Socio-Economic Planning Sciences 105 (2026) 102485

Contents lists available at ScienceDirect

Socio-Economic Planning Sciences

journal homepage: www.elsevier.com/locate/seps

Assessing regional digitalization in Europe: A spatial composite index approach

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ARTICLE INFO

Keywords:
Digital regions
Regional DESI
Spatial spillovers
Spatial heterogeneity

ABSTRACT

We develop composite indices to assess regional digitalization at the NUTS 2 level in Europe. Building on the structure of the Digital Economy and Society Index, a first baseline index is created using Principal Component Analysis. The framework is extended through Geographically Weighted Principal Component Analysis and spatial filtering to account for spatial heterogeneity and dependence. The introduced approach distinguishes between regions benefiting from digital spillovers and those limited by geographic isolation. We therefore add on a method to classify spatial winners and losers based on the regional digital performance. This tool can be used to assess territorial disparities and design local policies for digitalization.

1. Introduction

Digitalization is a multifaceted phenomenon that influences consumers, industries, and all levels of society [1]. The Organization for Economic Co-operation and Development (OECD) defines digitalization as "the use of digital technologies and data, along with interconnection, that leads to new or altered activities" ([2], p. 18). The European Union (EU) has devoted significant resources, incentives, and structural policies to promote digitalization across its member states. The Digital Europe Programme is the flagship initiative, supported by a dedicated budget of €7.6 billion. Complementary actions carried out through various EU mechanisms aim to foster digital development across member states [3].

Although digitalization is often perceived as driven primarily by non-geographical factors, it is deeply rooted in local contexts. Territorial factors play a crucial role in the diffusion of digital technologies [4,5]. A significant issue concerns the digital divide, defined as unequal access to and use of information and communication technologies or internet-based devices depending on one's place of residence.

It is not surprising that EU institutions are actively working to reduce disparities in digital access among European citizens as a foundation for future development. A persistent East–West divide remains in terms of the digital economy and innovation, posing a risk of exacerbating fragmentation within Europe [6]. Reflecting the Lisbon Treaty's objectives of socio-economic cohesion, the notion of digital cohesion promotes a regional agenda to prevent uneven patterns of digitalization [7].

Digitalization is inherently multidimensional [8]. At the EU level, it has traditionally been assessed through the Digital Economy and Society Index (DESI), a composite index summarizing several dimensions. More recently, this framework has evolved into a dashboard of Key Performance Indicators (KPIs) designed to monitor progress toward specific digital targets. While suitable for tracking national trajectories, applying a KPI-based approach at the NUTS2 regional level poses significant analytical challenges. Monitoring a large set of indicators at such a granular scale may complicate interpretation and hide the identification of territorial digital disparities across multiple dimensions.

Constructing a regional composite index of digitalization could offer a more effective strategy for monitoring digitalization and digital divide in European regions. Composite indices are widely used to investigate regional disparities across domains [9,10]. For example, Ferrarini et al. [11] developed a regional competitiveness index for EU NUTS2 regions to assess territorial gaps. The Regional Social Progress Index evaluates regional development beyond GDP per capita within the EU [12]. Fernández-García et al. [13] constructed a regional composite index for research and innovation across European regions.

In the field of digitalization, Ruíz-Rodríguez et al. [14] analyzed the digital divide in Spain using regional data, and Bruno et al. [15] developed a compact DESI-based index for Italian NUTS2 regions through Principal Component Analysis (PCA). Benecchi et al. [16]

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https://doi.org/10.1016/j.seps.2026.102485
Received 29 September 2025; Received in revised form 17 March 2026; Accepted 26 March 2026
Available online 30 March 2026
0038-0121/

emphasize the relevance of a regional perspective for digitalization studies.

However, three gaps remain for properly developing a regional DESI framework and making it a more effective tool that goes beyond a KPI-based approach. First, existing regional DESI applications focus on single-country cases, limiting broader comparative insights. Second, most frameworks assume that digitalization drivers have uniform relevance, potentially obscuring territory-specific dynamics given heterogeneous stages of development. Addressing spatial heterogeneity is therefore essential [17]. Third, spatial dependence should be explicitly incorporated. Digitalization processes can exhibit spatial spillovers [18–20], and ignoring spatial dependence may bias the assessment provided by composite indices [21].

Considering these gaps, we develop a new framework for a regional DESI composite index that ensures consistency with the official DESI definitions while accounting for issues specific to geographically distributed data, particularly spatial effects [17]. The index is first computed using PCA and subsequently extended to systematically incorporate spatial heterogeneity and spatial dependence.

To address spatial heterogeneity, we use a spatially augmented version of the DESI index based on Geographically Weighted Principal Component Analysis (GWPCA). GWPCA relaxes the assumption of global homogeneity by allowing weights to vary across space, thereby capturing region-specific drivers more accurately [9,22].

To incorporate spatial dependence, we extend the DESI-PCA based index through spatial filtering techniques [23]. Specifically, we decompose the regional DESI into a spatial component and a region-specific component to isolate the role of interregional spillovers from localized performance [21]. This decomposition enables the identification of areas that benefit from spatial spillovers versus those that do not. By formally disentangling these effects, the proposed framework advances the construction of regional composite indices and provides a methodological basis for measuring spatial spillovers in multidimensional digitalization [24].

On this basis, we introduce a taxonomy of “spatial winners” and “spatial losers,” providing a structured framework to distinguish areas that effectively leverage externalities from those constrained by geographic isolation. These insights enable the straightforward identification of critical areas and can inform targeted policy actions [25], an outcome that would be difficult to achieve within a fragmented KPI-based system relying on separate indicators.

We apply our approach to construct a regional DESI composite index for regions across 24 European countries. The index is built using official European data, primarily from the EUROSTAT regional database and, where necessary, complemented by the European Data Journalism Network. We select 12 variables, closely reflecting the four official DESI domains for 2022.

By embedding spatial effects into the composite index framework, we promote the use of regional synthetic indices that move beyond fragmented KPI-based monitoring logics. This approach provides an analytical basis for place-based strategies aimed at reducing digital divides and strengthening European digital initiatives such as the Digital Europe Programme.

The remainder of the paper is structured as follows. Section 2 reviews the relationship between digitalization measurement and spatial effects. Section 3 outlines the methodological approaches adopted to capture spatial patterns at the regional level and presents the sensitivity analysis. Section 4 reports the empirical results. Finally, Section 5 concludes.

2. Digitalization in European regions and the analysis of spatial effects

Enhanced data storage systems, mobile connectivity, data visualization tools, Big Data analytics, the Internet of Things (IoT), and artificial intelligence are among the transformative technologies reshaping all sectors of the economy [26]. The digitalization process rests on three pillars: digital infrastructure, technology adoption by firms, and digital competencies among individuals [18]. Access to Information and Communication Technologies (ICT) constitutes the essential precondition for enabling a digital society [27]. Equally relevant are digital skills, which empower individuals to actively engage in and benefit from digital environments. Moreover, the proactive adoption and integration of digital technologies by firms is crucial for enhancing industrial competitiveness in increasingly dynamic markets.

These key dimensions are effectively captured by the DESI, which was introduced as a comprehensive composite index for tracking progress in digitalization across EU Member States. The DESI is calculated using a broad set of indicators covering broadband access, digital skills, internet usage, and the digital integration of businesses and public services, among others [28,29]. Since its launch, the composite index has been regularly updated and methodological refined to reflect emerging trends and evolving priorities in the digital economy [30].

Nevertheless, a key limitation of the DESI lies in its geographic scale. As it primarily provides insights at the national level, the DESI is not fully aligned with European initiatives that emphasize the critical role of regions in addressing digital disparities across the continent. Variations in digitalization tend to be more pronounced at the subnational level and, in its current form, the DESI lacks the granularity needed to accurately capture within-country differences [15,16]. This shortcoming highlights the need for a regional-level digitalization index that can offer a more synthetic and precise picture of regional digital disparities.

Spatial heterogeneity plays a key role in the analysis of regional digitalization patterns. Applying GWPCA for the construction of a regional DESI can be useful, as it captures local differences and allows weighting schemes to adapt to the local digital context. This, in turn, helps identify the most relevant drivers in each area and illustrates how the digitalization process varies across European regions.

For example, the gap in digitalization levels between Northern and Southern Italy indicates that the same variables may not exert an equal impact across regions. Variables that drive digital growth in the North may be far less relevant in the South, where lower levels of digital infrastructure and digital skills call for different priorities [15].

Furthermore, given that technological transformations frequently generate positive or negative effects that diffuse across space [31], it is unrealistic to assume that the digitalization level of a given region is independent of that in its neighboring areas [32,33]. These spatial interdependencies are often driven by the mobility of human capital, interconnected firm networks, knowledge flows, and shared technological platforms [34].

Urban and capital regions play a leading role in this dynamic, often generating spillovers effects that benefit adjacent areas. Talent and entrepreneurship in these hubs facilitate knowledge exchanges, further driving positive spillovers in emerging digital trends [20].

Our methodological approach based on GWPCA and spatial filtering aims to explicitly capture both spatial heterogeneity and spatial dependence in the regional digitalization process across Europe. By integrating these spatial dimensions, our framework offers a more accurate and policy-relevant assessment of regional digitalization disparities, aligning with the EU's commitment to fostering territorial cohesion and promoting balanced digital development across regions.

3. Methods

3.1. Spatial approaches to composite indices built by PCA

PCA is based on the analysis of the $n \times p$ data matrix $\mathbf{X}$, where $i = 1, \ldots, n$ represents the observations and $j = 1, \ldots, p$ the variables used to construct the composite index. The $p \times p$ variance-covariance matrix $\boldsymbol{\Sigma}$ associated with the variables in $\mathbf{X}$ can be decomposed as [35]:

$$\boldsymbol{\Sigma} = \mathbf{A}\boldsymbol{\Lambda}\mathbf{A}^t \quad (1)$$

where Λ is a diagonal matrix of eigenvalues, $\mathbf{A}$ is the corresponding matrix of eigenvectors and $\mathbf{A}^t$ is its transpose. The eigenvalues on the main diagonal of Λ are arranged in descending order and represent the amount of variance explained by each principal component. Principal components are mutually orthogonal, and each component is obtained as a linear combination of the data $\mathbf{X}$ and its corresponding eigenvector A_j as defined in (1):

$$\mathbf{Y}_j = \mathbf{X}\mathbf{A}_j \tag{2}$$

where $\mathbf{A}_j$ is the $j-th$ column matrix of $\mathbf{A}$. The elements of each principal component in (2) are referred to as scores, and they can be interpreted as the values of the composite index for each observation i. The elements of $\mathbf{A}_j$ are denoted as loadings and are the statistical weights used to construct the composite index $\mathbf{Y}_j$.

Standard PCA has long been used to calculate composite indices at regional level. However, this approach raises key concerns, particularly regarding spatial effects [36]. Spatial heterogeneity poses a key challenge in applying standard PCA, as the method assumes that loadings are constant across all spatial units. This assumption is questionable when structural differences are expected to influence regional digitalization levels. GWPCA [22] offers a valid alternative to build local composite indices. GWPCA relaxes the assumption of stationarity of Σ, by defining local variance-covariance matrix for each observation i. Given the geographical coordinates (u_i, l_i) for each location i, the local variance–covariance matrix $\Sigma(u_i, l_i)$ can be defined as:

$$\Sigma(u_i, l_i) = \mathbf{X}^t\mathbf{W}(u_i, l_i)\mathbf{X} \tag{3}$$

where $\mathbf{W}(u_i, l_i)$ is a diagonal matrix of spatial weights, whose entries are determined by a kernel function of geographical distances. In our study, we use an exponential kernel [37] as:

$$w_{im} = \exp\left(-\frac{|d_{im}|}{\gamma}\right) \tag{4}$$

where w_{im} are the entries of the matrix $\mathbf{W}(u_i, l_i)$, γ is the bandwidth and d_{im} is the geographical distance calculated as the Euclidean distance between the centroids of spatial units i and other spatial units m.

Usually, results are not highly sensitive to the choice of the kernel, while the choice of the bandwidth should be carefully explored [38]. As discussed in Gollini et al. [39] bandwidth can be fixed (for example, set in kilometers or meters) or adaptive (expressed in terms of number of spatial units). The second option is suggested when dealing with irregular spatial structures. A cross-validation procedure is used to optimally select the bandwidth as suggested by Harris et al. [22].

Based on equation (3), the eigenvalues and eigenvectors of $\Sigma(u_i, l_i)$ can be computed at each locality unit i as:

$$\Sigma = \mathbf{A}(u_i, l_i)\Lambda(u_i, l_i)\mathbf{A}(u_i, l_i)^t \tag{5}$$

where $\mathbf{A}(u_i, l_i)$ is the matrix of the local eigenvectors and $\Lambda(u_i, l_i)$ is a diagonal matrix of local eigenvalues. Summarizing the results of GWPCA may be difficult due to the large number of outputs produced. Harris et al. [22] suggest some possible visualization techniques based on winning variables, defined as the variable corresponding to the loadings $\mathbf{A}_j(u_i, l_i)$ of any j component that exhibits the highest magnitude (in absolute value) at location i.

The interpretation of principal components as composite indices in GWPCA differs slightly from that in standard PCA. The scores are computed using a local variance-covariance matrix, allowing the capture of regional differences in the underlying data structure. Hence, the principal component composite local index y_{ij} are:

$$y_{ij} = \mathbf{X}_i{}^t\mathbf{A}_j(u_i, l_i) \tag{6}$$

where $\mathbf{X}_i$ is the vector of p variables measured at the location i and $\mathbf{A}_j(u_i, l_i)$ is the $j-th$ column of loadings of the matrix of the local eigenvectors $\boldsymbol{A}(u_i, l_i)$.

Before performing GWPCA, it is advised to test the non-stationarity of the variance-covariance matrix through a Monte Carlo (MC) experiment [22]. This procedure is used to evaluate whether the local eigenvalues in GWPCA vary significantly across space. The MC test is obtained by performing a large number of random permutations in which the observed data are randomly reassigned to the spatial coordinates of each unit. For each iteration, the local eigenvalues are calculated, and the optimal bandwidth is selected using cross-validation. The standard deviation of the local eigenvalues from first GWPCA component is then computed at each iteration to build an empirical distribution of such values. After (ideally) 999 permutations, the rank of the true value of GWPCA local eigenvalues standard deviation is compared against the empirical distribution to test significant non-stationarity of the eigenvalues. If the test shows significance, then GWPCA estimation is justified.

We now move a step ahead to capture spatial dependence and measure the extent of spatial spillovers in digitalization. To do so, we use spatial filtering techniques following the idea of Cartone and Postiglione [21]. Spatial filtering is typically used to remove spatial autocorrelation, viewed as a statistical nuisance, prior to the application of conventional methods on geo-referenced data. In this context, however, spatial filtering is employed to decompose the composite index into two components: a spatial component, which captures spatial dependence, and a residual component, which isolates region-specific effects by removing the spatial structure.

Generally, two main approaches can be adopted for spatial filtering. The first grounds on Getis' statistic G_i [40], while the second, proposed by Griffith [41], is based on the eigenvector decomposition of the spatial weights' matrix. It is worth noting that Getis' [40] technique requires input variables to be strictly positive and with natural origin. Since the DESI variables are standardized to have zero mean and unit variance to accommodate different units of measurement, they may include negative values of the variables, thereby violating Getis' conditions [23]. For this reason, in this paper, we only use the Griffith's approach to consider spatial spillovers in regional digitalization.

Griffith [41] filtering employs eigenvectors extracted from the modified spatial connectivity matrix:

$$\left(\mathbf{I} - \frac{\mathbf{1}\mathbf{1}^t}{n}\right)\mathbf{C}\left(\mathbf{I} - \frac{\mathbf{1}\mathbf{1}^t}{n}\right) \tag{7}$$

where $\mathbf{I}$ is an $n \times n$ identity matrix; $\mathbf{1}$ is $n \times 1$ vector of ones; and $\mathbf{C}$ is a binary spatial weight matrix [41]. The spatial autocorrelation contained in generic variable may be described using these eigenvectors as:

$$x_i = \mu_x + \mathbf{EV}_i^t\boldsymbol{\beta}_{EV} + \varepsilon_i \tag{8}$$

where x_i is the variable j at each location i and μ_x is the mean of X, $\mathbf{EV}_i$ s are the values associated to unit i included into the matrix of the $q < n$ selected eigenvectors $\mathbf{EV}$ of the matrix $\left(\mathbf{I} - \frac{\mathbf{1}\mathbf{1}^t}{n}\right)\mathbf{C}\left(\mathbf{I} - \frac{\mathbf{1}\mathbf{1}^t}{n}\right)$, $\boldsymbol{\beta}_{EV}$ is the set of parameters associated to the eigenvectors and ε_i is an independent and identically distributed error term.

The eigenvectors $\mathbf{EV}$ s describe latent spatial autocorrelation of each variable, and it is demonstrated that each of the eigenvalues of $\left(\mathbf{I} - \frac{\mathbf{1}\mathbf{1}^t}{n}\right)\mathbf{C}\left(\mathbf{I} - \frac{\mathbf{1}\mathbf{1}^t}{n}\right)$ is a Moran's I index value [42]. Equation (8) is estimated using a stepwise regression, where only a limited number of the available q eigenvectors are used to predict x_i. The stepwise procedure is applied to a parsimonious subset of candidate eigenvectors, selected on the strength of the Moran's I associated to each eigenvector. Only those eigenvectors that exhibit "*at least weak*" ([43]; p. 1202) positively or negatively autocorrelated spatial pattern are used in this procedure, leaving out eigenvectors related to substantially irrelevant spatial patterns. The stepwise search concludes when the spatial autocorrelation in the residuals of equation (8) does not significantly differ from zero.

Once the model in equation (8) is estimated, the filtered (non-spatial), local-specific component for a generic digitalization variable can be expressed as:

$$x^*_{i_E} = e_i \tag{9}$$

where $e_i = x_i - \widehat{x}_i$, and $\widehat{x}_i$ is the predicted value obtained estimating the parameters of equation (8). In this framework, the value $\widehat{x}_i$ represents the spatial component of the variable, while $x^*_{i_E}$ captures the filtered, region-specific component free from spatial dependence. Accordingly, for each observation i, the original variable x_i can be rewritten as the sum of the filtered part x^*_{iE} and its spatial component $\widehat{x}_i = s_{i_E}$ [21]:

$$x_i = x^*_{i_E} + s_{i_E} \tag{10}$$

Now define two vectors for each unit i: one including the p filtered variables, denoted as $\mathbf{X}^*_{i_E}$, and the other containing the corresponding spatial components, denoted as $\mathbf{S}_{i_E}$, for the same p variables of digitalization. Considering equation (2) for a specific unit i, and applying the decomposition introduced in Equation (10), we can write:

$$y_{ij} = \left(\mathbf{X}^*_{i_E} + \mathbf{S}_{i_E}\right)^t \mathbf{A}_j \tag{11}$$

$$y_{ij} = \mathbf{X}^{*\,t}_{i_E}\mathbf{A}_j + \mathbf{S}_{i_E}{}^t\mathbf{A}_j. \tag{12}$$

Thus, the scores of each component can be split into two additive parts, corresponding to the initial composite index obtained from the standard PCA. The first term of the right side of equation (12) ($\mathbf{X}^{*\,t}_{i_E}\mathbf{A}_j$) is the local-specific composite index, capturing the portion of digitalization not driven by spatial dependence. The second term ($\mathbf{S}_{i_E}{}^t\mathbf{A}_j$) is the spatial composite index, reflecting the extent to which spatial dependence contributes to the observed level of digitalization. This decomposition allows us to disentangle the region-specific achievements from the spatial effects, thereby quantifying both the intrinsic performance of each unit and the influence of neighboring regions.

Despite the usefulness of spatial filtering and spatial composite indices in measuring the role of spatial spillovers in regional digitalization, this paper introduces an additional exploratory tool to support policy definition. This explorative tool facilitates the investigation of spatial patterns through relevant indicators and visualizations.

In this paper, we propose that spatial spillovers embedded into composite indices can be visualized by leveraging the components introduced in equations (11) and (12). Specifically, we present a plot where the region-specific component is on the x-axis and the spatial component is on the y-axis, with a reference line of slope 1 to facilitate direct comparison. Regions located above the 45-degree line exhibit a stronger spatial influence relative to their specific component and are classified as spatial winners. Conversely, regions below the line, where the local-specific component dominates, are identified as spatial losers, suggesting that weak or adverse spatial spillovers may be limiting their digitalization progress.

This visualization provides an intuitive way to identify regions that effectively leverage interregional connections compared to those that may be lagging due to limited spatial integration. It therefore complements existing quantitative techniques and contributes to the definition of spatially targeted policy strategies.

3.2. Sensitivity analysis

To better assess the robustness of the regional DESI index and evaluate the contribution of each single indicator, we conduct a sensitivity analysis [44,45]. In the construction of composite indices, the assigned weights may not fully reflect the true influence of each input variable. Sensitivity analysis therefore allows to evaluate the effective importance of each variable to the overall index, ensuring consistency and alignment with policy aims.

Following the approach proposed by Becker et al. [46], we use the ratio $\widehat{S}_j$ calculated as:

$$\widehat{S}_j = \frac{\sum_{i=1}^n \left(\widehat{g}_{ij} - \overline{g}_j\right)^2}{\sum_{i=1}^n (y_i - \overline{y})^2} \tag{13}$$

where $\widehat{g}_{ij} = \widehat{f}_j(x_{ij})$ is the fitted values of a regression of the composite index $\mathbf{Y}$ on a particular variable $\mathbf{X}_j$ calculated for a particular point x_{ij}, and $\overline{g}_j = n^{-1}\sum_{i=1}^n \left(g_{ij}\right)$, y_i is the level of the composite index at i, and and $\overline{y}$ is the mean of the composite index across all spatial units.

The statistic $\widehat{S}_j$ is known as the first-order sensitivity index, and it can be expressed as the expected proportional reduction in the variance of the index $\mathbf{Y}$ that would occur if the single indicator $\mathbf{X}_j$ was fixed [47]. In the paper, we estimate $\widehat{S}_j$ using both a linear specification and a non-parametric local kernel regression to capture possible nonlinear relationships between $\mathbf{Y}$ and $\mathbf{X}_j$[46].

4. Data and results

To build a regional DESI, we rely on official sources of the European Community. Data come primarily from the EUROSTAT regional database, supplemented by the European Data Journalism Network for the 5G latency. The variables selected aims at creating correspondence between regional data as closely as possible with the national-level structure of the DESI. The official DESI is organized in four domains: digital skills, considered the foundational condition to reach an aware digitalization; digital infrastructure; digital transformation of businesses, reflecting both firm-level adoption and individual usage, and digitalization of public services, recognizing the central role of public administrations in enabling digital transition [28].

We select 12 variables for 175 European regions belonging to 24 countries: Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Portugal, Romania, Slovakia, Slovenia, Spain, and Sweden.

All countries are analyzed at the NUTS 2 level, with the exception of Germany. Due to the unavailability of several key indicators at the NUTS 2 level, Germany is consistently examined at the NUTS 1 level, without any disaggregation or estimation from national-level data. Although this implies a more aggregated territorial level than NUTS 2, German NUTS 1 macro-regions (Bundesländer) represent a meaningful and socio-economic heterogeneity and enjoy significant administrative and political autonomy, particularly in areas such as education, infrastructure, and digital policy. For these reasons, their inclusion still preserves an adequate degree of territorial granularity for regional analysis.

The reference year is 2022 for all selected variables, except for Broadband access and E-government pre-filled forms, which refer to 2021 due to the unavailability of more recent data at the regional level. Although this introduces a minor temporal inconsistency, its impact is expected to be limited. Both indicators tend to evolve gradually, and no major policy or market shifts occurred between 2021 and 2022 that would significantly compromise their comparability with the rest of the dataset [48].

Two indicators included in the national DESI — Digital technologies for businesses (within the broader area of Digital Transformation of Businesses) and e-Health (within the dimension of Digitalization of Public Services) — were excluded. This decision stems from the unavailability of harmonized and sufficiently detailed data at the regional level across a critical number of countries. Their exclusion inevitably results in a partial representation of the national DESI structure at the regional scale, particularly in terms of business and health digitalization. However, the remaining indicators still capture a substantial share of the core dimensions of DESI, allowing for meaningful regional comparisons while ensuring data reliability [16].

Table 1 provides correspondence between the national DESI inputs and the variables of our regional analysis.

We begin with a baseline PCA applied to the standardized indicators reported in Table 1. All variables have positive polarity, meaning that higher values correspond to higher levels of the DESI index. Results show that the first three components account for 79.62% of the total variability in the data, while the first component alone accounts for 55.96% of the global variability. This substantial explanatory power justifies the interpretation of the first component as a composite index of regional digitalization. The loadings for the first, second, and third components are reported in Table 2.

For the first component, the highest loadings (approximately 0.35) are associated with Internet interactors, Internet banking, Continuous access, and E-government. A marked contrast emerges between the loading for Internet Access (0.3230) and that for Latency 5G (0.0975). This discrepancy highlights persistent challenges in fixed network deployment, which remains highly uneven across European regions [49]. All first component loadings are positive, aligning with expectations that each of the 12 variables contribute positively to the multivariate index of digitalization.

Fig. 1 maps the regional DESI scores derived from the first component, where higher values correspond to greater levels of digitalization. A clear spatial divide emerges, as regions in Scandinavian countries, the Netherlands, and Belgium rank as the top performers [29], while many regions in Mediterranean and in Eastern Europe are largely concentrated in the lower quantiles. Capital regions (Paris, Berlin, Madrid, Prague, Budapest among others) appear in the highest quantiles. This reflects their role as innovation and economic hubs, benefiting from high levels of investments, infrastructure, and dense innovation ecosystems [50].

In Spain, the most economically developed regions (Catalonia, Madrid, and the Basque Country) also exhibit the highest levels of digitalization. Italy stands out as the only founding EU member where nearly all regions fall into the lowest quantile, with only modest improvements in northern regions (Lombardy, Emilia-Romagna, Trentino-Alto Adige, and Friuli-Venezia Giulia).

The regional breakdown of our regional DESI also reveals disparities within digitalized countries. In France, a North-South divide is evident: with southern regions outperforming their northern counterparts. In Germany, an East-West divide persists, with most former East German regions still lagging.

In order to verify the robustness of the PCA findings, a sensitivity analysis was performed. The results reported in Table 3 confirm consistency with the PCA loadings. The most influential variables are again Internet interactors (0.9179), Internet banking (0.9091), and Continuous access (0.8898). No evidence of severe imbalances or unexpected dominance of a single indicator emerges. The results remain coherent across both linear and non-linear methods ($\widehat{S}_{j,Lin}$ and $\widehat{S}_{j,LocLin}$). The sensitivity analysis confirms that all key domains of the DESI are represented by at least one influential variable.

Table 2
Loadings of the first principal component index.

Variables	PC1	PC2	PC3
Internet access	0.3230	0.1124	0.0445
Internet interactors	0.3542	0.0233	−0.0768
Active on social	0.2001	0.3416	0.5505
Internet banking	0.3508	−0.2069	0.0063
E-commerce	0.3023	−0.1703	0.1440
Broadband access	0.2924	0.2249	0.1436
E-Government	0.3350	−0.2765	−0.1125
Forms	0.3145	−0.3042	−0.0437
ICT specialists	0.0394	0.4583	−0.6539
Continuous access	0.3433	0.1410	0.0346
Latency 5G	0.0975	0.5895	0.1128
HRST	0.2996	0.0317	−0.4375
Proportion of variance explained	0.5596	0.1457	0.0909
Cumulative proportion	0.5596	0.7053	0.7962

The first spatial effect we consider, in the definition of the composite index of digitalization, is spatial heterogeneity. To capture this, we apply GWPCA. Before showing GWPCA results, we test non-stationarity of the variance-covariance matrix through a Monte Carlo experiment [22]. The results highlight significant non-stationarity of the eigenvalues, with a p-value of 0.06.

Due to irregularities in the shapes and sizes of region polygons, we adopt an adaptive kernel, as recommended by Gollini et al. [39]. Cross-validation (CV) is explored across different numbers of components using an exponential adaptive kernel. As shown in Fig. 2, a clear minimum of the CV function is obtained at three components, which correspond to a bandwidth of 14. This configuration is therefore used in our analysis.

Fig. 3 displays the winning variable for the first principal component in each region. The map highlights the specific dimension of digitalization that most strongly characterizes local digital performance. A clear territorial pattern emerges across Europe. In Western and Southern Europe, particularly in Spain and Italy, the leading winning variable is Internet Interactors, indicating that basic internet usage and frequency of access remain the primary forms of digital engagement in these regions.

In contrast, northern European countries such as Denmark, Sweden,

Table 1
DESI indicators and variables selected for the construction of our composite indicator of regional digitalization.

DESI DOMAINS	DESI INDICATORS	VARIABLES SELECTED	DESCRIPTION OF VARIABLES	SOURCE
DIGITAL SKILLS	Internet user skills	Internet interactors	Percentage of individuals at least one time per week connected to internet	Eurostat
		Active on social	Percentage of individuals who participate with contribution in social networks	Eurostat
		Internet Banking	Percentage of individuals who use internet banking	Eurostat
	ICT specialists	ICT specialists	Demand for ICT specialists	Eurostat
		ICT graduates	Persons with a degree in science and technology (HRST)	Eurostat
DIGITAL INFRASTRUCTURES	Overall fixed broadband	Overall internet take-up	Percentage of households with access to the Internet at home	Eurostat
		Share of fixed broadband subscription	Percentage of households with broadband access	Eurostat
	Mobile broadband	5G spectrum	Proportion of regional median latence (millisecond) with respect to the minimum 5G latence in Europe	European Data Journalism Network
		Mobile broadband take-up	Internet access daily	Eurostat
DIGITAL TRASFORMATION OF BUSINESSES	E-commerce	Selling online	Internet use: selling goods or services	Eurostat
DIGITALIZATION OF PUBLIC SERVICES	E-Government	E-Government users	Percentage of Individuals who used the internet for interaction with public authorities	Eurostat
		Pre-filled forms	Percentage of individuals who submit online a complete form	Eurostat

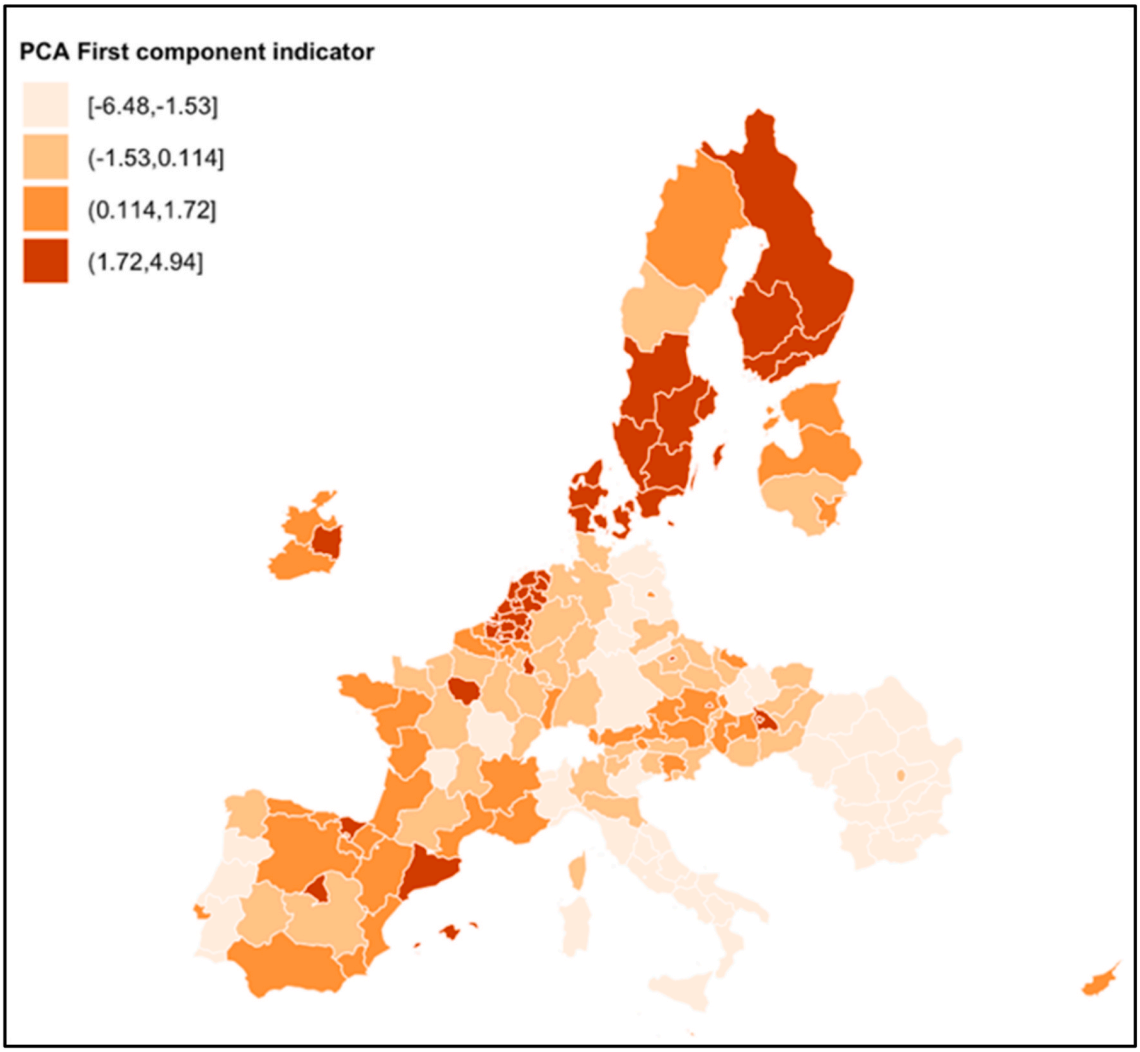

Fig. 1. Quantile map of the first principal component's scores.

Table 3
Results from sensitive analysis for DESI index.

Variables	*PC1*	$\hat{S}_{j,Lin}$	$\hat{S}_{j,LocLin}$
Internet access	*0.3230*	*0.8370*	*0.7158*
Internet interactors	*0.3542*	*0.9179*	*0.8600*
Active on social	*0.2001*	*0.5199*	*0.2981*
Internet banking	*0.3508*	*0.9091*	*0.8389*
E-commerce	*0.3023*	*0.7834*	*0.6370*
Broadband access	*0.2924*	*0.7578*	*0.5955*
E-Government	*0.3350*	*0.8683*	*0.7533*
Forms	*0.3145*	*0.8149*	*0.6726*
ICT specialists	*0.0394*	*0.1021*	*0.0109*
Continuous access	*0.3433*	*0.8898*	*0.8021*
Latency 5G	*0.0975*	*0.2525*	*0.0891*
HRST	*0.2996*	*0.7763*	*0.6086*

and Finland are characterized by the dominance of Forms, likely reflecting the advanced digital infrastructure that supports the widespread use of online public services [51].

Central European regions, including parts of Germany, France, and the Netherlands, display a more heterogeneous pattern. Several regions are driven by variables such as Broadband Access, Continuous Access, and Active on Social. Notably, Germany is particularly associated with Active on Social. This outcome may reflect specific socio-cultural dynamics that impact the diffusion of social media platforms by population [52].

Countries such as Latvia and Lithuania are predominantly characterized by the variable HRST, underscoring the importance of a skilled workforce in supporting regional digital advancement [53]. In eastern European countries the leading variables are Internet Banking and Internet Interactors.

Fig. 4 displays the values of the first component scores derived from the GWPCA, pointing out differences from those obtained using the global standard PCA. Several regions in western France show a decline in their digital performance, although the Pays de la Loire remains within the same quartile. In Germany, the situation changes significantly: northern regions exhibit lower levels of digitalization compared to the global PCA. In Italy, Lazio moves up to the second quartile, outperforming many other central and southern regions in terms of digital advancement.

Fig. 5 compares the performance of PCA and GWPCA in terms of the proportion of variance explained by the first three components. The solid black line represents the PCA results, while the dashed line shows the GWPCA outcomes, calculated in terms of the unit-by-unit average (indicated by circles). The comparison reveals that GWPCA achieves a higher overall variance explanation (0.83) than standard PCA (0.79). This suggests that a local approach such as GWPCA better captures regional specificities, offering a more accurate and detailed representation of the regional DESI.

The final rankings for PCA and GWPCA are presented in Table A.1 of

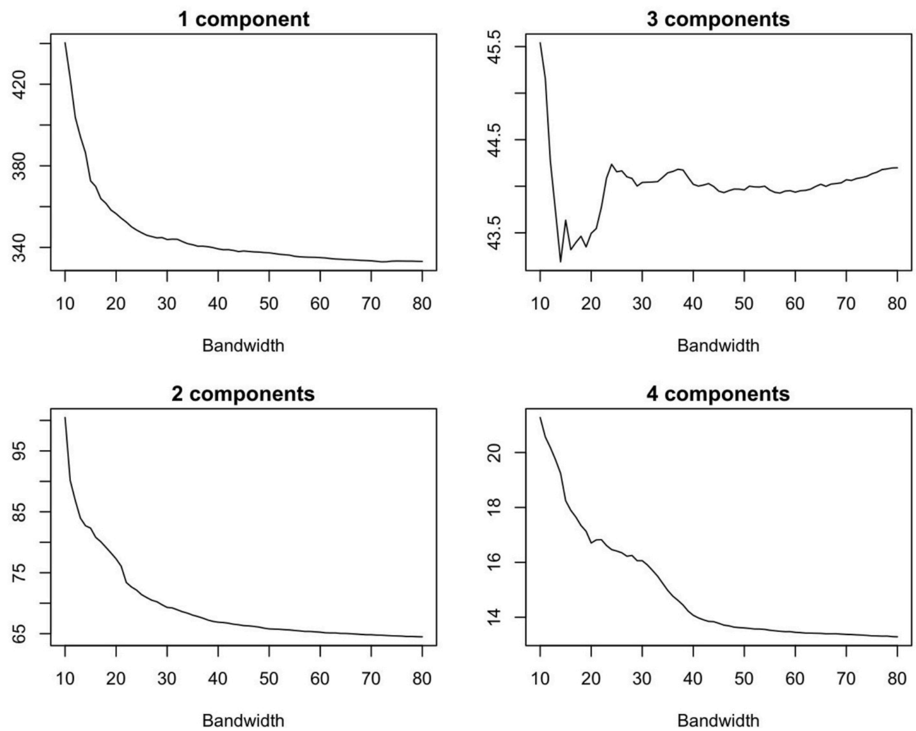

Fig. 2. Cross-validation scores for an adaptive exponential kernel.

Annex A and reveal some differences between the two techniques. Despite these variations, the results consistently highlight a clear digital advantage in some areas, particularly in the Netherlands and in Northern European countries, which systematically emerge among the top-performing regions.

We now consider spatial dependence in the composite index of digitalization. To address this, we apply spatial filtering technique to decompose the original index in two components. In the filtering process, a k-nearest neighbor binary contiguity matrix with $k = 4$ is finally used. Table 4 reports the results of the Moran's I test performed both on the original variables used to construct regional DESI and on the same variables after spatial filtering. The Moran's I indexes, and the associated p-values clearly confirm the presence of significant spatial autocorrelation in all the original variables.

Once the spatial components are filtered out, spatial autocorrelation is no longer statistically significant. Table 4 also report the number of eigenvectors used in the stepwise procedure for each filtered variable (see equation (8); [41]).

Fig. 6(A) displays the quantile map of the spatial component derived from the second term on the right-hand side of equation (12). The map highlights how positive spatial spillovers contribute to regional digitalization. Strong spatial effects are observed in Scandinavian countries, Belgium, Netherlands, and Luxembourg. Positive spillovers are also evident in selected areas of Czechia, Hungary, Slovakia, and eastern Austria. France is characterized by high levels of the spatial component in Haute Normandie, Franche Comte, and Provence-Alpes-Cote d'Azur. Conversely, Italy and Germany exhibit low levels of spatial spillovers, with only a few exceptions.

The spatial component captures the role of spatial spillovers, including the effects of knowledge diffusion, firms' proximity, and institutional linkages that influence each dimension of the DESI. It reflects territorial impacts from interregional interactions that foster digital business development, support adoption of new products and processes, and enhance productivity and growth [18]. Moreover, it includes diffusion mechanisms through interregional ties that promote digital skills and help reduce inequalities [19].

Fig. 6(B) presents the quantile map of the region-specific component, which captures the intrinsic contribution of each region's own characteristics to digital development. Several regions in France, Germany, and Lombardy in Northern Italy exhibit strong specific values despite limited spatial spillovers.

Rankings for the specific and spatial components are reported in Table A.2 of Annex A. The results highlight high values in Belgium and Finland, as well as regions that underperform on the spatial dimension, including Yugoiztochen in Bulgaria and the Sud-Est region of Romania.

Also, evidence indicates that high overall digital performance often arises from a combination of strong non-spatial and spatial components. For instance, certain regions in Finland and Sweden show less pronounced region-specific (non-spatial) values. However, their digital advantage stems from strong spatial performance supported by robust regional networks and spatial interdependencies.

Conversely, some regions underperform in overall outcomes despite strong specific (non-spatial) components, due to weak spatial integration. A clear example is Italy's Lombardy region, which excels in non-spatial components but ranks poorly in spatial metrics. A similar pattern can be seen in Romania's regions of Bucharest (Bucureşti) and Nord-Vest. This dynamic is also evident in France's Poitou–Charentes region and Spain's Valencian Community, where limited spatial connectivity constrains broader digital progress.

The patterns observed in Fig. 6(A) and (B) are fully synthesized in Fig. 7, serving as an effective diagnostic tool. This visualization clearly provides evidence of the dual nature of regional digital performance: while some regions excel due to strong internal capabilities, others benefit significantly from their geographic proximity to digital frontrunners. Strong spatial winners are predominantly located in the Netherlands, as well as parts of Belgium and Luxembourg. These regions show high levels of both specific digital development and spatial spillovers, reflecting dense innovation ecosystems, cross-border integration, and strong digital institutions. In contrast, spatial losers include areas of Italy, Spain, and Romania.

Importantly, a clear pattern emerging from the overall analysis concerns the persistent East–West divide in digitalization across Europe. Several regions in Romania, Hungary, Bulgaria, the Czech Republic, and Slovakia as well as some western areas of Germany, are characterized by

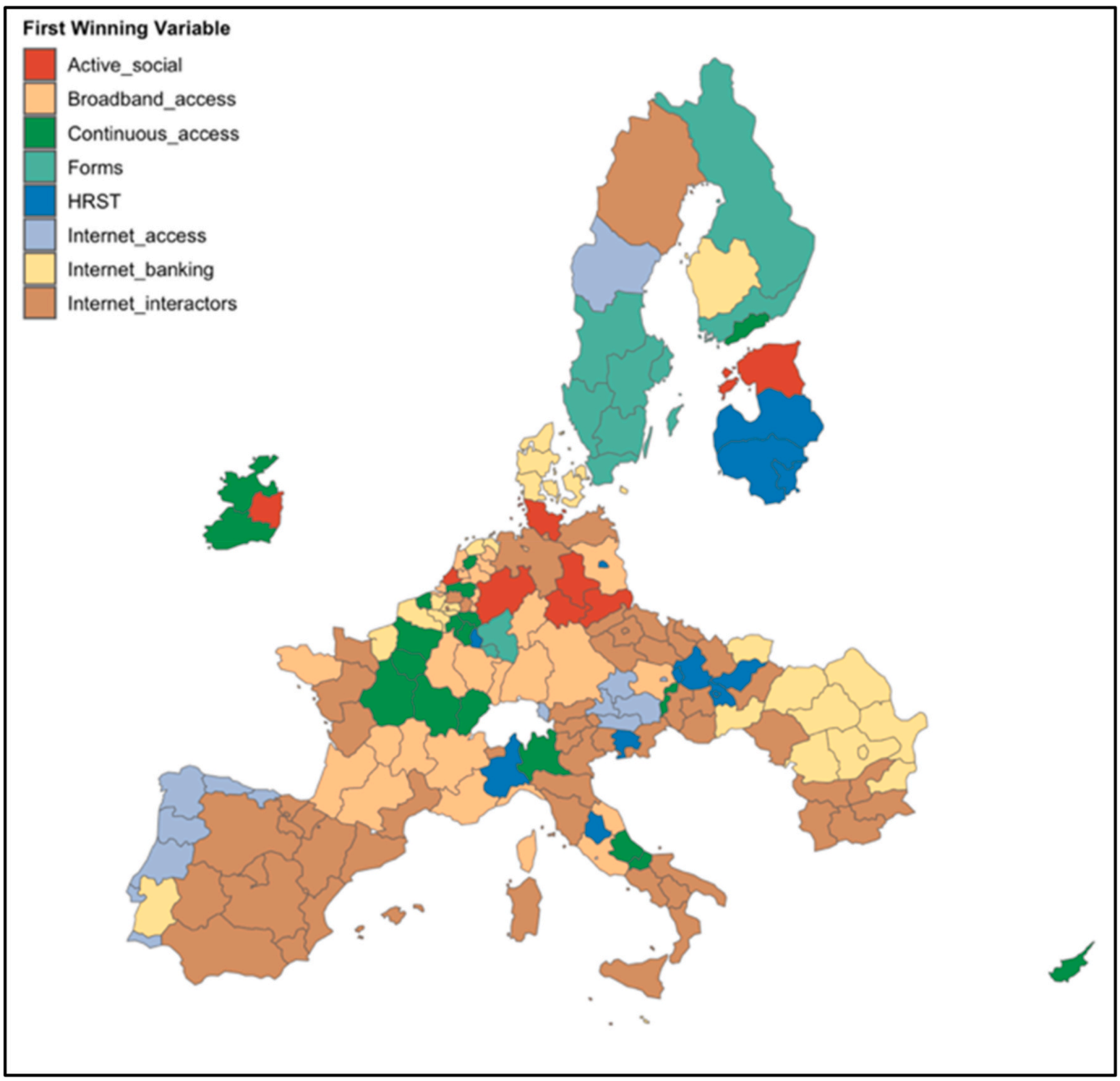

Fig. 3. Map of the winning variables for the first component obtained by GWPCA.

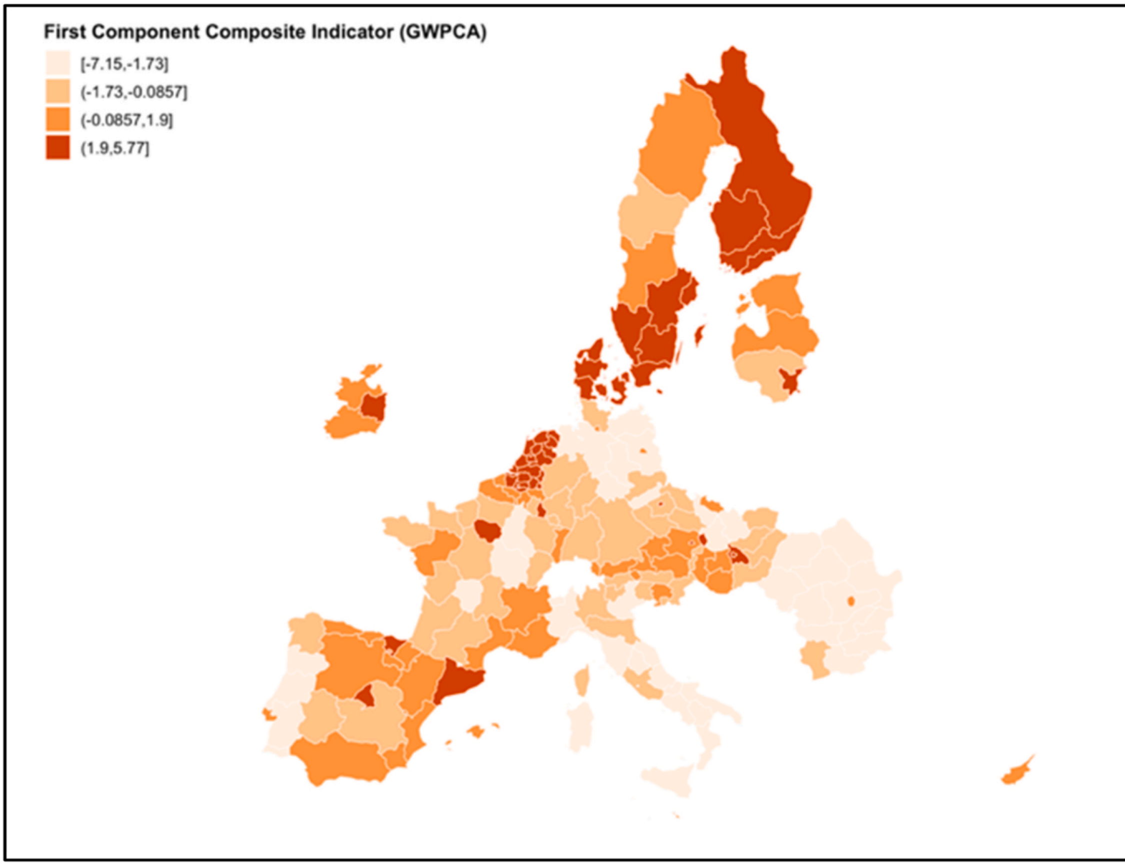

Fig. 4. Quantile map of GWPCA first component's scores.

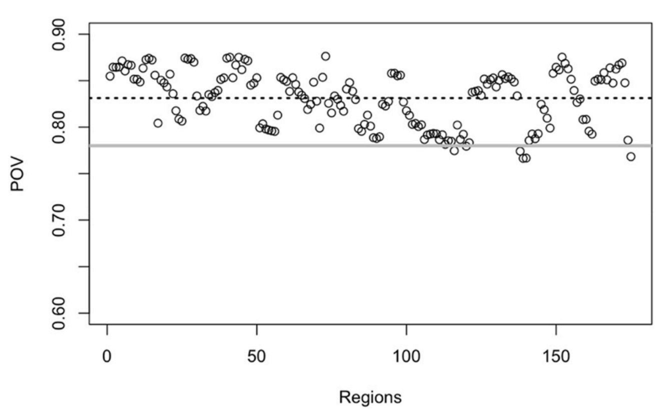

Fig. 5. Performance (average proportion of variance of the first three components) of global PCA (line) and GWPCA (dots). Circles show the unit-by-unit GWPCA performance of the 175 European regions.

Table 4
Moran's I value for variables (X) and filtered variables (X_{iE}). P-values in brackets.

Variables	Moran's I value for $\boldsymbol{X}$ (p-value)	Moran's I value for $\boldsymbol{X}_{iE}$ (p-value)	Number of eigenvectors selected
Internet access	0.1538 (0.0006)	−0.0715 (0.9079)	17
Internet interactors	0.2197 (0.0000)	−0.0908 (0.9575)	19
Active on social	0.4111 (0.0000)	−0.0941 (0.9633)	19
Internet banking	0.3473 (0.0000)	−0.0919 (0.9596)	20
E-commerce	0.5157 (0.0000)	−0.1227 (0.9910)	25
Broadband access	0.1560 (0.0005)	−0.0623 (0.8739)	15
E-Government	0.3999 (0.0000)	−0.1237 (0.9915)	25
Forms	0.3987 (0.0000)	−0.1339 (0.9952)	26
ICT specialists	0.1469 (0.0009)	−0.0225 (0.6328)	4
Continuous access	0.1941 (0.0000)	−0.0611 (0.8684)	23
Latency 5G	0.2293 (0.0002)	−0.0307 (0.6940)	6
HRST	0.2254 (0.0000)	−0.0688 (0.8989)	14

low levels of digital development. The evidence also reveals a marked urban–rural differences in these areas, where only capital regions—such as Bucharest, Budapest, Prague, Bratislava, and Berlin—achieving very high scores. These findings suggest that polarization of lagging regions in Eastern Europe can be largely interpreted through urban–rural gradient. In many of these countries, predominantly rural regions struggle integrating with urban areas closely connected to the "old" (i.e., Western) European markets [54].

The gap may reflect persistent weaknesses in digital knowledge and infrastructure [55]. Key indicators, such as internet banking and access, dominate the GWPCA winning variables in these areas. The spatial composite index also underperforms in several Eastern regions, indicating limited spillovers and knowledge diffusion, which may reinforce territorial disparities and widen the digital divide, especially in rural areas, calling for targeted policies.

Finally, findings open the possibility for a comparison with structural patterns of regional investments and policy interventions, highlighting whether their effects remain localized or propagate across territories to foster digitalization and the growth of new markets. The map of the spatial component can be used to assess the territorial impact of policies aimed at strengthening innovation systems or knowledge hubs, such as those implemented under the Digital Europe Programme, with the objective of maximizing positive spillovers.

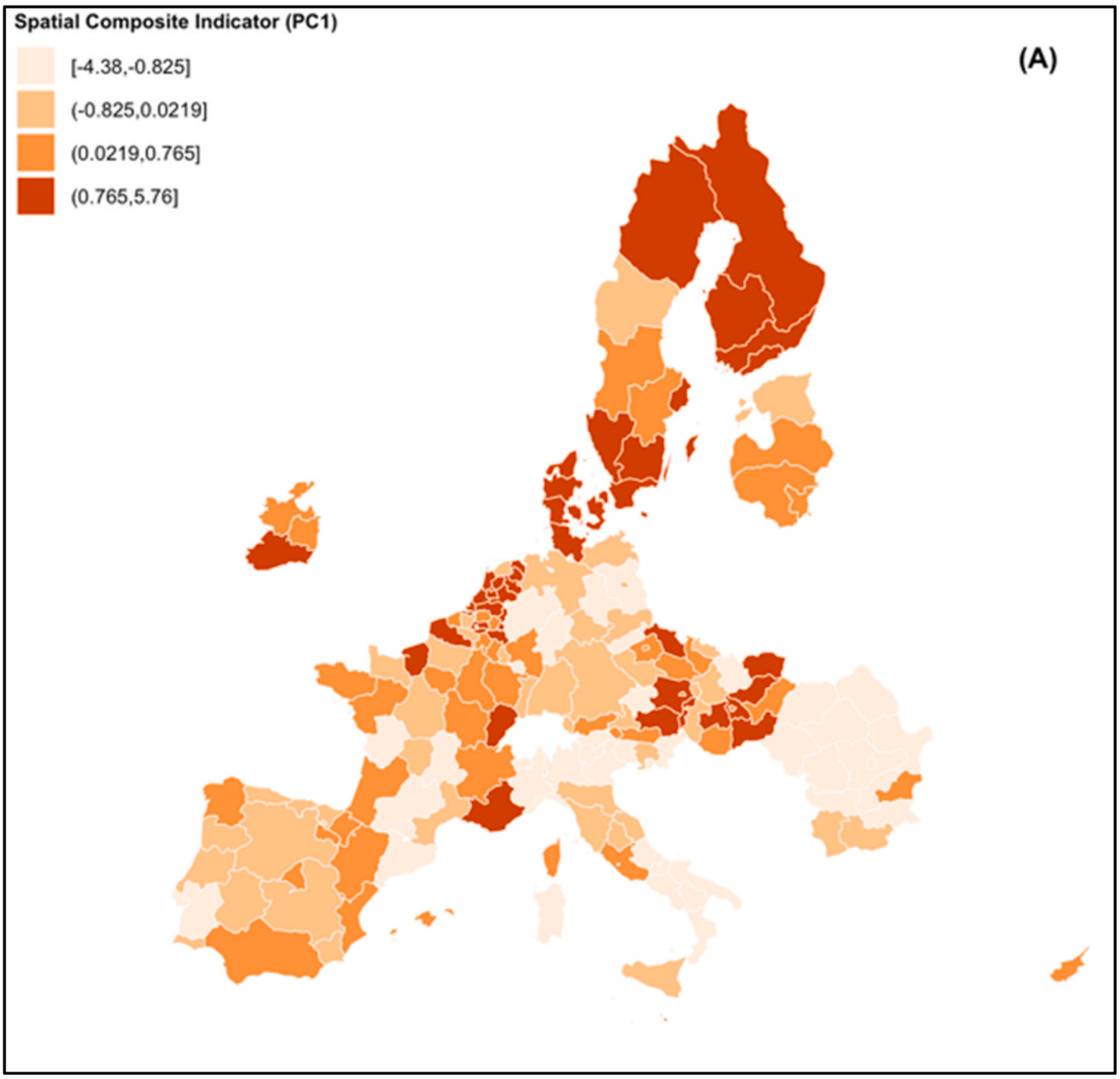

Fig. 6. Quantile map of the spatial (A) and the specific (B) components obtained from the first principal component using Griffith's filtering.

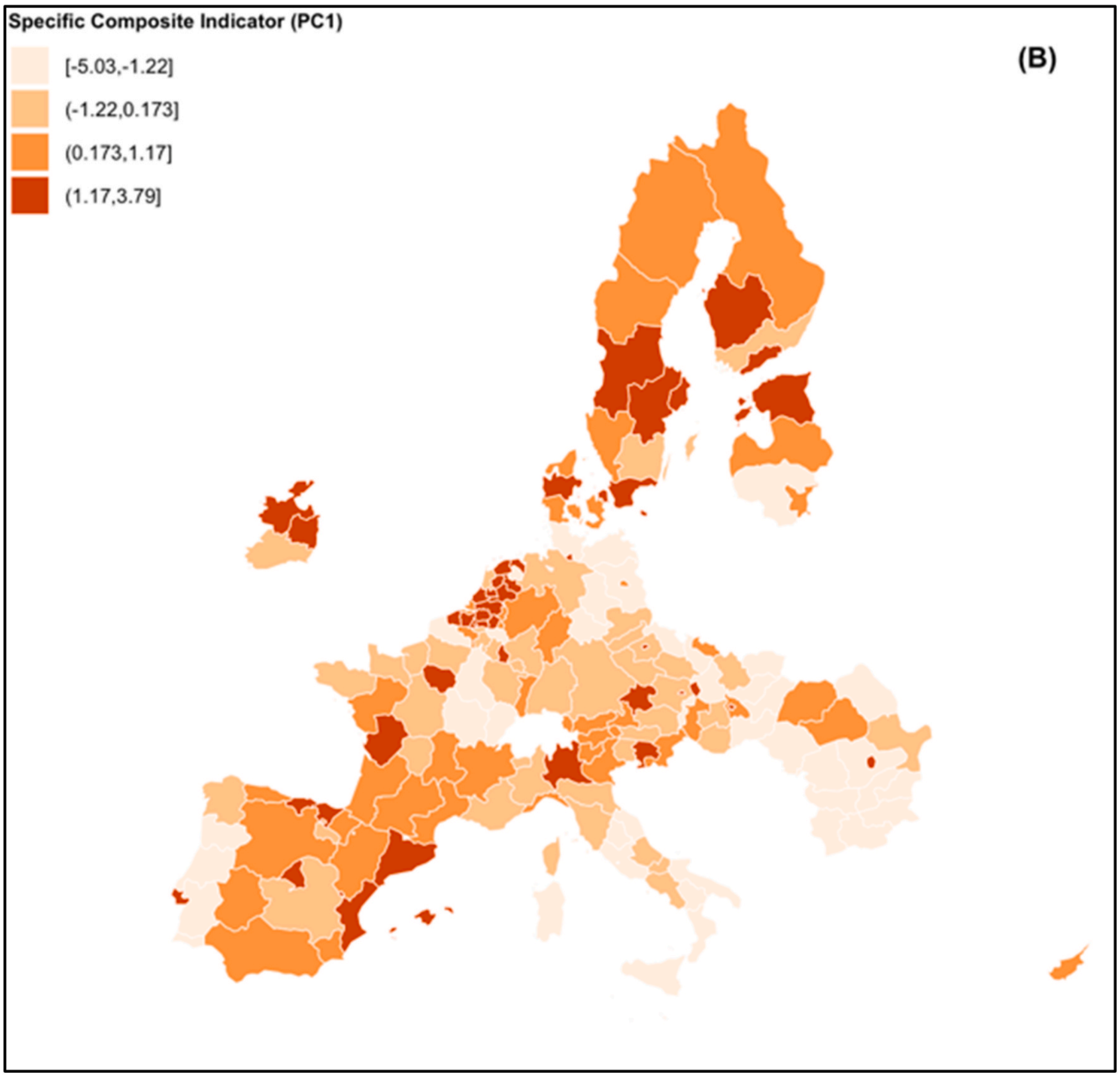

Fig. 6. (*continued*).

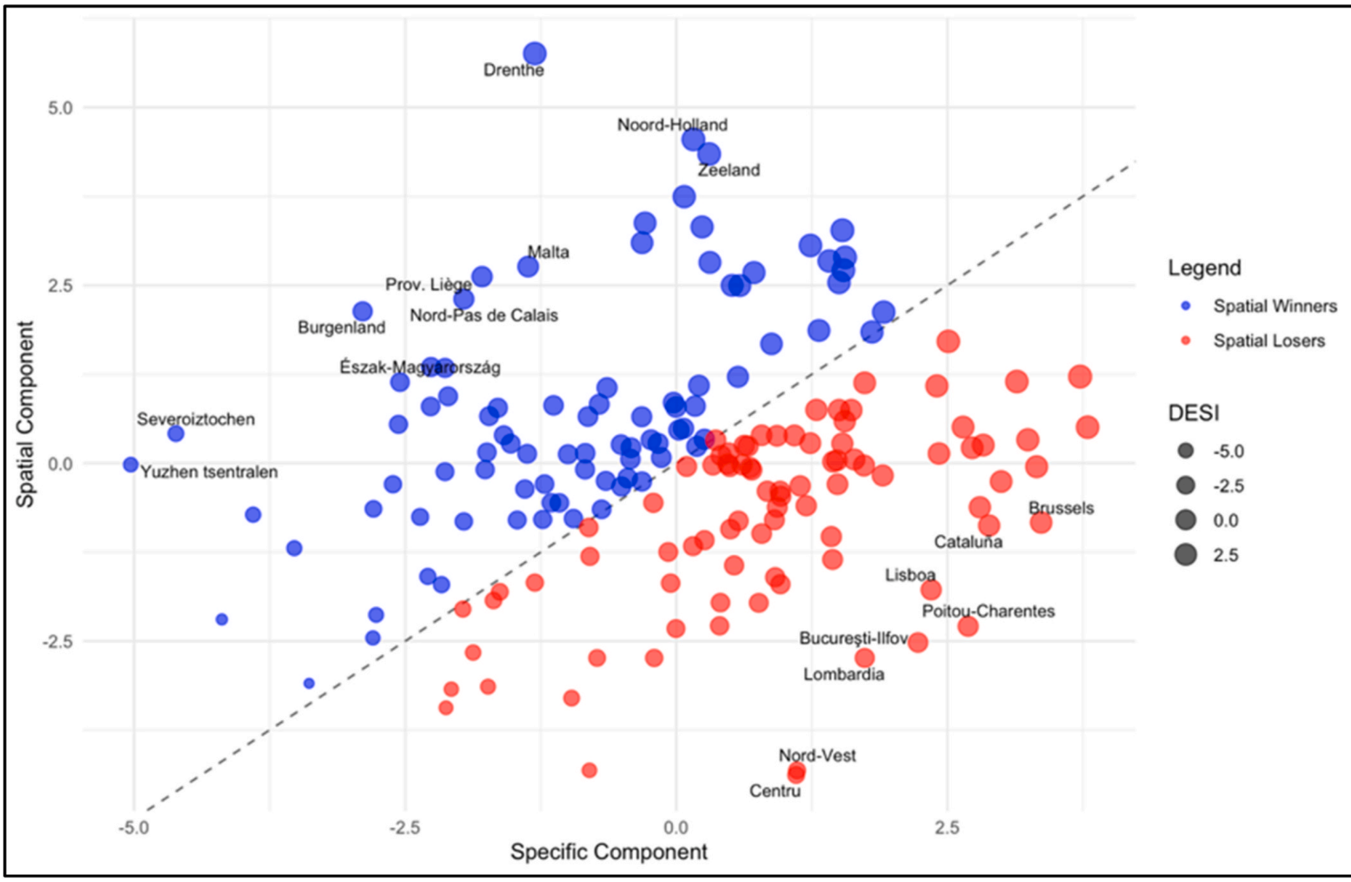

Fig. 7. Explorative analysis of the two components (spatial and specific) of the regional DESI in 2022. The dashed line represents a reference line with slope one dividing the scatter plot in spatial winners (blue) and spatial losers (red). The size of the circles is scaled based on the overall DESI score (spatial plus specific). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Besides, the specific (non-spatial) component can guide targeted investments in digital infrastructure and support initiatives like the Regional Innovation Valleys under the European Innovation Agenda. These results may also improve the efficiency of digital transformation investments among Small and Medium Enterprises, particularly in contexts where such expenditures risk being ineffective or major digital players are required ([56], for Italy).

5. Concluding remarks

This paper poses new empirical evidence on digitalization patterns across European regions, contributing to the definition of strategies for reducing the digital divide and promoting a more balanced digital transformation across the EU. By explicitly incorporating the spatial dimension of digital performance, our analysis offers critical insights that inform place-sensitive digital policies.

Methodologically, the use of GWPCA allowed to construct a regional composite index of digitalization that captures local heterogeneity. This approach provides a more detailed understanding of regional differences. Furthermore, the additional use of spatial filtering techniques to decompose digitalization scores into region-specific and spatial spillover components further enhances the analytical framework. This decomposition makes it possible to quantify the magnitude and direction of spatial spillovers, revealing how interregional dynamics shape digital outcomes.

We argue that regional composite indices combined with spatial augmented versions offer a compelling complement to the DESI dashboard, as they enable a more actionable identification of intra-national disparities and region-specific challenges relevant to the territorial implementation of the EU's Digital Agenda 2030.

The exploratory visualization tool identifies spatial winners and spatial losers, highlighting where strengthening interregional linkages and spillovers may be more effective than isolated investments. The results suggest that, without stable connections to more digitally advanced regions, financial support alone may not be sufficient to reduce the digital divide, underscoring the need for coordinated strategies across Europe [57]. The method also clearly identifies promising hubs targeted interventions could activate spillover dynamics benefiting lagging areas.

This study extends geo-localized and place-based insights to support Europe's digital future, which are becoming increasingly relevant [19]. However, as the analysis focuses on a single cross-sectional year (2022), future research should adopt a longitudinal perspective to assess convergence trends and persistent disparities over time. Relying on data from the years immediately following the COVID-19 outbreak may partly reflect pandemic-driven acceleration rather than fully stabilized structural patterns. Extending the spatial analysis over time would therefore enhance its predictive capacity and provide stronger guidance for policy design based on regional digitalization indices.

Lastly, the approach could be extended in future research by incorporating alternative proximity measures, including broader socio-economic metrics [58].

CRediT authorship contribution statement

Simone Mazzaferro: Validation, Software, Investigation, Data curation. **Alfredo Cartone:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Conceptualization. **Paolo Postiglione:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Andrea D'Isidoro:** Data curation.

Annex A.

Table A.1
Scores and rankings for DESI based on PCA and GWPCA for 175 regions in the European Union in 2022.

PCA				GWPCA			
Nuts ID	Region Name	Score	Rank	Nuts ID	Region Name	Score	Rank
NL31	Utrecht	4.942	1	NL31	Utrecht	5.765	1
FI1B	Helsinki-Uusimaa	4.804	2	NL32	Noord-Holland	5.365	2
NL32	Noord-Holland	4.707	3	HU11	Budapest	5.329	3
NL34	Zeeland	4.647	4	FI1B	Helsinki-Uusimaa	4.833	4
NL13	Drenthe	4.451	5	NL21	Overijssel	4.824	5
SE11	Stockholm	4.449	6	NL13	Drenthe	4.744	6
HU11	Budapest	4.300	7	NL22	Gelderland	4.660	7
NL21	Overijssel	4.297	8	ES30	Comunidad de Madrid	4.641	8
DK01	Hovedstaden	4.289	9	SE11	Stockholm	4.627	9
NL11	Groningen	4.255	10	NL41	Noord-Brabant	4.598	10
NL22	Gelderland	4.252	11	DK01	Hovedstaden	4.580	11
NL41	Noord-Brabant	4.221	12	NL23	Flevoland	4.579	12
NL23	Flevoland	4.040	13	NL34	Zeeland	4.558	13
NL33	Zuid-Holland (NUTS 2021)	4.036	14	NL11	Groningen	4.441	14
BE31	Prov. Brabant wallon	3.818	15	NL33	Zuid-Holland	4.379	15
SE22	Sydsverige	3.649	16	CZ01	Praha	4.185	16
CZ01	Praha	3.572	17	BE31	Prov. Brabant wallon	4.040	17
NL42	Limburg (NL)	3.558	18	LU00	Luxembourg	3.936	18
DK04	Midtjylland	3.490	19	DK02	Sjælland	3.688	19
DK02	Sjælland	3.395	20	AT13	Wien	3.686	20
NL12	Friesland (NL)	3.274	21	DK04	Midtjylland	3.655	21
FI19	Länsi-Suomi	3.181	22	NL42	Limburg (NL)	3.536	22
IE06	Eastern and Midland	3.153	23	NL12	Friesland (NL)	3.497	23
SE23	Västsverige	3.131	24	SE22	Sydsverige	3.256	24
FI1C	Etelä-Suomi	3.088	25	DK03	Syddanmark	3.162	25
ES30	Comunidad de Madrid	3.086	26	IE06	Eastern and Midland	3.150	26
DK03	Syddanmark	3.083	27	BE24	Prov. Vlaams-Brabant	3.065	27
DK05	Nordjylland	3.013	28	DK05	Nordjylland	3.039	28
SE12	Östra Mellansverige	2.946	29	BE10	Région de Bruxelles-Capitale/Brussels Hoofdstedelijk Gewest	3.001	29
BE24	Prov. Vlaams-Brabant	2.867	30	FR10	Ile de France	2.876	30
SE21	Småland med öarna	2.782	31	FI19	Länsi-Suomi	2.870	31
LU00	Luxembourg	2.739	32	SE23	Västsverige	2.695	32
AT13	Wien	2.559	33	BE21	Prov. Antwerpen	2.655	33
FI1D	Pohjois- ja Itä-Suomi	2.555	34	FI1C	Etelä-Suomi	2.615	34
BE10	Région de Bruxelles-Capitale/Brussels Hoofdstedelijk Gewest	2.532	35	SE12	Östra Mellansverige	2.528	35
BE21	Prov. Antwerpen	2.361	36	BE22	Prov. Limburg (BE)	2.443	36
BE22	Prov. Limburg (BE)	2.248	37	ES51	Cataluña	2.398	37
BE23	Prov. Oost-Vlaanderen	2.181	38	BE23	Prov. Oost-Vlaanderen	2.376	38
FR10	Ile de France	2.145	39	HU12	Pest	2.287	39
SE31	Norra Mellansverige	2.043	40	LT01	Sostinės regionas	2.130	40
ES51	Cataluña	2.010	41	SE21	Småland med öarna	2.077	41
ES53	Illes Balears	1.807	42	ES21	País Vasco	2.047	42
HU12	Pest	1.783	43	SK01	Bratislavský kraj	2.024	43
ES21	País Vasco	1.731	44	FI1D	Pohjois- ja Itä-Suomi	1.979	44
EE00	Eesti	1.699	45	EE00	Eesti	1.827	45
BE25	Prov. West-Vlaanderen	1.695	46	MT00	Malta	1.766	46
IE04	Northern and Western	1.520	47	BE25	Prov. West-Vlaanderen	1.762	47
ES52	Comunitat Valenciana	1.518	48	PT17	Área Metropolitana de Lisboa (NUTS 2021)	1.628	48
ES24	Aragón	1.480	49	SE31	Norra Mellansverige	1.453	49
SK01	Bratislavský kraj	1.468	50	ES53	Illes Balears	1.369	50
MT00	Malta	1.397	51	ES52	Comunitat Valenciana	1.363	51
ES22	Comunidad Foral de Navarra	1.314	52	ES22	Comunidad Foral de Navarra	1.304	52
SE33	Övre Norrland	1.301	53	ES24	Aragón	1.296	53
SI04	Zahodna Slovenija	1.192	54	SI04	Zahodna Slovenija	1.262	54
LT01	Sostinės regionas	1.180	55	RO32	Bucureşti-Ilfov	1.090	55
FRL0	Provence-Alpes-Côte d'Azur	0.977	56	DE3	Berlin	1.076	56

(continued on next page)

Table A.1 (*continued*)

PCA				GWPCA			
Nuts ID	Region Name	Score	Rank	Nuts ID	Region Name	Score	Rank
FRK2	Rhône-Alpes	0.901	57	CY00	Kýpros	0.970	57
FRG0	Pays de la Loire	0.878	58	IE04	Northern and Western	0.940	58
BE33	Prov. Liège	0.830	59	HU21	Közép-Dunántúl	0.892	59
HU21	Közép-Dunántúl	0.828	60	BE33	Prov. Liège	0.877	60
ES62	Región de Murcia	0.824	61	SE33	Övre Norrland	0.825	61
IE05	Southern	0.786	62	FRL0	Provence-Alpes-Côte d'Azur	0.768	62
LV00	Latvija	0.688	63	FRK2	Rhône-Alpes	0.701	63
ES61	Andalucía	0.627	64	DE6	Hamburg	0.619	64
AT32	Salzburg	0.620	65	LV00	Latvija	0.569	65
DE3	Berlin	0.602	66	AT32	Salzburg	0.569	66
ES13	Cantabria	0.601	67	ES62	Región de Murcia	0.519	67
FRI1	Aquitaine	0.597	68	FRG0	Pays de la Loire	0.468	68
FRF1	Alsace	0.585	69	ES13	Cantabria	0.453	69
PT17	Área Metropolitana de Lisboa	0.572	70	BE35	Prov. Namur	0.442	70
ES41	Castilla y León	0.563	71	ES41	Castilla y León	0.426	71
BE35	Prov. Namur	0.557	72	ES23	La Rioja	0.395	72
AT33	Tirol	0.521	73	AT12	Niederösterreich	0.389	73
AT34	Vorarlberg	0.501	74	AT33	Tirol	0.376	74
ES23	La Rioja	0.491	75	AT31	Oberösterreich	0.349	75
FRJ1	Languedoc-Roussillon	0.465	76	HU22	Nyugat-Dunántúl	0.330	76
CZ08	Moravskoslezsko	0.448	77	ES61	Andalucía	0.324	77
ES12	Principado de Asturias	0.447	78	BE32	Prov. Hainaut	0.320	78
CY00	Kýpros	0.425	79	FRE1	Nord-Pas de Calais	0.299	79
AT12	Niederösterreich	0.422	80	IE05	Southern	0.286	80
FRI3	Poitou-Charentes	0.400	81	ES12	Principado de Asturias	0.264	81
AT31	Oberösterreich	0.398	82	AT22	Steiermark	0.159	82
FRE1	Nord-Pas de Calais	0.348	83	CZ08	Moravskoslezsko	0.109	83
FRH0	Bretagne	0.335	84	FRF1	Alsace	0.098	84
BE32	Prov. Hainaut	0.313	85	HU23	Dél-Dunántúl	−0.065	85
HU22	Nyugat-Dunántúl	0.312	86	AT34	Vorarlberg	−0.069	86
AT22	Steiermark	0.119	87	FRJ1	Languedoc-Roussillon	−0.073	87
ES11	Galicia	0.114	88	CZ02	Střední Čechy	−0.086	88
ES43	Extremadura	0.109	89	FRI1	Aquitaine	−0.091	89
CZ02	Střední Čechy	0.097	90	BG41	Yugozapaden	−0.131	90
DE6	Hamburg	0.089	91	ES42	Castilla-La Mancha	−0.140	91
ES42	Castilla-La Mancha	0.049	92	ES43	Extremadura	−0.252	92
BE34	Prov. Luxembourg (BE)	−0.059	93	ES11	Galicia	−0.278	93
AT21	Kärnten	−0.158	94	FRH0	Bretagne	−0.291	94
HU23	Dél-Dunántúl	−0.198	95	FRI3	Poitou-Charentes	−0.291	95
FRJ2	Midi-Pyrénées	−0.201	96	FRJ2	Midi-Pyrénées	−0.292	96
SE32	Mellersta Norrland	−0.238	97	BE34	Prov. Luxembourg (BE)	−0.343	97
CZ06	Jihovýchod	−0.247	98	AT21	Kärnten	−0.375	98
RO32	Bucureşti-Ilfov	−0.291	99	CZ06	Jihovýchod	−0.415	99
FRD2	Haute-Normandie	−0.319	100	DE7	Hessen	−0.418	100
DEB	Rheinland-Pfalz	−0.365	101	DEB	Rheinland-Pfalz	−0.634	101
DE7	Hessen	−0.427	102	FRD2	Haute-Normandie	−0.701	102
CZ03	Jihozápad	−0.573	103	DEF	Schleswig-Holstein	−0.733	103
FRB0	Centre — Val de Loire	−0.657	104	LT02	Vidurio ir vakarų Lietuvos regionas	−0.740	104
FRK1	Auvergne	−0.691	105	AT11	Burgenland	−0.743	105
FRM0	Corse	−0.696	106	SE32	Mellersta Norrland	−0.767	106
ITH2	Provincia Autonoma di Trento	−0.740	107	ITC4	Lombardia	−0.803	107
AT11	Burgenland	−0.758	108	CZ03	Jihozápad	−0.812	108
FRD1	Basse-Normandie	−0.767	109	DE1	Baden-Württemberg	−0.816	109
HU33	Dél-Alföld	−0.794	110	ITH2	Provincia Autonoma di Trento	−0.880	110
DEA	Nordrhein-Westfalen	−0.822	111	DEA	Nordrhein-Westfalen	−0.889	111
FRE2	Picardie	−0.834	112	DED	Sachsen	−0.903	112
DEF	Schleswig-Holstein	−0.866	113	FRB0	Centre — Val de Loire	−1.048	113
FRF3	Lorraine	−0.873	114	DEC	Saarland	−1.090	114
DE1	Baden-Württemberg	−0.898	115	FRK1	Auvergne	−1.093	115
SI03	Vzhodna Slovenija	−0.903	116	SI03	Vzhodna Slovenija	−1.118	116
CZ05	Severovýchod	−0.910	117	ITI4	Lazio	−1.124	117
DED	Sachsen	−0.929	118	HU32	Észak-Alföld	−1.132	118
ITC4	Lombardia	−0.999	119	HU33	Dél-Alföld	−1.195	119
DEC	Saarland	−1.011	120	FRE2	Picardie	−1.233	120
LT02	Vidurio ir vakarų Lietuvos regionas	−1.064	121	CZ05	Severovýchod	−1.265	121
FRC2	Franche-Comté	−1.164	122	FRM0	Corse	−1.366	122
HU32	Észak-Alföld	−1.197	123	ITH1	Provincia Autonoma di Bolzano/Bozen	−1.398	123
ITH1	Provincia Autonoma di Bolzano/Bozen	−1.202	124	SK04	Východné Slovensko	−1.486	124
CZ07	Střední Morava	−1.242	125	HU31	Észak-Magyarország	−1.526	125
FRF2	Champagne-Ardenne	−1.252	126	ITH5	Emilia-Romagna	−1.543	126
ITH4	Friuli-Venezia Giulia	−1.321	127	FRF3	Lorraine	−1.551	127
ITH5	Emilia-Romagna	−1.336	128	FRD1	Basse-Normandie	−1.597	128
HU31	Észak-Magyarország	−1.408	129	ITH4	Friuli-Venezia Giulia	−1.630	129
SK04	Východné Slovensko	−1.468	130	FRC2	Franche-Comté	−1.664	130

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Table A.1 (*continued*)

PCA				GWPCA			
Nuts ID	Region Name	Score	Rank	Nuts ID	Region Name	Score	Rank
DE9	Niedersachsen	−1.507	131	DE2	Bayern	−1.706	131
ITH3	Veneto	−1.552	132	DE9	Niedersachsen	−1.757	132
ITI4	Lazio	−1.591	133	CZ07	Střední Morava	−1.759	133
FRI2	Limousin	−1.634	134	ITH3	Veneto	−1.759	134
DE2	Bayern	−1.708	135	FRF2	Champagne-Ardenne	−1.785	135
SK03	Stredné Slovensko	−1.710	136	SK03	Stredné Slovensko	−1.870	136
ITI1	Toscana	−1.726	137	CZ04	Severozápad	−1.986	137
CZ04	Severozápad	−1.738	138	SK02	Západné Slovensko	−2.020	138
BG41	Yugozapaden	−1.759	139	ITC3	Liguria	−2.065	139
SK02	Západné Slovensko	−1.853	140	ITI1	Toscana	−2.070	140
ITC3	Liguria	−1.885	141	FRI2	Limousin	−2.210	141
FRC1	Bourgogne	−2.015	142	ITC1	Piemonte	−2.277	142
ITI2	Umbria	−2.023	143	ITI2	Umbria	−2.454	143
ITC1	Piemonte	−2.106	144	PT15	Algarve	−2.517	144
ITI3	Marche	−2.252	145	FRC1	Bourgogne	−2.580	145
PT15	Algarve	−2.264	146	RO11	Nord-Vest	−2.738	146
ITC2	Valle d'Aosta/Vallée d'Aoste	−2.327	147	ITI3	Marche	−2.752	147
DEG	Thüringen	−2.777	148	RO12	Centru	−2.892	148
DE8	Mecklenburg-Vorpommern	−2.908	149	DE8	Mecklenburg-Vorpommern	−2.944	149
ITF1	Abruzzo	−2.941	150	ITC2	Valle d'Aosta/Vallée d'Aoste	−2.944	150
DE4	Brandenburg	−2.983	151	DEG	Thüringen	−3.161	151
PT16	Centro (PT) (NUTS 2021)	−3.117	152	ITF1	Abruzzo	−3.182	152
RO11	Nord-Vest	−3.204	153	RO42	Vest	−3.281	153
RO12	Centru	−3.276	154	DE4	Brandenburg	−3.290	154
PT11	Norte	−3.434	155	PT11	Norte	−3.493	155
ITG2	Sardegna	−3.434	156	PT16	Centro (PT)	−3.566	156
ITF2	Molise	−3.467	157	ITF2	Molise	−3.793	157
DEE	Sachsen-Anhalt	−3.615	158	DEE	Sachsen-Anhalt	−3.822	158
PT18	Alentejo (NUTS 2021)	−3.872	159	BG33	Severoiztochen	−4.025	159
RO42	Vest	−3.882	160	ITG2	Sardegna	−4.096	160
DE5	Bremen	−4.018	161	DE5	Bremen	−4.235	161
BG33	Severoiztochen	−4.198	162	PT18	Alentejo	−4.264	162
ITF3	Campania	−4.267	163	ITF3	Campania	−4.335	163
ITF5	Basilicata	−4.535	164	RO41	Sud-Vest Oltenia	−4.712	164
ITG1	Sicilia	−4.626	165	RO22	Sud-Est	−4.772	165
ITF4	Puglia	−4.717	166	BG42	Yuzhen tsentralen	−4.822	166
BG32	Severen tsentralen	−4.877	167	RO31	Sud-Muntenia	−4.897	167
RO41	Sud-Vest Oltenia	−4.900	168	ITF5	Basilicata	−4.961	168
BG42	Yuzhen tsentralen	−5.050	169	ITF4	Puglia	−4.961	169
RO22	Sud-Est	−5.117	170	BG32	Severen tsentralen	−4.975	170
RO31	Sud-Muntenia	−5.251	171	RO21	Nord-Est	−5.099	171
RO21	Nord-Est	−5.253	172	ITG1	Sicilia	−5.199	172
BG34	Yugoiztochen	−5.561	173	BG34	Yugoiztochen	−5.464	173
ITF6	Calabria	−6.386	174	BG31	Severozapaden	−6.637	174
BG31	Severozapaden	−6.480	175	ITF6	Calabria	−7.152	175

Table A.2
Scores and rankings for the filtered specific composite index and the spatial composite index obtained through spatial filtering for 175 regions in the European Union in 2022.

Specific Composite Index				Spatial Composite Index			
Nuts ID	Region Name	Score	Rank	Nuts ID	Region	Score	Rank
HU11	Budapest	3.793	1	NL13	Drenthe	5.755	1
NL31	Utrecht	3.724	2	NL32	Noord-Holland	4.549	2
BE10	Région de Bruxelles-Capitale/Brussels Hoofdstedelijk Gewest	3.365	3	NL34	Zeeland	4.344	3
NL12	Friesland (NL)	3.323	4	BE31	Prov. Brabant wallon	3.745	4
CZ01	Praha	3.242	5	FI1C	Etelä-Suomi	3.376	5
DK01	Hovedstaden	3.141	6	NL42	Limburg (NL)	3.320	6
LU00	Luxembourg	2.996	7	FI1B	Helsinki-Uusimaa	3.273	7
ES51	Cataluña	2.885	8	SE21	Småland med öarna	3.097	8
ES30	Comunidad de Madrid	2.830	9	NL21	Overijssel	3.060	9
BE23	Prov. Oost-Vlaanderen	2.800	10	SE11	Stockholm	2.893	10
SE12	Östra Mellansverige	2.728	11	NL22	Gelderland	2.842	11
FRI3	Poitou-Charentes	2.692	12	SE23	Västsverige	2.821	12
IE06	Eastern and Midland	2.645	13	MT00	Malta	2.763	13
NL41	Noord-Brabant	2.508	14	NL11	Groningen	2.713	14
AT13	Wien	2.422	15	DK02	Sjælland	2.679	15
DK04	Midtjylland	2.403	16	BE33	Prov. Liège	2.622	16
PT17	Área Metropolitana de Lisboa	2.351	17	NL23	Flevoland	2.540	17

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Table A.2 (*continued*)

Specific Composite Index				Spatial Composite Index			
Nuts ID	Region Name	Score	Rank	Nuts ID	Region	Score	Rank
RO32	București-Ilfov	2.229	18	DK05	Nordjylland	2.499	18
NL33	Zuid-Holland	1.913	19	DK03	Syddanmark	2.497	19
ES21	País Vasco	1.904	20	FRE1	Nord-Pas de Calais	2.307	20
SE22	Sydsverige	1.805	21	AT11	Burgenland	2.134	21
ITC4	Lombardia	1.738	22	NL33	Zuid-Holland	2.123	22
BE24	Prov. Vlaams-Brabant	1.737	23	FI19	Länsi-Suomi	1.866	23
EE00	Eesti	1.730	24	SE22	Sydsverige	1.844	24
BE25	Prov. West-Vlaanderen	1.642	25	NL41	Noord-Brabant	1.713	25
BE21	Prov. Antwerpen	1.614	26	FI1D	Pohjois- ja Itä-Suomi	1.677	26
SE11	Stockholm	1.557	27	CZ05	Severovýchod	1.352	27
FR10	Ile de France	1.554	28	HU33	Dél-Alföld	1.339	28
NL11	Groningen	1.542	29	NL31	Utrecht (NUTS 2021)	1.218	29
FI1B	Helsinki-Uusimaa	1.532	30	HU12	Pest	1.214	30
ES53	Illes Balears	1.531	31	DK01	Hovedstaden	1.148	31
NL23	Flevoland	1.501	32	HU31	Észak-Magyarország	1.139	32
BE22	Prov. Limburg (BE)	1.500	33	BE24	Prov. Vlaams-Brabant	1.130	33
SI04	Zahodna Slovenija	1.487	34	SE33	Övre Norrland	1.092	34
IE04	Northern and Western	1.480	35	DK04	Midtjylland	1.087	35
SK01	Bratislavský kraj	1.446	36	AT12	Niederösterreich	1.061	36
DE6	Hamburg	1.442	37	FRC2	Franche-Comté	0.940	37
AT31	Oberösterreich	1.429	38	HU21	Közép-Dunántúl	0.853	38
NL22	Gelderland	1.411	39	AT22	Steiermark	0.830	39
FI19	Länsi-Suomi	1.315	40	FRD2	Haute-Normandie	0.813	40
SE31	Norra Mellansverige	1.292	41	FRL0	Provence-Alpes-Côte d'Azur	0.804	41
NL21	Overijssel	1.237	42	SK04	Východné Slovensko	0.798	42
ES52	Comunitat Valenciana	1.235	43	IE05	Southern	0.789	43
ES13	Cantabria	1.198	44	DEF	Schleswig-Holstein	0.779	44
ES62	Región de Murcia	1.142	45	SE31	Norra Mellansverige	0.750	45
RO11	Nord-Vest	1.114	46	BE21	Prov. Antwerpen	0.747	46
RO12	Centru	1.105	47	BE22	Prov. Limburg (BE)	0.747	47
ES24	Aragón	1.089	48	LT02	Vidurio ir vakarų Lietuvos regionas	0.662	48
AT34	Vorarlberg	0.963	49	AT21	Kärnten	0.656	49
ITH2	Provincia Autonoma di Trento	0.960	50	FRH0	Bretagne	0.654	50
ES41	Castilla y León	0.958	51	FR10	Ile de France	0.591	51
BE32	Prov. Hainaut	0.931	52	FRC1	Bourgogne	0.547	52
ES22	Comunidad Foral de Navarra	0.928	53	IE06	Eastern and Midland	0.508	53
FRK1	Auvergne	0.912	54	HU11	Budapest	0.507	54
ES43	Extremadura	0.905	55	BE35	Prov. Namur	0.491	55
FI1D	Pohjois- ja Itä-Suomi	0.878	56	ES23	La Rioja	0.467	56
ES12	Principado de Asturias	0.839	57	BG33	Severoiztochen	0.417	57
FRJ2	Midi-Pyrénées	0.788	58	HU32	Észak-Alföld	0.394	58
LT01	Sostinės regionas	0.787	59	LT01	Sostinės regionas	0.393	59
ITH1	Provincia Autonoma di Bolzano/Bozen	0.760	60	ES24	Aragón	0.391	60
DK02	Sjælland	0.716	61	ES22	Comunidad Foral de Navarra	0.386	61
DE3	Berlin	0.695	62	FRI1	Aquitaine	0.337	62
AT32	Salzburg	0.682	63	CZ01	Praha	0.330	63
FRK2	Rhône-Alpes	0.660	64	CZ02	Střední Čechy	0.330	64
FRG0	Pays de la Loire	0.628	65	LV00	Latvija	0.324	65
FRF1	Alsace	0.607	66	ES52	Comunitat Valenciana	0.283	66
DK03	Syddanmark	0.586	67	ES11	Galicia	0.281	67
SE32	Mellersta Norrland	0.573	68	ES53	Illes Balears	0.276	68
HU12	Pest	0.569	69	FRF2	Champagne-Ardenne	0.274	69
SI03	Vzhodna Slovenija	0.533	70	CZ06	Jihovýchod	0.263	70
DK05	Nordjylland	0.514	71	ES30	Comunidad de Madrid	0.256	71
DE7	Hessen	0.499	72	FRG0	Pays de la Loire	0.250	72
CZ08	Moravskoslezsko	0.493	73	FRK2	Rhône-Alpes	0.241	73
ES61	Andalucía	0.482	74	CY00	Kýpros	0.237	74
FRJ1	Languedoc-Roussillon	0.475	75	HU23	Dél-Dunántúl	0.219	75
AT33	Tirol	0.413	76	SE12	Östra Mellansverige	0.218	76
ITH3	Veneto	0.407	77	ITI4	Lazio	0.155	77
ITC3	Liguria	0.399	78	ES61	Andalucía	0.145	78
LV00	Latvija	0.363	79	FRM0	Corse	0.143	79
HU22	Nyugat-Dunántúl	0.338	80	AT13	Wien	0.137	80
SE23	Västsverige	0.310	81	CZ07	Střední Morava	0.133	81
NL34	Zeeland	0.303	82	FRF3	Lorraine	0.127	82
DEA	Nordrhein-Westfalen	0.260	83	AT33	Tirol	0.108	83
FRI1	Aquitaine	0.260	84	BE34	Prov. Luxembourg (BE)	0.080	84
NL42	Limburg (NL)	0.238	85	DEB	Rheinland-Pfalz	0.058	85
SE33	Övre Norrland	0.209	86	BE25	Prov. West-Vlaanderen	0.053	86
CY00	Kýpros	0.188	87	IE04	Northern and Western	0.040	87
FRL0	Provence-Alpes-Côte d'Azur	0.173	88	SK01	Bratislavský kraj	0.022	88
NL32	Noord-Holland	0.157	89	FRJ1	Languedoc-Roussillon	−0.010	89
DEC	Saarland	0.154	90	BG42	Yuzhen tsentralen	−0.020	90
ES42	Castilla-La Mancha	0.095	91	FRF1	Alsace	−0.022	91

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Table A.2 (*continued*)

Specific Composite Index				Spatial Composite Index			
Nuts ID	Region Name	Score	Rank	Nuts ID	Region	Score	Rank
BE31	Prov. Brabant wallon	0.073	92	HU22	Nyugat-Dunántúl	−0.025	92
BE35	Prov. Namur	0.067	93	EE00	Eesti	−0.032	93
ES23	La Rioja	0.024	94	CZ08	Moravskoslezsko	−0.045	94
ITC2	Valle d'Aosta/Vallée d'Aoste	−0.003	95	ES42	Castilla-La Mancha	−0.046	95
IE05	Southern	−0.003	96	NL12	Friesland (NL)	−0.048	96
HU21	Közép-Dunántúl	−0.026	97	AT32	Salzburg	−0.062	97
CZ04	Severozápad	−0.052	98	DED	Sachsen	−0.088	98
ITH4	Friuli-Venezia Giulia	−0.074	99	SK02	Západné Slovensko	−0.090	99
BE34	Prov. Luxembourg (BE)	−0.138	100	DE3	Berlin	−0.094	100
ES11	Galicia	−0.167	101	ITI3	Marche	−0.119	101
ITF1	Abruzzo	−0.204	102	ES21	País Vasco	−0.172	102
FRD1	Basse-Normandie	−0.211	103	FRB0	Centre — Val de Loire	−0.208	103
CZ02	Střední Čechy	−0.233	104	DE1	Baden-Württemberg	−0.248	104
FI1C	Etelä-Suomi	−0.288	105	CZ03	Jihozápad	−0.256	105
SE21	Småland med öarna	−0.316	106	LU00	Luxembourg	−0.257	106
CZ03	Jihozápad	−0.317	107	DE9	Niedersachsen	−0.293	107
FRH0	Bretagne	−0.319	108	SI04	Zahodna Slovenija	−0.295	108
HU23	Dél-Dunántúl	−0.417	109	DE8	Mecklenburg-Vorpommern	−0.295	109
DEB	Rheinland-Pfalz	−0.423	110	ES62	Región de Murcia	−0.318	110
FRB0	Centre — Val de Loire	−0.450	111	FRE2	Picardie	−0.327	111
FRE2	Picardie	−0.506	112	BG41	Yugozapaden	−0.362	112
CZ06	Jihovýchod	−0.510	113	ES12	Principado de Asturias	−0.393	113
AT12	Niederösterreich	−0.639	114	ES41	Castilla y León	−0.394	114
DE1	Baden-Württemberg	−0.650	115	AT34	Vorarlberg	−0.463	115
ITH5	Emilia-Romagna	−0.689	116	DE2	Bayern	−0.555	116
AT22	Steiermark	−0.711	117	FRD1	Basse-Normandie	−0.556	117
ITF2	Molise	−0.731	118	FRI2	Limousin	−0.556	118
ITC1	Piemonte	−0.796	119	ES13	Cantabria	−0.597	119
RO22	Sud-Est	−0.801	120	BE32	Prov. Hainaut	−0.618	120
SK03	Stredné Slovensko	−0.807	121	BE23	Prov. Oost-Vlaanderen	−0.618	121
AT21	Kärnten	−0.815	122	PT11	Norte	−0.641	122
FRM0	Corse	−0.839	123	ITH5	Emilia-Romagna	−0.648	123
DED	Sachsen	−0.841	124	ITG1	Sicilia	−0.723	124
ITI1	Toscana	−0.949	125	PT16	Centro (PT) (NUTS 2021)	−0.755	125
ITF3	Campania	−0.966	126	ITI1	Toscana	−0.778	126
FRF3	Lorraine	−0.999	127	ITI2	Umbria	−0.791	127
FRI2	Limousin	−1.078	128	ES43	Extremadura	−0.796	128
FRD2	Haute-Normandie	−1.132	129	PT15	Algarve	−0.797	129
DE2	Bayern	−1.153	130	SE32	Mellersta Norrland	−0.811	130
DE9	Niedersachsen	−1.215	131	DEG	Thüringen	−0.818	131
ITI2	Umbria	−1.232	132	BE10	Région de Bruxelles-Capitale/Brussels Hoofdstedelijk Gewest	−0.832	132
DE4	Brandenburg	−1.305	133	ES51	Cataluña	−0.875	133
NL13	Drenthe	−1.305	134	SK03	Stredné Slovensko	−0.903	134
MT00	Malta	−1.366	135	DE7	Hessen	−0.926	135
CZ07	Střední Morava	−1.375	136	FRJ2	Midi-Pyrénées	−0.988	136
BG41	Yugozapaden	−1.396	137	AT31	Oberösterreich	−1.031	137
PT15	Algarve	−1.467	138	DEA	Nordrhein-Westfalen	−1.082	138
FRF2	Champagne-Ardenne	−1.526	139	DEC	Saarland	−1.165	139
HU32	Észak-Alföld	−1.591	140	ITF4	Puglia	−1.194	140
ITG2	Sardegna	−1.627	141	ITH4	Friuli-Venezia Giulia	−1.247	141
DEF	Schleswig-Holstein	−1.645	142	ITC1	Piemonte	−1.309	142
DEE	Sachsen-Anhalt	−1.686	143	DE6	Hamburg	−1.353	143
LT02	Vidurio ir vakarų Lietuvos regionas	−1.726	144	SI03	Vzhodna Slovenija	−1.436	144
BG32	Severen tsentralen	−1.736	145	RO42	Vest	−1.591	145
ITI4	Lazio	−1.746	146	FRK1	Auvergne	−1.603	146
SK02	Západné Slovensko	−1.763	147	DE4	Brandenburg	−1.678	147
BE33	Prov. Liège	−1.791	148	CZ04	Severozápad	−1.685	148
ITF5	Basilicata	−1.874	149	ITH2	Provincia Autonoma di Trento	−1.700	149
FRE1	Nord-Pas de Calais	−1.959	150	PT18	Alentejo (NUTS 2021)	−1.706	150
DEG	Thüringen	−1.960	151	PT17	Área Metropolitana de Lisboa (NUTS 2021)	−1.779	151
DE5	Bremen	−1.968	152	ITG2	Sardegna	−1.807	152
RO31	Sud-Muntenia	−2.075	153	DEE	Sachsen-Anhalt	−1.929	153
FRC2	Franche-Comté	−2.105	154	ITH3	Veneto	−1.959	154
BG34	Yugoiztochen	−2.124	155	ITH1	Provincia Autonoma di Bolzano/Bozen	−1.963	155
ITI3	Marche	−2.133	156	DE5	Bremen	−2.050	156
HU33	Dél-Alföld	−2.133	157	RO41	Sud-Vest Oltenia	−2.131	157
PT18	Alentejo	−2.165	158	ITF6	Calabria	−2.195	158
CZ05	Severovýchod	−2.262	159	ITC3	Liguria	−2.285	159
SK04	Východné Slovensko	−2.266	160	FRI3	Poitou-Charentes	−2.292	160
RO42	Vest	−2.291	161	ITC2	Valle d'Aosta/Vallée d'Aoste	−2.324	161
PT16	Centro (PT)	−2.362	162	RO21	Nord-Est	−2.455	162
HU31	Észak-Magyarország	−2.548	163	RO32	București-Ilfov	−2.520	163
FRC1	Bourgogne	−2.562	164	ITF5	Basilicata	−2.661	164

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Table A.2 (*continued*)

Specific Composite Index				Spatial Composite Index			
Nuts ID	Region Name	Score	Rank	Nuts ID	Region	Score	Rank
DE8	Mecklenburg-Vorpommern	−2.613	165	ITF1	Abruzzo	−2.737	165
RO41	Sud-Vest Oltenia	−2.768	166	ITF2	Molise	−2.737	166
PT11	Norte	−2.793	167	ITC4	Lombardia	−2.737	167
RO21	Nord-Est	−2.798	168	BG31	Severozapaden	−3.094	168
AT11	Burgenland	−2.892	169	BG32	Severen tsentralen	−3.140	169
BG31	Severozapaden	−3.386	170	RO31	Sud-Muntenia	−3.176	170
ITF4	Puglia	−3.523	171	ITF3	Campania	−3.301	171
ITG1	Sicilia	−3.903	172	BG34	Yugoiztochen	−3.437	172
ITF6	Calabria	−4.191	173	RO22	Sud-Est	−4.316	173
BG33	Severoiztochen	−4.615	174	RO11	Nord-Vest	−4.318	174
BG42	Yuzhen tsentralen	−5.031	175	RO12	Centru	−4.381	175

Data availability

Data will be made available on request.

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