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Circular, Cultural and Creative City Index: a Comparison of Indicators-based Methods with a Machine-Learning Approach

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Abstract. Culture, creativity and circularity are driving forces for the transition of cities towards sustainable development models. This contribution proposes a data-driven quantitative methodology to compute cultural performance indices of cities (C4 Index) and thus compare results derived by subjective and objective assessment methods within the case study of the Metropolitan City of Naples. After data processing with Machine-Learning (ML) algorithms, two methods for weighting the indicators were compared: principal component analysis (PCA) and geographically weighted linear combination (WLC) with budget allocation. The results highlight similar trends among higher performance in seaside cities and lower levels in the inner areas, although some divergences between rankings. The proposed methodology was addressed to fill the research gap in comparing results obtained with different aggregation methods, allowing a choice consistent with the decision-making environment.

Keywords: Benchmarking cultural cities, Composite indicator(s), Machine learning, Urban monitoring.
JEL codes: O21, C44, C52.

1. INTRODUCTION

1.1 Conceptual background

Cultural and creative cities deliver spatial, economic, and social benefits to their citizens by reinforcing the physical and digital environment, human capital, social networks, institutions, and regulatory frameworks. They host Cultural and Creative Industries (CCIs,) which contribute to 3% of the global GDP. However, it has been estimated that higher-income cities do not necessarily correlate with the higher number of people employed in cultural jobs, as opposed to lower-GDP cities, whereas about 10% of people are employed in creative and cultural sectors (Solutions for Youth Employment (S4YE), 2020, p.4). UNESCO and World Bank (2021) defined creative cities as the "*places where culture, arts, cultural and creative industries (CCIs), diverse expressions, and imagination flourish and contribute to sustainable urban* *development and inclusive growth"* (UNESCO and World Bank, 2021, p. 8). These cities are also rich in intrinsic values (Fusco Girard et al., 2019; Cerreta et al., 2022) and cultural capital, which embraces all the *"Cultural goods serving as capital assets that, in combination with other inputs, contribute to the production of other cultural goods and services, jobs, and overall well-being of local communities"* (UNESCO and World Bank, 2021, p. 8).

The Circular Economy (CE) model, based on the principle that nothing can be considered 'waste' in nature, and everything can become a 'resource', aims to make sustainable development principles operative. The United Nations introduced into the New Urban Agenda (United Nations, 2016), the final document of the Habitat III conference, the notion of CE as a general development model that impacts natural and social contexts while generating new economic wealth. This stimulates an indefinite extension of the resources' life and the values of their use and promotes cooperation circuits among stakeholders. CE can be recognized as a general development model, capable of transforming linear urban metabolism into a new circular urban metabolism in which input and output flows are 'closed'. Therefore, the concept of circular processes can be applied not only to the flows of matter and nature (zero-waste approach), but also to broader issues, such as economic models of investment/ re-investment, or political systems of multi-level participatory governance. CE can and must be considered the engine of strategic planning development policies, as highlighted by strategies and measures adopted by the European Commission to stimulate the European path towards the CE (European Commission, 2015). The sectoral approach of waste cycle management with which the CE is associated must therefore be considered an approach to the global organization of the city, its economy, its social system, and its governance to improve urban productivity.

The Circular City Model incorporates the principles of the CE, establishing a regenerative and accessible urban system. The closure of the cycles is, in fact, a fundamental concept at the basis of this model (Ellen MacArthur Foundation, 2015a). In addition, flexibility in the design of the built environment, collaborative/cooperative behaviour, integration and recycling, and digital technology support for the circularization of processes are key concepts of the Circular City (Ellen MacArthur Foundation, 2015b; World Economic Forum, 2018).

The European Circular City Models are focusing their strategies and actions mainly on the sectors where the flows of materials are more consistent. Circular city models and, in particular, the experiences of European circular cities have highlighted the need to focus on "immaterial" flows relating to the human and cultural dimension (Fusco Girard and Nocca, 2019). The relationship between the CE and job creation is a key factor, highlighting the contribution of this model to improving the quality of life. Employment is also a key word linked to the concept of well-being: it contributes to making people 'feel good', not only for the economic aspects, but because it allows people to be in relationships with each other. Therefore, the challenge is to consider the cultural 'waste' as potential resources to favour new approaches to sustainable urban regeneration and thus to encourage autopoietic systems, which is capable of self-regenerating. In particular, the cultural challenges for the transition to the circular city model concern norms, ideas, customs, and social behaviour of people (Williams, 2019).

In this perspective, there is the need to determine evaluation approaches and tools, with particular concern on indicators, which represent one of the relevant tools for structuring an evaluation approach, allowing both to analyse existing phenomena and to evaluate impacts. Indicators assessing the circular economy's benefits are necessary to support the transition and implementation towards this new urban development model, demonstrate the multidimensional benefits of the circular economy and convince policymakers, communities, businesses, etc., that investing in the CE is worthwhile. Indicators-based frameworks, together with institutional change, can be the driving forces for transitions to unfold in cities. Indeed, the former helps circular cities to evidence advancements towards urban sustainability, while the latter guarantee the operational level of transitions (Cerreta et al., 2021; Ehnert et al., 2018; Paoli et al., 2022).

This article focuses on monitoring and evaluating specific urban sustainability indicators linked to culture, creativity, and circularity. Multiple worldwide institutions have recognised the importance of indicators as tools to investigate different facets of culture, especially those linked to the social-economic development of cities (UNESCO, 2014). Nevertheless, to the best of our knowledge, culture has not been formally recognised as crucial for urban economic development up to 2009, when UNESCO released the Framework for Cultural Statistics (FCS) with a corpus of 460 indicators selected by previous international classifications – e.g. the Harmonised Commodity Description (HS) and Coding System, the Central Product Classification (CPC), the International Standard Industrial Classification (ISIC) – aimed to measure the economic dimension of cultural activities and products (Ortega-Villa and Ley-Garcia, 2017). In 2015, the Sustainable Development Goals (SDGs) highlighted the culture's contribution to sustainable development by attaching the cultural issue to education (target 4.7), the promotion of local culture through sustainable forms of tourism (target 8.9), and the safeguarding of cultural heritage (target 11.4). The SDGs contain a set of 231 performance indicators to measure the progress in achieving targets (United Nations, 2015). However, these indicators are not always available for all the world countries and, for this reason, knowledge tools for data disaggregation (Asian Development Bank, 2021) and guidelines for indicators proxy identification (Economic and Social Council, 2019) have been recently emerging.

The need to measure material and non-material factors enabling a cultural and creative city, by means of variables and indicators, was stressed by the international scientific literature, global organisations like UNESCO and the World Bank, European research centres, i.e. JRC, and, at the local level, Italian Institutes for National Statistics (ISTAT) and the National Council for Economy and Labour (CNEL). The Organisation for Economic Co-operation and Development (OECD, 2008) designed methodological guidelines for constructing indicators and composite indicators concerned with the quality of information and rigorous procedures to check data consistency and affordability. This methodology was followed by many data analysts, practitioners, and researchers to support policy-makers and institutions at the European level. In particular, composite indicators express the complexity of different phenomena by assessing multidimensional issues at once, thus providing cross-cutting indications and a "big picture" (Galli et al., 2018, p. 161). Through the global creativity index, Florida et al. (2015) aimed to rank worldwide nations according to the three main variables of economic development: technology, talent, and tolerance. To derive their index, these authors have aggregated different qualitative metrics and quantitative indicators which explore, i.e.: the number of patents per capita, GDP invested in R&D sectors, the share of adults with higher levels of education, and people's perceptions about the level of liveability and tolerance against minorities. Furthermore, Florida et al. (2013) have analysed the role of human capital in citizens' well-being by aggregating statistics at the metropolitan level and using variables as proxies to forecast economic performance and community fulfilment (Florida, 2013, p. 614). However, in their investigation, the authors do not explicitly mention the concept of culture, but indeed they consider it as a positive externality produced by the human capital in terms of better education, more spending on cultural amenities, and higher openness and tolerance in a community (Florida, 2013, p. 624). In Italy, creativity – recognised as economic innovation – has been internalised into BES (Istat, 2015), a monitoring tool of Italian cities which collects performance indicators related to 12 domains of well-being at national levels. Nevertheless, the cultural issues analysed in this tool relate only to cultural heritage physical features, and culture is conceived as an education facet.

One of the relevant aims linking most of these studies and projects has been to benchmark cities' cultural performance for tailoring fit-for-purpose policies or monitoring. The most frequently used approaches to point out this goal include descriptive statistics and mathematics, i.e.: Linear regressions and explanatory variables models, data envelopment analysis (DEA), principal components analysis (PCA), and participatory methods such as the multi-criteria decision analysis (MCDA). To select the fit-for-purpose assessment method, indeed, particular attention must be paid to the choice of the indicators weighting system and aggregation procedures (Garcia-Bernabeu et al., 2020), which can be substantially based on the upper two mentioned categories: statistical aggregation rules or participatory approaches (Nardo et al., 2005). By way of example, the Cultural and Creative City Monitor (CCCM) is a monitoring tool of 155 European cities – selected for their active engagement in the promotion of culture and creativity (Van Puyenbroeck et al., 2021, p.584) – with the ambition of a more informed and strategic decision-making process toward the management of cultural and creative assets of cities. CCCM experimented with Equal Weighting (EW) assigned by experts to measure the degree of relevance of each dimension and domain in which cultural and creative facets have been clustered (Montalto et al., 2019). On the contrary, De Jorge-Moreno and De Jorge-Huertas (2020) proposed an alternative approach to the equal weighting of CCCM's variables by implementing DEA with a metafrontiers analysis to measure the impact of each variable in the determination of a cultural and creative efficiency index (IEC3) at the level of cities and groups of cities (De Jorge-Moreno and De Jorge-Huertas, 2020).

In the field of Operative Research and MCDA, among several experimentations to derive composite indicators that rank cities in terms of urban sustainability (Carli et al., 2018; Della Spina, 2019; Giffinger et al., 2007; Munda, 2016; Munda and Saisana, 2010; Phillis et al., 2017; Torre et al., 2017; Zhang et al., 2016), culture has been not included or, often, categorised as an economics or well-being sub-domain. In these studies, the most recurring indicators to measure Country or City cultural level – and creativity conceived as innovation – relate to GDP invested for R&D or education, technological patents, high-education expenditure, and people with education higher than a master's degree. In particular, Corrente et al. (2021) implemented a Stochastic Multi-Criteria Acceptability Analysis (SMAA) combined with the PROMETHEE method to rank 20 European cities in the 2012-2015 timespan. Although this contribution was particularly innovative for different reasons – i.e. the methodological accuracy, robust recommendations concerning the adopted sustainability criteria, the possibility to rank-order the cities concurrently at a comprehensive level and according to each macro-criterion – the authors adopted 9 elementary criteria in their analysis by including the amount of waste as a unique indicator of Circular Economy and excluding cultural issues (Corrente et al., 2021). With a different approach, Ferrara and Nisticò (2015) calculated a composite index of well-being at the city and regional scale with PCA by representing the results in spatial GIS maps. Also, in this study, the cultural issue has been analysed as a subdomain of well-being by means of a regression-based decomposition method to measure the contribution of each partial indicator (Ferrara and Nisticò, 2015, p. 377).

This contribution was addressed to fill conceptual and methodological gaps detected in the literature. On the one hand, culture, creativity, and circularity have been considered comprehensive domains – and not as sub-domains of well-being, education, social dimension, or economy – by exploring the dimensions in which they can be declined, and the variables needed to understand each dimension. On the other hand, the comparison of cultural indices, derived by different aggregation procedures and methods, has been explored to identify a suitable methodological approach and fill a gap found in scientific literature.

The innovative contributions of the proposed methodology are aimed at: (i) the inclusion of small and medium-sized cities (with a population above 50,000 inhabitants) within the scoreboard, unlike other monitoring tools that generally only estimate large European cities; (ii) the selection of CE indicators to enrich the analysis framework, in the belief that cultural 'waste' can become a resource if managed correctly; (iii) the use of open-source data and ML techniques that can be easily replicated in other contexts; (iv) the balance of subjective and objective weightings of indicators which, in this study, represent the proxy variables for measuring indeterminate concepts such as circularity, culture and creativity.

1.2 Research questions and purposes

Considering the identified gaps, the main research questions were addressed: (RQ1) How to expand the methodology for assessing composite indicators to benchmark cities in circular, cultural, and creative terms?; (RQ2) How to effectively produce performance indices through subjective and objective assessment methods to better inform decision-making?

The purpose of this work is not to guide users and policy-makers to choose the best benchmarking method, but rather to open a debate on the potential of comparisons between subjective and objective weighting to scoreboard the cities, exploring the reason why the results change depending on the method used, and how they can be implemented in the monitoring of fit-for-purpose policies and recommendations for cultural cities policies and strategies. Therefore, the primary aim of this work is to understand the meaning of the differences between subjective and objective dimensions of policy-making to guide decision-makers toward more informed and aware choices. To do so, a data-driven quantitative methodology was designed to compute cultural performance indices of cities and, thus, to compare results derived by subjective and objective assessment methods.

The Metropolitan City of Naples (Italy) was chosen as a testing area because it featured by large, small, and medium-sized cities that differ significantly in social-economic conditions, cultural features, and morphological characteristics.

2. MATERIALS AND METHODS

Starting from the declared goal, the proposed data-driven methodology enforced two methods for weighting indicators, which made it possible to create composite indices and compare them in the last methodological step. A method based on principal components analysis (PCA) allowed objective weights to be determined through statistical and mathematical aggregation procedures. The other assessment method based on the joint application of a geographically weighted linear combination (WLC) with a budget allocation method has allowed experts' preferences to be transferred from literature and cultural composite indicators to be implemented. Henceforth, we refer to the former as the *PCA-driven* method and the latter as the *Expert-driven* method.

The proposed methodology was tested on the Metropolitan City of Naples' 92 urban districts – referred to as municipalities and corresponding to the NUTS3 classification (Eurostat, 2015) – and it can be summarised into 5 main steps (Figure 1):

- Step 1. *Theoretical and operative background*;
- Step 2. *Knowledge model*;
- Step 3. *Data processing methods*;

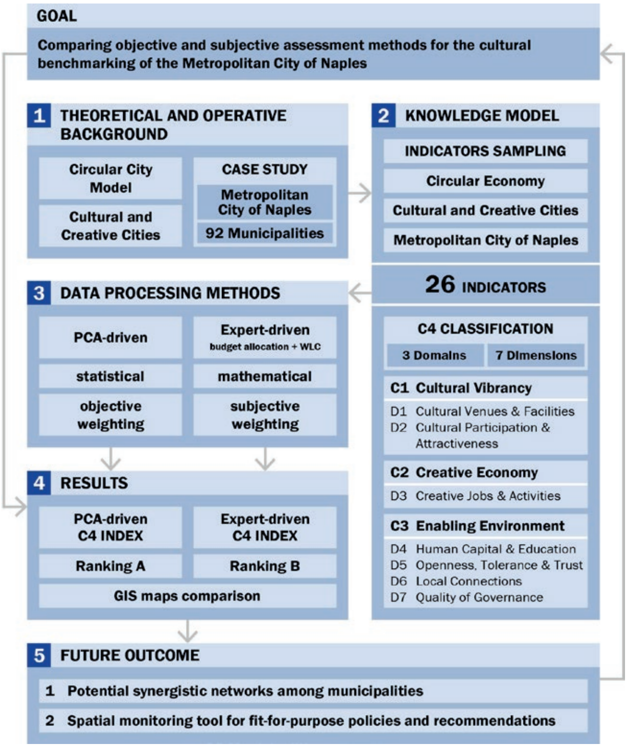

Figure 1. Graphical abstract with the 5-steps data-driven methodology.

- Step 4. *Results*;
- Step 5. *Future outcome.*

In Step 1, the conceptual framework to determine the criteria for indicator selection has been reviewed from the scientific literature. The results of this step revealed that culture had been generally considered a sub-domain of well-being, economy, education, or social category. However, except for the CCCM, few studies have treated culture as a comprehensive category. At the same, the authors have mostly intended creativity as innovation in technology transfer and research (Dubickis and Gaile-Sarkane, 2015); while circularity has been expressing a variable to measure the transition towards a Circular Economy (Cheshire, 2021; Ellen MacArthur Foundation, 2015b), particularly focussed on waste management and closing the loop in technological processes (Bridgens et al., 2019).

In Step 2, a set of 26 variables with related indicators has been selected, considering the former as the key concept to be explored to give consistency to the output, and the latter as the way the variables were measured, including the indicator's direction[1].

[1] For the sake of brevity, the unscaled and standardised datasets are not shown, but they are available from the authors on request at this link: https://bit.ly/3AZYSDY.

In Step 3, statistical procedures for data harmonisation and methods for data comparison have been elaborated. Some correlation analyses were useful in reducing data dimensionality passing from a starting dataset of 70 variables to 26 selected ones. At the same time, the KMO test allowed us to choose the most appropriate method to process the dataset between PCA and Factor Analysis. This study implemented an ML algorithm to perform statistical tests, data harmonisation, and Principal Components Analysis (PCA). Regarding the computational steps, the authors have manipulated, and adjusted to their objectives, part of the python code released by Bucherie et al. (2022) to produce a multidimensional index of vulnerability to flooding (Bucherie et al., 2022, *supplementary materials*). These preparatory steps allowed the implementation of the *Expert-driven* and *PCA-driven* methods to provide the cities' indices.

Step 4 allowed us to interpret the results of the comparison between the two experimented methods understanding the similarities and differences within the obtained results. Furthermore, the spatial visualisation of results in a GIS environment allowed the indices to be represented by choropleth maps and the indices' differences for each city to be better highlighted.

Step 5 concerned the research outcomes and further pathways of development.

The article remainder proceeds as follows: Subsections 2.1-2.4 focus on the knowledge model (step 2) related to criteria for indicators selection, and data processing methods (step 3) referring to data harmonisation, *Expert-driven* method, and *PCA-driven* method; Section 3 highlights the threefold results obtained by the application of the proposed methodology to a case study (step 4); in particular, Sub-section 3.1 shows Expert-driven method results, while Sub-section 3.2 presents the results from the application of PCA-driven method, and Sub-section 3.3 highlights the comparison of city rankings obtained from two above mentioned methods; Section 4 discusses results while Section 5 draws conclusions about the research innovative contribution and follow-ups (step 5).

2.1 Knowledge model: an Operative framework for the selection and processing of cultural indicators for the Metropolitan City of Naples

The indicators selection analyses the intersection and comparison between Circular Cities indicators and Cultural and Creative Cities indicators identified by the JRC Monitor, combining them with the available indicators of the Metropolitan City of Naples (Figure 2). In this way, a set of 70 indicators was generated, capable of

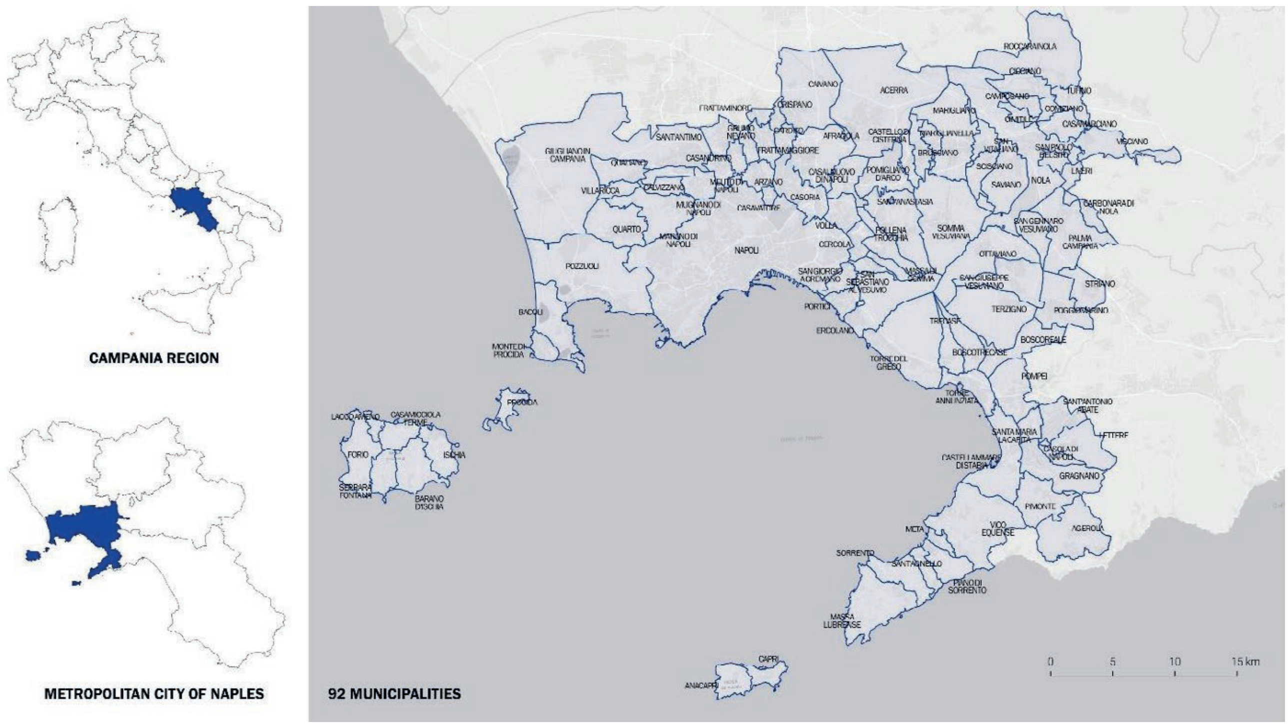

Figure 2. The study area.

describing the cultural specificities of 92 municipalities according to the three main categories of Sustainability: environmental indicators, economic indicators, and social indicators.

The criteria for selecting the indicators included, with reference to the data set construction manuals: relevance, analytical soundness, timeliness and accessibility.

Since there are multiple combinations of reliable indicators, the data selection process might be extremely subjective (OECD, 2008, p. 23). The core-set of 26 indicators was thus assembled through a series of statistical tests and, specifically, multivariate analysis (i.e. Cronbach Coefficient Alpha) performed on different combinations of indicators. The selection considered the indicators identified by the mentioned sector studies on the cultural benchmarking of cities (see 1.1), according to the identified selection criteria. The final set, shown in Table 1, is the result of the elimination of indicators that show too high co-dependencies between each other or that are not relevant to the context according to a critical choice from literature and used sources.

Therefore, it was possible to develop a spatial database of the municipalities, visualising it in a GIS environment, a geographic information system capable of spatially localising and returning information relating to the territory.

The proposed classification framework represents a reinterpretation of the CCCM one, including the 3 main domains and 7 dimensions. The 3 domains are:

- C1. Cultural Vibrancy: culture expressed in terms of places and participation;
- C2. Creative Economy: employment in the cultural and creative economic sector;
- C3. Enabling Environment: the resources that make cities fertile ground for triggering cultural processes.

The 7 dimensions are the following:

- D1. Cultural Venues & Facilities: the presence of places and infrastructures linked to culture;
- D2. Cultural Participation & Attractiveness: the ability of cities to attract people into their cultural life;
- D3. Creative Jobs & Activities: businesses and non-profit organizations in the cultural and creative sector;
- D4. Human Capital & Education: the number of young graduates and, in contrast, early school leaving;
- D5. Openness, Tolerance & Trust: the presence of different cultures and social participation;
- D6. Local Connections: the public and private mobility system;
- D7. Quality of Governance: the investments of municipalities in culture.

Table 1. The indicators set.

Domains	Dimensions	Indicators (i)	ID	Source	U.M.	KMO
Cultural Vibrancy	Cultural Venues & Facilities	Museums, monuments and archaeological areas	01	ISTAT	n	0.81
		Architectural heritage	02	ISTAT	n	0.87
		Archaeological heritage	03	ISTAT	n	0.60
		Libraries	04	Campania Region	n	0.56
		Theaters	05	teatri.it	n	0.81
		Cinema screens	06	SIAE	n	0.48
		Entertainment and cinema organizations	07	Campania Region	n	0.69
		Parishes	08	italia.indettaglio.it	n	0.56
	Cultural Participation & Attractiveness	Visitors to museums, monuments and archaeological areas	09	ISTAT	n	0.45
		Entrances to cinemas	10	SIAE	n	0.30
		Cultural events	11	Authors' processing of MiBACT and Campania Region data	n	0.63
		Hotel accommodation rate	12	Authors' processing of ISTAT data	n	0.69
		Non-hotel accommodation rate	13	Authors' processing of ISTAT data	n	0.66
Creative Economy	Creative Jobs & Activities	Incidence of cultural and creative enterprises	14	ISTAT	%	0.80
		Incidence of employees of cultural and creative enterprises	15	ISTAT	%	0.67
		Incidence of cultural and creative non-profit organizations	16	ISTAT	%	0.76
Enabling Environment	Human Capital & Education	Incidence of young people with university education	17	ISTAT	%	0.65
		Early exit from the education and training system	18	ISTAT	%	0.76
	Openness, Tolerance & Trust	Social participation index	19	ISTAT	%	0.71
		Incidence of foreign residents	20	ISTAT	%	0.45
	Local Connections	Railway stations density index	21	Authors' processing of OpenStreetMap data	n	0.67
		Bus stop density index	22	OpenStreetMap	n	0.43
		Vehicle fleet density index	23	comuni-italiani.it	n	0.75
	Quality of Governance	Per capita expenditure for the enhancement of cultural heritage and activities	24	openpolis	€	0.61
		Per capita expenditure on tourism	25	openpolis	€	0.72
		Per capita expenditure on sports and leisure activities	26	openpolis	€	0.66

All indicators have been recalculated as the expression of a ratio: indicators 01-13 and 23 as the ratio on the total resident population, per 1000 inhabitants; indicators 14-18 as the percentage ratio on the total of the reference entity of the indicator; indicators 19-20 as the percentage ratio on the total resident population; indicators 21-22 as the ratio on the municipal area per 100 sq. km of the area; indicator 24-26 as the ratio on the total resident population.

This method allowed the cultural performance of cities to be expressed in per capita terms and municipalities which are different in terms of surface area and population to be compared according to equal parameters. Therefore, if the CCCM allows the comparison among large European cities, the proposed framework aims to investigate the comparison in cultural terms among cities belonging to the same territorial body, which therefore have close geographical, but also social and, therefore, cultural ties.

Data for this study were extracted entirely by open-source databases in the chronological range 2015-2019, and they refer to: ISTAT, Campania Region, SIAE, Italian statistics (italiaindettaglio.it and openpolis), OpenStreetMap for geographical crowdsourced data, and MiBACT (now MIC).

2.2 Statistical tests and data harmonisation

Data cleaning and standardisation are essential operations that must be performed to reduce statistical errors in calculations and make data comparable. This was done by applying ML algorithms to data processing. ML is a type of artificial intelligence (AI) that uses algorithms to analyse data and make predictions based on the patterns it finds. It enables practitioners to automate complex data processing tasks and make more accurate decisions faster. ML can take advantage of larger datasets with more variables than traditional econometric models, allowing for more complex relationships to be explored. In this study, it has been used to detect anomalies in data that may be difficult to detect using traditional methods.

The indicators listed in Table 1 were normalised and transformed to establish the same preferred direction in terms of indicator values, and then standardised to a set of z-values with a mean of zero and a standard deviation of one. Such standardisation makes the variables observable and comparable and removes the dependencies on the measurement scale (Wang, 2009, p. 1).

Two statistical tests helped us choose the best-fit approach to construct the composite index of cities: the correlation analysis and the Kaiser-Meyer-Olkin (KMO) test. First, the correlation analysis helped us to determine the dependencies between the data, while the KMO test allowed us to determine whether the factor analysis was appropriate (Dziuban and Shirkey, 1974).

Correlation analysis aims to calculate correlation coefficients, representing the relationships among variables in a dataset ranging from -1 to 1. At the extremes, the coefficient expresses a completely negative or positive linear relationship, while the value 0 excludes relationships among variables (Dodge, 2008, p. 115). Figure 3 shows a symmetrical and square matrix – referred to as the correlogram – with the 26 standardised indicators on the axes and the correlation coefficients on the cross. The lighter the colour of the cell, the stronger the positive correlation and vice versa. It highlights that, although most indicators show a positive correlation, the overall values are not very high (Figure 3). An exception is the coefficient of 0.81, which indicates the correlation between i03 (Archaeological heritage) and i09 (Visitors to museums, monuments, and archaeological areas). In general, i25 (Per capita expenditure on tourism) has a correlation of up to 0.6 with all other variables six times, namely: i01 (Museums, monuments and archaeological areas) with 0.71; i02 (Architectural heritage) with 0.61; i05 (Theatres) with 0.64; i11 (Cultural events); i12 (Hotel accommodation rate) with 0.73; i13 (Non-hotel accommodation rate) with 0.74.

The indicators listed with the highest correlation are all related to resources and facilities associated with tourism expenditure by cities. It is also noticeable that i18 (Early exit from the education and training system) is negatively correlated with all the other indicators, as is i23 (Vehicle fleet density index). However, the correlation coefficients are not relevant, except for the record value of 0.68, which is the correlation between i18 and i17 (Incidence of young people with university education).

The KMO is a statistical test to measure sampling adequacy for factor analysis (Kaiser, 1970, p. 404) by determining it using a semantic rating scale from *unacceptable* to *marvellous* (Kaiser and Rice, 1974, p. 112) about a threshold that should be above 0.8 to be acceptable in a standardised range of 0-1. However, as can be seen in Table 2, the KMO results indicate that the factor analysis cannot be justified, as only four indicators with scores up to 0.8 are classified as *meritorious*, while five indicators with scores up to 0.7 are classified as *middling*. Furthermore, the mean value of the entire data set is 0.67, which is considered *mediocre* on the KMO scale.

Therefore, we decided to exclude factor analysis to weigh the indicators to derive the final index in favour of PCA.

2.3 Principal Component Analysis (PCA)

PCA is commonly used to reduce the complexity of large datasets and has the twofold objective of eliminating correlation among variables and identifying the variables with the highest eigenvalues, i.e. those with high informational relevance. Unlike factor analysis, PCA is not used for data reduction and preserves the information because the number of components is the same as that of the original variables (Wang, 2009, p. 2).

Table 3 shows the results of PCA using three metrics: the percentage of explained variance, the percentage of cumulative explained variance, and the eigenvalues of the 26 principal components. The same results are represented through a graph in Figure 4. The generalized equation to produce the aggregated final index follows:

$$PCAdriven\ index=\sum_{i=1}^{n}(\eta^2\times PC_{ki}) \tag{1}$$

in which η^2 is the explained variance belonging to the variables of the dataset, while PC_{ki} the eigenvalues attached to the Principal Components. In this analysis, the final index has been calculated using the eigenvalue k = 1 only since it shows the highest score compared to the other components with a relevant deviation

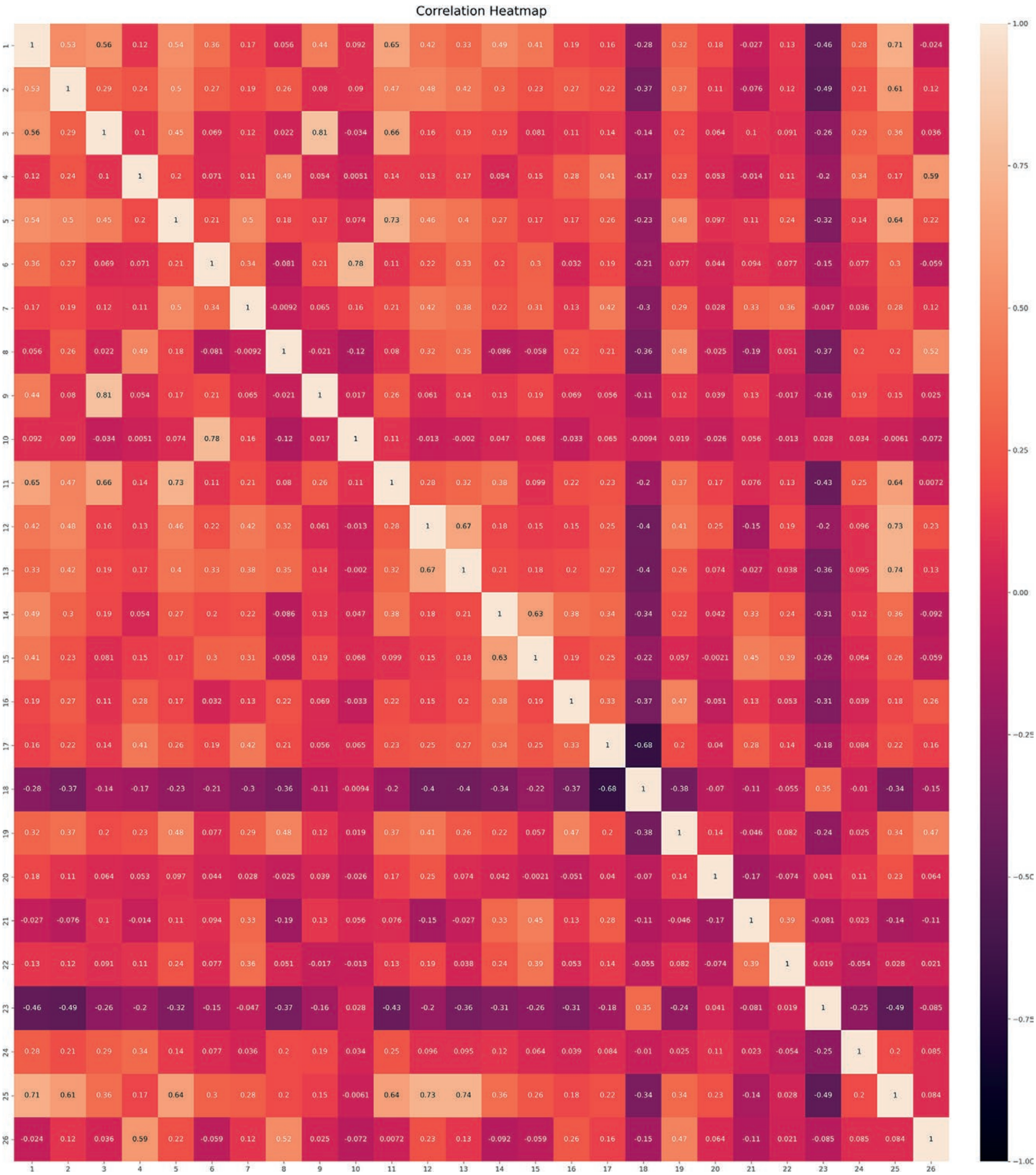

Figure 3. The correlogram – or matrix of correlation coefficients – represents the co-dependencies among the variables in a range between -1 and 1.

between the first (6.948451) and the second (2.732930) components.

The results obtained in this way are an alternative to equal weighting and they can be compared with the out-

Table 2. The Kaiser-Meyer-Olkin (KMO) scores.

ID	KMO	ID	KMO	ID	KMO
01	0.81	10	0.30	19	0.71
02	0.87	11	0.63	20	0.45
03	0.60	12	0.69	21	0.67
04	0.56	13	0.66	22	0.43
05	0.81	14	0.80	23	0.75
06	0.48	15	0.67	24	0.61
07	0.69	16	0.76	25	0.72
08	0.56	17	0.65	26	0.66
09	0.45	18	0.76	**Mean**	**0.67**

put of the *Expert-driven* method, which is shown in the next section (2.4).

2.4 Budget Allocation and Weighted Linear Combination (WLC)

It was required to give each indicator, dimension and domain a weight in order to build the scores achieved by the municipalities that define the partial, aggregated, and global indices. Therefore, the weights created for the framework created by the JRC were considered. Table 4 shows the weights determined using the Budget Allocation Method, in which a group of experts were given a sum of n points to allocate among the dimensions and domains, giving more points to those whose significance was intended to be stressed.

The scores that each municipality earned for dimensions, domains and globally were computed starting with the weights allocated to the indicators in an arithmetic manner. The Weighted Linear Combination, a spatial Multi-Criteria approach, was thus used to calculate the indices. This algorithm is provided in the QGIS software through the *geoWeightedSum* algorithm. The values obtained through the weighted sum algorithm allow drawing a map that returns the geography of the scores on a chromatic scale. Lastly, the indicators have been suitably maximized or minimized (i.e. i18 and i23) according to the resilience or the vulnerability expressed by them.

$$Experdriven\ index = \sum_{j=1}^{n} w_j \times v(x_{kj}) \quad (2)$$

Where k is used to indicate the municipality; $v(x_{kj})$ is the value of the kth alternative with respect to the jth attribute (indicator) and w_j is the expert weight.

Table 3. Percentage of Explained variance, Cumulative percentage of variance and eigenvalues attached to the 26 Principal Components (PC).

PC	% Explained variance (η^2)	Cumulative explained variance (%)	Eigenvalues
1	0.264343	0.264343	6.948451
2	0.103970	0.368313	2.732930
3	0.089567	0.457880	2.354336
4	0.072339	0.530219	1.901484
5	0.060189	0.590409	1.582129
6	0.054612	0.645022	1.435540
7	0.045660	0.690682	1.200219
8	0.043227	0.733910	1.136270
9	0.041040	0.774951	1.078787
10	0.036272	0.811223	0.953437
11	0.027007	0.838231	0.709913
12	0.024615	0.862846	0.647033
13	0.022799	0.885645	0.599293
14	0.019811	0.905456	0.520751
15	0.018428	0.923885	0.484399
16	0.014292	0.938178	0.375701
17	0.012237	0.950416	0.321684
18	0.010589	0.961005	0.278349
19	0.008324	0.969329	0.218803
20	0.007902	0.977232	0.207723
21	0.006571	0.983803	0.172724
22	0.005501	0.989305	0.144622
23	0.005374	0.994679	0.141269
24	0.002197	0.996877	0.057773
25	0.001603	0.998480	0.042152
26	0.001519	1.000000	0.039928

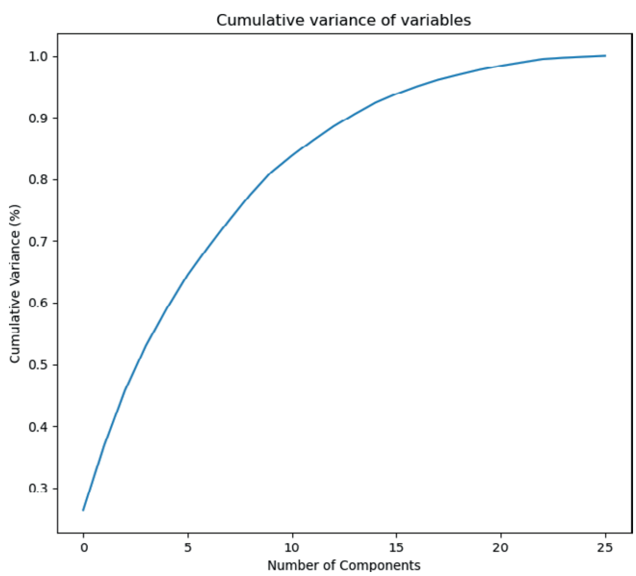

Figure 4. The cumulative variance of variables.

Table 4. Weights matrix.

Domains		Weights	Dimensions		Weights	Indicators	Weights	MAX/MIN
C1	Cultural Vibrancy	40,00%	D1	Cultural Venues & Facilities	50,00%	01	12,50%	MAX
						02	12,50%	MAX
						03	12,50%	MAX
						04	12,50%	MAX
						05	12,50%	MAX
						06	12,50%	MAX
						07	12,50%	MAX
						08	12,50%	MAX
			D2	Cultural Participation & Attractiveness	50,00%	09	20,00%	MAX
						10	20,00%	MAX
						11	20,00%	MAX
						12	20,00%	MAX
						13	20,00%	MAX
C2	Creative Economy	40,00%	D3	Creative Jobs & Activities	100,00%	14	33,33%	MAX
						15	33,33%	MAX
						16	33,33%	MAX
C3	Enabling Environment	20,00%	D4	Human Capital & Education	40,00%	17	50,00%	MAX
						18	50,00%	MIN
			D5	Openness, Tolerance & Trust	40,00%	19	50,00%	MAX
						20	50,00%	MAX
			D6	Local Connections	15,00%	21	33,33%	MAX
						22	33,33%	MAX
						23	33,33%	MIN
			D7	Quality of Governance	5,00%	24	33,33%	MAX
						25	33,33%	MAX
						26	33,33%	MAX

3. RESULTS

3.1 PCA-driven index

Table 5 highlights the partial results of PCA that show the variance explained by each indicator on the first nine principal components (PC), which were reported since their eigenvalues score with values up to 1, following the approach proposed by Filmer and Pritchett (2001) and replicated by Bucherie et al. (2022).

It can be noticed that i25 (Per capita expenditure on tourism) shows the highest absolute load on the first principal component, confirming its relevance within the entire dataset. Furthermore, all the loadings factors on the first component have the same positive direction, except for i23 (Vehicle fleet density index), which does not seem to correlate with all the other variables. In the second and third positions, the most relevant variables on the same principal components are i01 (Museums, monuments and archaeological areas) and i05 (Theatres), scoring respectively 0.286 and 0.281, which are close to the values of i02 (Architectural heritage) and i11 (Cultural events). The above-mentioned are the variables that most contributed to the final PCA-driven ranking. It can be confirmed by comparing these results with table 4, where Capri and Sorrento take first place for tourism, architecture, and cultural events. They are followed by Anacapri and Pompei, which, although at different levels, supply museums and very relevant archaeological areas.

3.2 Expert-driven index

Starting from the scores of Dimensions and Domains, it was possible to derive the Circular, Cultural and Creative City Index (C4I), specifically obtained as a weighted average of the aggregate indices of the 3 Domains. In this average, Cultural Vibrancy and Creative Economy have double the weight of Enabling Envi-

Table 5. Loading factors of indicators associated with each principal component, showing the first nine components with the first three highest variables per each component (in bold).

Indicators	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
i01	**0.286**	-0.161	-0.239	0.039	-0.008	-0.099	0.068	-0.032	0.109
i02	0.266	0.051	-0.086	-0.097	-0.039	-0.156	0.145	-0.162	-0.014
i03	0.201	-0.137	-0.318	**0.331**	0.122	0.218	-0.217	0.095	-0.114
i04	0.146	**0.267**	0.170	0.184	**0.335**	0.040	**0.309**	0.141	0.092
i05	**0.281**	-0.020	-0.083	-0.025	-0.072	0.324	0.039	-0.251	-0.012
i06	0.149	-0.240	0.064	-0.387	**0.444**	-0.079	-0.024	-0.032	-0.038
i07	0.187	-0.126	0.266	-0.172	-0.036	**0.393**	-0.054	0.082	-0.079
i08	0.141	**0.431**	0.092	0.073	0.101	-0.051	0.103	-0.008	-0.225
i09	0.131	-0.172	-0.238	**0.301**	0.251	0.131	-0.307	0.246	-0.144
i10	0.041	-0.208	0.057	-0.354	**0.546**	-0.034	-0.046	-0.253	0.070
i11	0.268	-0.093	-0.245	0.115	-0.050	0.110	-0.020	-0.232	0.095
i12	0.252	0.134	-0.021	-0.308	-0.207	0.142	0.034	0.182	-0.062
i13	0.249	0.088	-0.013	-0.258	-0.124	-0.040	-0.018	0.212	-0.344
i14	0.204	-0.252	0.150	0.134	-0.168	-0.270	0.049	-0.058	**0.272**
i15	0.163	-0.292	0.250	0.097	-0.070	-0.154	0.275	0.092	0.083
i16	0.165	0.112	0.208	0.201	-0.012	-0.236	-0.250	-0.283	0.184
i17	0.192	0.017	**0.333**	0.051	0.069	-0.048	-0.246	**0.332**	0.061
i18	0.220	0.085	0.229	-0.034	-0.053	-0.222	-0.391	0.244	-0.028
i19	0.220	0.231	0.067	0.031	-0.005	0.140	-0.239	-0.358	0.210
i20	0.066	0.058	-0.163	-0.146	-0.062	0.098	0.030	**0.345**	**0.705**
i21	0.048	-0.318	**0.332**	**0.251**	-0.017	0.113	0.028	0.014	-0.110
i22	0.092	-0.168	**0.271**	0.086	-0.160	**0.356**	**0.321**	-0.101	-0.070
i23	-0.223	-0.042	0.071	-0.130	0.015	**0.397**	-0.121	0.139	**0.244**
i24	0.114	0.033	-0.151	0.187	0.287	-0.085	**0.418**	**0.261**	0.036
i25	**0.310**	0.023	-0.199	-0.203	-0.188	-0.067	0.104	0.052	-0.053
i26	0.102	**0.395**	0.144	0.111	0.218	0.233	0.052	-0.080	0.102

ronment. The combined ranking thus obtained shows that the island of Capri, for its two respective municipalities, gained the best scores in terms of culture and creativity. Among the top 10 municipalities, 40% are municipalities of the islands (Capri, Anacapri, Forio, Procida), 40% are municipalities of the coastal area (Portici, Sorrento, Meta, Naples), 20% are municipalities of inland areas (Scisciano, Cimitile).

Specifically, the municipality of Capri gains the first position in both partial rankings relating to the Cultural Vibrancy and Enabling Environment domains, thanks to the high number of theatres and cultural events and the largest per capita expenditure on tourism. The municipality of Scisciano, thanks to a strong incidence of cultural and creative enterprises, obtains the first position in the partial ranking of the Creative Economy domain. Lastly, the municipality of Naples obtained the tenth score, contrary to what would have emerged if the data had been expressed in absolute terms and not in per capita ones.

3.3 The comparison of PCA-driven and Expert-driven indices: a composite index of the percentage difference

As shown in Table 6, the composite indices derived from *PCA-driven* and *Expert-driven* methods highlight similar trends toward higher performance in the coastal cities and islands and lower levels in the inner areas.

However, the comparison of the two indices, represented with GIS maps in Figure 5, reveals some significant divergences. The percentage difference between the *Expert-driven* index compared to the *PCA-driven* index for each city was derived from Equation (3), showing the extent of this divergence.

$$\textit{Percentage difference} = \frac{(PCA\ index - Expert\ index) \times 100}{(PCA\ index + Expert\ index) \div 2} \tag{3}$$

First, it can be noticed a concordance between the two methods in relation to the top ranking which is placed by Capri for both indices. In addition, it can be

Table 6. The comparison of PCA and WLC rankings.

Municipalities	C4I values (PCA)	PCA ranking	C4I values (WLC)	WLC ranking	Municipalities	C4I values (PCA)	PCA ranking	C4I values (WLC)	WLC ranking
Capri	1.000	1	1.000	1	Palma Campania	0.130	47	0.227	42
Sorrento	0.729	2	0.721	4	Boscotrecase	0.127	48	0.168	58
Anacapri	0.551	3	0.817	2	San Paolo Bel Sito	0.126	49	0.143	67
Pompei	0.476	4	0.490	12	Cicciano	0.124	50	0.167	59
Procida	0.453	5	0.555	8	Roccarainola	0.122	51	0.218	43
Serrara Fontana	0.448	6	0.442	15	Pimonte	0.122	52	0.106	72
Ischia	0.409	7	0.482	13	Brusciano	0.122	53	0.201	49
Portici	0.379	8	0.789	3	Frattamaggiore	0.121	54	0.193	51
Forio	0.348	9	0.622	7	Poggiomarino	0.119	55	0.162	62
Meta	0.342	10	0.660	6	Mariglianella	0.118	56	0.229	39
Piano di Sorrento	0.335	11	0.368	19	San Giuseppe Vesuviano	0.118	57	0.190	54
Napoli	0.333	12	0.514	10	Casoria	0.116	58	0.177	55
Sant'Agnello	0.330	13	0.498	11	Acerra	0.114	59	0.141	68
Bacoli	0.327	14	0.410	17	San Vitaliano	0.113	60	0.170	56
Cimitile	0.300	15	0.545	9	Villaricca	0.110	61	0.192	53
Agerola	0.289	16	0.356	22	Casalnuovo di Napoli	0.109	62	0.163	61
Nola	0.288	17	0.434	16	Afragola	0.109	63	0.210	46
Vico Equense	0.280	18	0.359	21	Camposano	0.108	64	0.123	69
Scisciano	0.276	19	0.702	5	Grumo Nevano	0.101	65	0.151	65
Liveri	0.275	20	0.289	30	Marano di Napoli	0.098	66	0.198	50
Casamicciola Terme	0.255	21	0.334	25	Sant'Antonio Abate	0.098	67	0.108	71
Massa Lubrense	0.234	22	0.241	37	Quarto	0.098	68	0.158	64
Pozzuoli	0.229	23	0.340	23	Tufino	0.091	69	0.100	76
Lacco Ameno	0.228	24	0.203	47	Ottaviano	0.091	70	0.105	74
Castellammare di Stabia	0.224	25	0.318	27	Castello di Cisterna	0.090	71	0.192	52
San Sebastiano al Vesuvio	0.216	26	0.366	20	Casavatore	0.089	72	0.166	60
Ercolano	0.209	27	0.227	41	San Gennaro Vesuviano	0.085	73	0.105	73
Casamarciano	0.205	28	0.233	38	Striano	0.085	74	0.201	48
Trecase	0.198	29	0.373	18	Giugliano in Campania	0.084	75	0.169	57
Torre del Greco	0.189	30	0.315	28	Arzano	0.081	76	0.080	78
San Giorgio a Cremano	0.189	31	0.335	24	Cercola	0.081	77	0.104	75
Massa di Somma	0.184	32	0.146	66	Casola di Napoli	0.076	78	0.069	82
Barano d'Ischia	0.182	33	0.322	26	Caivano	0.072	79	0.095	77
Torre Annunziata	0.182	34	0.228	40	Visciano	0.069	80	0.073	81
Comiziano	0.177	35	0.247	36	Carbonara di Nola	0.068	81	0.038	87
Somma Vesuviana	0.177	36	0.300	29	Terzigno	0.067	82	0.109	70
Sant'Anastasia	0.172	37	0.216	44	Mugnano di Napoli	0.054	83	0.052	84
Pomigliano d'Arco	0.169	38	0.275	33	Frattaminore	0.052	84	0.000	92
Monte di Procida	0.161	39	0.287	31	Cardito	0.049	85	0.041	86
Pollena Trocchia	0.158	40	0.445	14	Melito di Napoli	0.048	86	0.067	83
Gragnano	0.153	41	0.247	34	Volla	0.043	87	0.032	89
Saviano	0.151	42	0.247	35	Calvizzano	0.038	88	0.021	91
Lettere	0.148	43	0.074	80	Casandrino	0.036	89	0.037	88
Marigliano	0.146	44	0.284	32	Sant'Antimo	0.024	90	0.044	85
Santa Maria la Carità	0.137	45	0.159	63	Crispano	0.019	91	0.026	90
Boscoreale	0.133	46	0.213	45	Qualiano	0.000	92	0.079	79

highlighted a lower dispersion in *PCA-driven* C4I values where the data mean is equal to 0.18 and the standard deviation is 0.15; while the *Expert-driven* index shows a mean of 0.25 and a standard deviation of 0.19. Furthermore, the *PCA-driven* index scores lower values overall, and the deviation between the first position (corresponding to 1 with Capri) and the second position – corresponding to 0.729 with Sorrento – is upper than the *Expert-driven* index, in which the second-ranking position scores 0.817 with Anacapri. A further consideration in relation to the indices difference involves the data intervals. According to the *PCA-driven* index, only three cities exceed the threshold value of 0.50, while the *Expert-driven* index includes ten cities with a score up to 0.50.

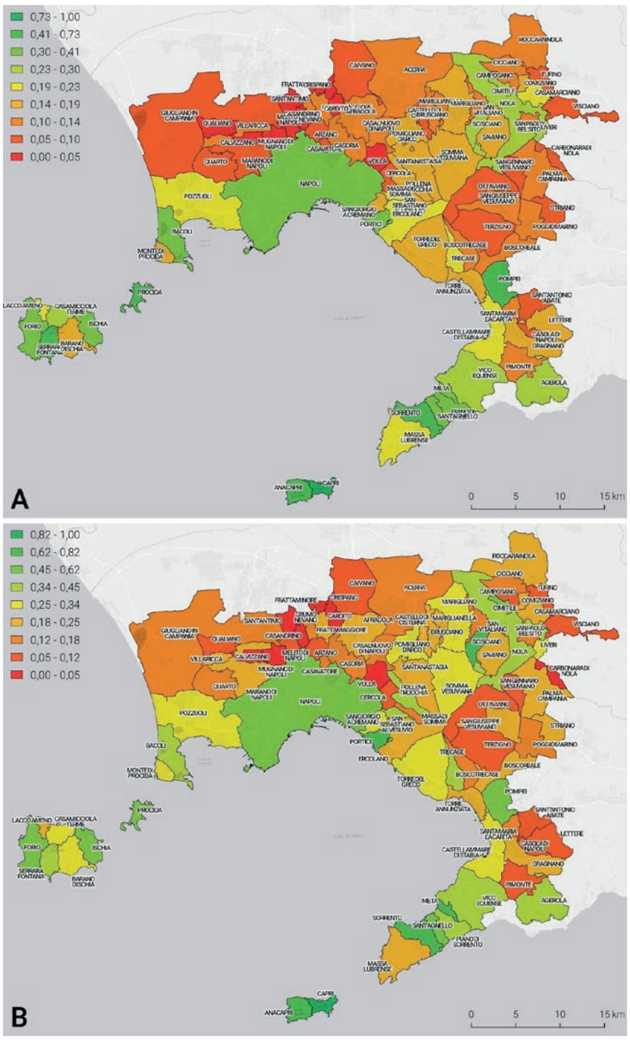

Figure 5. The comparison of spatial indices. At the top, C4I with the Expert-driven method (A), and at the bottom, C4I with the PCA-driven weighting procedure (B).

In Figure 6, the choropleth map shows the deviation of indices for each municipality as coloured values from red to green, where red colours indicate the assessment of the composite index using the *Expert-driven* method is lower than using the *PCA-driven* one, and vice-versa. These spatial maps are substantial to underline urban districts with an increased index sensitivity which depends on the methods used. It remarks on the most relevant research's purpose, which is inherent to estimating the sensitivity of results when different methods are applied and, particularly, the likely uncertainty linked to the cultural indices assessment and cities benchmarking.

In particular, the *Expert-driven* index for the seven municipalities of Portici, Qualiano, Marano di Napoli, Giugliano in Campania, Cercola, Pollena Trocchia, Scisciano and Striano ranks above the *PCA-driven* index with the most marked differences. In contrast, the PCA-driven index ranks the municipalities of Crispano, Calvizzano, San Sebastiano al Vesuvio, Lettere, and Carbonara di Nola below the Expert-driven index. Some differences can be noticed for Portici and Frattaminore, which reverse the ranking from 0.379 (PCA) to 0.789 (Expert) with a gap of five positions for the former, and from 0.052 (PCA) to 0 (Expert) with a gap of six positions for the latter. Despite these deviations, both cities remain in the top and bottom ten. Although the cities of Pompei, Serrara Fontana and Ischia, on the other hand, lose their top-ten position when switching from objective to subjective evaluation methods, the index of discordance is not very high. It means that the sensitivity of methods does not affect the first and last ten ranking

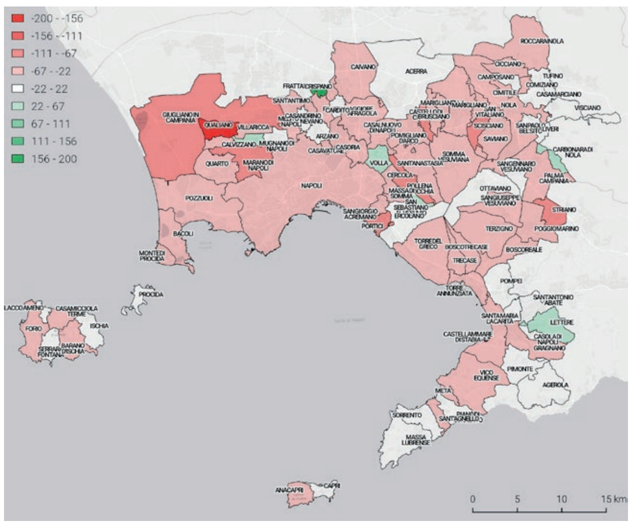

Figure 6. Percentage difference between PCA-driven/Expert-driven methods with the deviation of the rankings.

places. Ultimately, while there are significant deviations in terms of positions between the two rankings, the difference between the values of the indices obtained with the two methods is limited.

4. DISCUSSION

This contribution aimed at benchmarking cities in terms of culture, creativity, and circularity through a data-driven quantitative methodology, thus comparing results obtained by subjective and objective assessment methods. Starting from the declared goal, the structured methodological process for the Metropolitan City of Naples represents an experimental context to highlight the cultural, creative and circular potential of a homogeneous territorial system. A critical concern on the meaningfulness of fit-for-purpose indicators was part of the knowledge phase of this study, which has been further implemented with an ML algorithm to derive indicators with higher information content. Among the multiple purposes, indicators are useful for – i.e. improving communication and awareness, engaging stakeholders, co-designing visions of the future, evaluating pathways for social and institutional changes, or supporting policy evaluation – Lehtonen et al. (2016) have mentioned the monitoring and assessment of performance to support policymakers in detecting signals to decide whether or not to act (Lehtonen et al., 2016, p. 2). In this perspective, as decision-making tools, indicators and composite indicators should not only measure but also accelerate the multidimensional transitions of cities (Köhler et al., 2019, p. 44). However, it is necessary to pay particular attention to the ways in which composite indicators have been processed, as different methods may lead to completely different results (Greco et al., 2018), so it is useful to focus not only on the intrinsic quality of the information used to analyse the issues (Lehtonen et al., 2016, p. 1) but also on comparing the results obtained with different aggregation methods, making a choice with respect to the decision-making environment and the objectives set at an early stage (De Montis et al., 2004). The data-driven methodology was addressed to fill these research gaps.

In particular, the proposed approach has been addressed to answer RQ1, which concerns the expansion of the methodology for evaluating composite indicators for benchmarking cities. From a conceptual point of view, the findings outlined how culture can and should be considered as a comprehensive domain, and not only as an education-related positive externality or as an economic or well-being sub-domain. This is set in the perspective of considering, measuring with appropriate metrics, and evaluating cultural issues in their entirety, including those related to cultural 'waste', appropriately considered as a potential resource according to the principles of CE. The circular, cultural and creative approach can ultimately contribute to sustainable urban development and inclusive growth. From a procedural point of view, it has been shown how ML accelerates the process of harmonisation and comparison of numerous variables with different typological data characteristics, thus expanding the possibilities of data manipulation according to procedures already tested in the literature but not appropriately compared.

A core-set of 26 significant indicators was produced and analysed in response to RQ2 – which focused on the capability of providing performance indices using subjective and objective assessment methods – by testing the research hypothesis through the case study. Following the proposal of a classification framework based on the JRC Cultural and Creative City Monitor (CCCM), it was possible to implement *Expert-driven* and *PCA-driven* methods for weighting indicators and thus computing the C4 composite indices of the 92 municipalities. As a result, comparing the implemented assessment methods to compute composite indices allowed the sensitivity of the proposed model to be evaluated when weighting procedures change, by consistently identifying a concordance of indices between the highest and lowest performing cities. The critical analysis of the results makes it possible to think in multi-dimensional terms, compensating the subjectivity linked to the weighing methods of the indicators with the objectivity linked to their performance values.

5. CONCLUSION

The discussion of the results highlighted the innovative contribution of this research, which aimed to advance knowledge in the field of econometric approaches and spatial decision-making systems, as well as the main potential provided by the proposed methodological approach and the limitations encountered.

Therefore, the main limitations of the methodology concern the snapshot data, which were useful to test, on a preliminary basis, the functioning of the operational steps by providing a "big picture" but were not useful to assess the sensitivity of the indicators to the transformation of cities or to policy impacts. Time-series data are better suited to fully understand these dynamics and effectively measure policy impacts. Furthermore, ML techniques, while reducing the computation time for data processing, can produce a "black box" effect by generating logical processes that are unclear to humans (Traub and Pianykh, 2022). Furthermore, the budget allocation method used in phase 3 should be implemented with local stakeholders to assess the stability of the ranking when new priority preferences emerge. Finally, the WLC method was well adapted to the representation of GIS data, but allowed for compensation between indicators that should be approved as a decision rule before data processing.

As for the potentials, C4I can support decision-makers, practitioners and researchers by highlighting different forms of knowledge related to the cultural dimensions of cities, namely: comparing the cultural performance through different sources and thus deciding whether to improve or maintain the *status quo* of the cultural resource in question, also taking into account the geographical location at the city and regional levels; to make decisions regarding a cultural policy both subjectively and objectively through the combined application of the two identified methods; measure the impact before and after the implementation of policies or regulations related to the use of cultural resources according to the city's performance; provide a comprehensive picture of a city's overall performance to facilitate understanding by non-experts.

This contribution tried to make a step forward in the benchmark analysis of the cities' cultural and creative performances by using objective and subjective assessment methods on the same dataset to compare the results. The ambition relates to data downscaling on the NUTS-3 level to make operational a methodological tool for policy-makers and users addressed to regional planning.

As a future research pathway, the objective is to critically assess the cultural opportunities of the selected case study, identifying, through appropriate MCDA methods, potential coalitions and synergistic networks among municipalities according to their specific cultural vocations. This assessment shall highlight the vulnerability and resilience factors from which to set territorial strategies and thus provide a useful tool for policy-makers of strategic planning.

A further step to be pursued is implementing a spatial monitoring tool for fit-for-purpose policies and recommendations to better inform decision-makers, exploiting the potential of combining GIS, MCDA and ML tools in real-time simulation scenarios.

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