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Spatially conditioned Multi-Directional Composite Indicators: assessing performance and improvement directions

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Spatially conditioned Multi-Directional Composite Indicators: assessing performance and improvement directions

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Abstract

This paper presents an original methodology for constructing composite indicators capable of exploring potential improvements for each unit and each simple indicator with respect to a local peer group. From a technical standpoint, the concept of "spatial conditioning" is incorporated into the Multi-directional Benefit of the Doubt model. The model accounts for spatial conditions, such as geographical or contextual characteristics, to adapt to local specificity, thereby enabling comparisons among neighboring units and local benchmarks, rather than global ones, avoiding misleading policy recommendations. This methodological advancement enables the separation of individual units' performance and their specific directions for improvement from the contributions of their respective territories, enhancing the precision and relevance of the indicators for each unit analyzed. Empirical validation is conducted using simulated data and the ISTAT Equitable and Sustainable Well-being dataset for Italian provinces, demonstrating the model's ability to produce context-sensitive evaluations and actionable insights.

Keywords: Data envelopment analysis, Composite indicator, Multi-Directional Benefit of the Doubt, Spatial heterogeneity, Well-being evaluation

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1. Introduction

In recent years, composite indicators (CIs) have become fundamental to performance measurement and benchmarking in complex social and economic areas, as they are framed as a *relative* concept in most modern methodological approaches (Mizobuchi, 2014; Huang et al., 2018; Greco et al., 2019). This perspective acknowledges that knowledge is constructed through comparison. Consequently, defining an appropriate reference set is a crucial, non-neutral step, conditioned by historical, political, and economic factors. Globally defined peer sets can therefore be unfair and lead to misleading policy recommendations.

This issue is acutely evident in geographical and territorial performance evaluation. Neglecting context means ignoring spatial dependence and heterogeneity (Anselin, 1988; Haining, 2003), leading to "spatially blind" benchmarks that fail to account for the local constraints defining each territory's realistic "field of play" (Espa et al., 2013).

The construction of CIs involves several methodological challenges, with the weighting scheme being arguably the most debated issue. As reviewed by Decancq and Lugo (2013), approaches to measuring multidimensional phenomena can be broadly categorized into statistical/data-driven methods and normative/frontier methods. Applied to geographical problems, this methodological spectrum is reflected in a wide pluralism (Libório et al., 2023b). Common approaches range from simple additive weighting (e.g., Hübelová et al., 2019; Müller-Frączek, 2019; Bell and Burns, 2022) to multivariate statistics like Principal Component Analysis (e.g., Libório et al., 2022). A diverse set of other techniques—including the Generalized Reduced Gradient algorithm (Libório et al., 2023a), TOPSIS (Correa Machado et al., 2023), CRITIC (Rhouma et al., 2025), the Pena Distance method (Montero et al., 2010), Ordered Weighted Averaging (Libório et al., 2024), and Stochastic Multi-Attribute Acceptability Analysis (Greco, 2018)—have also been applied. Critically, comparative analyses confirm that no single method is universally superior across different geographical contexts (Libório et al., 2022; Libório et al., 2023b). Statistical methods, such as Principal Component Analysis (PCA), rely on the correlation structure of the data to assign common weights for all units. While effective for data reduction, these methods present important limitations for policy-oriented performance measurement in formative frameworks (Mazziotta and Pareto, 2024), as they tend to penalize conceptually relevant but statistically weakly correlated indicators and implicitly assume full compensability among dimensions.

In this context, the operational framework of Data Envelopment Analysis (DEA) offers properties that are well suited for geographical analysis (Nitkiewicz et al., 2014; Sherly et al., 2015; Muñuzuri and Muñoz-Díaz, 2019). In particular, the Benefit of the Doubt (BoD; Cherchye et al., 2007) approach, a DEA variant designed for composite indicators, employs endogenous, unit-specific weights (Libório et al., 2022). This approach constitutes an important strand in the geographical literature, valued for its ability to capture local nuances through endogenous weighting (Libório et al., 2022, 2023c). This frontier-based paradigm is particularly relevant for benchmarking inherently multidimensional and spatially heterogeneous phenomena—such as well-being, environment, and urban infrastructure—where local priorities legitimately differ (Fusco et al., 2024; D'Inverno et al., 2025). It offers three key advantages over statistical aggregation: First, by evaluating each unit in its "best possible light," it fosters policy acceptance and contextual fairness, avoiding arbitrary subjective weights. Second, it respects spatial heterogeneity by acknowledging that different territories may prioritize different dimensions (e.g., valuing environmental strengths over service provision), thus reflecting diverse development paths. Third, and crucially for benchmarking, unlike PCA's variance-based ranking, BoD explicitly identifies a "best practice frontier," enabling the identification of reference peers and the calculation of intuitive, actionable distance-to-frontier scores for policy targeting.

However, this weighting flexibility comes with a limitation: the standard BoD framework operates with a "spatially blind" benchmark, comparing all units against a single global frontier. While notable exceptions exist—such as exploratory techniques like Geographically Weighted PCA (GWPCA; Harris et al., 2015; Cartone and Postiglione, 2021; Cartone and Panzera, 2021; Libório et al., 2025) or multi-criteria approaches like Ordered Geographically Weighted Averaging (OGWA; Fusco et al., 2024)—these methods address the descriptive challenge of building a spatially-sensitive index, not the normative challenge of relative performance measurement.

Moving from description to benchmarking requires a paradigm shift: from "how do we build a local index?" to "who is the relevant peer group for a fair comparison?". This is the logic of spatial peer selection, where geographical or structural context directly conditions the reference set. This paradigm has been successfully implemented in frontier-based efficiency analysis, notably in the work of Fusco et al. (2018) (compensatory framework) and Fusco et al. (2020) (directional framework), which use spatially constrained peers to ensure evaluation against a feasible local frontier.

This spatial conditioning becomes critically prescriptive within a multi-directional composite indicator framework (Fusco, 2023; Vidoli et al., 2024). Here, the goal is not merely to score units but to define unique improvement trajectories. The central question thus extends beyond "who is my benchmark?" to the operational "which specific sub-indicator should I improve to reach it most effectively?". In this context, the peer group identified through spatial selection does not only determine a performance score; it directly and uniquely shapes the unit-specific direction for improvement. Misidentifying this spatially conditioned reference set, therefore, does not just skew scores—it risks prescribing incorrect and infeasible developmental paths.

Building on this logic, the present study integrates the principle of spatial peer selection into a multi-directional framework, proposing the *Spatial Multi-Directional Benefit of the Doubt* (Spatial MDBoD) model. By embedding spatial constraints into the multi-directional optimization, our model ensures that the resulting improvement paths are not only optimal but are also contextually relevant and actionable for each territory's specific "field of play."

The measurement of multidimensional well-being—a deeply territorial phenomenon characterized by diverse local priorities and, consequently, individual development paths—provides an ideal test case. It perfectly illustrates the need for a benchmarking approach that conditions the peer group on geographical context and is multi-directional in identifying the specific improvement trajectories that each territory should follow.

Our main empirical findings, based on the ISTAT BES dataset, indicate that the proposed Spatial MDBoD method enhances transparency and coherence in the choice of the comparison set, thereby preventing distortions arising from the omission of spatial conditional factors. This result is achieved within a frontier-based framework that minimizes arbitrary assumptions and through a multi-directional logic that provides not only a performance evaluation but, crucially, a clear and specific improvement path for each unit.

The remainder of the paper is structured as follows. Section 2 reviews the literature on frontier composite indicators. Section 3 introduces the spatial multi-directional method. Section 4 presents a simulation study, while Section 5 details the application to Italian provinces. Finally, Section 6 discusses policy implications and conclusions.

2. Frontier composite indicators

As established in the introduction, the Benefit of the Doubt (BoD) approach provides a robust foundation for relative performance measurement through endogenous weighting and frontier identification. This section reviews its methodological evolution, tracing the advancements designed to overcome its two main limitations for territorial analysis: full compensability among indicators and a spatially homogeneous reference set.

The standard BoD method relies on certain underlying assumptions that may be overly restrictive and may not fully reflect the complexities of the real world. One of the primary limitations of BoD method is the inherent compensability among indicators. This means that a deficiency in one dimension can be offset by an improvement in another, leading to an implicit selection of benchmarks based on proportional enhancements relative to past performance. This assumption does not always hold in practical scenarios, as different indicators may have distinct importance levels, and improvements in one area do not necessarily make up for shortcomings in another.
Furthermore, BoD does not sufficiently account for the heterogeneity within the comparison set, as it compares all units with one another without considering their geographical or contextual characteristics. As a result, the selected benchmarks may not be truly representative or attainable for units operating under different local conditions, potentially making it more difficult - if not outright misleading - to achieve optimal performance levels.
To address these limitations, several methodological advancements have been proposed in recent years.

2.1. Directional approaches

The Directional Benefit of the Doubt (Directional BoD) model, introduced by Fusco (2015); Vidoli et al. (2015); Rogge et al. (2017), sought to mitigate the issue of compensability by imposing a global subjective direction for improvements. This approach ensure that performance enhancements follow a predefined trajectory, rather than allowing unrestricted compensatory adjustments. However, while this method introduce a single preference structure, it did not allow for objective differentiation in improvement directions across units. Differentiation in the economic evaluation of the DMUs is crucial because different DMUs may operate under unique constraints and opportunities, may specialize in distinct areas or conditions, or be subject to varying subsidies and regulations, all conditions that are often linked to local spatial constraints.

It is, therefore, necessary to generalize the standard Directional BoD model towards two distinct improvements: *(i)* obtaining specific improvement directions for each unit and *(ii)* introducing the spatial constraints to which individual units are bound.

Concerning the first point, a more refined model, the Multi-directional Benefit of the Doubt (MDBoD) model, developed by Fusco (2023); Vidoli et al. (2024), builds upon this framework by permitting different objective directions of potential improvement for each unit and each individual indicator. This enhancement allows for a more tailored assessment of performance, ensuring that improvements are aligned with the specific strengths and weaknesses of each entity.

As to the second point, instead, the Spatial BoD model (Fusco et al., 2018) introduced the ability to account for spatial influences, acknowledging that performance is often affected by geographical and contextual factors.

The essence of our methodological proposal (see Section 3), therefore, lies in the seamless integration of these enhancements, which extend beyond mere methodological refinements to address fundamental requirements in comparative analysis, namely, the establishment of a well defined set of comparisons and the exploration of potential individual pathways for improvement.

3. The Spatial Multi-Directional Benefit of the Doubt model

To overcome the limitations of global benchmarking, we propose the *Spatial Multi-Directional Benefit of the Doubt* (Spatial MDBoD) model. The core innovation of this approach lies in a spatially conditioned redefinition of the Production Possibility Set (PPS), in which the benchmark against which each unit is evaluated is structured by a spatial network of neighboring units. In standard DEA/BoD approaches, the performance of a unit is evaluated against a global frontier constructed from all observed units in the sample. Conversely, our proposal restricts the comparison to a *conditionally defined* subset of units. Formalizing this requires the introduction of a spatial weight matrix W, which plays a constitutive role in defining the feasible reference set underlying the optimization procedure. Far from merely "filtering out" spatial dependence (as in spatial filtering techniques), the inclusion of W explicitly introduces the spatial network structure into the measurement model through the definition of the feasible set. It conditions the results by defining the feasible improvements based on the performance of neighboring units. This is a crucial property for composite indicators applied at lower spatial scales, where local spatial configurations heavily influence development trajectories (Demšar et al., 2013). This perspective aligns with the foundational principles of spatial data analysis established by Thioulouse et al. (1995) and Griffith (2003), who demonstrated that spatial structure should be explicitly modeled as an intrinsic feature of geographical data rather than treated as noise to be removed. Spatial autocorrelation is interpreted here as an indication of underlying spatial structure and substantive geographic processes, rather than as a purely statistical artifact. Our Spatial MDBoD model operationalizes these principles within the performance measurement framework. By embedding the spatial weight matrix W directly into the definition of the feasible set, we ensure that the evaluation respects the spatial structure of the data, yielding a spatially aware and locally relevant composite indicator.

The process starts with the identification of the optimal direction of improvement for each unit, o, relative to its spatial peers. Specifically, the direction of improvement for unit o is determined relative to a cluster of spatial peers belonging to a specific portion of the territory, S_j, among the total set of observations, $j = 1, ...n$. The subset S_j is formally derived using a weight matrix W, which encodes the spatial structure by specifying which units are considered neighbors.[1] This matrix plays a pivotal role in shaping S_j, as it filters the reference group based on contiguity, distance, or other proximity criteria.

It is important to clarify that in this context, the term "reference group" does not refer to a clique (a fully connected subgraph) or a group derived from clustering algorithms. Rather, it represents the specific set of neighbors, the "ego-network", against which unit i is benchmarked. Consequently, the multivariate measurement of well-being becomes context-dependent: the optimization problem seeks the optimal weights and improvement directions not in absolute terms, but strictly within the boundaries defined by the convex hull of the units in S_j.

In formal terms, the primary objective, analogous to MDBoD, is to ascertain the maximum possible enhancement in a single simple indicator to reach the local frontier, assuming the other indicators remain fixed. The maximum

[1] We emphasize once again that the neighborhood matrix can be defined not only in physical terms, but also in terms of political, economic, or social contiguity.

possible increment of all simple indicators is attainable by solving a system of K linear programming problems (one for each indicator h):

$$\begin{aligned}
\max_{\mathbf{I}_h,\gamma^1,\ldots,\gamma^n} \quad & \mathbf{I}_h \\
s.t. \quad & \mathbf{I}_h^o \leq \sum_{j \in S_j} \gamma^j \mathbf{I}_h^j \\
& \mathbf{I}_{(-h)}^o \leq \sum_{j \in S_j} \gamma^j \mathbf{I}_{(-h)}^j, \qquad -h = 1, ..., h-1, h+1, ...K \\
& \gamma^j \geq 0
\end{aligned} \tag{1}$$

where $\gamma^j \geq 0$ represent the weights, assuming constant returns to scale to ensure a direct comparison with MDBoD.

Let $(\gamma^*, \widehat{\mathbf{I}}_h)$ be the solution to the above problems for $h = 1, \ldots, K$, such that the *ideal* reference point is given by $\widehat{\mathbf{I}}^o = (\widehat{\mathbf{I}}_1^o, \ldots, \widehat{\mathbf{I}}_h^o, \ldots, \widehat{\mathbf{I}}_K^o)$. The selection of the benchmark S_o^{PI}, corresponding to the specific potential improvement of the simple indicator, is determined by solving the following linear programming problem. This optimization maximizes the parameter $\beta \in [0, 1]$, which quantifies the proportion by which each simple indicator has to be adjusted to reach the local frontier.

$$\begin{aligned}
\max_{\beta,\gamma^1,\ldots,\gamma^n} \quad & \beta \\
s.t. \quad & \mathbf{I}_h^o + \beta_o \mathbf{g}_{ho}^{PI} \leq \sum_{j \in S_j} \gamma^j \mathbf{I}_h^j \\
& \gamma^j \geq 0
\end{aligned} \tag{2}$$

where $\mathbf{g}_o^{PI} = (\widehat{\mathbf{I}}^o - \mathbf{I}^o) = (\widehat{\mathbf{I}}_1^o - \mathbf{I}_1^o, \widehat{\mathbf{I}}_h^o - \mathbf{I}_h^o, \ldots, \widehat{\mathbf{I}}_K^o - \mathbf{I}_K^o)$ represents the directional vector for a generic unit o, containing the local *potential improvements* for that unit.

The Spatial MDBoD method determines the optimal direction of improvement for each unit relative to its set of spatial peers by selecting a balanced trajectory that maximizes progress across multiple indicators. This localized approach ensures that the direction of improvement is defined relative to spatial peers, allowing for a more context-sensitive evaluation.

Similar to MDBoD, Spatial MDBoD computes an overall performance score while also assigning unit-specific scores to each individual indicator, capturing the potential improvement relative to the empirical benchmark within the local reference set. This localized approach provides a more detailed assessment of strengths and weaknesses, ensuring that performance evaluation reflects local conditions rather than a global reference point. The total score and the corresponding multi-directional specific simple indicator scores are determined following the same methodology as in MDBoD.

The fundamental hypothesis of the Spatial MDBoD is that the shift from a global to a local reference set fundamentally changes the evaluation. In the standard MDBoD, improvement directions and scores are determined relative to the highest-performing units across the entire dataset. This global perspective can disadvantage units that perform well within their local context but appear weaker in a global comparison. Conversely, the Spatial MDBoD defines the ideal direction of improvement for each unit strictly relative to its subset of spatial peers. By conditioning the benchmark on local context, the model aims to capture performance variations and feasible improvement paths that are masked by a global frontier, yielding more context-aware and locally relevant evaluations.

The effectiveness and utility of the proposed approach will be further illustrated and validated using simulated data (Section 4) and the ISTAT Equitable and Sustainable Well-being dataset for Italian provinces (Section 5).

4. Simulations

This section presents an experimental test using simulated data to evaluate the effectiveness and robustness of the Spatial MDBoD model. The simulation is designed to test the hypothesis outlined in the previous section and to compare the results obtained with those derived from the standard MDBoD approach. The simulation reproduces spatial heterogeneity in a controlled setting; however, no clustering structure is imposed in the evaluation stage, which relies exclusively on the spatial weight matrix W.

To this end, a simulated dataset was constructed consisting of about 700 points, with latitude and longitude values drawn from multiple Normal distributions with different means and a fixed standard deviation equal to 0.05. The points are created to form 7 distinct clusters as shown in Figure 1. The values of the two indicators were generated based on latitude and longitude, resulting in clusters with distinct patterns: some characterized by very low values, others by a mix of values, and some composed entirely of higher values. This approach ensures the creation of spatially distinct groups, reflecting different levels of the indicators across the territorial space. For the Spatial MDBoD, an ad hoc neighborhood structure (Figure 2) was defined using a distance threshold of 0.15. This value was chosen to ensure strong intra-cluster connectivity among units within the simulated spatial clusters, resulting in an intra-cluster connection ratio of 98.63%.

Figure 1: Simulated data

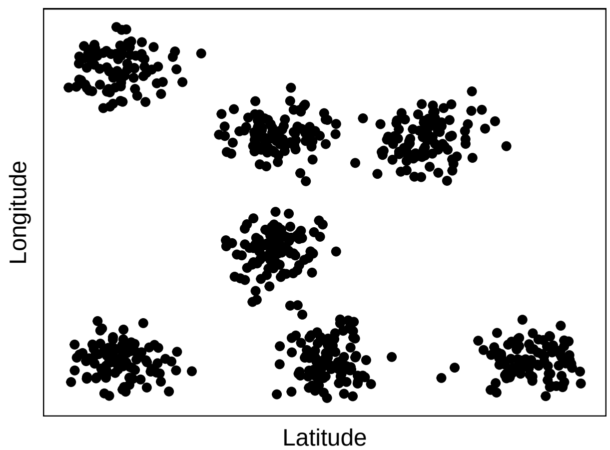
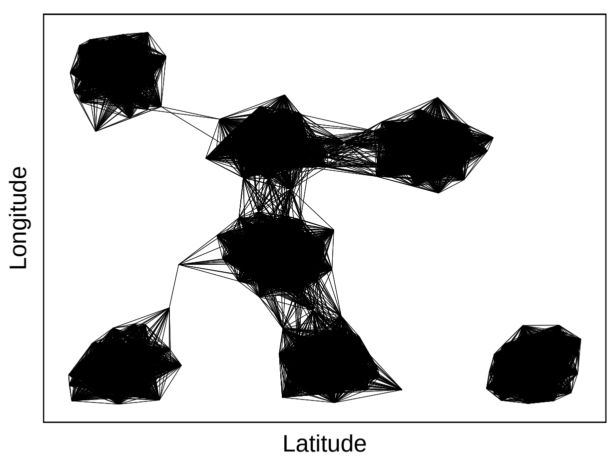


Figure 2: Spatial neighborhood (distance=0.15)



The results of the simulation support the core hypothesis. The MDBoD and Spatial MDBoD exhibit significant differences in both overall and specific scores, as well as in their respective directions of improvement, confirming that the choice of reference set critically shapes the evaluation.

More precisely, some graphical illustrations can better clarify the results and the properties of the proposed method with respect to standard multi-directional methods: in MDBoD, in fact, the directions of improvement are determined relative to global peers, *i.e.*, the highest-performing units across the entire dataset (see the black arrows in Subfigure (a) of Figure 3). As a result, units with low indicator values tend to receive lower scores since they are assessed against top-performing global benchmarks (see the colors of the points in Subfigure (a) of Figure 3). This global perspective applies a uniform evaluation across all units, disregarding their spatial context, which may lead to a disadvantage for units that perform well within their own cluster, but appear weaker when compared to the overall dataset.

Conversely, Spatial MDBoD focuses on local peers, comparing units that are spatially close and likely share similar characteristics (see the black arrows in Subfigure (b) of Figure 3). This localized approach accounts for variations in performance within each cluster, resulting in more heterogeneous scores (see the colors of the points in Subfigure (b) of Figure 3). By emphasizing local context, Spatial MDBoD provides a more nuanced understanding of each unit's performance. This localized comparison enables Spatial MDBoD to capture subtle performance variations that might be masked by the global MDBoD method. Consequently, Spatial MDBoD provides more accurate, context-aware evaluations, offering a clearer picture of strengths and weaknesses within specific territorial contexts.

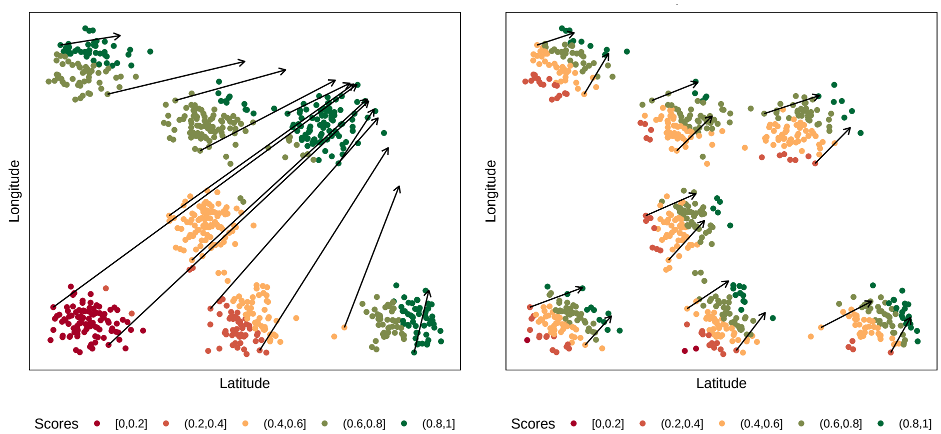
These differences are particularly evident when examining the specific scores (Figure 4, in the left column, the multidirectional scores for indicators $I1$ and $I2$ are reported, while on the right, the spatially conditioned estimates are presented), where the variation across units within the local reference sets is much more pronounced compared to the global approach. In other terms, scores may be interpreted as global in the first case, whereas in the second, they are considered as locally conditioned.

5. Equitable and Sustainable Well-being application

The concept of sustainable development, introduced by the Brundtland Commission in 1987 (please read the interesting reconstruction in the Borowy (2013) book) and later evolved by Sen (2009) and Nussbaum (2000), concep-

Figure 3: MDBoD vs Spatial MDBoD scores and directions

(a) MDBoD (b) Spatial MDBoD

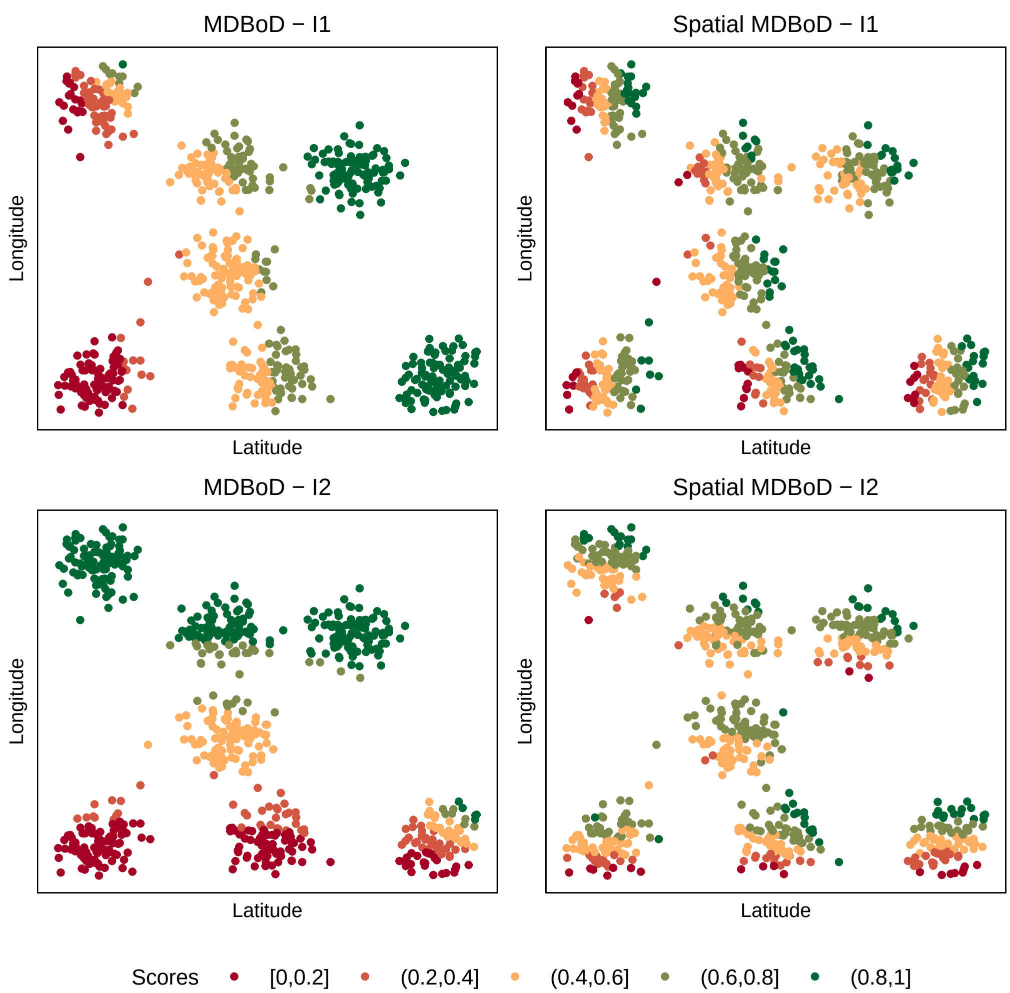


tualizes human beings as the center of *capability*, understood as interconnected substantive freedoms.

In this composite and inherently non-compensatory perspective, economic development is no longer solely defined by material needs, as maximizing economic growth is not a sufficient goal in itself. Instead, development should serve as a means to enhance human well-being in the broadest sense, ensuring that individuals are the ultimate beneficiaries of economic activity rather than merely instruments of it. As Sen (2009) states, "*development can be seen [...] as a process of expanding the real freedoms that people enjoy*" and "*the goal of development is the promotion and expansion of valuable capabilities*". The role of public action, therefore, is to broaden personal freedoms by inclusively expanding individuals' choices, enabling them to lead fulfilling and creative lives within a sustainable economic system.
It is therefore a comprehensive, latent, not-compensatory, and inherently "composite concept", yet it must be distilled into a measurable form to be applicable.

Equitable and Sustainable Well-Being, or BES, an acronym for the Italian term *Benessere Equo e Sostenibile*, has its roots deeply related to the Beyond GDP initiative and the Commission on the Measurement of Economic Performance and Social Progress's report (Stiglitz et al., 2009). In short, the so-called Stiglitz Commission recommends that progress be measured by a

Figure 4: Results: MDBoD vs Spatial MDBoD specific scores



multidimensional approach in which social and environmental well-being are as important as economic well-being (D'Urso et al., 2020).

Based on these theoretical foundations, the Italian National Institute of Statistics (ISTAT) and the Italian Council for Economics and Labour in 2010 created a steering committee to develop a system of indicators that would allow an adequate measurement of Italian well-being (Onori and Jona Lasinio, 2022). The following year, the committee initiated a national consultation to identify a shared set of progress indicators in Italian society (Giovannini and Rondinella, 2012; Chelli et al., 2016). The first BES was published in March 2013, containing 130 single indicators divided into twelve domains for the twenty Italian regions (Alaimo et al., 2020). Five years later, in 2018, the BES indicator system was made available at the NUTS3 level for the first time (Monte and Schoier, 2022).

From a methodological point of view, ISTAT calculates the BES composite indicator using the Adjusted Mazziotta-Pareto Index (AMPI). The AMPI is a partially non-compensatory approach based on a Min-Max standardization and rescaling of the basic indicators in a range (70; 130) according to two targets representing the minimum value and maximum value of each variable for all units and periods (Mazziotta and Pareto, 2016, 2018).

5.1. BES literature: applications, methods, and recent findings

Since its implementation, scholars have explored BES from three main research fronts. The first is associated with analyzing BES and its relationships with other contexts and phenomena. Studies in this research front evaluate the electric transition by relating BES with electricity consumption and renewable electricity consumption (Balletto et al., 2023), whether the gender of elected politicians affects the performance of Italian local governments in providing equitable BES (Ermini et al., 2023), the relationship between BES and the provinces' ability to achieve regulators' selective waste collection rate targets (Romano et al., 2022), and the relationship between BES and healthy diet in Italy (Fiore et al., 2020). Still, on this front, the BES framework also proves helpful in evaluating the multidimensional poverty in Italy (De Rosa, 2022).

The second and most frequent research front is the representation of BES by different methods. Several studies propose BES using methods, e.g., factor analysis (Chelli et al., 2016; Monte and Schoier, 2022), Bayesian latent variable model (Ciommi et al., 2020), partial least squares structural Tomaselli et al. (2021), and then analyze the results using clustering techniques, while others analyze BES using clustering techniques directly (Porreca et al., 2019; D'Urso et al., 2020; Bocci et al., 2021). Other studies apply several methods and offer comparisons of the results. Among these are min–max and Technique for Order of Preference by Similarity to Ideal Solution (D'Adamo et al., 2025), the min-max method, and distance versus the maximum or minimum method, aggregating them by arithmetic mean (D'Adamo et al., 2024), simple arithmetic mean, Adjusted Mazziotta-Pareto Index, Gini coefficient-based weights, and their combination (Ciommi et al., 2017b). Mixed approaches to represent BES are also proposed in the literature, such as Data Envelopment Analysis and Shannon's Entropy (Nissi and Sarra, 2018) and Geographically Weighted Principal Component Analysis and the Benefit of Doubt (Sarra and Nissi, 2020). At this point, it is worth highlighting that few studies consider the spatial variability of data in BES (e.g., Sarra and Nissi, 2020; Montorsi and Gigliarano, 2024).

A third research front is associated with analyzing BES's internal structure. Among these studies, those that explore the relationships among BES indicators using methods such as Bayesian Networks (D'Urso and Vitale, 2021, 2020; Onori and Jona Lasinio, 2022) and Structural Equation Modeling (Davino et al., 2018; De Rosa, 2018) stand out. Another interesting study in this research front is the assessment of the accuracy of the BES Labor Force Survey indicators (Ceccarelli et al., 2020).

Although rarer, few studies analyze BES by a non-aggregative approach (Alaimo et al., 2020). In general, studies on BES offer valuable information on Italian provinces (Montorsi and Gigliarano, 2024), Italian regions (Porreca et al., 2019), Italian provinces and regions (D'Adamo et al., 2025), and Italian province capital cities (Nissi and Sarra, 2018). These studies indicate that the pronounced divide between Northern and Southern Italy has widened over time (Monte and Schoier, 2022); however, they fail to account for local disparities, instead collapsing the comparison into broad contrasts between regions that are scarcely comparable. There is a territorial gap between northern and southern regions regarding economic, social, and environmental dimensions, while central regions have diversified behavior (D'Urso et al., 2020). Furthermore, new approaches allow us to unravel the evolution of well-being over 150 years (Ciommi et al., 2017a).

Finally, although there are other frameworks of composite well-being indicators, as detailed by Facchinetti and Siletti (2022), the literature surrounding BES shows its suitability and robustness in representing well-being beyond the economic dimension, justifying its choice in this research.

5.2. Proposed approach

In accordance with this more holistic framework for societal progress, the construction of 11 BES composite indicators is proposed in this paper. The Spatial MDBoD method was employed to calculate an indicator for each domain. A comparison with the classical MDBoD was made to appreciate the properties of the former. The construction of these indicators was informed by data from provincial-level sub-indicators, as articulated in Table A.1 for the year 2024.[2] The spatial structure for each domain has been delineated on the basis of the shortest distance that yields non-significant Moran's I and Geary's C tests in Spatial MDBoD scores, as illustrated in Table 1. Note that, the use of Moran's I and Geary's C serves as an operational criterion to define locally comparable reference sets, rather than as an attempt to model or correct spatial dependence in an econometric sense. [3] The use of both indices is due to their complementary nature: Moran's I assesses global spatial autocorrelation, highlighting overall similarity between neighbors, while Geary's C focuses on local differences, making it more sensitive to variations.

Given the well-documented spatial autocorrelation of individual indicators across the Italian territory (Sarra and Nissi, 2020; Giacalone et al., 2022), a pattern rooted in longstanding income and wealth disparities, we expect the composite MDBoD scores to prominently reflect this spatial structure, potentially obscuring each province's specific performance. This is clearly illustrated in Table 1, which reports the results of Moran's I and Geary's C tests for spatial autocorrelation.[4]

For nearly all domains, spatial autocorrelation is both high and statistically significant. The fact that Moran's I and Geary's C are significant at different distances indicates that the intensity and scale of spatial interaction

[2]Data collected the February 21, 2025, from
https://www.istat.it/statistiche-per-temi/focus/benessere-e-sostenibilita/la-misurazione-del-benessere-bes/il-bes-dei-territori/,
https://esploradati.istat.it. In case of missing data, previous years' data were used to ensure a complete dataset across the 11 domains, and extreme values have been cleaned. Finally, the min-max method is used to normalize the data in the range [0.01,1] by adjusting for polarity (see Table A.1). Descriptive statistics are provided in Table A.2.

[3]A sensitivity analysis was performed by varying the distance from 100 km to 300 km by 10 km. The results can be obtained from the authors upon request.

[4]Note that for the "Safety" dimension, the maximum distance (approximately 1291 km in Italy) is used, as no spatial autocorrelation is detected. As a result, the MDBoD and Spatial MDBoD scores for this dimension are identical regardless of the distance applied.

vary across dimensions. Significant values at shorter distances suggest local spatial dependence, while significance at larger distances points to broader spatial structures. This finding constitutes a relevant contribution, as it underscores the dimension-specific spatial nature of well-being and implies that policy interventions may need to be tailored by both domain and geography. It also reinforces the rationale for adopting spatially explicit measures such as the Spatial MDBoD.

Table 1: Moran and Geary spatial autocorrelation tests for MDBoD and spatial MDBoD by BES domain

Dimension	Distance (Km)	MDBoD		Spatial MDBoD	
		Moran's I	Geary's C	Moran's I	Geary's C
Health	110	0.208***	0.785***	−0.006	1.017
Education	110	0.293***	0.719***	−0.061	1.106
Work	110	0.483***	0.521***	0.009	1.005
Economic	120	0.499***	0.511***	−0.027	1.028
Social	110	0.055	0.945	0.018	0.975
Politics	120	0.146***	0.85**	0.070	0.946
Safety	Max	0.057	0.940	0.057	0.94
Landscape	120	0.158***	0.835***	−0.025	1.013
Environment	110	0.115**	0.902*	−0.011	1.076
Innovation	120	0.344***	0.652***	−0.046	1.047
Services	120	0.211***	0.787***	−0.038	1.065

As a matter of fact, once spatial conditioning is incorporated into the multi-directional calculation, spatial autocorrelation is no longer significant (columns 2 and 4) across any of the domains. The distance used for the spatial conditioning was deliberately selected to to yield non-significant residual spatial autocorrelation. This ensures that the spatially adjusted scores are no longer significantly influenced by latent regional patterns, but are instead shaped by direct, localized comparisons. Consequently, they provide a more accurate and differentiated representation of each province's specific performance.

The Spearman correlation values (Table 2) indicate the extent to which the spatial adjustment affects the MDBoD and Spatial MDBoD scores. The high correlation values indicate that the adjustment does not have a substantial impact on the rankings of the provinces. Conversely, lower correlation values suggest a greater effect of the spatial correction. For all dimensions, the spatial adjustment modifies the scores, underscoring the importance of considering spatial autocorrelation in provincial well-being policies.

Table 2: MDBoD vs Spatial MDBoD scores - Spearman correlation

Dimension	Spearman correlation
Health	0.566
Education	0.446
Work	0.490
Economic	0.513
Social	0.733
Politics	0.510
Safety	1
Landscape	0.776
Environment	0.307
Innovation	0.613
Services	0.507

In the interest of furthering the discourse on the subject, a more thorough examination of the results is warranted. This examination will concentrate on the domains that demonstrate the most pronounced spatial autocorrelation. Specifically, the present study examines the "economic well-being", the "work and life balance" and "innovation, research, and creativity" domains, where spatial correlations are most pronounced. The ability to reveal local performance beyond the exogenous influence of factors such as economic well-being and work and life balance differentials is illustrated in Figures 5 and 6.

These figures display, respectively, the multi-directional and spatially conditioned composite provincial scores for the economic and work and life balance domains. Notably, certain southern provinces, when compared with one another, reveal relative differentials that were previously obscured by the overarching North–South divide, as highlighted in Montorsi and Gigliarano (2024); Porreca et al. (2019); D'Adamo et al. (2025). Similar patterns can be observed in the "innovation, research and creativity" dimension in Figures 7a and 7b, where the performance of southern provinces, particularly the districts of Puglia and Campania in the innovation domain[5], is better

[5]Consider, for instance, the aerospace, the high-tech transport and logistics, and the

Figure 5: MDBoD vs Spatial MDBoD scores - Economic well-being

(a) MDBoD

(b) Spatial MDBoD

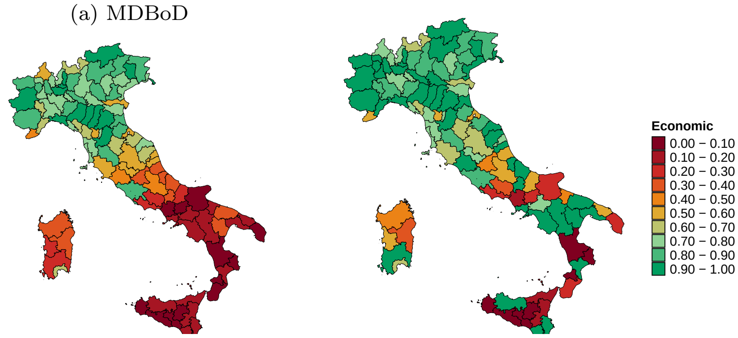
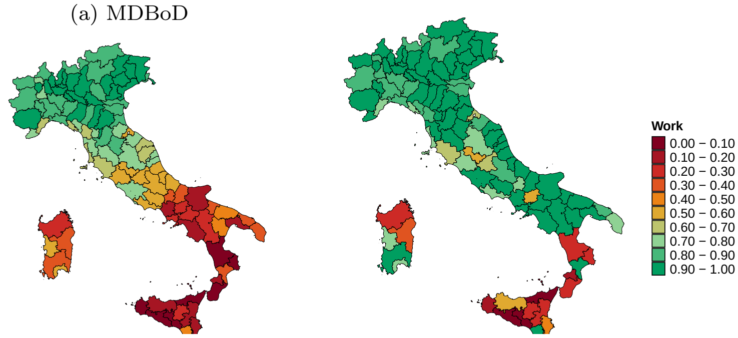


Figure 6: MDBoD vs Spatial MDBoD scores - Work and life balance

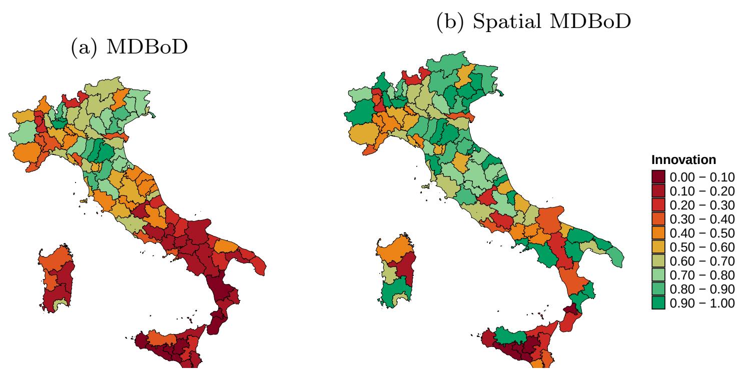
(a) MDBoD

(b) Spatial MDBoD



highlighted in relation to their neighboring provinces. This reveals a greater degree of heterogeneity than when comparing all provinces collectively. In other words, a nationwide comparison inherently favors northern provinces, not necessarily due to their relative performance in the innovation domain, but because they belong to wealthier and more interconnected regions of the country.

Figure 7: MDBoD vs Spatial MDBoD scores - Innovation, research and creativity



Therefore, as highlighted in the introduction, comparative analysis risks being not only misleading but also potentially detrimental, as it may reinforce existing biases rather than offering valuable new insights.[6]

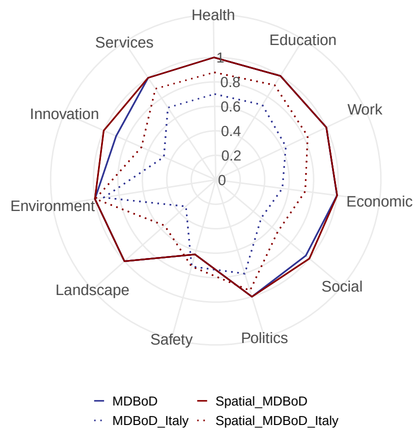
Figures from 8 to 11 illustrate examples of different performance patterns at both global (MDBoD blue lines) and local levels (Spatial MDBoD red lines), showing scores across different dimensions. The radar charts for Trieste, Sud Sardegna, Latina and Agrigento offer a comprehensive overview of their standing in areas such as health, education, employment, economy, social aspects, politics, safety, landscape, environment, innovation and public services.

As illustrated in Figure 8, the Trieste province consistently exhibits elevated scores on a global and local scale, reflecting robust performance across all dimensions. A comparative analysis reveals that Trieste outperforms the

advanced composites and polymer materials industrial districts in Campania, as well as the aerospace technology, the information and communication technologies and the nanotechnologies and advanced materials districts in Puglia.

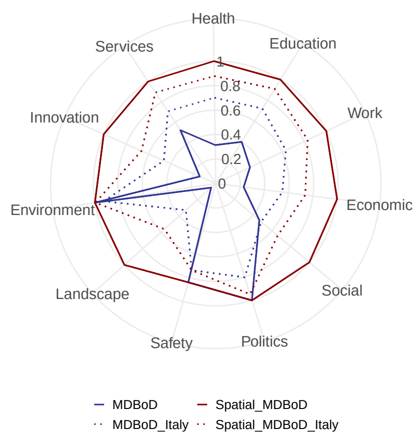
[6]Maps for the other dimensions are provided in the Appendix C.

Figure 8: Radar example - Trieste



national average, as represented by the Italian lines, in all categories. This suggests that the province possesses a high degree of competitiveness, characterized by the provision of quality health and education services, robust labor markets, economic stability, social cohesion, political reliability, environmental sustainability, innovative capacity, and efficient public services.

Figure 9: Radar example - Sud Sardegna



Conversely, the Sud Sardegna province (Figure 9) manifests a distinct profile, exhibiting low global scores yet high local scores. A comparative analysis reveals that its global performance is below the national average, indicating limited competitiveness on a broader scale. However, its local scores exceed the national average, indicating robust regional performance. The findings indicate the existence of regional strengths, including effective local governance, community engagement, and the preservation of natural and cultural landscapes. These qualities are highly regarded by local residents.

Figure 10: Radar example - Latina

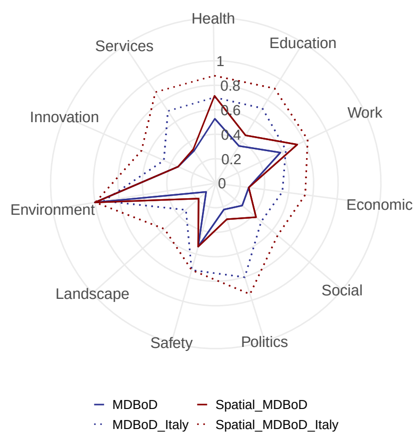
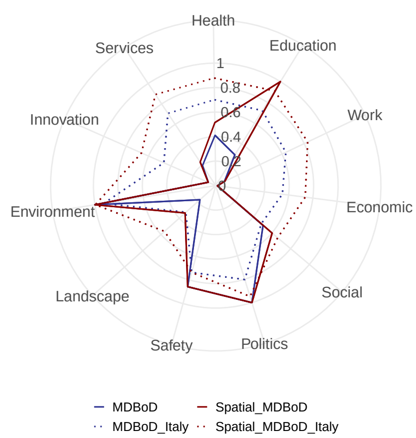


Figure 11: Radar example - Agrigento



Finally, the Latina and Agrigento provinces (Figures 10 and 11, respectively) exhibit low scores in both the global and local assessments. Their performance consistently falls below the national average in numerous domains, suggesting a broad spectrum of challenges. This underscores the urgency of targeted interventions and policy reforms.

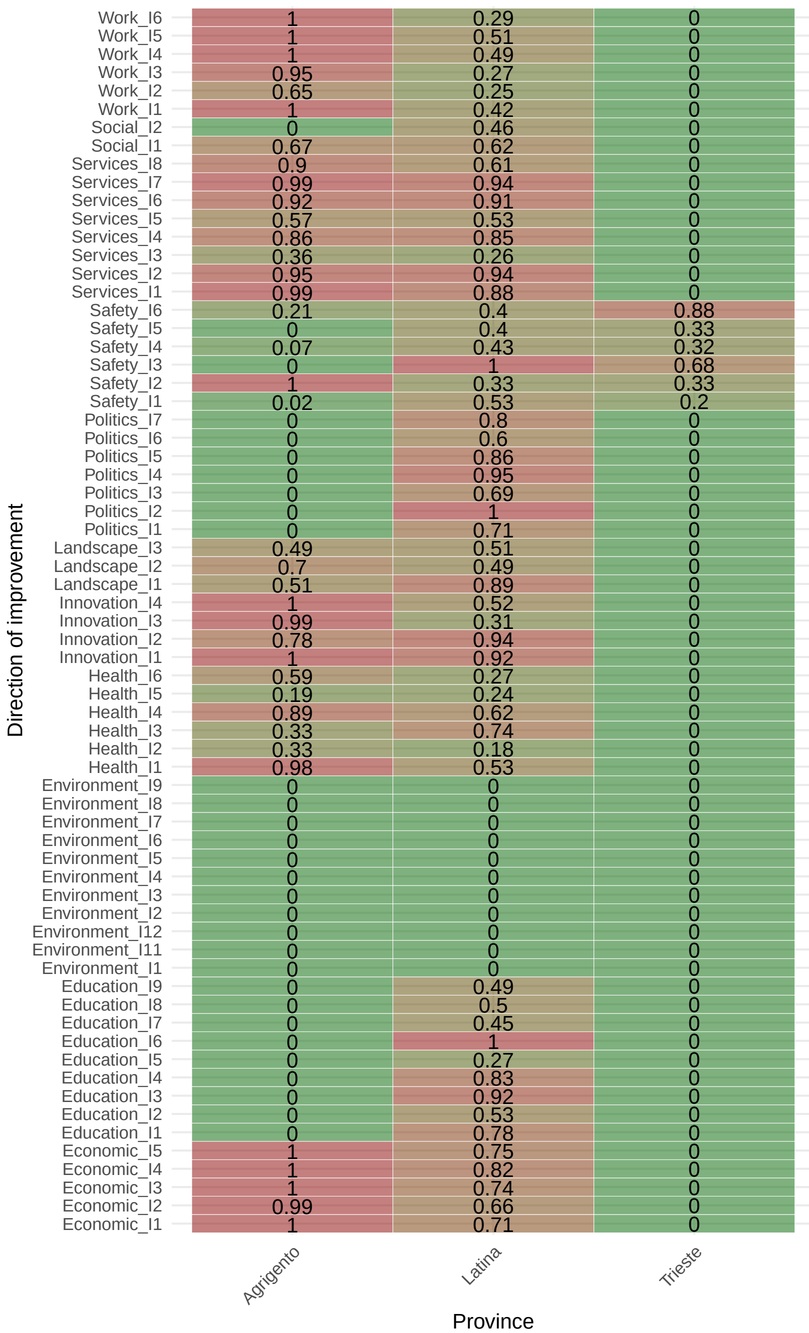
However, it is not merely a matter of relative positioning; in multi-directional models, this information is further enriched by identifying the specific path of improvement that each individual unit must undertake. The Spatial MDBoD approach facilitates the identification of potential improvement directions for the sub-indicators within each dimension. The heatmap presented in Figure 12 provides comprehensive sample analysis of the provinces of Agrigento, Latina, and Trieste. [7] This analysis underscores the domains in which each province demonstrates particular proficiency and identifies areas that necessitate enhancement. Specifically, the "direction of improvement" is defined as the extent to which each province falls short of optimal performance for each indicator. In essence, it quantifies the relative effort required by each province to enhance its performance across indicators and move closer to the optimal frontier.

In particular, the province of Agrigento demonstrates a range of performance across various sub-indicators. The heatmap reveals moderate scores in health sub-indicators, suggesting a stable healthcare system. However, the province of Agrigento is confronted with challenges in economic sub-indicators, signifying the necessity for policies aimed at stimulating economic growth. With respect to educational attainment, the Agrigento province exhibits a moderate level of participation in early childhood education, though it faces challenges in the domains of higher education and lifelong learning. Innovation sub-indicators also exhibit lower scores, indicating a necessity for the promotion of technological advancement and research. Addressing these deficiencies through targeted investments and policy modifications could enhance Agrigento's overall performance.

Instead, the province of Latina exhibits substandard performance across a wide range of sub-indicators. The heatmap reveals significant struggles in economic sub-indicators, indicating economic challenges. The sub-indicators of education demonstrate low scores, indicating a necessity for the enhancement of educational programs. Innovation sub-indicators are also low, indicating a need for fostering innovation. The health sub-indicators indicate

[7] This example is provided for illustrative purposes only and does not include the full set of Sub-indicators.

Figure 12: Directions of improvement example (Spatial MDBoD)



the presence of opportunities for enhancement, suggesting the necessity for the development of enhanced healthcare facilities and services. By addressing these areas, Latina can work towards improving its competitiveness and quality of life for its residents.

Finally, the Trieste province has demonstrated notable success, achieving high scores across multiple sub-indicators. The heatmap reveals Trieste's proficiency in health sub-indicators, suggesting the presence of a robust healthcare system. Education sub-indicators demonstrate high scores, indicating the presence of an effective educational infrastructure. Concurrently, economic sub-indicators have reached commendable heights, further substantiating the robust economic health of the nation. Innovation sub-indicators demonstrate robust performance, indicating a dedication to technological advancement and research. Trieste's high scores on environment sub-indicators indicate a commitment to sustainability. Sustaining investment in these domains, in conjunction with upholding elevated standards in public services and community safety, will assist Trieste in maintaining its competitive advantage.

6. Final remarks

This paper proposes an innovative extension of the MDBoD framework by incorporating the concept of spatial conditioning to refine the assessment process and by shifting from a global benchmark to comparisons within conditionally defined local reference sets. In this framework, the spatial dimension is defined broadly to encompass not only physical proximity but also functional and structural connectivity.
This approach allows each unit to explore potential improvements with respect to a group of peers sharing similar contextual characteristics, thereby increasing the relevance and applicability of the results.

From a policy perspective, our results have three main implications. First, the shift from global to local benchmarks fundamentally changes the incentive structure for local administrators. Comparing a lagging province in Southern Italy directly with a top-performing province in the North often results in an unattainable gap, potentially leading to "reform fatigue" or resignation. By conditioning the assessment on a spatially defined peer group, the Spatial MDBoD identifies achievable targets. A province is challenged to outperform its neighbors or structurally similar territories, making the "policy competition" fairer and more engaging.

Second, the multi-directional nature of the index offers precise guidance for resource allocation. Unlike standard indices that provide a single scalar score, our method identifies specific "directions of improvement" for each dimension. This allows policy makers to move beyond generic objectives (e.g., "improve services") and focus financial and organizational resources on the specific components where the gap with the local frontier is greatest.

Third, when applied in a longitudinal setting, this framework allows policymakers to monitor how inputs translate into development outcomes over time. By tracking a unit's position relative to its evolving local frontier over time, it becomes possible to verify if local actions and investments are effectively driving convergence, thereby offering a dynamic tool for impact evaluation.

From a technical standpoint, this advancement enhances the precision of composite indicators by distinguishing between a unit's intrinsic performance and the influence of its surrounding environment. This distinction enables policymakers and researchers to derive more meaningful insights, leading to better-informed decision-making. The effectiveness of this novel approach is validated through empirical analysis using simulated data, demonstrating its potential to provide more accurate and context-sensitive evaluations of performance across different units.

Finally, efforts to construct composite indicators underscore critical issues, but also reveal the limitations of a single measure in guiding meaningful improvements for individual nations. In the authors' view, this novel spatial multi-directional approach not only provides an aggregate assessment but also aligns with the trajectory of achievable improvements for each DMU, accounting for its specific local constraints. This approach goes beyond merely reflecting the current status; it serves as a strategic guide, identifying the key factors each unit should prioritize for further progress.

We believe that this class of methodologies represents not just a methodological refinement, but a fundamental evolution in measurement, transforming it into an evaluative and policy-oriented tool capable of delivering precise, data-driven recommendations. Future developments could focus on improving robustness to extreme values (also from a spatial point of view) by adopting frontier estimation techniques less sensitive to outliers, as suggested by Vidoli and Mazziotta, 2013; Vidoli et al., 2015; Fusco et al., 2020; Vidoli et al., 2024. Additionally, extending the model to a dynamic setting would allow for tracking performance changes over time, offering insights into structural trends and the impact of policy interventions.

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Appendix A. Dimensions, indicators and polarities

Table A.1: Dimensions, Indicators, and Polarity

Dimension	Sub-indicators	Polarity
Health	Life expectancy at birth (Health_I1)	+
	Infant mortality rate (Health_I2)	-
	Road accidents mortality rate (15–34 years) (Health_I3)	-
	Age-standardised cancer mortality rate (20–64 years) (Health_I4)	-
	Mortality from dementia and nervous system diseases (65+) (Health_I5)	-
	Avoidable mortality (age 0–74) (Health_I6)	-
Education and training	Participation in school system (age 4–5) (Education_I1)	+
	First-time university entry rate (Education_I2)	+
	Early childhood services access (Education_I3)	+
	Upper secondary education (age 25–64) (Education_I4)	+
	Life-long learning participation (Education_I5)	+
	Tertiary education completed (Education_I6)	+
	NEET rate (Education_I7)	-
	Low numeracy (grade 8) (Education_I8)	-
	Low literacy (grade 8) (Education_I9)	-
Work and life balance	Paid leave days (Work_I1)	+
	Fatal/permanent work injuries (Work_I2)	-
	Non-participation rate (Work_I3)	-
	Employment rate (20–64 years) (Work_I4)	+
	Youth employment rate (15–29 years) (Work_I5)	+
	Youth non-participation rate (Work_I6)	-

Table A.1 (continued): Dimensions, Indicators, and Polarity

Dimension	Sub-indicators	Polarity
Economic well-being	Bad loan entry rate (Economic_I1)	-
	Average annual salary (Economic_I2)	+
	Pension income per capita (Economic_I3)	+
	Low-income pensioners (Economic_I4)	-
	Disposable income per capita (Economic_I5)	+
Social relationships	Nonprofit organizations (Social_I1)	+
	Accessible schools (Social_I2)	-
Politics and Institutions	Voter turnout (Politics_I1)	+
	Voter turnout (Regional Councils) (Politics_I2)	+
	Women municipal councilors (Politics_I3)	+
	Young municipal councilors (<40) (Politics_I4)	+
	Prison density (Politics_I5)	-
	Municipal collection capacity (Politics_I6)	+
	Provincial/Metro collection capacity (Politics_I7)	+
Safety	Road mortality (non-urban) (Safety_I1)	-
	Homicide rate (Safety_I2)	-
	Reported deadly crimes (Safety_I3)	-
	Reported burglaries (Safety_I4)	-
	Reported pick-pocketings (Safety_I5)	-
	Reported robberies (Safety_I6)	-
Landscape and cultural heritage	Museums' heritage density (Landscape_I1)	+
	Rural tourism facilities (Landscape_I2)	+
	Presence of historic parks (Landscape_I3)	+
Environment	Urban water losses (Environment_I1)	-
	Urban green areas (Environment_I2)	+
	Landslide risk population (Environment_I3)	-
	Flood risk population (Environment_I4)	-
	Protected natural areas (Environment_I5)	+
	Renewable electricity (Environment_I6)	+
	Waste separate collection (Environment_I7)	+
	Waste generated (Environment_I8)	-
	Warm spell index (Environment_I9)	-
	Extreme rain events (Environment_I10)	-
	Consecutive dry days (Environment_I11)	-
	Soil sealing (Environment_I12)	-
Innovation, research and creativity	Patent propensity (Innovation_I1)	+
	Cultural enterprise employment (Innovation_I2)	+
	Municipal digital services (Innovation_I3)	+
	Brain circulation (25–39) (Innovation_I4)	+
	Power supply irregularities (Services_I1)	-

Quality of services

Table A.1 (continued): Dimensions, Indicators, and Polarity

Dimension	Sub-indicators	Polarity
	Public transport seat-km (`Services_I2`)	+
	Interregional hospital emigration (`Services_I3`)	-
	Hospital beds per 10,000 (`Services_I4`)	+
	Waste collection service (`Services_I5`)	+
	Medical specialists (`Services_I6`)	+
	High-care hospital beds (`Services_I7`)	+
	VHCN internet coverage (`Services_I8`)	+

Table A.2: Sub-indicators descriptive statistics

Sub-indicator	Mean	Median	St. Dev.	Max	Min
Health_I1	0.549	0.571	0.327	1.000	0.031
Health_I2	0.506	0.541	0.320	1.000	0.010
Health_I3	0.565	0.625	0.321	1.000	0.033
Health_I4	0.546	0.598	0.336	1.000	0.022
Health_I5	0.548	0.566	0.339	1.000	0.014
Health_I6	0.552	0.602	0.325	1.000	0.021
Education_I1	0.545	0.548	0.314	1.000	0.038
Education_I2	0.555	0.586	0.319	1.000	0.026
Education_I3	0.441	0.361	0.328	1.000	0.013
Education_I4	0.542	0.580	0.323	1.000	0.012
Education_I5	0.509	0.535	0.344	1.000	0.010
Education_I6	0.453	0.371	0.347	1.000	0.010
Education_I7	0.664	0.817	0.345	1.000	0.011
Education_I8	0.619	0.697	0.337	1.000	0.012
Education_I9	0.595	0.666	0.328	1.000	0.014
Work_I1	0.561	0.553	0.342	1.000	0.010
Work_I2	0.517	0.505	0.326	1.000	0.013
Work_I3	0.684	0.854	0.342	1.000	0.013
Work_I4	0.651	0.801	0.352	1.000	0.010
Work_I5	0.579	0.648	0.343	1.000	0.011
Work_I6	0.655	0.800	0.343	1.000	0.010
Economic_I1	0.589	0.724	0.335	1.000	0.010
Economic_I2	0.518	0.522	0.351	1.000	0.016
Economic_I3	0.530	0.606	0.348	1.000	0.015
Economic_I4	0.614	0.711	0.358	1.000	0.013
Economic_I5	0.520	0.563	0.346	1.000	0.012
Social_I1	0.500	0.503	0.325	1.000	0.010
Social_I2	0.480	0.443	0.340	1.000	0.013

Table A.2 (continued): Spatial MDBoD sub-indicators directions descriptive statistics

Sub-indicator	Mean	Median	St. Dev.	Max	Min
Politics_I1	0.541	0.580	0.341	1.000	0.012
Politics_I2	0.530	0.563	0.333	1.000	0.011
Politics_I3	0.549	0.609	0.320	1.000	0.020
Politics_I4	0.477	0.452	0.343	1.000	0.012
Politics_I5	0.567	0.558	0.330	1.000	0.010
Politics_I6	0.557	0.580	0.304	1.000	0.016
Politics_I7	0.621	0.732	0.334	1.000	0.020
Safety_I1	0.542	0.566	0.329	1.000	0.010
Safety_I2	0.579	0.593	0.299	1.000	0.010
Safety_I3	0.537	0.588	0.337	1.000	0.010
Safety_I4	0.509	0.541	0.340	1.000	0.019
Safety_I5	0.653	0.748	0.326	1.000	0.033
Safety_I6	0.627	0.693	0.325	1.000	0.047
Landscape_I1	0.324	0.198	0.323	1.000	0.010
Landscape_I2	0.360	0.259	0.320	1.000	0.011
Landscape_I3	0.306	0.195	0.327	1.000	0.010
Environment_I1	0.534	0.551	0.319	1.000	0.016
Environment_I2	0.313	0.201	0.309	1.000	0.010
Environment_I3	0.663	0.735	0.309	1.000	0.037
Environment_I4	0.750	0.902	0.314	1.000	0.028
Environment_I5	0.454	0.384	0.341	1.000	0.010
Environment_I6	0.306	0.177	0.333	1.000	0.010
Environment_I7	0.546	0.585	0.326	1.000	0.022
Environment_I8	0.544	0.580	0.308	1.000	0.026
Environment_I9	0.553	0.558	0.357	1.000	0.010
Environment_I10	0.741	1.000	0.379	1.000	0.010
Environment_I11	0.575	0.698	0.341	1.000	0.021
Environment_I12	0.550	0.597	0.325	1.000	0.014
Innovation_I1	0.381	0.274	0.341	1.000	0.011
Innovation_I2	0.477	0.385	0.318	1.000	0.048
Innovation_I3	0.469	0.439	0.325	1.000	0.018
Innovation_I4	0.544	0.615	0.330	1.000	0.013
Services_I1	0.635	0.738	0.341	1.000	0.018
Services_I2	0.399	0.295	0.326	1.000	0.019
Services_I3	0.630	0.704	0.339	1.000	0.012
Services_I4	0.505	0.510	0.342	1.000	0.013
Services_I5	0.596	0.639	0.350	1.000	0.013
Services_I6	0.362	0.250	0.336	1.000	0.014
Services_I7	0.500	0.518	0.339	1.000	0.019
Services_I8	0.493	0.488	0.322	1.000	0.017

Appendix B. Spatial MDBoD directions

Table B.3: Spatial MDBoD sub-indicators directions descriptive statistics

Sub-indicator	Mean	Median	St. Dev.	Max	Min
Health_I1	0.141	0.000	0.275	0.979	0.000
Health_I2	0.130	0.000	0.252	1.000	0.000
Health_I3	0.136	0.000	0.254	0.977	0.000
Health_I4	0.161	0.000	0.287	0.988	0.000
Health_I5	0.130	0.000	0.247	0.994	0.000
Health_I6	0.143	0.000	0.256	0.989	0.000
Education_I1	0.094	0.000	0.199	0.784	0.000
Education_I2	0.087	0.000	0.203	0.984	0.000
Education_I3	0.104	0.000	0.243	0.997	0.000
Education_I4	0.113	0.000	0.240	0.996	0.000
Education_I5	0.121	0.000	0.259	1.000	0.000
Education_I6	0.152	0.000	0.308	1.000	0.000
Education_I7	0.077	0.000	0.201	0.999	0.000
Education_I8	0.071	0.000	0.177	0.953	0.000
Education_I9	0.082	0.000	0.189	0.996	0.000
Work_I1	0.175	0.000	0.282	1.000	0.000
Work_I2	0.187	0.000	0.268	0.997	0.000
Work_I3	0.143	0.000	0.255	0.997	0.000
Work_I4	0.148	0.000	0.254	1.000	0.000
Work_I5	0.161	0.000	0.258	0.999	0.000
Work_I6	0.145	0.000	0.251	1.000	0.000
Economic_I1	0.234	0.143	0.284	1.000	0.000
Economic_I2	0.231	0.127	0.293	0.994	0.000
Economic_I3	0.250	0.167	0.287	0.995	0.000
Economic_I4	0.211	0.072	0.279	0.997	0.000
Economic_I5	0.249	0.172	0.294	0.998	0.000
Social_I1	0.278	0.155	0.285	1.000	0.000
Social_I2	0.383	0.351	0.336	0.997	0.000
Politics_I1	0.037	0.000	0.116	0.707	0.000
Politics_I2	0.073	0.000	0.208	0.999	0.000
Politics_I3	0.063	0.000	0.180	0.949	0.000
Politics_I4	0.052	0.000	0.149	0.947	0.000
Politics_I5	0.060	0.000	0.167	0.864	0.000
Politics_I6	0.056	0.000	0.153	0.798	0.000
Politics_I7	0.085	0.000	0.236	0.984	0.000
Safety_I1	0.341	0.274	0.307	1.000	0.000
Safety_I2	0.322	0.250	0.302	1.000	0.000

Table B.3 (continued): Spatial MDBoD sub-indicators directions descriptive statistics

Sub-indicator	Mean	Median	St. Dev.	Max	Min
Safety_I3	0.399	0.357	0.345	1.000	0.000
Safety_I4	0.385	0.333	0.341	0.991	0.000
Safety_I5	0.293	0.190	0.315	0.970	0.000
Safety_I6	0.311	0.214	0.320	0.963	0.000
Landscape_I1	0.385	0.319	0.370	1.000	0.000
Landscape_I2	0.355	0.299	0.340	0.999	0.000
Landscape_I3	0.454	0.506	0.374	1.000	0.000
Environment_I1	0.006	0.000	0.041	0.349	0.000
Environment_I2	0.010	0.000	0.057	0.417	0.000
Environment_I3	0.002	0.000	0.013	0.109	0.000
Environment_I4	0.007	0.000	0.049	0.490	0.000
Environment_I5	0.009	0.000	0.044	0.260	0.000
Environment_I6	0.008	0.000	0.045	0.381	0.000
Environment_I7	0.007	0.000	0.038	0.259	0.000
Environment_I8	0.004	0.000	0.028	0.264	0.000
Environment_I9	0.007	0.000	0.042	0.312	0.000
Environment_I11	0.007	0.000	0.060	0.615	0.000
Environment_I12	0.007	0.000	0.046	0.394	0.000
Innovation_I1	0.316	0.188	0.333	0.999	0.000
Innovation_I2	0.376	0.313	0.334	0.963	0.000
Innovation_I3	0.309	0.256	0.292	0.992	0.000
Innovation_I4	0.241	0.159	0.269	0.997	0.000
Services_I1	0.085	0.000	0.209	0.992	0.000
Services_I2	0.165	0.000	0.314	0.991	0.000
Services_I3	0.083	0.000	0.207	0.998	0.000
Services_I4	0.151	0.000	0.300	0.997	0.000
Services_I5	0.103	0.000	0.230	0.997	0.000
Services_I6	0.132	0.000	0.276	0.996	0.000
Services_I7	0.133	0.000	0.283	0.991	0.000
Services_I8	0.115	0.000	0.245	0.993	0.000

Appendix C. MDBoD vs Spatial MDBoD scores

Figure C.1: MDBoD vs Spatial MDBoD scores - Education

(a) MDBoD

(b) Spatial MDBoD

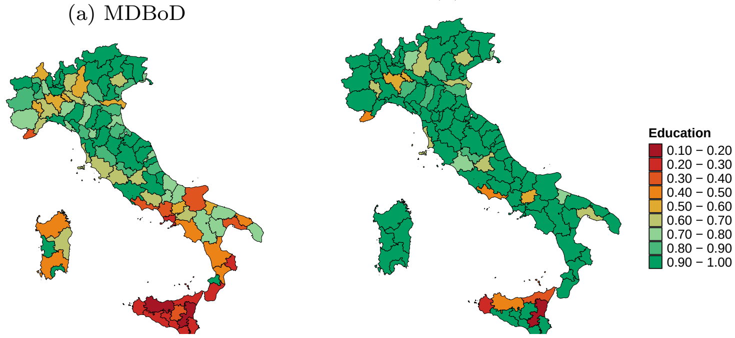

Figure C.2: MDBoD vs Spatial MDBoD scores - Environment

(a) MDBoD

(b) Spatial MDBoD

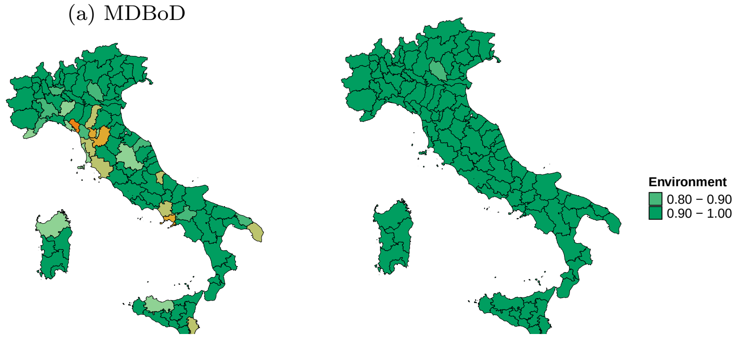

Figure C.3: MDBoD vs Spatial MDBoD scores - Health

(b) Spatial MDBoD

(a) MDBoD

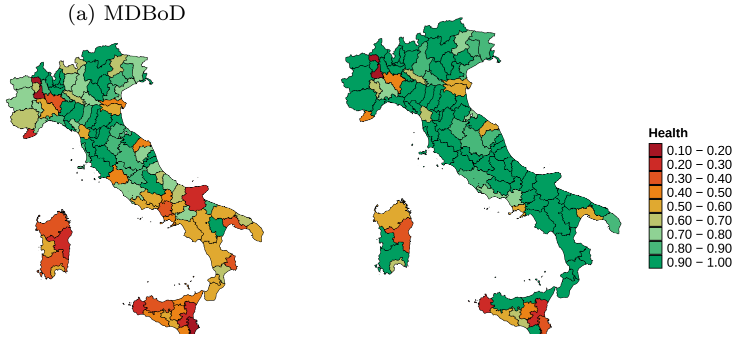

Figure C.4: MDBoD vs Spatial MDBoD scores - Landscape

(b) Spatial MDBoD

(a) MDBoD

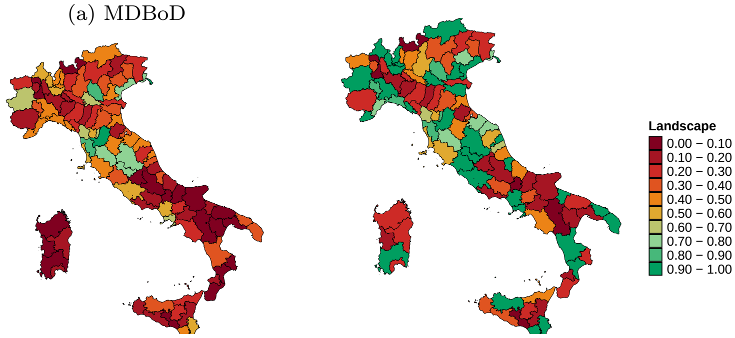

Figure C.5: MDBoD vs Spatial MDBoD scores - Politics

(b) Spatial MDBoD

(a) MDBoD

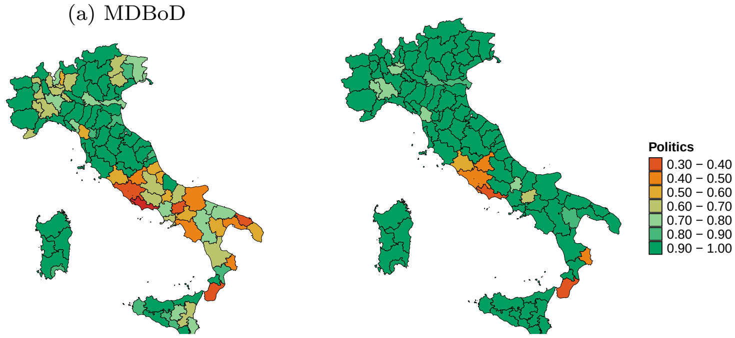

Figure C.6: MDBoD vs Spatial MDBoD scores - Safety

(a) MDBoD

(b) Spatial MDBoD

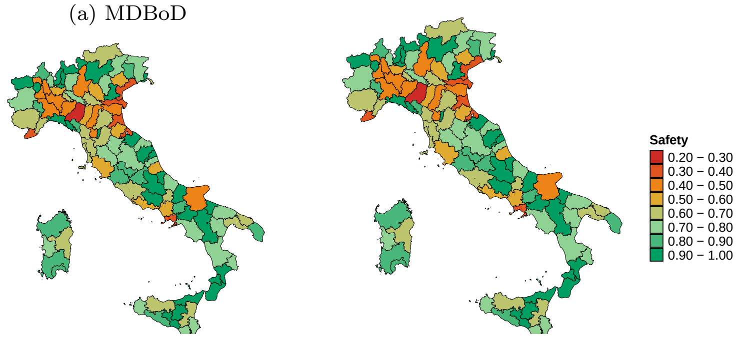

Figure C.7: MDBoD vs Spatial MDBoD scores - Services

(a) MDBoD

(b) Spatial MDBoD

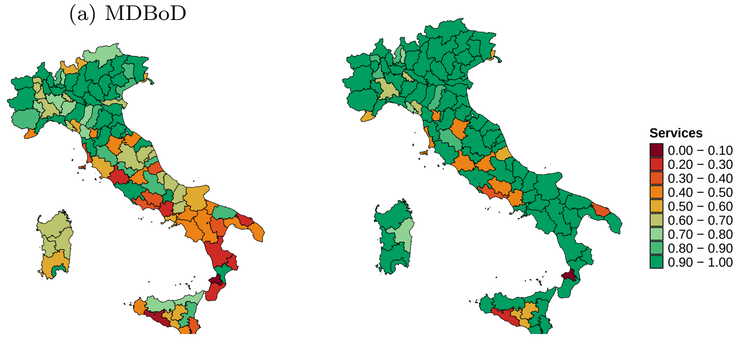

Figure C.8: MDBoD vs Spatial MDBoD scores - Social

(a) MDBoD

(b) Spatial MDBoD