of neighbours (5, 10, 15) with the aggregation of donor values (distance-weighted mean against median); k = 10 with distance-weighted averaging dominated on all three variables. Compared against the best Random Forest configuration, mean out-of-sample R^2 was 0.537 for kNN against 0.507, with kNN superior on two of the three variables. Imputation was fixed at kNN given the marginal difference between methods and its faster execution.

Weighting was likewise held constant, since varying it would test a hypothesis the index does not make: equal weighting is a substantive position on the absence of theoretical grounds for differentiation, not a default to be perturbed.

The three factors varied are the following. Winsorisation was declined in 23 configurations crossing z-score and percentile methods, thresholds, and population cut-offs from 500 to 5,000 inhabitants. Normalisation opposed min-max onto [1, 100] to z-standardisation with mean 100 and standard deviation 10, floored at 1 for compatibility with geometric aggregation. Aggregation opposed four functions spanning the continuum of compensability between dimensions: the harmonic mean ($p = -1$), which penalises imbalance most strongly; the geometric mean (p tending to 0); a mixed scheme applying the arithmetic mean at the indicator level and the geometric mean above it; and the generalised mean with $p = 2$, which rewards specialisation.

The response variable is the mean absolute rank displacement from the nominal index, a statistic introduced by Saisana et al. (2005) to capture in a single number the relative shift in the position of an entire system of units. It is never a difference in scores: because the normalisation methods produce different numerical scales, comparing raw scores would measure the change of scale rather than the change of ranking.

Alongside the Sobol indices, a variance decomposition by ANOVA was run on the same regenerations, using a factorial model that includes the interaction term explicitly. The two approaches are complementary. Sobol indices reveal that a factor operates through interaction whenever its total-order index exceeds its first-order index, but they do not identify which interaction is at work; the factorial model isolates and quantifies each two-way term. The ANOVA also provides a check on the Sobol estimates, η^2 being bounded in [0, 1] by construction whereas the Monte Carlo estimator of S_i and ST_i is not.

A.3 Robustness to data treatment

Outlier treatment exercises almost no influence on the classification. Across the totality of the 23 winsorisation configurations, including deliberately aggressive variants truncating 20 per cent of each tail and applying the correction to municipalities of up to 5,000 inhabitants, that is approximately 31,000 of the 34,827 units, winsorisation explains 5.6 per cent of the variance of rank displacement, against 93.6 per cent for aggregation and 0.8 per cent for their interaction. The Sobol total-order index is correspondingly negligible ($ST_i = 0.015$, 90 per cent CI [0.010, 0.021]). Following the customary use of the total-order index, a factor with a very small ST_i may be declared non-influential and fixed in a subsequent iteration of the analysis (Saisana et al., 2005).

A.4 The dominant term: the interaction between normalisation and aggregation

Term	Sobol Si [90% CI]	Sobol STi [90% CI]	ANOVA eta²
Aggregation	0.233 [-0.064, 0.540]	0.800 [0.654, 0.955]	0.356
Normalisation	-0.083 [-0.331, 0.164]	0.538 [0.430, 0.650]	0.136
Normalisation x Aggregation			**0.508**

Table A1. Decomposition of the variance of rank displacement relative to the nominal index. Sobol indices estimated with N = 300 and 5,000 bootstrap replications; ANOVA eta² on the factorial design, whose residual variance is null, the design being deterministic and completely crossed.

The two approaches converge. The first-order Sobol indices of both factors have confidence intervals containing zero, while their total-order indices attain 0.80 and 0.54: almost the whole of the effect passes through terms of higher order. The factorial decomposition names the term in question, attributing 50.8 per cent of the variance to the joint effect of normalisation and aggregation, against 35.6 and 13.6 per cent for the two main effects.

The mechanism follows from a property of the power means to which the four aggregators belong: the harmonic mean ($p = -1$), the geometric mean (p tending to 0), the arithmetic mean ($p = 1$) and the generalised mean with $p = 2$. These functions coincide when the aggregated values are equal, and the distance between any two of them depends on the coefficient of variation of the values within the vector being aggregated, not on their level. Min-max normalisation preserves a substantial dispersion between the dimension scores of a given municipality, whereas z-standardisation compresses it: the median within-municipality coefficient of variation across the five dimensions is 0.394 in the first case and 0.029 in the second. Since the aggregation functions differ from one another only to the extent that the values they combine differ, this compression determines how much the choice of aggregator matters. The mean rank displacement between the four aggregation functions is 6,062 positions under min-max and 1,548 under z-standardisation, and the two most distant specifications of the entire design oppose the harmonic mean to the generalised mean under min-max, that is the two extremities of the compensability continuum.

This result qualifies rather than contradicts the conclusion of Saisana et al. (2005), who find the normalisation method to be without influence on the ranking of the units they examine. Their design holds aggregation fixed at the weighted arithmetic mean while varying normalisation, the weighting scheme and the weights. Since normalisation acts here exclusively through its interaction with aggregation, a design in which the aggregator is additive and fixed leaves that interaction without a partner, and normalisation necessarily appears inconsequential. The present analysis identifies the condition under which it becomes influential.

A.5 Uncertainty of individual positions

Across 500 regenerations, the median amplitude of the interval between the 5th and 95th percentile of rank attains 11,616 positions, that is 33.4 per cent of the distribution. This uncertainty is considerably unequal along the classification: 2,569 positions among the first 1,000 municipalities, against 13,906 in the interval from 10,001 to 25,000. The explanation resides in the density of the score distribution, documented in Section 3.1: FLAIR scores are concentrated in a narrow band, so that in the central region of the distribution a minimal perturbation of score displaces a municipality by several thousand positions, whereas at the extremities the scores are more dispersed and the positions correspondingly more stable.

The width of these intervals is not a property of the index alone but of the space of alternatives admitted into the design. Extending the set of aggregation functions from three to four raises the median interval from 24.5 to 33.4 per cent of the distribution. Since the four functions correspond to distinct positions on compensability rather than to variants of a single position, this increase measures the disagreement between theoretical positions rather than any instability of the estimation.

These marginal intervals also overstate the uncertainty attached to comparisons between municipalities. As Saisana et al. (2005) note, part of the apparent overlap disappears once the correlation between the simulated values of two units is acknowledged: the specifications displace municipalities jointly rather than independently. Among pairs drawn from distinct regions of the ranking, 48 per cent have overlapping intervals but only 28 per cent are non-unanimous, and the mean probability that the higher-placed municipality dominates is 0.927. Unanimity increases with distance, from 56 per cent for municipalities separated by roughly ten thousand ranks to 94 per cent beyond thirty thousand.

The ordering of aggregate groups is only partly robust. The two rural categories occupy the lowest positions under every specification, and peri-urban belts remain among the first three throughout. Large urban centres, by contrast, move from first to last place depending on the aggregation function, and intermediate categories shift by three to four positions. This is the compensability assumption operating at the scale of a territorial type: whether a territory that performs unevenly across dimensions should be ranked by its strengths or by its weaknesses is precisely what the choice of aggregator decides. FLAIR is accordingly to be read as an instrument of territorial typology rather than as a detailed hierarchical classification, and the contrast between rural and peri-urban categories is more securely established than the position of the dense urban categories.

A.6 Structural sensitivity

A complementary diagnostic eliminates elements of the index structure and measures the resulting displacement. This procedure constitutes the formative equivalent of internal consistency testing: since the indicators constitute the construct rather than reflecting it, the pertinent question is not whether they correlate, but whether the classification depends excessively on any one of them. It also covers a source of uncertainty that Saisana et al. (2005) acknowledge leaving aside, namely the inclusion or exclusion of individual sub-indicators.

The classification does not depend excessively on any of them. The elimination of any individual indicator conserves a median rank correlation of 0.998 with the nominal classification, and never inferior to 0.903. The elimination of an entire dimension produces a minimum of 0.902, and that of a sub-dimension 0.859. Among the sub-dimensions, Connectivity is the most influential, with a mean displacement of 4,105 positions, more than double that of the following one; Employment and Enterprises, at 856 and 978, produce the smallest displacement.

A.7 Indicators with a large mass of zeros

Under min-max normalisation, an indicator comprising many null values assigns the floor of the scale to a substantial fraction of municipalities, and under geometric aggregation a floor value operates as a multiplicative penalty. As Mazziotta and Pareto (2025) observe, the greater the differences between the distributions of the individual indicators, the greater the distortion introduced by min-max rescaling, so that part of the imbalance penalised by geometric aggregation is an artefact of normalisation rather than a property of the municipality. No winsorisation parameter corrects this, the difficulty residing in the inferior tail of the distribution rather than in the superior one; a transformation of such variables prior to normalisation would be the appropriate remedy.