Multi-criteria decision-making for sustainable metropolitan cities assessment

Original Citation:
Multi-criteria decision-making for sustainable metropolitan cities assessment / Carli, Raffaele; Dotoli, Mariagrazia; Pellegrino, Roberta. - In: JOURNAL OF ENVIRONMENTAL MANAGEMENT. - ISSN 0301-4797. - STAMPA. - 226:(2018), pp. 46-61. [10.1016/j.jenvman.2018.07.075]

Published version
DOI:10.1016/j.jenvman.2018.07.075

Published source:
Raffaele Carli, Mariagrazia Dotoli, Roberta Pellegrino, Multi-criteria decision-making for sustainable metropolitan cities assessment, *Journal of Environmental Management*, Volume 226, 2018, Pages 46-61, ISSN 0301-4797, https://doi.org/10.1016/j.jenvman.2018.07.075.

Multi-criteria Decision-Making for Sustainable Metropolitan Cities Assessment

Raffaele Carli[a*], Mariagrazia Dotoli[a], Roberta Pellegrino[b]
[a] Dept. of Electrical and Information Engineering, Politecnico di Bari, Bari, Italy
[b] Dept. of Mechanics, Mathematics and Management, Politecnico di Bari, Bari, Italy
{raffaele.carli, mariagrazia.dotoli, roberta.pellegrino}@poliba.it

---

[*] Corresponding author

The paper is written in the framework of the "UCCSM" project, supported by European Regional Development Fund in the "Apulian Technology Clusters SMARTPUGLIA 2020" program.

ABSTRACT

The recent development of metropolitan cities, especially in Europe, requires an effective integrated management of city services, infrastructure, and communication networks at a metropolitan level. A preliminary step towards a proper organizational and management strategy of the metropolitan city is the analysis, benchmarking and optimization of the metropolitan areas through a set of indicators coherent with the overall sustainability objective of the metropolitan city. This paper proposes the use of the Analytic Hierarchy Process multi-criteria decision making technique for application in the smart metropolitan city context, with the aim of analysing the sustainable development of energy, water and environmental systems, through a set of objective performance indicators. Specifically, the 35 indicators defined for the Sustainable Development of Energy, Water and Environment Systems Index framework are used. The application of the approach to the real case study of four metropolitan areas (Bari, Bitonto, Mola, and Molfetta) in the city of Bari (Italy) shows its usefulness for the local government in benchmarking metropolitan areas and providing decision indications on how to formulate the sustainable development strategy of the metropolitan city. Based on the Analytic Hierarchy Process characteristics, the results highlight that although one specific area (Mola in the considered case) is globally ranked at the first place, it is only ranked first with respect to some dimensions. Such a result has strong implications for the metropolitan city's manager who has the possibility to identify and implement targeted actions, which may be designed ad hoc to improve specific dimensions based on the current state of the city, thus maximizing the efficiency and effectiveness of the actions undertaken for the sustainable development of energy, water and environmental systems of the whole metropolitan city.

KEYWORDS

Multi-criteria decision making, Performance evaluation, Analytic Hierarchy Process, Sustainable development, Planning.

1 INTRODUCTION

Modern cities are complex systems that accommodate massive number of citizens, businesses, different modes of transport, communication networks, services and utilities (Neirotti *et al.*, 2014). Data about cities over the globe reveal that the world is experiencing an unprecedented level of urban population growth and urbanization (Dirks *et al.*, 2009). Today, 55% of the world's population lives in urban areas, a proportion that is expected to increase to 68% by 2050. Projections show that urbanization, the gradual shift in residence of the human population from rural to urban areas, combined with the overall growth of the world's population could add another 2.5 billion people to urban areas by 2050, with close to 90% of this increase taking place in Asia and Africa (United Nations, 2018). This phenomenon raises a variety of technical, social, economic, and organizational problems that tend to jeopardize the economic and environmental sustainability of cities and make the sustainable development and better livability of cities imperative (Washburn *et al.*, 2010). Among the challenges due to the expansion of cities, traffic congestion, air pollution, difficulty in waste management, and inadequate, deteriorating and aging infrastructures may be singled out (Toppeta, 2010). Another set of problems is social and organizational rather than technical, physical or material, and refers to the increasing social inequality and human health concerns (Kim and Han, 2012). Such phenomena impose governments to manage cities in an innovative way in order to avoid for urban population growth and urbanization to become critical issues (Carli *et al.*, 2017). This has led to the current debate among governments and scientists on how new technology-based solutions and new approaches to urban planning and living can ensure the sustainable development and livability of cities (Dirks *et al.*, 2009; Wang *et al.*, 2017b). An emerging solution is the concept of smart cities, the new paradigm of intelligent urban development and sustainable socio-economic growth (Neirotti *et al.,* 2014). To add to this complex environment, in the context of cities the recent developments in transport, communication, and information technology have increased material and information flows considerably, leading to a change from the traditional vision of city as distinct from its hinterland and from other cities to a new concept in which barriers between people living in and outside the city are disregarded, with regular commuters (e.g., students, workers, and people looking for healthcare or for cultural facilities). Economic activities, transport flows, and air pollution clearly cross the administrative boundaries of a city as well.

This evolution that is affecting modern cities, especially in Europe, has favored the formation of metropolitan cities, which may be defined as the functional urban area that extends beyond the core city defined by administrative and/or political boundaries (Fujita *et al.*, 2001). As a result, there is a general consensus on the need for a level of government that reflects the *de facto* city rather than the *de jure* city. Strategic planning as well as public policies on economic development, labor market, mobility, transport, housing, education, water, energy, waste, immigration, etc. cannot be addressed at a pure city level. Effective government and governance structures at a metropolitan level are indeed a key condition for the city competitiveness (Carli *et al.*, 2014). The better a city is managed, the more competitive its position in the global metropolitan network. Hence, metropolitan cities are required to assume roles and responsibilities that embrace new tasks: the strategic development of the metropolitan areas (belonging to the metropolitan city) and the promotion and integrated management of services, infrastructure and communication networks at a metropolitan level.

The challenge is to make the metropolitan city closer to the needs of its users (inhabitants) in terms of better quality of services, reduction of the impact on the environment, containment of energy consumption, through the use of innovative technologies, namely, Information and Communication Technologies (ICTs). Governmental authorities are required to intervene in the coming years in order to make metropolitan cities “more accessible, functional and sustainable and, at the same time, more cohesive and inclusive” (Dipartimento per lo Sviluppo e la Coesione Economica, 2014). Such objective in the development of metropolitan cities may be reached by ensuring the diffusion and widespread use of ICT (i.e., improving the structural conditions in accessing Internet, making Internet available for families and individuals, also through an overall increase in digital skills widespread in the population) as well as by working through policies aimed at improving key aspects related to the energy, water and environment systems (Papa *et al.*, 2016).

The sustainable development of energy, water and environment systems of metropolitan cities requires, as a first step, the analysis of the propensity and susceptibility of the individual metropolitan areas to adopt a sustainable development approach, measured through a set of indicators that are coherent with the objectives of the metropolitan city. In other words, to monitor the performance of a metropolitan city, its metropolitan areas (which are often represented by multiple towns of the metropolitan city) have to be analyzed and benchmarked across a common set of aspects that relate to sustainability. This requires an integrated approach to capture multiple aspects characterizing the concept of sustainable development of energy, water and environment systems, as proposed by (Kılkış, 2015) for cities, as well as the experience and preferences of the decision makers about the priority among these aspects (Boselli *et al.*, 2015). While the literature provides several examples on benchmarking cities in only one aspect (Wang *et al.*, 2017b), very few studies provide a composite cities’ benchmarking indicator incorporating multiple aspects of sustainability as well as the preferences of the decision makers. To the best of author’s knowledge, the few studies that pursue this objective (see (Kılkış, 2016) for a review) address the issue at country/city level, with no efforts at metropolitan city level. Although these few studies represent first attempts toward the direction of benchmarking cities in a holistic way, they do not provide operative indications about specific areas of intervention (e.g., sectors, neighborhoods) that need improvements in order to increase sustainability.

Hence, there is a clear need for decision making and performance analysis tools to measure the sustainable development of metropolitan cities. This paper advances the state of the art by providing an answer to such a need. It enhances the existing studies by developing a decision making and performance analysis tool to measure the sustainable development of metropolitan cities, which includes multiple aspects of sustainability as well as the preferences of the decision makers. This advancement is accomplished through the innovative application of the Analytic Hierarchy Process (AHP) multi-criteria decision making technique (Saaty, 2008) to the metropolitan city context, using a framework of indicators previously developed in the literature (Kılkış, 2015). Although AHP is a well-established technique for supporting local government decision makers, its application to the metropolitan city context, and particularly to the assessment of its sustainability based on multiple and contrasting dimensions, is new. Indeed, to the best of the authors' knowledge, until now AHP has been used only for supporting local decision making initiatives related to urban environments, always with the aim of addressing specific issues encountered by local governments. For instance, it has been adopted for the sustainability assessment of local distributed energy systems (Väisänen *et al.*, 2016), for the selection of optimal schemes for storage tanks under different rainfall scenarios (Wang *et al.*, 2017c), and for the assessment of the capacity of agricultural landscapes to provide ecosystem services (ES) (Inkoom *et al.*, 2018).

Through the application of the approach to the real case of the metropolitan city of Bari (Italy), it has been shown how the AHP-based approach may be used to support local government decision makers in benchmarking the metropolitan areas with respect to sustainable development and its multiple dimensions and, as a result, in providing decision indications on how to formulate the optimal strategy to promote the metropolitan city's process of innovation of its organizational and management structure.

The rest of the paper is organized as follows. Section 2 reviews the performance indicators that are currently used to assess the sustainable development of cities. Section 3 presents the formulation of the AHP model as a multi-criteria decision making tool for benchmarking metropolitan areas with respect to the sustainable development of energy, water and environment systems. Section 4 applies the proposed technique to the metropolitan city of Bari. Section 5 provides a summary of the paper with concluding remarks. A reference list closes the paper.

2 LITERATURE REVIEW

The evolution of modern cities towards complex systems has spurred researchers to focus on the theme of sustainable development of cities, through a multi-disciplinary approach embracing discourses on science, technology and environmental policy related to the sustainability of humanity's activities (Urbaniec *et al.*, 2016, 2017).

The analysis of the related literature reveals that most of the existing studies use quantitative and/or qualitative indicators to assess specific aspects of the sustainable development and benchmark cities on these aspects. For instance, recently some authors have focused on CO_2 emission factors and energy aspects. Yajie *et al.* (2014) present a model for measuring the carbon footprint of urban areas, that is a fundamental quantization parameter of carbon emissions measurement, thus contributing to providing benchmarks and expanding the understanding of carbon emissions. Tan *et al.* (2017) establish an indicator framework for the evaluation of low-carbon city from the perspectives of economic, energy pattern, social and living, carbon and environment, urban mobility, solid waste, and water. The framework is then applied to ten cities to rank their low-carbon levels. Wang *et al*. (2017b) develop an urban energy performance evaluation system, for determining the energy performance level based on input-output analysis as well as helping explain differences in performance against a set of urban energy performance assessment indicators and influencing factors based on existing theory and literature (e.g., capital, labor, energy, gross domestic product, carbon dioxide emissions, population density) (Wang *et al*., 2017a). Other authors focus on waste management, another aspect of sustainable development. For example, Wilson *et al.* (2015) present an indicator set for integrated sustainable waste management (ISWM) in cities both North and South, to allow benchmarking of a city's performance, comparing cities and monitoring developments over time. Zaman and Lehmann (2013) conceptualise the concept of the 'zero waste city' and propose a new tool to measure the performance of waste management systems called the 'zero waste index', which is then adopted to analyse three high consuming cities (Adelaide, San Francisco and Stockholm).

As a matter of fact, the sustainable development of energy, water and environment systems of a city is per se a multidisciplinary concept. In analogy to other fields where composite indices are well established ways to successfully summarise complex or multi-faceted issues and then support decision-makers (Nardo *et al.*, 2015), composite indices consisting of specific dimensions of the sustainable development of energy, water and environment systems are used for benchmarking performance of cities. Kılkış (2015) develops a composite index, named Sustainable Development of Energy, Water and Environment Systems (SDEWES) Index that provides an integrated approach to benchmark the sustainable development of energy, water, environment systems in cities. Such an index allows to benchmark twenty-two Mediterranean port cities (Kılkış, 2015), twelve Southeast European (SEE) cities (Kılkış, 2016) and eighteen additional cities in Southeast Europe (Kılkış, 2018a). This index has also been recently used to develop a benchmarking tool to trigger policy learning based on the index performance and to stimulate innovation for more sustainable cities (Kılkış, 2018b).

Synthetic quantitative indicators are also receiving increasing attention among city managers and policy makers to decide where to focus time and resources, as well as to communicate city performance to citizens, visitors, and investors (Berardi, 2013). One of the values of these systems is the capacity to represent a metric of comparison, which overcomes self-proclaims of sustainable development of a city. For example, Afgan *et al.* (2000, 2005) merged environmental, social and economic indicators for analyzing the case of an island. Hsieh *et al.* (2011) and PA Forum (2012) addressed the transformation and aggregation of city variables and indicators into a global final index in order to attempt to provide a comprehensive overall measure, which characterizes the smartness of cities. The Siemens Green City Index (Siemens) adopted 30 indicators related to environment, energy, water, waste, land use and pollution in order to benchmark 30 European capital cities, 10 additional cities in Germany and other cities around the world. The University of Vienna developed an assessment metric which uses a certain number of indicators for six dimensions of a smart city: smart economy, smart people, smart governance, smart mobility, smart environment and smart living. This metric is then used to rank 70 European medium sized cities (Giffinger *et al.*, 2007). Carli *et al.* (2013) proposed a framework to analyze and compare measurement systems for smart cities, which extends the set of indicators beyond physical infrastructures and context data by including citizens' satisfaction and perception of well-being. The authors also focused on the way in which indicators are measured by differentiating between objective and subjective indicators.

While the existing studies represent a significant progress in the literature for benchmarking cities in a holistic way, the developed composite indices do not provide operative indications about specific areas of intervention (e.g., sectors, neighborhoods) that need improvements. Also, when applied to the metropolitan city context, composite indices present two major shortcomings. First, quantitative data on some indicators used in the composite indices are not available at a metropolitan area level (namely, towns of the metropolitan city). Indeed, statistics or data on these indicators are generally available at country, region or metropolitan city level, not for single towns within the metropolitan city. Second, most qualitative indicators englobed in the composite indices require a subjective estimation by experts, which is difficult to provide simultaneously, for all the metropolitan areas, in the given scale.

Differently from the cited literature, and to answer to the two previously highlighted needs, this paper proposes the application of the AHP multi-criteria decision making technique (Saaty, 2008) to benchmark metropolitan areas in terms of the sustainable development of their energy, water and environment systems. The paper also discusses the difference between the proposed AHP-based approach and the existing studies based on composite indices. The application to a real case study shows the ability of the proposed approach not only to benchmark the metropolitan areas, but also to provide indications of the metropolitan areas that need an overriding intervention and the specific sectors on which it is strategic to intervene for promoting the sustainable development of the metropolitan city. In other words, this represents the preliminary step towards the formulation of a proper strategy that promotes the metropolitan city's process of innovation of its organizational and management structure. Finally, to show the effectiveness of the proposed approach with respect to the existing approaches, the results obtained through the AHP application are compared with the ones determined using a composite index with the same set of indicators: the SDEWES set of indicators (Kılkış, 2015), as detailed in the next section.

3 EVALUATING THE SUSTAINABLE DEVELOPMENT OF METROPOLITAN CITIES

This section presents the formulation of the AHP model as a multi-criteria decision making tool for benchmarking metropolitan areas with respect to the sustainable development of energy, water and environment systems, and then discusses the difference between the proposed AHP-based approach and the existing studies based on composite indices.

3.1 The proposed methodology based on the AHP

AHP is a commonly used method for a systematic and structured analysis and decision making in complex situations. For instance, Giri and Nejadhashemi (2014) use AHP as a comprehensive approach in which environmental, economic, and social aspects are simultaneously considered for ranking best management practices in the Saginaw River Watershed (Michigan, USA). To deal with the complex and uncertain sustainability assessment process for coastal beach exploitation, Tian *et al.* (2013) develop an assessment framework based on AHP, consisting of indicators derived from the three dimensions of suitability, economic and social value, and ecosystems. To deal with the complexity of waste management systems in fast-growing regions, Wang *et al.* (2009) propose an AHP based procedure to select the appropriate solid waste landfill site, considering multiple alternative solutions and evaluation criteria. In particular, AHP is a Multi-Criteria Decision Making (MCDM) technique that accounts for both qualitative and quantitative aspects of decisions (Saaty, 2008). It reduces complex decisions to a series of one-by-one comparisons and then synthesizes quantitative results. Because of its intuitive appeal and flexibility, some governments even use AHP for taking major policy decisions (Elkarni and Mustafa, 1993).

Synthetically, the AHP methodology involves the following four steps (for a more detailed description of AHP and its application issues, the reader is referred to Saaty (1980, 2008).

In the following, the AHP methodology is described with reference to the measurement of the sustainable development of a metropolitan city.

3.1.1 Structuring the decision problem into a hierarchical model

This activity involves the decomposition of the decision problem into elements constituting the problem and a hierarchical model having different levels. The topmost level is the "focus" of the problem, namely the goal. Intermediate levels correspond to criteria and sub-criteria, while the lowest level contains the so-called "decision alternatives".

With respect to the metropolitan city context, the problem is structured in a hierarchy having 4 levels, where the goal at level 1 is the sustainability of energy, water and environment systems, the H criteria $\{D_{1,}, \dots, D_h, \dots, D_H\}$ at level 2 are the sustainability dimensions, the K subcriteria $\{I_{11}, \dots, I_{1K_1}, \dots, I_{h1}, \dots, I_{1K_h}, \dots, I_{H1}, \dots, I_{1K_H}\}$ (with $\sum_{h=1}^{H} K_h = K$) at level 3 are some of the indicators proposed in the literature for each dimension (as outlined in Section 2) reflecting the local governance and objective in terms of sustainability, and finally the N decision alternatives $\{A_1, \dots, A_n, \dots, A_N\}$ at level 4 are the metropolitan areas (or towns) that form the metropolitan city.

3.1.2 Developing pairwise comparisons and obtaining the judgmental matrices

In this step, the elements of a level are pairwise compared, with respect to a specific element in the immediate upper level.

First, the judgmental matrix $\boldsymbol{C}^1$ is defined pairwise comparing the H criteria, with respect to the main goal. Second, for each hth criterion (with $h = 1, \dots, H$) the judgmental matrix $\boldsymbol{C}^{2h} \in \mathbb{R}^{K_h \times K_h}$ is formed to assert the importance of the K_h pertaining subcriteria $\{I_{h1}, \dots, I_{hk}, \dots, I_{1K_h}\}$ in reaching the objectives of the considered hth criterion. Finally, the K judgmental matrices $\boldsymbol{C}^{3hk} \in \mathbb{R}^{N \times N}$ are formed to assert the importance of the N decision alternatives in reaching the objectives of the considered kth subcriterion pertaining to the hth criterion. More in detail, each element $c^{3hk}(n, m)$ of $\boldsymbol{C}^{3hk}$ represents the relative importance of alternative A_n compared to A_m with respect to the indicator I_{hk}. In all the pairwise comparisons, a ratio scale of 1-9 is used (named the fundamental scale or Saaty's scale), reported in Table 1, while interviewing the decision maker. For judgmental matrices expressing how satisfactory every alternative is with respect to the subcriteria (i.e., for matrices $\boldsymbol{C}^{3hk}$), numerical performance indicators may be available. In this case, the value of $c^{3hk}(n, m)$ may be computed in an automated fashion as follows:

$$c^{3hk}(n,m) = \begin{cases} \dfrac{8\big(v_{hk}(n) - v_{hk}(m)\big)}{\max_i\,(v_{hk}(i)) - \min_i\,(v_{hk}(i))} + 1, \text{if } v_{hk}(n) \geq v_{hk}(m) \\ 1/\left(\dfrac{8\big(v_{hk}(n) - v_{hk}(m)\big)}{\max_i\,(v_{hk}(i)) - \min_i\,(v_{hk}(i))} + 1\right), \text{if } v_{hk}(n) < v_{hk}(m) \end{cases} \tag{1}$$

$$c^{3hk}(n,m) = \begin{cases} 1/\left(\dfrac{8\big(v_{hk}(n) - v_{hk}(m)\big)}{\max_i\,(v_{hk}(i)) - \min_i\,(v_{hk}(i))} + 1\right), \text{if } v_{hk}(n) \geq v_{hk}(m) \\ \dfrac{8\big(v_{hk}(n) - v_{hk}(m)\big)}{\max_i\,(v_{hk}(i)) - \min_i\,(v_{hk}(i))} + 1, \text{if } v_{hk}(n) < v_{hk}(m) \end{cases} \tag{2}$$

where $v_{hk}(n)$ and $v_{hk}(m)$ denote the values of indicator I_{hk} related to areas A_n and A_m, respectively. Equation (1) and (2) convert the absolute-scaled values of performance indicators into the 1-9 ratio-scale values expected by AHP. It is noteworthy that (1) assumes that the given indicator has a range whose lower level stands for poor performance, while its upper level indicates excellent performance. Conversely, (2) holds for indicators having decreasing function. Furthermore, note that in case an indicator I_{hk} assumes equal values for all the metropolitan areas (i.e., $\min_i(v_{hk}(i)) = \max_i(v_{hk}(i))$), the relative importance of metropolitan areas A_n as opposed to A_m is set to $c^{3hk}(n,m) = 1$ (for each n, m) by convention.

Finally, the relative importance of metropolitan area A_m as opposed to A_n is computed:

$$c^{3hk}(m,n) = 1/c^{3hk}(n,m)\,. \tag{3}$$

3.1.3 Determining the local priorities and consistency of comparisons.

This activity consists in calculating the local priorities of criteria and the consistency of judgements.

The maximum eigenvalue and its eigenvector $\boldsymbol{v}^1 \in \mathbb{R}^H$ are determined for comparison matrix $\boldsymbol{C}^1$. Consequently, the priority vector $\boldsymbol{p}^1 = [p^1(1), \dots, p^1(h), \dots, p^1(H)]$ is computed:

$$\boldsymbol{p}^1 = \boldsymbol{v}^1/\textstyle\sum_{h=1}^{H} v^1(h) \tag{4}$$

representing the normalized importance degrees of all the criteria. Similarly, the vectors $\boldsymbol{p}^{2h} \in \mathbb{R}^{K_h}$ (with $h = 1, \dots, H$) –representing the normalized importance degrees of all the subcriteria– and the vectors $\boldsymbol{p}^{3hk} \in \mathbb{R}^N$ (with $h = 1, \dots, H, k = 1, \dots, K_h$) –representing the normalized importance degrees of all the alternatives– are determined.

Since inconsistency is natural in human judgements, AHP copes with this issue through the computation of the consistency ratio (CR) (Saaty, 1980, 2008) The consistency ratio $CR(\boldsymbol{C})$ of a consistency matrix $\boldsymbol{C}$ having dimension $dim\,(\boldsymbol{C})$ is defined as follows:

$$CR(\boldsymbol{C}) = CI(\boldsymbol{C})/RCI(\boldsymbol{C}) \tag{5}$$

where $RCI(\boldsymbol{C})$ is the so-called Random Consistency Index (RCI) of a $dim\,(\boldsymbol{C})$-dimensional square matrix generated with values belonging to set {1/9, 1/8, 1/7,…,1,…,7,8,9} (Saaty, 2008) and $CI(\boldsymbol{C})$ is the Consistency Index (CI) of the matrix $\boldsymbol{C}$ having λ_{max} as the maximum eigenvalue:

$$CI(\boldsymbol{C}) = (\lambda_{max} - \dim(\boldsymbol{C}))/(dim(\boldsymbol{C}) - 1). \tag{6}$$

If the CR of the judgmental matrix is higher than a threshold value, then the input judgements are not consistent, hence they are not reliable. It was proven that inconsistencies in answers can be tolerated if the consistency ratio remains within a small interval. In general, a consistency ratio equal to or lower than 0.10 is considered acceptable. Conversely, judgments may be un reliable and have to be elicited again.

3.1.4 Determining the final priorities. In order to obtain the final priority vector $\boldsymbol{p}^{AHP} = [p^{AHP}(1), \dots, p^{AHP}(n), \dots, p^{AHP}(N)]$ of the alternatives, the local priorities of elements of different levels, calculated as outlined in the previous step, are aggregated according to the principle of hierarchical composition (Saaty, 2008):

$$p^{AHP}(n) = \sum_{h=1}^{H} \sum_{k=1}^{K_h} p^1(h) p^{2h}(k) p^{3hk}(n) \,. \qquad (7)$$

The final priorities thus obtained represent the rating of the alternatives in achieving the goal of the problem. Finally, the ranking of alternatives $\boldsymbol{r}^{AHP} = [r^{AHP}(1), \dots, r^{AHP}(n), \dots, r^{AHP}(N)]$ is computed by ordering the final priorities in decreasing order.

3.1.5 AHP for the sustainable development of metropolitan cities.

The outlined approach is here applied to the metropolitan city context, where the decision alternatives are the metropolitan areas forming the metropolitan city. The output of the approach is the final priority vector of the alternatives, expressing a measurement of how each alternative (i.e., metropolitan areas) contributes to achieving the focus (goal) of the problem, namely the sustainability of energy, water and environment systems of the metropolitan city. By applying this approach to the *status quo* (no implementation of programs or development projects), it is also possible to benchmark the performance of the individual metropolitan areas across aspects that relate to the sustainable development of energy, water and environment systems, through a suitable set of indicators. These indicators must reflect not only the characteristics of the observed real systems, but also the aspects that the decision maker considers as priorities in the sustainable development of metropolitan cities (e.g., energy consumption and climate, water and environmental quality, etc.). Consequently, the proposed approach enables the analysis of the propensity and susceptibility of the individual metropolitan areas towards the sustainable development of energy, water and environment systems.

Table 1. The AHP semantic scale of relative importance of alternative A_n as opposed to A_m (adapted from Saaty (2008)).

Intensity of importance	**Definition**	**Description**
1	Equal importance	Elements A_n and A_m are equally important
3	Weak importance of A_n over A_m	Experience and Judgement slightly favour A_n over A_m
5	Essential or strong importance	Experience and Judgement strongly favour A_n over A_m
7	Demonstrated importance	A_n is very strongly favoured over A_m
9	Absolute importance	The evidence favouring A_n over A_m is of the highest possible order of affirmation
2, 4, 6, 8	Intermediate	When compromise is needed, values between two adjacent judgements are used
Reciprocals of the above judgements	If A_n has one of the above judgements assigned to it when compared with A_m, then A_m has the reciprocal value when compared with n	

3.1.6 Sensitivity analysis for AHP

As shown in Equation (7), the AHP overall ratings are actually dependent on the priority values assigned by the decision maker to criteria (i.e., $p^1(h)$ with $h = 1, \dots, H$) and subcriteria (i.e., $p^{2h}(k)$ with $k = 1, \dots, K_h$, $h = 1, \dots, H$) used in the hierarchical model. Relatively small changes in priority values at the various hierarchical levels may generally lead to a different outcome (Saisana *et al.*, 2005). Since these priority values are usually based on subjective judgments, the stability and robustness of the overall ratings to variations in the weights of criteria and sub-criteria has to be evaluated. In other words, a sensitivity analysis is useful in exploring the response of the overall ratings of alternatives to changes in the relative weights of criteria and sub-criteria, to investigate whether such changes are capable of causing rank reversal among the alternatives, and which criteria and sub-criteria are the mostly influential factors in the calculation of the overall AHP ratings.

Several approaches for sensitivity analysis are described in the literature: a review of the main techniques is reported in Saltelli *et al.* (2000a). In case of a composite index, as for AHP, variance-based techniques for sensitivity analysis -such as the variance-based method proposed by Sobol (2001)- are the most appropriate (Saltelli *et al.* 2000b). In such a method, for a given index described by a nonlinear model $Y = f(X_1, \dots, X_m, \dots, X_M)$, depending on factors X_m (with $m = 1, \dots, M$), the first-order sensitivity coefficient is defined as follows (Saltelli *et al.* 2000b):

$$S_m = \frac{V_{X_m}(E_{\boldsymbol{X}_{\sim m}}(Y|X_m))}{V(Y)} \tag{8}$$

where $V(Y)$ is the variance of model output, $V_{X_m}(\cdot)$ is the variance of argument taken over model factor X_m and $E_{\boldsymbol{X}_{\sim m}}(\cdot)$ is the mean of the argument taken over all the model factors except X_m. The sensitivity index in Equation (8) measures the first order (e.g., additive) effect of X_m on the model output variance. S_m takes values between 0 and 1, i.e., from a dummy to a totally influential factor. The first-order terms do not add up to more than one: $\sum_{m=1}^{M} S_m \leq 1$. If the index model is purely additive (i.e., if the model does not include interactions between the input factors), then $\sum_{m=1}^{M} S_m = 1$ and the computation of first-order coefficients is completely satisfactory to measure the sensitivity of models. Conversely, in case of non-additive models or when the additive property is not guaranteed, further measures are needed. One of these is the total effect sensitivity coefficient, which aims at measuring the total effect, i.e., first and higher order effects (interactions), of model factor X_m on the model output variance. The total effect sensitivity coefficient is defined as follows (Saltelli *et al.* 2000b):

$$S_{Tm} = 1 - \frac{V_{\boldsymbol{X}_{\sim m}}(E_{X_m}(Y|\boldsymbol{X}_{\sim m}))}{V(Y)}. \tag{9}$$

The total effect sensitivity coefficients add up to more than one: $\sum_{m=1}^{M} S_{Tm} \geq 1$, where equality holds only if there are no interactions (i.e., for additive models).

In general, the estimation of the Sobol's indices in Equations (8) and (9) may be performed based on a Monte Carlo approach, such as the computational efficient method proposed by Saltelli *et al.* (2010).

3.2 An alternative methodology based on a composite index

Composite indices are popular tools for measuring multi-dimensional concepts such as the sustainable development, which are not uniquely defined and cannot be captured by a single indicator (Becker *et al.*, 2017). A composite index is formed merging individual indicators into a meaningful index, on the basis of an underlying model of the multi-dimensional concept that is being measured. Ideally, a composite index should be based on a theoretical framework definition, which allows individual indicators to be selected, aggregated and weighted in a manner that reflects the dimensions or structure of the concept being assessed (Saisana and Tarantola, 2002). Even though the main advantage of such an approach is simplicity, the construction of a composite index is not unique (Becker *et al.*, 2017). For instance, many subjective choices may be made in the weighting (e.g., weighted arithmetic average, etc.) or normalization (e.g., Min-Max method, etc.) procedures.

Without loss of generality, in the sequel a specific composite index widely accepted in the literature to benchmark the sustainable development of energy, water and environment systems in cities (Kılkış, 2016, 2018a, 2018b) is described. Such a composite index - based on the Min-Max normalization and the arithmetic weighting scheme - is named SDEWES Index (Kılkış2015). It adopts the same set of individual indicators that will be used in the case study in subsequent Section 4.

The computation of the SDEWES Index is performed by two phases. The first phase consists in data collection, aimed at estimating the value of the set of 35 SDEWES indicators grouped into 7 dimensions (Kılkış, 2016). The second phase consists in the value aggregation for estimating a composite index. The SDEWES Index aggregates all the normalized values of selected indicators in accordance to a weighted arithmetic average:

$$p^{SDEWES}(n) = \sum_{h=1}^{7} \sum_{k=1}^{5} \alpha(h) \tilde{v}_{hk}(n) \tag{10}$$

where $\alpha(h)$ is the dimension weights ($\sum_{h=1}^{7} \alpha(h) = 1$) and $\tilde{v}_{hk}(n)$ is the value of the indicator I_{hk} for the metropolitan area A_n normalized based on the Min-Max method:

$$\tilde{v}_{hk}(n) = (v_{hk}(n) - \max_i (v_{hk}(i)))/(\min_i (v_{hk}(i)) - \max_i (v_{hk}(i))) \tag{11}$$

$$\tilde{v}_{hk}(n) = (v_{hk}(n) - \min_i (v_{hk}(i)))/(\max_i (v_{hk}(i)) - \min_i (v_{hk}(i))). \tag{12}$$

Equation (11) normalizes the value of indicator v_{hk} having a range whose lower level stands for poor performance, while its upper level indicates excellent performance; the opposite holds for Equation (12). Note that in case an indicator I_{hk} assumes equal values for all the metropolitan areas (i.e., it holds $\min_i (v_{hk}(i)) = \max_i (v_{hk}(i))$), the normalized value is set to $\tilde{v}_{hk}(n) = 1$ (for each n) by convention.

4 THE CASE STUDY: THE BARI SMART METROPOLITAN CITY

The discussed AHP based decision making technique has been applied to the metropolitan city of Bari. Bari is the capital city of the Apulia (*Puglia* in Italian) region, which is located on the Adriatic Sea, in southern Italy. The city enjoys a Mediterranean climate (in particular, Csa climate in accordance to the Köppen classification) with mild winters and hot, dry summers. Bari covers more than 200 km^2 and its metropolitan area counts 1 million inhabitants over 41 areas (Città metropolitana). For the sake of clarity and brevity, this paper restricts the analysis to N =4 metropolitan areas, namely the areas of Bari, Bitonto, Mola, and Molfetta. Clearly, the proposed approach may straightforwardly be applied considering all the 41 areas. The chosen metropolitan area sample encompasses a fair geographical distribution in the metropolitan city of Bari: Bari is chosen being the capital, whereupon Molfetta, Mola and Bitonto are chosen as representative of the coast zone to the north, coast zone to the south, and the inland zone, respectively. The metropolitan area of Bari is currently engaged in a series of smart city initiatives promoted by the EU and mainly dedicated to the reduction of CO_2 emissions, increase in energy efficiency, and improving the quality of life. These include energy efficiency projects, urban planning, improvements for heating and lighting infrastructure and networks, intelligent buildings, introducing renewable energy sources, and education campaigns. Also, Bari is one of the 22 Mediterranean port cities, which represent the sample to which SDEWES Index is applied (Kılkış, 2015).

4.1 Sustainable metropolitan areas' rating through AHP

Following the indicators proposed by the literature (as discussed in Section II) as well as the suggestion received by the metropolitan city's manager in charge of the promotion of the sustainability of the metropolitan city of Bari, the set of K =35 SDEWES indicators reported in Table 2 grouped into H =7 dimensions is considered. Note that for qualitative indicators (i.e., indicators I_{22}, I_{23}, I_{24}, I_{25}, I_{62}, I_{71}, I_{72}) numerical values are not provided; rather, the assessment of experts are adopted to evaluate the pairwise comparisons of the considered areas.

The objective is to assess how the chosen metropolitan areas contribute to the overall sustainability of the metropolitan city and its dimensions (e.g., energy consumption and climate, water and environmental quality, etc.).

Following the steps detailed in the previous section, the discussed AHP is applied to the metropolitan city of Bari.

4.1.1 Hierarchical structure of the decision model.

The overall criterion is the sustainability of the metropolitan city. The second level includes the seven dimensions that contribute to the overall sustainability concept, as proposed in (Kılkış, 2015). The third level contains the SDEWES indicators chosen for assessing the sustainability of the metropolitan city (Table 2). The fourth (or bottom) level contains the considered metropolitan areas, which are to be evaluated in terms of the criteria in the second level. Figure 1 shows the outcome of this first step, namely the AHP structure for evaluating the sustainability of the metropolitan areas in Bari.

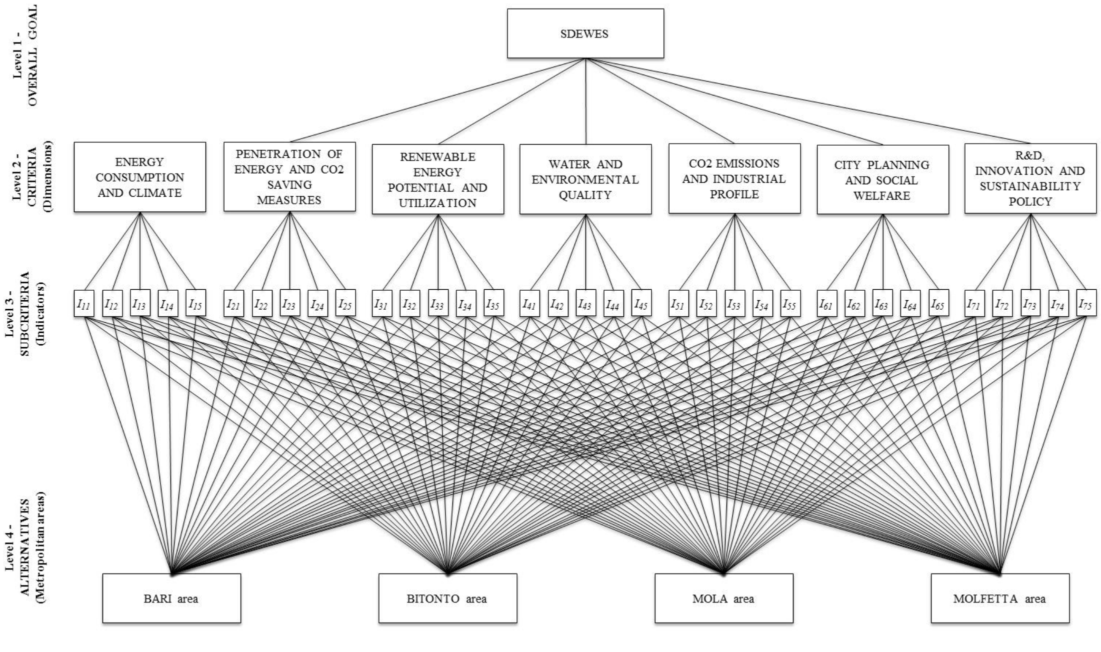

Figure 1 - Hierarchical 4-level structure of the proposed AHP decision making model for measuring the sustainability development of a metropolitan city.

4.1.2 Judgmental matrices.

The Bari metropolitan city's manager is asked to compare pairwise the seven dimensions (criteria) of the second AHP level in Fig.1, with respect to the overall sustainability (Table 3). The level 2 priorities (last column of Table 3) is obtained as the first outcome, which represents the importance that the metropolitan city's manager in charge of the promotion of the sustainability of the metropolitan city of Bari assigns to each dimension with respect to the overall sustainability. Specifically, the last column of Table 3 shows that the energy consumption and climate dimension has the highest importance (p^1(1)=0.4098), higher than the penetration of energy and CO_2 saving measures dimension (p^1(2)=0.2480) and the renewable energy potential and utilization dimension (p^1(3)=0.1291) and the water and environmental quality dimension (p^1(4)=0.0986), which are rated almost at the same level, and are followed by the city planning and social welfare dimension (p^1(6)=0.0543). The R&D, innovation and sustainability policy dimension (p^1(7)=0.0379) and the CO_2 emissions and industrial profile dimension (p^1(5)=0.0224) close the ranking.

Secondly, the Bari metropolitan city's manager is asked to compare pairwise the indicators (subcriteria) of the third level, with respect to the dimension of the upper level to which each subset of indicators belong (Table 4). As an example, for the energy consumption and climate dimension (D_1), the Bari metropolitan city's manager evaluated the pairwise comparison of indicators I_{11}, I_{12}, I_{13}, I_{14}, I_{15} against the given criterion (first sub-table of Table 4). As a second outcome of this step, there are the level 3 priorities (last column of Table 4), which represent the importance that the metropolitan city's manager attributes to each indicator with reference to its corresponding dimension at the upper level. For instance, against dimension D_1 (h =1), indicator I_{12} (k =2) has the highest priority (p^{21}(2)=0.5128) whilst indicators I_{15} ($k = 5$) has the lowest priority (p^{21}(5)=0.0333).

Thirdly, the metropolitan areas of the fourth level are pairwise compared, with respect to each indicator of the third level. For the pairwise comparison of non-numerical indicators (i.e., indicators I_{22}, I_{23}, I_{24}, I_{25}, I_{62}, I_{71}, I_{72}), the expert judgments (expressed by a scale as in Table 1) are used, obtaining the comparison matrices reported in Table 5. As for the pairwise comparison of numerical indicators, the relative importance of metropolitan areas A_n as opposed to A_m is calculated in accordance with (1)-(3).

As a third outcome of this step, the level 4 priorities (Table 4) are obtained; they provide the rating of metropolitan areas with respect to each indicator. This finding provides an important managerial implication to the Bari metropolitan city's manager that has to concretely act on the metropolitan areas to ensure the sustainable development of their energy, water and environmental systems. In particular, it gives the indication of the metropolitan areas that require an overriding intervention to improve a specific indicator. As an example, against indicator I_{12}, the second row of Table 6 shows that the best city is Mola (p^{312}(3)=0.4012), while the worst one is Bari (p^{312}(1)=0.0367).

Note that in all the considered pairwise comparison matrices, the obtained CR is lower than the critical limit of 0.10; consequently, all comparisons are consistent (Saaty, 2008).

4.1.3 Local priorities and consistency of comparisons.

Table 7 reports the local weights of the selected indicators, which provide a measure of the importance that the metropolitan city's manager attributes to each indicator with respect to the overall sustainability achievement. For instance, given that the Energy consumption and climate dimension is overriding the others (last columns of Table 3), and that the Energy consumption for transport is the most important indicators within this dimension (last columns of the first sub-table of Table 4), the Table 7 shows that the most important indicator is I_{12}, having a weight equal to 0.2102. Similarly, given that the CO_2 emission and industrial profile has the lowest priority (last columns of Table 3), and that the Airport ACA level is the least important indicators within this dimension (last columns of the fifth sub-table of Table 4), the Table 7 shows that the least important indicator is I_{55}, having a weight equal to 0.0007.

Table 2. Value of SDEWES indicators for the Bari metropolitan city.

Dimension	Indicator definition	Unit	Label	Source	Metropolitan areas			
					Bari	*Bitonto*	*Mola*	*Molfetta*
Energy Consumption and Climate (D_1)	Energy consumption of buildings	MWh	I_{11}	(Comune di Bari-a, Comune di Bitonto-a, Comune di Mola-a, Comune di Molfetta-a)	1956540.00	188778.00	125614.00	365402.00
	Energy consumption of transport	MWh	I_{12}	(Comune di Bari-a, Comune di Bitonto-a, Comune di Mola-a, Comune di Molfetta-a)	1671577.00	346945.00	57482.00	243922.00
	Energy consumption per capita	MWh/capita	I_{13}	(Comune di Bari-a, Comune di Bitonto-a, Comune di Mola-a, Comune di Molfetta-a)[a]	11.92	9.69	7.12	10.76
	Heating degree-days (HDD)	Days °C	I_{14}	(National Renewable Energy Laboratory-a)	1076.00	1076.00	878.00	1076.00
	Cooling degree-days (CDD)	Days °C	I_{15}	(National Renewable Energy Laboratory-a)	2806.00	2806.00	2910.00	2806.00
Penetration of Energy and CO_2 Saving Measures (D_2)	Sustainable Energy Action Plan (SEAP)	Dimensionless	I_{21}	(Comune di Bari-a, Comune di Bitonto-a, Comune di Mola-a, Comune di Molfetta-a)[b]	2	2	2	2
	Combined heat and power based DH/C	Dimensionless	I_{22}	experts[c]	-	-	-	-
	Energy savings in end-usage (buildings)	Dimensionless	I_{23}	experts[c]	-	-	-	-
	Density of public transport network	Dimensionless	I_{24}	experts[c]	-	-	-	-
	Efficient public lighting armatures	Dimensionless	I_{25}	experts[c]	-	-	-	-
Renewable Energy Potential and Utilization (D_3)	Solar energy potential	Wh/m^2/day	I_{31}	(JRC Photovoltaic Geographical Information System)	5300.00	5300.00	5300.00	5300.00
	Wind energy potential	m/s	I_{32}	(National Renewable Energy Laboratory-b)	5.24	5.04	5.58	5.34
	Geothermal energy potential	mW/m^2	I_{33}	(European Communities - Global Energy Research Institute, 2005)	65.00	65.00	65.00	65.00
	Renewable energy in electricity production	Dimensionless	I_{34}	(Comune di Bari-a, Comune di Bitonto-a, Comune di Mola-a, Comune di Molfetta-a)[d]	0.01	0.02	0.03	0.03
	Biofuel share in transport energy usage	Dimensionless	I_{35}	(Comune di Bari-a, Comune di Bitonto-a, Comune di Mola-a, Comune di Molfetta-a)	0.04	0.00	0.00	0.00
Water and Environmental Quality (D_4)	Domestic water consumption per capita	m^3	I_{41}	(Hoekstra and Mekonnen, 2012; Hoekstra et al., 2011)	54.60	53.60	55.60	52.30
	Drinking water quality index	Dimensionless	I_{42}	(Acquedotto Pugliese)[e]	87.90	87.90	87.90	87.90
	Annual mean PM10 concentration	μg/m^3	I_{43}	(European Environment Agency)	19.55	18.40	27.09	24.24
	Ecological footprint per capita	gha	I_{44}	(Global Footprint Network and National Footprint Accounts, 2010)	3.69	3.65	3.59	3.62
	Biocapacity per capita	gha	I_{45}	(Global Footprint Network and National Footprint Accounts, 2010)	1.05	1.03	1.01	1.02
CO_2 Emissions and Industrial Profile (D_5)	CO_2 emissions of buildings	t CO_2	I_{51}	(Comune di Bari-a, Comune di Bitonto-a, Comune di Mola-a, Comune di Molfetta-a)	480392.00	54040.00	40429.00	115122.00
	CO_2 emissions of transport	t CO_2	I_{52}	(Comune di Bari-a, Comune di Bitonto-a, Comune di Mola-a, Comune di Molfetta-a)	422737.00	88018.00	14816.00	63020.00
	Average CO_2 intensity	t CO_2/MWh	I_{53}	(Comune di Bari-a, Comune di Bitonto-a, Comune di Mola-a, Comune di Molfetta-a)[f]	0.27	0.30	0.29	0.25
	Number of CO_2 intense industries	Dimensionless	I_{54}	(Comune di Bari-a, Comune di Bitonto-a, Comune di Mola-a, Comune di Molfetta-a)	6.00	2.00	1.00	4.00
	Airport ACA level (0, 1, 2, 3), -1 means no airport	Dimensionless	I_{55}	(Aeroporti di Puglia)	0	-1	-1	-1
City Planning and Social Welfare (D_6)	Accessibility of public transport	Dimensionless	I_{61}	(Comune di Bari-b, Comune di Bitonto-b, Comune di Mola-b, Comune di Molfetta-b)[g]	1.48	1.89	0.10	1.39
	Urban form and protected sites (GIS)	Dimensionless	I_{62}	(Federparchi)	0.40	0.40	0.20	0.20
	Gross domestic product per capita	Dimensionless	I_{63}	experts[c]	-	-	-	-
	Inequality adjusted well-being	Dimensionless	I_{64}	(Istituto Nazionale di Statistica - ISTAT)	3.50	6.40	4.20	3.40
	Tertiary education rate	Dimensionless	I_{65}	(Istituto Nazionale di Statistica - ISTAT)	56.40	41.60	52.70	52.70
R&D, Innovation and Sustainability Policy (D_7)	R&D and innovation policy orientation	Dimensionless	I_{71}	experts[c]	-	-	-	-
	Patents in clean technologies	Dimensionless	I_{72}	experts[c]	-	-	-	-
	Local public/private universities	Dimensionless	I_{73}	(Ministero dell'Istruzione dell'Università e della Ricerca)	5	0	0	0
	h-index (citations per paper)	Dimensionless	I_{74}	(SCImago Research Group)	766.00	0.00	0.00	0.00
	Reduction Target for CO_2 Emissions	Dimensionless	I_{75}	(Comune di Bari-a, Comune di Bitonto-a, Comune di Mola-a, Comune di Molfetta-a)	0.35	0.20	0.23	0.27

[a] calculated from SEAP asthe total final energy consumption of a city (per inhabitant) for the building sector (I_{11}), the transport sector (I_{12}), public lighting, and industry, if any.

[b] based on submitted SEAP (2), prepared SEAP (1), and non-CoM signatory (0).

[c] numerical values are not provided for qualitative indicators with sub-indicators; the assessment of such indicators is done by experts.

[d] based on energy produced by renewable plants within the total energy production.

[e] based on customer satisfaction index provided by Acquedotto Pugliese.

[f] calculated from SEAP as (I_{51}+I_{52})/inhabitants.

[g] based on transportation lines.

Table 3. Pairwise comparison matrix ($\boldsymbol{C}^1$) and priorities ($\boldsymbol{p}^1$) for level 2.

	D_1	D_2	D_3	D_4	D_5	D_6	D_7	**Level 2 priorities**
D_1	1	3	4	5	9	7	8	0.4098
D_2	1/3	1	3	4	8	5	6	0.2480
D_3	1/4	1/3	1	2	6	3	4	0.1291
D_4	1/5	1/4	1/2	1	5	3	4	0.0986
D_5	1/9	1/8	1/6	1/5	1	1/4	1/3	0.0224
D_6	1/7	1/2	1/3	1/3	4	1	2	0.0543
D_7	1/3	1/6	1/4	1/4	3	1/2	1	0.0379

Table 4. Pairwise comparison matrices ($\boldsymbol{C}^{2h}$) and priorities ($\boldsymbol{p}^{2h}$) for level 3.

		I_{11}	I_{12}	I_{13}	I_{14}	I_{15}	**Level 3 priorities**
D_1	I_{11}	1	1/3	3	5	7	0.2615
	I_{12}	3	1	5	7	9	0.5128
	I_{13}	1/3	1/5	1	3	5	0.1290
	I_{14}	1/5	1/7	1/3	1	3	0.0634
	I_{15}	1/7	1/9	1/5	1/3	1	0.0333
		I_{21}	I_{22}	I_{23}	I_{24}	I_{25}	**Level 3 priorities**
D_2	I_{21}	1	9	7	5	3	0.5128
	I_{22}	1/9	1	1/3	1/5	1/7	0.0333
	I_{23}	1/7	3	1	1/3	1/5	0.0634
	I_{24}	1/5	5	3	1	1/3	0.1290
	I_{25}	1/3	7	5	3	1	0.2615
		I_{31}	I_{32}	I_{33}	I_{34}	I_{35}	**Level 3 priorities**
D_3	I_{31}	1	3	9	5	7	0.5128
	I_{32}	1/3	1	7	3	5	0.2615
	I_{33}	1/9	1/7	1	1/5	1/3	0.0333
	I_{34}	1/5	1/3	5	1	3	0.1290
	I_{35}	1/7	0.2	3	1/3	1	0.0634
		I_{41}	I_{42}	I_{43}	I_{44}	I_{45}	**Level 3 priorities**
D_4	I_{41}	1	1/3	3	5	7	0.2615
	I_{42}	3	1	5	7	9	0.5128
	I_{43}	1/3	1/5	1	3	5	0.1290
	I_{44}	1/5	1/7	1/3	1	3	0.0634
	I_{45}	1/7	1/9	1/5	1/3	1	0.0333
		I_{51}	I_{52}	I_{53}	I_{54}	I_{55}	**Level 3 priorities**
D_5	I_{51}	1	3	5	7	9	0.5128
	I_{52}	1/3	1	3	5	7	0.2615
	I_{53}	1/5	1/3	1	3	5	0.1290
	I_{54}	1/7	1/5	1/3	1	3	0.0634
	I_{55}	1/9	1/7	1/5	1/3	1	0.0333
		I_{61}	I_{62}	I_{63}	I_{64}	I_{65}	**Level 3 priorities**
D_6	I_{61}	1	9	5	3	5	0.4423
	I_{62}	1/9	1	1/5	1/7	1/5	0.0258
	I_{63}	1/5	5	1	1/3	1	0.0919
	I_{64}	1/3	7	3	1	3	0.2259
	I_{65}	2	5	1	1/3	1	0.2141
		I_{71}	I_{72}	I_{73}	I_{74}	I_{75}	**Level 3 priorities**
D_7	I_{71}	1	3	5	7	1/3	0.2615
	I_{72}	1/3	1	3	5	1/5	0.1290
	I_{73}	1/5	1/3	1	3	1/7	0.0634
	I_{74}	1/7	1/5	1/3	1	1/9	0.0333
	I_{75}	3	5	7	9	1	0.5128

Table 5. Pairwise comparison matrices ($\boldsymbol{C}^{3hk}$) for level 4.

		Bari	*Bitonto*	*Mola*	*Molfetta*
I_{22}	*Bari*	1	6	4	9
	Bitonto	1/6	1	1/4	4
	Mola	1/4	4	1	6
	Molfetta	1/9	1/4	1/6	1
I_{23}	*Bari*	1	6	4	9
	Bitonto	1/6	1	1/4	4
	Mola	1/4	4	1	6
	Molfetta	1/9	1/4	1/6	1
I_{24}	*Bari*	1	6	4	9
	Bitonto	1/6	1	1/4	4
	Mola	1/4	4	1	6
	Molfetta	1/9	1/4	1/6	1
I_{25}	*Bari*	1	6	4	9
	Bitonto	1/6	1	1/4	4
	Mola	1/4	4	1	6
	Molfetta	1/9	1/4	1/6	1
I_{63}	*Bari*	1	4	9	6
	Bitonto	1/4	1	6	4
	Mola	1/9	1/6	1	1/4
	Molfetta	1/6	1/4	4	1
I_{71}	*Bari*	1	4	9	6
	Bitonto	1/4	1	6	4
	Mola	1/9	1/6	1	1/4
	Molfetta	1/6	1/4	4	1
I_{72}	*Bari*	1	4	9	6
	Bitonto	1/4	1	6	4
	Mola	1/9	1/6	1	1/4
	Molfetta	1/6	1/4	4	1

Table 6. Priorities for level 4 ($\boldsymbol{p}^{3hk}$).

Indicator	**Level 4 priorities**			
	Bari	*Bitonto*	*Mola*	*Molfetta*
I_{11}	0.0367	0.3388	0.4012	0.2233
I_{12}	0.0376	0.2164	0.4615	0.2844
I_{13}	0.0465	0.1927	0.6660	0.0948
I_{14}	0.3214	0.3214	0.0357	0.3214
I_{15}	0.0559	0.2145	0.6738	0.0559
I_{21}	0.2500	0.2500	0.2500	0.2500
I_{22}	0.6068	0.1001	0.2509	0.0422
I_{23}	0.6068	0.1001	0.2509	0.0422
I_{24}	0.6068	0.1001	0.2509	0.0422
I_{25}	0.6068	0.1001	0.2509	0.0422
I_{31}	0.2500	0.2500	0.2500	0.2500
I_{32}	0.1136	0.0433	0.6361	0.2071
I_{33}	0.2500	0.2500	0.2500	0.2500
I_{34}	0.0423	0.1007	0.2454	0.6115
I_{35}	0.7500	0.0833	0.0833	0.0833
I_{41}	0.0978	0.2321	0.0433	0.0978
I_{42}	0.2500	0.2500	0.2500	0.2500
I_{43}	0.3402	0.5264	0.0404	0.3402
I_{44}	0.1688	0.0409	0.1952	0.0411
I_{45}	0.1533	0.6684	0.1323	0.6574
I_{51}	0.0367	0.3522	0.4082	0.2029
I_{52}	0.0376	0.2170	0.4629	0.2825
I_{53}	0.2385	0.0451	0.0819	0.6346
I_{54}	0.0401	0.3006	0.5535	0.1057
I_{55}	0.7500	0.0833	0.0833	0.0833
I_{61}	0.1100	0.0513	0.7019	0.1368
I_{62}	0.4500	0.4500	0.0500	0.0500
I_{63}	0.6068	0.2509	0.0422	0.1001
I_{64}	0.0685	0.7149	0.1572	0.0594
I_{65}	0.5309	0.0390	0.2151	0.2151
I_{71}	0.6068	0.2509	0.0422	0.1001
I_{72}	0.6068	0.2509	0.0422	0.1001
I_{73}	0.7500	0.0833	0.0833	0.0833
I_{74}	0.7500	0.0833	0.0833	0.0833
I_{75}	0.6752	0.0484	0.0842	0.1921

Table 7. Local weights.

Indicator	**Weights for overall rating**
I_{11}	0.1072
I_{12}	0.2102
I_{13}	0.0529
I_{14}	0.0260
I_{15}	0.0137
I_{21}	0.1272
I_{22}	0.0083
I_{23}	0.0157
I_{24}	0.0320
I_{25}	0.0648
I_{31}	0.0662
I_{32}	0.0338
I_{33}	0.0043
I_{34}	0.0166
I_{35}	0.0082
I_{41}	0.0258
I_{42}	0.0506
I_{43}	0.0127
I_{44}	0.0063
I_{45}	0.0033
I_{51}	0.0115
I_{52}	0.0059
I_{53}	0.0029
I_{54}	0.0014
I_{55}	0.0007
I_{61}	0.0240
I_{62}	0.0014
I_{63}	0.0050
I_{64}	0.0123
I_{65}	0.0116
I_{71}	0.0099
I_{72}	0.0049
I_{73}	0.0024
I_{74}	0.0013
I_{75}	0.0194

4.1.4 Final priorities.

The overall rating is shown in Table 8 (second column), which represents the rating of the four analyzed metropolitan areas in achieving the overall sustainability of the metropolitan city. Furthermore, Table 8 (third to ninth columns) shows the partial ratings of the metropolitan areas with respect to each of the considered dimensions. These results provide a drill-down analysis for the metropolitan city's manager, highlighting how each metropolitan area contributes to the overall sustainability across the seven dimensions.

It is apparent that, even though the area of Mola is globally first ranked, it is only ranked first with respect to dimensions D_1, D_3, D_5, and D_6. Conversely, the area of Bari is ranked first with respect to D_2 and D_7, while Molfetta is first with respect to D_4. The achieved results are of practical relevance for the implementation of the sustainability initiatives that the city of Bari is putting into place (Comune di Bari). In particular, these results are being used by the metropolitan city's manager in decision making of strategic plans aimed at improving the sustainable development of energy, water and environmental systems of the whole metropolitan city.

In the sequel the outcome of a discussion with the metropolitan city's manager as decision maker on the usability of these results are reported. First, the metropolitan city's manager has been able to identify from the rating results some best practices in specific metropolitan areas that may be implemented by other areas to improve dimension performance. For instance, Bitonto has the highest accessibility of public transport (I_{61}). The other areas could benefit from implementing an improvement strategy (e.g., introducing no car zones, encouraging bike sharing infrastructure, increasing the local bus network density) in the public transport network similar to that of Bitonto. At the same time, the metropolitan city's manager has been able to identify from the rating results the weakest areas that need the highest priority for intervention. As an example, Bari has the highest consumption of energy and emission of CO_2 in buildings (I_{11} and I_{51}). Consequently, a strategy for improving the energy efficiency of buildings in Bari is being defined by implementing the following retrofit actions: stimulating the energy retrofit of private buildings, financing the energy retrofit of public building, introducing CHP (Combined Heat and Power) and DHC (District Heating and/or Cooling) networks; increasing the utilization of renewable energy for electricity generation.

Finally, it is noteworthy that the proposed approach could be straightforwardly used as a scenario analyzer to evaluate ex-post the improvement in sustainability that may be achieved implementing specific action plans, and thus helping the decision maker in selecting the optimal strategy among a set of optimal candidates.

Table 8. Rating of the Metropolitan areas based on the proposed AHP method.

		Overall AHP rate (Level 1 priority)	D_1	D_2	D_3	D_4	D_5	D_6	D_7
Metropolitan areas	***Bari***	0.2188	0.0571	0.4238	0.2192	0.2222	0.0869	0.2452	0.6558
	Bitonto	0.2185	0.2520	0.1770	0.1661	0.2705	0.2650	0.2272	0.1309
	Mola	0.3420	0.4522	0.2505	0.3398	0.1838	0.3788	0.3972	0.0677
	Molfetta	0.2207	0.2387	0.1488	0.2748	0.3236	0.2692	0.1304	0.1457

4.2 Comparison with respect to the related literature

To show the effectiveness of the proposed AHP-based methodology, it is compared with the use of a composite index applied to the same set of individual indicators, namely the SDEWES Index. As previously mentioned, the computation of the SDEWES Index is performed by two phases. The first phase consists in data collection. For the numerical indicators (e.g., indicators I_{11}, I_{12}, etc.), the values reported in Table 2 are used. As for the non-numerical indicators (i.e., indicators I_{22}, I_{23}, I_{24}, I_{25}, I_{62}, I_{71}, I_{72}), experts are asked to provide for all the considered metropolitan areas an estimate in the absolute scale indicated in (Kılkış, 2016), which is reported in Table 9.

Table 9. Value of SDEWES indicators considered in the case study.

Indicator definition	**Unit**	**Label**	**Source**	**Metropolitan areas**			
				Bari	*Bitonto*	*Mola*	*Molfetta*
Combined heat and power based DH/C	Dimensionless	I_{22}	experts	2	1	1	1
Energy savings in end-usage (buildings)	Dimensionless	I_{23}	experts	1	1	1	1
Density of public transport network	Dimensionless	I_{24}	experts	2	1	1	1
Efficient public lighting armatures	Dimensionless	I_{25}	experts	2	1	1	1
Gross domestic product per capita	Dimensionless	I_{63}	experts	5	3	2	4
R&D and innovation policy orientation	Dimensionless	I_{71}	experts	4	1	1	2
Patents in clean technologies	Dimensionless	I_{72}	experts	3	1	1	2

The second phase consists in the computation of Equation (10) once the dimension weights are assigned. In order to guarantee significance in the approaches comparison, the dimension weights to be used in the SDEWES Index are set equal to the dimension priorities used in the AHP method (i.e., the Level 2 priorities reported in the last column of Table 3): $\alpha(h)$ $=p^1(h)$ for each $h = 1, \dots, H$. It is worth to remark that indicators of a given dimension are equally weighted because no weighting coefficient for indicators of a given dimension is defined in the SDEWES Index computation procedure.

Table 10 (second column) represents the rating of the four analyzed metropolitan areas in achieving the overall sustainability of the metropolitan city in accordance to the SDEWES Index. The top-ranked metropolitan area is Mola (SDEWES = 2.9914), followed by Bari (2.7996), Molfetta (2.7155) and Bitonto (2.6596). Furthermore, Table 10 (third to ninth columns) shows the partial rating of metropolitan areas with respect to each of the considered dimensions. The top-ranked city has accordingly the best value in most of dimensions having higher priorities.

Table 10. Rating of the Metropolitan areas based on the SDEWES Index.

		SDEWES Index	D_1	D_2	D_3	D_4	D_5	D_6	D_7
Metropo-litan areas	***Bari***	2.7996	1.0000	5.0000	3.3704	3.1707	1.6000	3.2624	5.0000
	Bitonto	2.6596	3.2508	2.0000	2.3333	3.5061	2.5896	2.3333	0.0000
	Mola	2.9914	4.0000	2.0000	3.6517	2.0000	3.2000	2.0167	0.1733
	Molfetta	2.7155	2.9952	2.0000	3.5556	3.2780	3.1121	1.6960	1.2733

Comparing results in Tables 8 and 10, it is apparent that the two approaches provide similar results from a high-level perspective. The top-ranked city is Mola using both the AHP method and the SDEWES Index. Figure 2 puts in comparison the overall and the partial ratings of Metropolitan areas with respect to each dimension for the two approaches. Even though the AHP and the SDEWES Index methodology use different scales, Fig. 2a and 2b show that the partial ratings with respect to dimensions D_1, D_3, and D_5 are consistent and rank the considered cities in the same order. Conversely, the partial ratings are slightly different for the remaining dimensions where cities are differently ranked in some cases. These different behaviors are motivated by two main reasons. First, in the AHP method weighting coefficients are used to differently weight indicators of a given dimension. On the contrary, in the computation of the SDEWES Index, only dimension weighting coefficients are defined.

Secondly, for estimating the qualitative indicators with sub-indicators, the AHP method uses the pairwise comparison as reported in Table 1, whilst the SDEWES Index uses an absolute scale to simultaneously assess the value of indicators for all the metropolitan areas. To highlight this second effect, Fig. 2c shows the overall and the partial ratings of Metropolitan areas with respect to each dimension using the AHP with equal indicator weighting coefficients (i.e., equal to 0.2 instead of the values indicated in the last column of Table 4).

Finally, although different ranking methods such as the SDEWES Index procedure may lead to similar results, AHP exhibits several distinctive and advantageous features. First, AHP is a flexible and powerful tool that allows specifically prioritizing all the levels of decision criteria (i.e., dimensions and indicators). Secondly, the final ranking is obtained on the basis of the pairwise relative evaluations of both criteria and alternatives provided by the decision maker. This is particularly relevant for qualitative assessment of alternatives, where the pairwise comparison procedure exhibits an enhanced accuracy with respect to other approaches. AHP can thus be considered as a tool that is able to translate the evaluations (both qualitative and quantitative) made by the decision maker into a multi-criteria ranking. Finally, AHP is simple because it is able to embed the decision maker’s knowledge into the evaluation procedure through the straightforward pairwise comparisons without the need of a complex expert system.

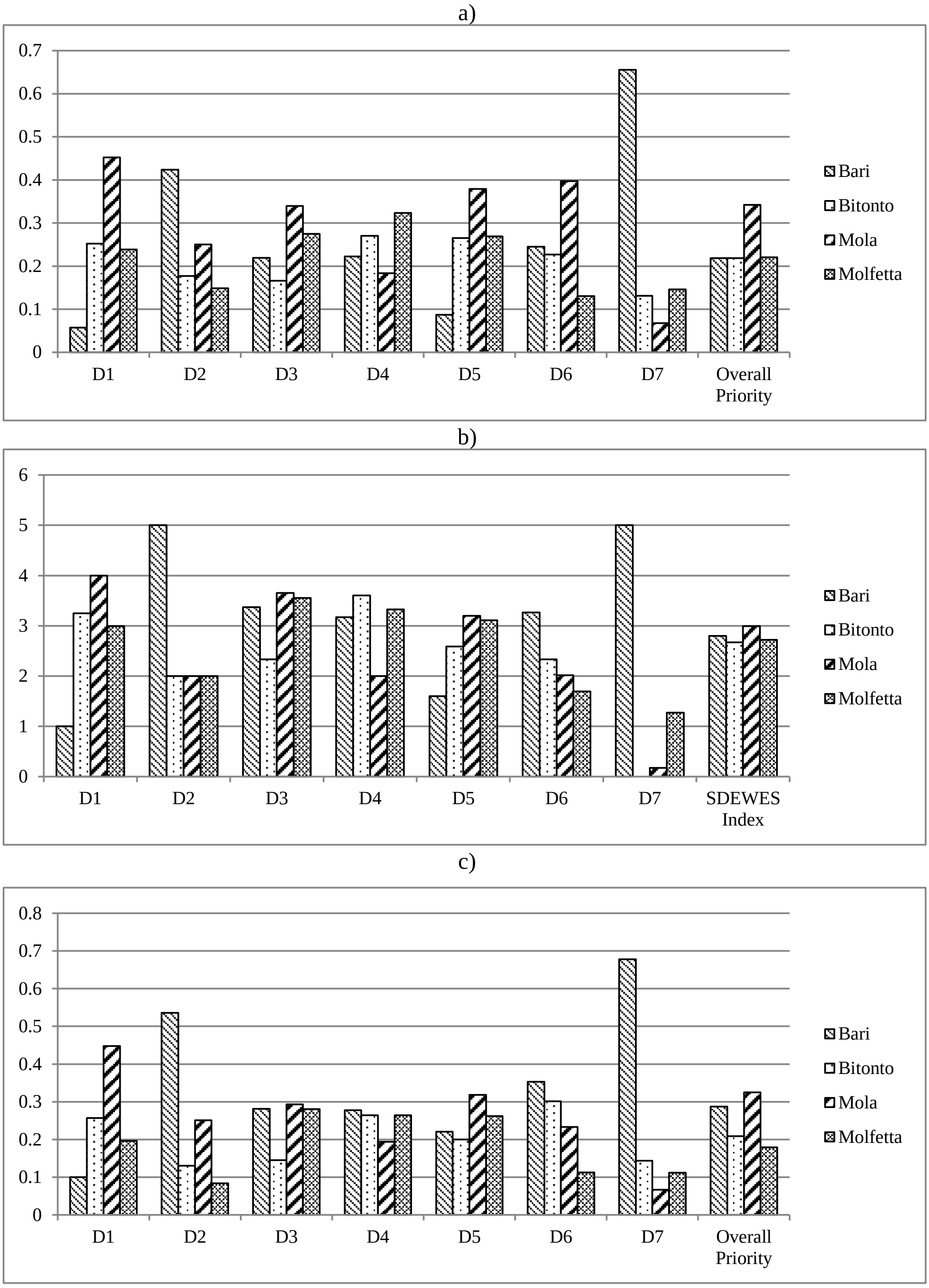

Figure 2 - Rating of the metropolitan areas with respect to dimensions and overall sustainability: case a) AHP method with different indicator weighting coefficients; case b) SDEWES Index; case c) AHP method with equal indicator weighting coefficients.

4.3 Results of the sensitivity analysis

According to Subsection 3.1.6, an AHP sensitivity analysis is conducted considering 42 input factors: $H = 7$ criteria priorities (i.e., level 2 priorities) and $\sum_{h=1}^{H} K_h = 35$ subcriteria priorities (i.e., level 3 priorities) collected in vectors $\boldsymbol{p}^1$ and $\boldsymbol{p}^{2h}$ (with $h = 1, \dots, H$). The baseline scenario for factors $\boldsymbol{p}^1$ and $\boldsymbol{p}^{2h}$ is reported in Tables 3 and 4 respectively, whilst the ratings presented in Table 8 are referred as the baseline ratings $\boldsymbol{p}^{AHP}$, implying that the baseline ranking for the set of metropolitan areas is $\boldsymbol{r}^{AHP} = [4, 2, 1, 3]$.

Preliminarily, the weights of criteria and sub-criteria are sampled using a uniformly distributed quasi-random scheme. In particular, for each criterion/sub-criterion, the weight is randomly generated in an interval whose centre is the baseline value and half-width is the 50% of the baseline value. In total, $W = 42.000$ combinations of input weights are totally generated. The input scenario for the w-th combination is thus characterized by the criteria priorities values collected in vector $\boldsymbol{p}^1{}_w = [p^1{}_w(1), \dots, p^1{}_w(h), \dots, p^1{}_w(H)]$ and the subcriteria priorities collected in vectors $\boldsymbol{p}^{2h}{}_w = [p^{2h}{}_w(1), \dots, p^{2h}{}_w(k), \dots, p^{2h}{}_w(K_h)]$ with $h = 1, \dots, H$. Note that in each w-th combination, all the weights reflect the relative nature of the weights, i.e., the criteria priorities as well as all the subcriteria priorities have to add up to unitary value: $\sum_{h=1}^{H} p^1{}_w(h) = 1$ and $\sum_{k=1}^{K_h} p^{2h}{}_w(k) = 1, h = 1, \dots, H$.

Subsequently, W simulation runs (one for each input combination) are performed to calculate the ratings $\boldsymbol{p}^{AHP}{}_w = \left[p^{AHP}{}_w(1), \dots, p^{AHP}{}_w(n), \dots, p^{AHP}{}_w(N)\right]$ and associated ranking $\boldsymbol{r}^{AHP}{}_w = [r^{AHP}{}_w(1), \dots, r^{AHP}{}_w(n), \dots, r^{AHP}{}_w(N)]$ (with $w = 1, \dots, W$).

The simulation results are consequently processed in order to accomplish the following three goals:

1. identify criteria and subcriteria that are especially sensitive to weight changes;
2. investigate the stability of AHP ratings by introducing variations to subcriteria and criteria weights;
3. identify criteria and subcriteria that have the strongest impact on differences in the metropolitan areas ranking with respect to the baseline ranking.

The first-order indices and the total effect indices in Equations (8) and (9) are calculated for the rating of each considered metropolitan area in accordance with the method proposed in (Saltelli *et al.*, 2010), and reported in Table 11. It is apparent that the first-order sensitivity indices S_m for each metropolitan area (Table 11, third to sixth columns), show that the AHP ratings are mainly influenced by changes in the second criterion (i.e., the Penetration of Energy and CO_2 Saving Measures dimension), and first criterion (i.e., the Energy Consumption and Climate dimension) for Bari, and Bitonto, Mola and Molfetta, respectively. Furthermore, it is evident that the interactions between input factors do not have an impact on the rating for either metropolitan areas, since first-order sensitivity indices sum to an almost unitary value (i.e., the proposed AHP model is almost additive over the criteria and subcriteria weights). This also means that total effect indices S_{Tm}, for each metropolitan area's rating, do not provide any additional detail to the sensitivity analysis (Table 11, seventh to tenth columns).

Secondly, the Monte Carlo simulation results are summarized in Fig. 3 that shows the box-and-whisker plots of the W values for the AHP metropolitan areas' ratings and confirms that Mola is generally better rated than the other three areas, which in turn have comparable performances. In fact, it is evident from Fig. 3 that the box related to ratings of Mola never overlaps other boxes and that the bottom whisker related to ratings of Mola shortly overlaps other whiskers; conversely, the boxes and the whiskers related to ratings of Bari, Bitonto, and Molfetta show significant overlap. As a result, this shows that the first ranking of Mola is robustly stable and mostly independent from changes in weights definition, whilst the rankings of other metropolitan areas may suffer from shift effects.

Finally, an estimation of the effect of weights variation on differences in the metropolitan areas' ranking with respect to the baseline ranking is performed. Following (Saltelli *et al.* 2008), an indicator R_w for the cumulative shift from the baseline ranking is introduced to quantify the cumulative number of relative shift in the rank positions of metropolitan areas:

$$R_w = \sum_{n=1}^{N} | \, r^{AHP}(n) - r^{AHP}{}_w(n) \, |. \qquad (13)$$

Figure 4 provides the histograms of the W Monte Carlo computation of indicator R_w for the three cases of analysis. In most cases the cumulative shift with respect to the baseline ranking is of 2 positions, which means that it is more frequent that the ranks of only two metropolitan areas between Bari, Bitonto, and Molfetta is reversed. The first-order indices and the total effect indices are calculated for cumulative number of relative shift R_w, and reported in Table 12. It is apparent from Table 12 that only 42% of the variance of R_w is explained by the single factors, a great part of which is attributable to third criterion (i.e., the Renewable Energy Potential and Utilization dimension) and the first subcriterion of second criterion 2 (i.e., the Sustainable Energy Action Plan (SEAP) indicator). This also confirms the high non-linearity of R_w (see the presence of absolute value in Equation (13)), where the interactions between weights account for 58% of its variance. The most influential factors for interactions are the second criterion (i.e., the Penetration of Energy and CO_2 Saving Measures dimension) and the first subcriterion of second criterion (i.e., the Sustainable Energy Action Plan (SEAP) indicator).

Summing up, all the outcomes from the sensitivity analysis are useful for the decision maker to identify the most important factors for each metropolitan area. Indeed, these results guide the decision maker in carefully reviewing the choice of criteria and subcriteria weights, to improve the reliability of the weights' values that are most crucial to the rating and ranking of metropolitan areas.

Table 11. Value of sensitivity indices for the metropolitan areas' AHP rankings*.

		Sensitivity indices for the metropolitan areas' AHP ratings							
		First-order coefficients S_m				**Total effect coefficients** S_{Tm}			
Factors		**Metropolitan areas**				**Metropolitan areas**			
identifier m	description	*Bari*	*Bitonto*	*Mola*	*Molfetta*	*Bari*	*Bitonto*	*Mola*	*Molfetta*
1	$p^1(1)$	0.0308	**0.5527**	**0.6106**	**0.4898**	0.0272	0.5564	0.6122	0.4938
2	$p^1(2)$	**0.6250**	0.0994	0.0691	0.0692	0.6227	0.1041	0.0714	0.0741
3	$p^1(3)$	0.0454	0.0235	0.0348	0.0646	0.0410	0.0272	0.0362	0.0678
4	$p^1(4)$	0.0272	0.0363	0.0063	0.0516	0.0230	0.0411	0.0083	0.0565
5	$p^1(5)$	0.0001	0.0010	0.0015	0.0012	0.0041	0.0054	0.0035	0.0056
6	$p^1(6)$	0.0093	0.0067	0.0081	0.0018	0.0058	0.0116	0.0106	0.0064
7	$p^1(7)$	0.0345	0.0005	0.0004	0.0010	0.0304	0.0049	0.0024	0.0053
8	$p^{21}(1)$	0.0007	0.0677	0.0331	0.0288	0.0034	0.0723	0.0351	0.0333
9	$p^{21}(2)$	0.0034	**0.1071**	**0.1677**	**0.1830**	0.0009	0.1099	0.1688	0.1856
10	$p^{21}(3)$	0.0000	0.0045	0.0221	0.0007	0.0040	0.0088	0.0240	0.0050
11	$p^{21}(4)$	0.0039	0.0029	0.0003	0.0031	0.0004	0.0072	0.0023	0.0073
12	$p^{21}(5)$	0.0002	0.0004	0.0018	0.0006	0.0044	0.0040	0.0037	0.0038
13	$p^{22}(1)$	0.0564	0.0512	0.0180	0.0505	0.0539	0.0568	0.0205	0.0563
14	$p^{22}(2)$	0.0011	0.0008	0.0004	0.0006	0.0031	0.0036	0.0023	0.0038
15	$p^{22}(3)$	0.0049	0.0007	0.0005	0.0006	0.0007	0.0037	0.0025	0.0038
16	$p^{22}(4)$	0.0207	0.0004	0.0013	0.0005	0.0172	0.0042	0.0034	0.0039
17	$p^{22}(5)$	**0.0871**	0.0015	0.0052	0.0002	0.0836	0.0058	0.0070	0.0042
18	$p^{23}(1)$	0.0154	0.0138	0.0053	0.0138	0.0113	0.0178	0.0071	0.0178
19	$p^{23}(2)$	0.0006	0.0007	0.0084	0.0019	0.0034	0.0038	0.0108	0.0065
20	$p^{23}(3)$	0.0002	0.0008	0.0003	0.0005	0.0043	0.0037	0.0023	0.0038
21	$p^{23}(4)$	0.0002	0.0007	0.0006	0.0048	0.0044	0.0037	0.0025	0.0090
22	$p^{23}(5)$	0.0018	0.0008	0.0003	0.0006	0.0021	0.0037	0.0023	0.0038
23	$p^{24}(1)$	0.0001	0.0011	0.0003	0.0129	0.0041	0.0054	0.0023	0.0169
24	$p^{24}(2)$	0.0087	0.0076	0.0032	0.0077	0.0044	0.0118	0.0050	0.0119
25	$p^{41}(3)$	0.0007	0.0014	0.0003	0.0005	0.0033	0.0059	0.0023	0.0039
26	$p^{24}(4)$	0.0003	0.0008	0.0005	0.0004	0.0044	0.0036	0.0025	0.0039
27	$p^{24}(5)$	0.0000	0.0008	0.0003	0.0006	0.0041	0.0036	0.0023	0.0038
28	$p^{25}(1)$	0.0003	0.0000	0.0007	0.0003	0.0044	0.0046	0.0027	0.0041
29	$p^{25}(2)$	0.0003	0.0007	0.0004	0.0004	0.0044	0.0037	0.0024	0.0039
30	$p^{25}(3)$	0.0003	0.0008	0.0003	0.0004	0.0044	0.0036	0.0023	0.0039
31	$p^{25}(4)$	0.0003	0.0008	0.0003	0.0006	0.0044	0.0036	0.0023	0.0038
32	$p^{25}(5)$	0.0003	0.0008	0.0003	0.0006	0.0044	0.0036	0.0023	0.0038
33	$p^{26}(1)$	0.0001	0.0008	0.0051	0.0001	0.0041	0.0037	0.0072	0.0043
34	$p^{26}(2)$	0.0003	0.0008	0.0003	0.0006	0.0044	0.0036	0.0023	0.0038
35	$p^{26}(3)$	0.0003	0.0007	0.0003	0.0006	0.0038	0.0037	0.0023	0.0038
36	$p^{26}(4)$	0.0002	0.0035	0.0004	0.0005	0.0043	0.0077	0.0023	0.0038
37	$p^{26}(5)$	0.0019	0.0008	0.0004	0.0002	0.0022	0.0036	0.0024	0.0042
38	$p^{27}(1)$	0.0018	0.0005	0.0003	0.0006	0.0021	0.0039	0.0023	0.0038
39	$p^{27}(2)$	0.0002	0.0007	0.0003	0.0006	0.0039	0.0037	0.0023	0.0038
40	$p^{27}(3)$	0.0001	0.0008	0.0003	0.0006	0.0042	0.0036	0.0023	0.0038
41	$p^{27}(4)$	0.0002	0.0008	0.0003	0.0006	0.0043	0.0036	0.0023	0.0038
42	$p^{27}(5)$	0.0092	0.0008	0.0003	0.0000	0.0055	0.0037	0.0023	0.0046
Sum		0.9944	0.9990	0.9995	0.9983	1.0323	1.1499	1.0931	1.1571

*Values in bold indicate most influential criteria and subcriteria based on S_m

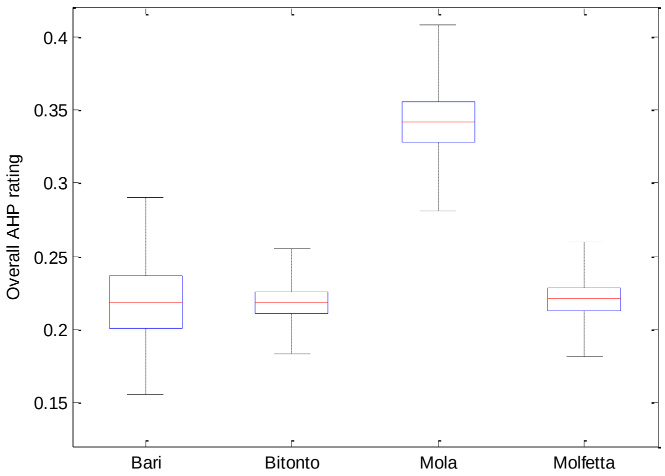

Figure 3 – Box-and-whisker plot of the Monte Carlo values for the AHP ratings in the variance based sensitivity analysis: inputs are uniformly distributed in intervals with centre in the baseline values and half-width equal to 50% of the baseline values. On each box, the central mark indicates the median, and the bottom and top edges indicate the first and third quartiles; whiskers identify values from minimum the maximum.

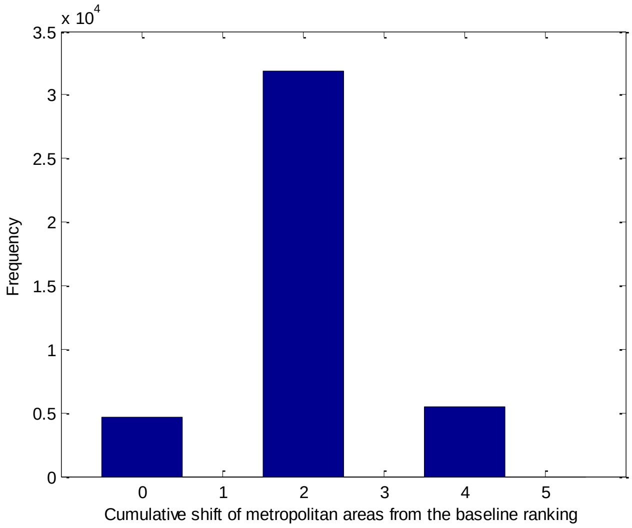

Figure 4 – Histogram of the cumulative shift from the baseline ranking for metropolitan areas: in the Monte Carlo simulation inputs are uniformly distributed in intervals with centre in the baseline values and half-width equal to 50% of the baseline values.

Table 12. Value of sensitivity indices for the cumulative shift from the baseline AHP ranking*.

		Sensitivity indices for the cumulative shift from the baseline AHP ranking	
Factors		**First-order coefficients** S_m	**Total effect scoefficients** S_{Tm}
identifier m	description		
1	$p^1(1)$	0.0293	**0.4974**
2	$p^1(2)$	0.0173	0.4869
3	$p^1(3)$	**0.0641**	0.3063
4	$p^1(4)$	0.0093	0.1670
5	$p^1(5)$	0.0018	0.0558
6	$p^1(6)$	0.0106	0.1278
7	$p^1(7)$	0.0017	0.2166
8	$p^{21}(1)$	0.0563	0.4539
9	$p^{21}(2)$	**0.0619**	**0.5575**
10	$p^{21}(3)$	0.0110	0.1450
11	$p^{21}(4)$	0.0015	0.0044
12	$p^{21}(5)$	0.0037	0.0507
13	$p^{22}(1)$	0.0015	0.0044
14	$p^{22}(2)$	0.0018	0.0652
15	$p^{22}(3)$	0.0013	0.1171
16	$p^{22}(4)$	0.0043	0.2144
17	$p^{22}(5)$	0.0046	0.3544
18	$p^{23}(1)$	0.0015	0.0044
19	$p^{23}(2)$	0.0105	0.1188
20	$p^{23}(3)$	0.0015	0.0044
21	$p^{23}(4)$	0.0228	0.1930
22	$p^{23}(5)$	0.0018	0.0701
23	$p^{24}(1)$	0.0324	0.2618
24	$p^{24}(2)$	0.0015	0.0044
25	$p^{41}(3)$	0.0102	0.1216
26	$p^{24}(4)$	0.0022	0.0280
27	$p^{24}(5)$	0.0017	0.0312
28	$p^{25}(1)$	0.0027	0.0650
29	$p^{25}(2)$	0.0015	0.0254
30	$p^{25}(3)$	0.0017	0.0403
31	$p^{25}(4)$	0.0017	0.0115
32	$p^{25}(5)$	0.0015	0.0104
33	$p^{26}(1)$	0.0024	0.0467
34	$p^{26}(2)$	0.0014	0.0163
35	$p^{26}(3)$	0.0017	0.0424
36	$p^{26}(4)$	0.0239	0.1794
37	$p^{26}(5)$	0.0039	0.0931
38	$p^{27}(1)$	0.0016	0.0785
39	$p^{27}(2)$	0.0019	0.0423
40	$p^{27}(3)$	0.0017	0.0238
41	$p^{27}(4)$	0.0015	0.0147
42	$p^{27}(5)$	0.0047	0.1700
Sum		0.4216	5.5225

*Values in bold indicate most influential criteria or subcriteria based on S_m or S_{Tm}

5 CONCLUSION

This paper discusses the application of the Analytic Hierarchy Process multi-criteria decision making technique to benchmarking metropolitan areas in terms of the sustainable development of their energy, water and environment systems.

The scientific contribution of the paper is twofold. From an academic perspective, it contributes to the existing literature on the performance evaluation of the sustainable development of cities, which lacks studies investigating the sustainability of metropolitan cities, a concept of recent formulation. In fact, while the existing studies made efforts to benchmark cities in a holistic way through the development of composite indices, they fail to provide operative indications about specific areas of intervention (e.g., sectors, neighborhoods) that need improvements. Also, AHP overcomes the issues of estimating indicators of the composite indices for which quantitative data are not available in case of metropolitan areas (namely, towns of the metropolitan city). It enables experts to provide a pairwise subjective estimation of qualitative indicators englobed in the composite indices, which, contrarily, becomes difficult if the estimation is done simultaneously, for all the metropolitan areas, in a given scale. Also, through the comparison of the proposed approach to well-established ranking methods, such as the SDEWES Index, the robustness and the novelty of the approach is demonstrated. From one hand, AHP provides similar results to those obtained by such established procedures, thus, confirming its robustness. On the other hand, AHP exhibits distinctive and advantageous features. The prioritizing of decision criteria at all the levels (i.e., dimensions and indicators) provides the decision maker with useful flexibility in defining the decision structure. The use of pairwise relative evaluations of both criteria and alternatives emphasizes the utility of such approach in contexts characterized by a lack of numerical data or needing subjective estimations, where the pairwise comparison procedure exhibits an enhanced accuracy with respect to other approaches.

From a practical perspective, the application of the approach to the real case study of four metropolitan areas (Bari, Bitonto, Mola, and Molfetta) in the city of Bari (Italy) shows its usefulness for the local government in benchmarking metropolitan areas and providing decision indications on how to formulate the sustainable development strategy of the metropolitan city. Representing a bridge between theory and practice, it shows how metropolitan city’s managers may practically use the decision making approach to benchmark the metropolitan areas in terms of their contribution to the overall metropolitan city sustainability. Indications of the areas that need an overriding intervention and the specific sector on which it is strategic to intervene for promoting the sustainability of energy, water and environment systems of the metropolitan city are also obtained. By taking into account the experience and preferences of the decision makers, it allows assessing the propensity and susceptibility of the individual metropolitan areas to adopt a “sustainable” development approach through a set of indicators coherent with the objectives of the metropolitan city and their importance. Finally, the sensitivity analysis carried out on the subjective weights of criteria and sub-criteria enables to understand how much the strategy formulated by the decision maker to promote the sustainable development of metropolitan city based on the AHP rating depends on his/her subjective judgments.

The proposed approach is however not without limitations. The main limitation derives from the genuine uncertainty and vagueness that characterize the human reasoning and decision making. These aspects complicate the exact estimation of the pairwise comparisons as well as the visualization of the difference between close values (e.g., 1 and 2 in the AHP semantic scale of relative importance of alternatives). Further research will be devoted to overcoming this limitation by introducing an approach based on fuzzy logic, which provides a natural framework to express and deal with this kind of uncertainty.

REFERENCES

Acquedotto Pugliese, Customer Satisfaction Audit, www.aqp.it/portal/pls/portal/docs/1/1282932.PDF (in Italian).

Aeroporti di Puglia, http://www.aeroportidipuglia.it.

Afgan, N., Carvalho, M., Hovanov, N., 2000. Energy system assessment with sustainability indicators. *Energy Policy* 28, 603-612.

Afgan, N., Carvalho, M., Hovanov, N., 2005. Modeling of energy system sustainability Index. *Therm. Sci.* 9 (2), 3-16.

Becker, W., Saisana, M., Paruolo, P., & Vandecasteele, I. (2017). Weights and importance in composite indicators: Closing the gap. *Ecological indicators, 80*, 12-22.

Berardi, U. (2013) Sustainability assessments of communities through rating systems, *Environment, Development and Sustainability*, Vol. 15, No. 6, pp. 1573-1591.

Boselli, R., Cesarini, M., Mercorio, F., & Mezzanzanica, M. (2015). Applying the AHP to Smart Mobility Services: A Case Study. In *DATA* (pp. 354-361).

Carli, R., Dotoli, M., Pellegrino, R., & Ranieri, L. (2013, October). Measuring and managing the smartness of cities: A framework for classifying performance indicators. In Proc. of *Systems, Man, and Cybernetics (SMC), 2013 IEEE International Conference on* (pp. 1288-1293).

Carli, R., Deidda, P., Dotoli, M., & Pellegrino, R. (2014, September). An urban control center for the energy governance of a smart city. In Proc. of *Emerging Technology and Factory Automation (ETFA), 2014 IEEE International Conference on* (pp. 1-7).

Carli, R., Dotoli, M., Pellegrino, R. (2017), "A Hierarchical Decision Making Strategy for the Energy Management of Smart Cities", *IEEE Trans. Autom. Sci. Eng.*, vol. 14, no. 2, pp. 505-523. doi: 10.1109/TASE.2016.2593101.

Città metropolitana, http://www.cittametropolitana.ba.it/ (in Italian).

Comune di Bari-a, Piano d'Azione Energia Sostenibile (PAES). http://www.comune.bari.it/portal/page/portal/bari/temiBari/ambienteEverde/pianoDiAzionePerLEnergiaSostenbilePaes (in Italian).

Comune di Bari-b, http://www.comune.bari.it (in Italian).

Comune di Bitonto-a, Piano d'Azione Energia Sostenibile (PAES). http://www.comune.bitonto.ba.it/paes.html (in Italian).

Comune di Bitonto-b, http://www.comune.bitonto.ba.it (in Italian).

Comune di Mola-a, Piano d'Azione Energia Sostenibile (PAES). http://www.comune.moladibari.ba.it/paes.html (in Italian).

Comune di Mola-b, http://www.comune.moladibari.ba.it (in Italian).

Comune di Molfetta-a, Piano d'Azione Energia Sostenibile (PAES). http://www.comune.molfetta.ba.it/trasparenza/piano-dazione-per-lenergia-sostenibile-paes/ (in Italian).

Comune di Molfetta-b, http://www.comune.molfetta.ba.it (in Italian).

Dipartimento per lo Sviluppo e la Coesione Economica (2014). Programma Operativo Nazionale Città Metropolitane 2014-2020. http://www.agenziacoesione.gov.it/opencms/export/sites/dps/it/documentazione/PON_metro/PON_Citta_Metropolitane.pdf.

Dirks, S., Keeling, M., & Dencik, J. (2009). How smart is your city?: Helping cities measure progress. *IBM Institute for Business Value, IBM Global Business Services, New York*.

Elkarni, F. and Mustafa, I. (1993). Increasing the utilization of solar energy technologies (SET) in Jordan: Analytic Hierarchy Process. *Energy Policy* 21, 978–984.

European Communities e Global Energy Research Institute, 2005. Atlas of Geothermal Resources in Europe. In: Heat-flow Density. http://www.geni.org/globalenergy/library/renewable-energy-resources/world/europe/hydro-europe/indexbig.shtml

European Environment Agency PM10 Interpolated Maps, Particulate Matter (PM10): Annual Mean Concentrations in Europe, http://www.eea.europa.eu/themes/air/ interactive/pm10

Federparchi, http://www.parks.it/regione.puglia (in Italian).

Fujita, M., Krugman, P.R. and Venables, A. *The spatial economy: cities, regions and international trade*. MIT Press, 2001.

Giffinger, R., Fertner, C., Kramar, H., Kalasek, R., Pichler- Milanović, N., & Meijers, E. (2007) "Smart Cities: Ranking of European Medium-Sized Cities". Vienna, Austria: Centre of Regional Science (SRF), Vienna University of Technology. Available at http://www.smartcities.eu/download/smart_cities_final_report.pdf.

Giri, S., & Nejadhashemi, A. P. (2014). Application of analytical hierarchy process for effective selection of agricultural best management practices. *Journal of environmental management*, 132, 165-177.

Global Footprint Network and National Footprint Accounts 2010, National Ecological Footprint and Biocapacity, www.footprintnetwork.org

Hoekstra, A., Mekonnen, M., 2012. The water footprint of humanity. Proc. Natl. Acad. Sci. 109 (9), 3232e3237.

Hoekstra, A., Chapagain, A., Aldaya, M., et al., 2011. *Water Footprint Assessment Manual: Setting the Global Standard*. Earthscan, London.

Hsieh, H. N., Chou, C. Y., Chen, C. C., & Chen, Y. Y. (2011). The evaluating indices and promoting strategies of intelligent city in Taiwan. In *Multimedia Technology (ICMT), 2011 International Conference* on (pp. 6704-6709). IEEE.

Inkoom, J. N., Frank, S., Greve, K., & Fürst, C. (2018). A framework to assess landscape structural capacity to provide regulating ecosystem services in West Africa. *Journal of environmental management*, 209, 393-408.

Istituto Nazionale di Statistica - ISTAT, http://ottomilacensus.istat.it/provincia/072/ (in Italian)

JRC Photovoltaic Geographical Information System (PVGIS), Incident Global Irradiation for the Chosen Location http://re.jrc.ec.europa.eu/pvgis/apps4/pvest.php#.

Kılkış, Ş. "Composite index for benchmarking local energy systems of Mediterranean port cities." *Energy* 92 (2015): 622-638.

Kılkış, Ş. "Sustainable Development of Energy, Water and Environment Systems Index for Southeast European Cities." *J. Clean. Prod* 130 (2016): 222-234.

Kılkış, Ş. (2018a). Benchmarking South East European Cities with the Sustainable Development of Energy, Water and Environment Systems Index. Journal of Sustainable Development of Energy, Water and Environment Systems, 6(1), 162-209.

Kılkış, Ş. (2018b). Sustainable Development of Energy, Water and Environment Systems (SDEWES) Index for policy learning in cities. International *Journal of Innovation and Sustainable Development*, 12(1-2), 87-134.

Kim, H.M., and Han, S.S. (2012). City profile: Seoul. *Cities*, 29(2), 142–154.

Ministero dell'Istruzione dell'Università e della Ricerca, http://www.miur.gov.it/web/guest/home (in Italian)

Nardo, M., Saisana, M., Saltelli, A., Tarantola, S., 2005. *Tools for Composite Indicators Building*. European Communities.

National Renewable Energy Laboratory-a, NASA Atmospheric Science Data Center Datasets http://maps.nrel.gov/swera.

National Renewable Energy Laboratory-b, Solar and Wind Energy Research Assessment Resource Graphs (SWERA), NASA Atmospheric Science Data Center and NASA/MED Datasets http://maps.nrel.gov/swera.

Neirotti, P., De Marco, A., Cagliano, A. C., Mangano, G., & Scorrano, F. (2014). Current trends in Smart City initiatives: Some stylised facts. *Cities*, *38*, 25-36.

PA Forum (2012). “Icity rate. La classifica delle città intelligenti italiane”. Available at: http://www.icitylab.it/il-rapporto-icityrate/cose/ (in Italian).

Papa, R., Gargiulo, C., Battarra, R., Niglio, R., Fabricatti, K., Pappalardo, G., Tremiterra, M. R., Raimondo, M., Mello, D., Lombardi, C., Oliva, J.S., Boiano, D.A., Arena, A., Cassella, S., Russo, L., D'Agostino, D.C., Leccisi, E., Fini, G., Galliano, R. and Carlin, M. (2016) *Città Metropolitane e Smart Governance Iniziative di successo e nodi critici verso la Smart City.* Smart City, Urban Planning for a Sustainable Future, 1. FedOAPress - Federico II Open Access University Press, Napoli, Italy.

Saaty, T.L., 1980. *The Analytical Hierarchy Process*. NY McGraw Hill.

Saaty, T. L. (2008). Decision making with the analytic hierarchy process, *International Journal of Services Sciences*, 1(1), 83–98.

Saisana, M., Saltelli, A., & Tarantola, S. (2005). Uncertainty and sensitivity analysis techniques as tools for the quality assessment of composite indicators. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, *168*(2), 307-323.

Saisana, M., & Tarantola, S. (2002). *State-of-the-art report on current methodologies and practices for composite indicator development* (p. 214). European Commission, Joint Research Centre, Institute for the Protection and the Security of the Citizen, Technological and Economic Risk Management Unit.

Saltelli, A., K. Chan, and M. Scott, (2000a), *Sensitivity analysis*, Probability and Statistics series (New York: John Wiley & Sons).

Saltelli, A., Tarantola, S. and Campolongo, F. (2000b) Sensitivity analysis as an ingredient of modelling. *Statist. Sci.*, 15, 377-395.

Saltelli, Andrea, et al. *Global sensitivity analysis: the primer*. John Wiley & Sons, 2008.

Saltelli, Andrea, et al. "Variance based sensitivity analysis of model output. Design and estimator for the total sensitivity index." Computer Physics Communications 181.2 (2010): 259-270.

SCImago Research Group, http://www.scimagojr.com/countryrank.php

Siemens, Green City Index http://www.siemens.com/entry/cc/en/greencityindex

Sobol, I.M. (2001), Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates. MATH COMPUT SIMULAT,55(1–3),271-280.

Tan, S., Yang, J., Yan, J., Lee, C., Hashim, H., & Chen, B. (2017). A holistic low carbon city indicator framework for sustainable development. *Applied Energy*, 185, 1919-1930.

Tian, W., Bai, J., Sun, H., & Zhao, Y. (2013). Application of the analytic hierarchy process to a sustainability assessment of coastal beach exploitation: a case study of the wind power projects on the coastal beaches of Yancheng, China. *Journal of environmental management*, 115, 251-256.

Toppeta, D. (2010). The Smart City Vision: How Innovation and ICT Can Build Smart, “Livable”, Sustainable Cities: The Innovation Knowledge Foundation. Available at http://www.thinkinnovation.org/file/research/23/en/Toppeta_Report_005_2010.pdf.

United Nations (2018). World urbanization prospects: The 2018 revision. United Nations, New York: Department of Economic and Social Affairs.

Urbaniec, K., Mikulčić, H., Duić, N., & Lozano, R. "SDEWES 2014–Sustainable Development of Energy, Water and Environment Systems." *J. Clean. Prod.* 130 (2016): 1-11.

Urbaniec, K., Mikulčić, H., Rosen, M. A., & Duić, N. (2017). A holistic approach to sustainable development of energy, water and environment systems. *J. Clean. Prod*, 155, 1-11.

Väisänen S., Havukainen, J., Sokka L., Luoranen M., Horttanainen M., Using a multi-method approach for decision-making about a sustainable local distributed energy system: A case study from Finland, *Journal of Cleaner Production*, Volume 137, 20 November 2016, pp. 1330-1338.

Yajie, D., Beicheng, X., Weidong, C., 2014. Carbon footprint of urban areas: an analysis based on emission sources account model. *Environ. Sci. Policy* 44, 181-189.

Wang, G., Qin, L., Li, G., & Chen, L. (2009). Landfill site selection using spatial information technologies and AHP: a case study in Beijing, China. *Journal of environmental management*, 90(8), 2414-2421.

Wang, L., Long, R., & Chen, H. (2017a). Study of urban energy performance assessment and its influencing factors based on improved stochastic frontier analysis: A case study of provincial capitals in China. Sustainability, 9(7), 1110.

Wang, L., Yuan, G., Long, R., & Chen, H. (2017b). An urban energy performance evaluation system and its computer implementation. *Journal of environmental management*, 204, 684-694.

Wang, M., Sun, Y., & Sweetapple, C. (2017b). Optimization of storage tank locations in an urban stormwater drainage system using a two-stage approach. *Journal of environmental management*, 204, 31-38.

Washburn, D., Sindhu, U., Balaouras, S., Dines, R. A., Hayes, N. M., & Nelson, L. E. (2010). Helping CIOs Understand “Smart City” Initiatives: Defining the Smart City, Its Drivers, and the Role of the CIO. Cambridge, MA: Forrester Research, Inc. Available at http://public.dhe.ibm.com/partnerworld/pub/smb/smarterplanet/forr_help_cios_und_smart_city_initiatives.pdf.

Wilson, D. C., Rodic, L., Cowing, M. J., Velis, C. A., Whiteman, A. D., Scheinberg, A., Vilches, R., Masterson, D., Stretz, J. & Oelz, B. (2015). ‘Wasteaware’ benchmark indicators for integrated sustainable waste management in cities. *Waste Management*, 35, 329-342.

Zaman, A., Lehmann, S., 2013. The zero waste index: a performance measurement tool for waste management systems in a ‘zero waste city’. *J. Clean. Prod.* 50, 123-132.