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Role and development of composite indicators for climate change and sustainable development policies and practices

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Role and development of composite indicators for climate change and sustainable development policies and practices

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To my beloved parents and my lovely Rana

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ABSTRACT

Indicator-based assessments are important tools for environmental risks and policy analysis[1]. By definition, indicator-based assessments (or composite indices) are instruments by which individual indicators can be selected, weighted and combined to simplify and synthetize multifaceted processes (OECD, 2008). Nevertheless, there are several challenges associated with robustness and subjectivity issues of the assessments encountered by scholars and analysts. Applying various set of indicators and methodological steps including variant weighting and aggregation schemes involves judgmental decisions and may yield non-robust policy messages. The aforesaid challenges can be tackled by implementing sensitivity and robustness analysis along with improvements in transparency of the judgments. To develop a scientifically sound and transparent assessments, several analytical methods have to be examined to explore the possible trade-offs among methodological and theoretical modularities. These trade-offs should be made explicit to bring additional insight to identify sound policies and practices. My thesis contributes to the debate on the indicators-based assessments by providing a transparent framework addressing multiple methodological aspects used to develop consistent and robust fit-for-purpose and policy-relevant assessments. The thesis is a collection of three research articles in which I developed and applied indicator-based assessments to various policy areas. The first article published in the journal of Environmental Management (Marzi et al., 2018) explores how to conceptualize and measure adaptive capacity at various administrative levels, and how to factor-in the variability at a lower administrative level in the assessment of the next higher levels. The second article describes the energy efficiency country attractiveness index, developed to boost efficient and effective resource allocations and to promote energy efficiency as part of the climate mitigation policies. The index combines political, economic, social and technological factors using complex fuzzy-set techniques. The third article addresses disaster resilience and is meant to inform the implementation of the Sendai Framework for Disaster Risk Reduction 2015-2030 (SFDRR) in Europe. It reconciles various indicators used for describing “resilience”, including innovative distance-decay based attributes using a range of advanced statistical techniques employed to normalize, transform and combine the variables.

Keywords: Indicator-based assessments, adaptive capacity, energy efficiency, disaster resilience

[1] Their importance is reflected by 4337 publications obtained for a search of keyword “indicator-based” in SCOPUS database over the period 1935-2018. Some 851 pertain to the “environmental sciences”.

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INTRODUCTION

Climate change is the defining challenge in achieving sustainable development as a way to build an inclusive and resilient future for the people and planet. The linkage between climate change and sustainable development are traverse and complex. Climate change impacts may disrupt current sustainable development policies and potentially counterbalance already attained advances. Climate change mitigation policies have the potential to keep the climate risk at a moderate rather than extreme level, and adaptation will enhance the ability of socioecological systems to reconcile the remaining impacts, hence modulating adverse effects on sustainable development. In addition, several elements that outline susceptibility to climate change impacts and the consequent mitigation and adaptation policies are firmly entrenched in development processes (Denton et al., 2014; Kyte, 2014; UN, 2018).

To promote sustainable development in the context of climate change, climate resilient pathways are defined to tackle the biophysical and social stressors that impinging on resilience, now and in the future (IPCC, 2014a). Climate resilient pathways are described as “development trajectories that combine adaptation and mitigation to realize the goal of sustainable development” and may involve transformations in economic, social, technological and political decisions and actions at different scales (Denton et al., 2014). Climate resilient pathways comprise strategies and actions to implement and sustain the effective risk management at different scales to diminish the climate change impacts. These strategies and actions need to take into consideration transformations at different scales in order to foster positive synergies and avoid adverse feedbacks between them. Generally, strategies regarding the mitigation policies can be better understood at global scale whereas in the case of adaptation, more localized strategies would be required (Denton et al., 2014; IPCC, 2014a).

Climate risk management policies embrace adaptive learning, improvements in scientific knowledge, effective adaptation and mitigation measures and management of different resource flows and distributional effects related to adaptation and mitigation. Examining progress made in planning and implementing effective climate risk management policies require systems and approaches designed to monitor, report and evaluate (MRE) the evolution of the socioecological systems in terms of resilience and development goals (EEA, 2015).
Indicator-based assessments are stated as an important tool for monitoring and reporting on progress related to resilience and development issues. Quantitative indicator-based assessments (IBA) can translate multifaceted processes into simplified concepts and communicate clear

messages that are easy to grasp for policy makers. In addition, they allow continuous measurements which enables policy makers to identify the existing trends (EEA, 2015). The IBAs generally combine separate indicators into a composite index which reflects relative capacities of geographic units or population groups. This process involves separate steps namely, indicator selection, variable transformation, normalization, weighting and aggregation procedures (Fernandez et al., 2017; OECD, 2008). Developers are usually faced with a spectrum of choices between plausible alternatives during each stage of construction procedure (Tate, 2012). Some scholars referred to perceptions of subjectivity and robustness that are often associated with IBAs construction steps as existing implications of deploying them for MRE purposes. To create “fit for purpose” IBAs for MRE, they have to be scientifically sound, robust and transparent (EEA, 2015).

The thesis aims to contribute to the debate on the application of IBAs to monitor, report and evaluate the transformational mitigation and adaptation as part of the climate resilient pathways. IBAs are adopted to estimate three “fit for purpose” assessments that are empirically based, theoretically sound and innovative, and capable of advising climate adaptation and sustainable development policy. The thesis reviews the main theoretical and methodological concepts characterizing mainstream literature on available IBAs in the context of adaptation and mitigation, and introduces three distinct indices addressing various implications regarding the structure of the IBAs including the variation of scale, the choice of indicators, data transformation, aggregation, compensability issues and robustness analysis.

Structure of this thesis

The thesis is structured as a collection of three research articles applying IBAs to various components of climate risk management and resilience. The first article, published in the Journal of Environmental Management[2] (Marzi et al., 2018) previously contributed to the Italian National Climate Adaptation Plan (MATTM, 2017) with an innovative approach to analyze adaptive capacity. For this work, a large body of knowledge addressing economic, social, and institutional ability was collected to induce and promote climate adaptation. The article explores the adaptive capacity at various administrative levels (NUTS2 and NUTS3),

[2] CiteScore: 4.54, Impact Factor: 4.005, SCImago Journal Rank (SJR): 1.161

JEMA is a prestigeous journal covering various aspects of management and the managed use of the environment, both natural and man-made, and embraces sizable publications in the context of indicator-based assessments (SCOPUS).

and factors-in the variability at a lower administrative level in the assessment of the next higher levels using a robust methodological framework which encompasses advanced statistical and fuzzy-set techniques. The results employed as an input for the construction of a climate risk index (J. Mysiak et al., 2018) which is one of the fundaments of the Italian Climate Adaptation Plan.

The second article, submitted to the Energy[3] addresses energy efficiency country attractiveness index, developed to inform efficient and effective resource allocations to promote energy efficiency as part of the climate mitigation policies. The index is built for various developing countries (OPEC members), and combines political, economic, social and technological factors (PEST) for the purpose of designing incentives to integrate public and private interests with collectively agreed environmental goals. The methodological framework, comprising complex fuzzy-set techniques (Choquet integral) relies on the contribution of a range of stakeholders, including scientific experts, stakeholders within key energy sectors and business organizations. The outcomes caution against one-size-fits-all solutions, and support case-specific choices that draw on sound analytical principles.

The third article considered to be submitted in the Science of the Total Environment[4] journal, measures disaster resilience and is meant to inform the implementation of the Sendai Framework for Disaster Risk Reduction 2015-2030 (SFDRR) in Europe (UNISDR, 2015a). It reconciles various indicators used for describing “resilience”, including novel distance-decay based attributes such as travel distance to service centres, that embodies the contemporary rural development policies and take into account various aspects of less favoured (remote) areas. The methodological framework, includes a range of advanced statistical techniques employed to normalize, transform and aggregate the variables (OWA). The results have been compared with the similar official indices to verify the robustness and consistency of the outcomes.

[3] Cite Score: 5.60, Impact Factor: 4.968, SCImago Journal Rank (SJR): 1.990
ENERGY addresses economic and policy issues within the context of the broader multi-disciplinary scope of *Energy* which perfectly fits the agenda of the second article.

[4] Cite Score: 4.98, Impact Factor: 4.610, SCImago Journal Rank (SJR): 1.546
Science of the Total Environment is an international multi-disciplinary journal covering aspects of the total environment, including risk assessment and management, and environmental management and policy. The resilience paper addresses the disaster risk management which suits the agenda of this journal.

Throughout my PhD study I contributed to other pieces of research. In Mysiak et al. (2018), I have contributed to developing the adaptive capacity index as a crucial element of vulnerability assessment, used to estimate the climate risk index. In Amadeo et al. (2018), I conducted the social vulnerability index used to map socio-economic variables by means of a spatially-weighted dasymetric approach based on the combination of multiple diverse ancillary data. The above articles are included in the annexes of this thesis.

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1 COMPARING ADAPTIVE CAPACITY INDEX ACROSS SCALES: THE CASE OF ITALY

Abstract

Measuring adaptive capacity as a key component of vulnerability assessments has become one of the most challenging topics in the climate change adaptation context. Numerous approaches, methodologies and conceptualizations have been proposed for analyzing adaptive capacity at different scales. Indicator-based assessments are usually applied to assess and quantify the adaptive capacity for the use of policy makers. Nevertheless, they encompass various implications regarding scale specificity and the robustness issues embedded in the choice of indicators selection, normalization and aggregation methods. We describe an adaptive capacity index developed for Italy's regional and sub-regional administrative levels, as a part of the National Climate Change Adaptation Plan, and that is further elaborated in this article. The index is built around four dimensions and ten indicators, analysed and processed by means of a principal component analysis and fuzzy logic techniques. As an innovative feature of our analysis, the sub-regional variability of the index feeds back into the regional level assessment. The results show that composite indices estimated at higher administrative or statistical levels neglect the inherent variability of performance at lower levels which may lead to suboptimal adaptation policies. By considering the intra-regional variability, different patterns of AC can be observed at regional level as a result of the aggregation choices. Trade-offs should be made explicit for choosing aggregators that reflects the intended degree of compensation. Multiple scale assessments using a range of aggregators with different compensability are preferable. Our results show that within-region variability can be better demonstrated by bottom-up aggregation methods.

1.1 Introduction

A shift from impacts- to vulnerability-driven approaches for identifying adverse effects of climate variability and change has become one of the most challenging research topics in recent years. The impacts-driven approaches explore the evolution and pattern of current and future climate-related hazards and analyse their potential impacts. Vulnerability-driven approaches examine socio-economic, demographic, cultural, environmental, political and institutional constituents of vulnerability and risk, which help to explain how the society and individuals perceive and respond to climate-related hazards. The latter are more suitable as a measurement of people's needs in terms of adaptation as well as their ability to cope with climate shocks (Adger et al., 2004; Cutter et al., 2003; Engle, 2011).

Vulnerability is commonly defined as a "propensity or predisposition to be adversely affected" (IPCC, 2014b). In the earlier Assessment Reports of the Intergovernmental Panel on Climate Change (IPCC) it was common to portray vulnerability as a function of exposure, sensitivity and adaptive capacity (IPCC, 2007). More recently, the IPCC embraced vulnerability as a main constituent of risk, along with hazard and exposure. Under this view, vulnerability comprises "sensitivity or susceptibility to harm" and "lack of capacity to cope and adapt" (KC et al., 2015; Smit and Wandel, 2006; Tapia et al., 2017)

Adaptive capacity (AC) has been defined as "the ability of systems, institutions, humans and other organisms to adjust to potential damage, to take advantage of opportunities, or to respond to consequences" (IPCC, 2014c). AC is hence a property of a system that is able to adjust its characteristics or behaviour to expand its coping range under existing climate variability or future climate conditions (Brooks and Adger, 2005). AC also refers to capabilities, resources and institutions for implementing effective adaptation measures (Bizikova et al., 2009). AC plays an important role in designing effective adaptation strategies in which the ultimate aim is to reduce vulnerability to climate change (Adger et al., 2007; Vincent, 2007).

Despite the copious body of literature on how AC could be framed and conceptualized (Acosta et al., 2013; Brooks and Adger, 2005; Pelling and High, 2005; Vincent, 2007; G Yohe and Tol, 2002), no single framework has been found to be broad and flexible enough to serve the various interpretations and policy designs. Practical applications of ACI embrace economic wealth, technology, information and skills, infrastructure, institutions, equity, resource-dependency, demographics and interconnectivity as main determinants (ESPON, 2011; IPCC, 2016; Swanson et al., 2007; Vincent, 2007). Improving AC means addressing structural deficits such as access to education and health, income inequalities and poverty, or digital divide. Capacities include access to and an efficient use of resources - such as natural, financial, cognitive, social, and institutional capital - that can be mobilized for adaptation (Lemos et al., 2013; Metzger et al., 2005, 2008; Smit and Pilifosova, 2003).

AC is inherently multi-dimensional. It may include a degree of organizational and institutional capacity at the national level (macro-analytic) as well as factors at the household level (micro-analytic) that portray how individuals anticipate change and identify new livelihood opportunities (Hinkel et al., 2013; Vincent, 2007). However, it was observed that the same methodology applied at different geographic scales may (and usually does) yield different outcomes. For instance, national level assessments may conceal unequal distribution of resources at local level (Kenney et al., 2012; Mclaughlin and Cooper, 2010; Sullivan, 2002; Vincent, 2007, 2004). Kenney et al. (2012) show that in order to take a “nested” approach that can be adapted to various scales, some scale-specific information may be dismissed. They argue that some climate impact variables are more useful at lower administrative units. In this case, an analysis based on higher administrative units may mask distributions of those variables at lower units. Scale implications of AC have also been explored in Preston and Stafford-Smith (2009), Vincent (2007) and Huynh and Stringer (2018). Vincent (2007) found that, notwithstanding the common constituents of AC at the national and local scales, the outcomes may reveal different patterns, and this should be considered when conducting multiscale assessments. Most of the literature addressing variations of vulnerability and adaptive capacity across scales focus on the difference between collective (national, regional, provincial and community scales) and individual or household vulnerability and neglect the potential variations at collective scale. In addition, there is no consensus on how the variation of scale affect the assessment and what implications this variation should have for practical policy.

AC is assessed by using either quantitative indicators or stakeholders’ judgements and scenarios (S. Juhola and Kruse, 2015). Indicator-based assessments are widely used to assess the relative AC values of geographic units by aggregating separate indicators into one composite index (Hinkel et al., 2013). However, the choice of aggregation operators and the level of compensation between indicators represent major sources of uncertainty that should be assessed and made explicit through robustness and sensitivity analysis (Fernandez et al., 2017; Tate, 2012). The “compensation” degree denotes trade-offs between higher performance in some indicators and lower performance in other ones. Using additive aggregators with high degree of compensation implies that underperformance with respect to one or more indicators may not receive the adequate attention. The choice of aggregator with intended degree of compensation should be made with respect to the context and scope of the analysis and expert judgements (Aggarwal, 2015; Fernandez et al., 2017; Langhans et al., 2014; Liu et al., 2014).

In this paper we describe the adaptive capacity index (ACI) developed for the purpose of the Italian Climate Change Adaptation Plan (MATTM, 2017). ACI is a key component of a comprehensive climate risk index (CRI) (Jaroslav Mysiak et al., 2018) for which anomalies of extreme climate indices derived from high resolution regional climate models' simulations were used as proxies of climate change-altered weather and climate-related hazards. We perform the AC analysis, in a similar way as in ESPON (2011) and Araya-Muñoz et al. (2016), at both the regional and provincial levels, and estimate the variability of the ACI score intra-regionally. The provincial ACI scores are then aggregated with different degrees of compensation in order to regenerate the regional scores and to explore the consistency and robustness of the index. The results of our analysis show that decision and policy makers should pay attention to the variability of the ACI scores at lower administrative levels when constructing the index at higher national or sub-national scales. The article is structured as follows: section 2 explains the methodological framework and multivariate analysis performed to narrow down the choice the indicators for the composite index. In Section 3 we perform the aggregation at regional and provincial scales, and explore the robustness of the composite index. In Section 4 we discuss the results obtained and draw general conclusions of our analysis.

1.2 Data and methodology

1.2.1 Conceptual framework and indicators used

Figure 1.1 displays the main stages of the analysis. It starts with a regular composition of the indices comprising the theoretical framework used, selection of indicators, and multivariate analysis and data transformation to estimate the AC index at both the regional and provincial levels.

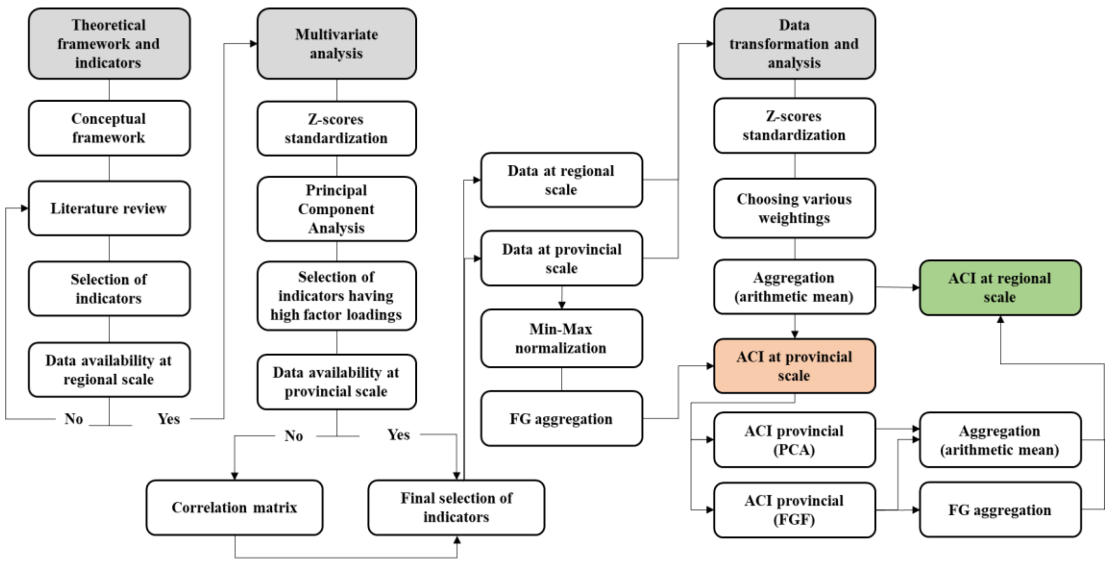


Figure 1.1 Workflow diagram of the analysis.

We follow the framework of the European Spatial Planning Observation Network (ESPON, 2011), which is composed of three dimensions (awareness, ability and action) comprising five determinants (economic resources, knowledge and awareness, infrastructure, institutions and technology). Four indicators had been considered within each determinant, aggregated by using weights estimated by a two-round Delphi survey (ESPON, 2011). The ESPON analysis and the Delphi method used are described in detail in supplementary electronic material. In our framework knowledge, and awareness and technology are consider together (Figure SM4) in supplementary electronic material) to represent strategic assets driving competitive advantages, and also because technological innovation relies on solid knowledge foundation (Lai and Lin, 2012).

The indicators for each component of the framework have been chosen on the basis of literature review and advice from the experts consulted in the context of the national climate change adaptation planning. Examples of frequently used indicators used in the scientific literature for various components of AC are as follows:

- *Economic resources:* Income per capita (GDP, GNI, etc.), poverty (percentage of population living in poverty), lack of financial resources, standard of living, population growth, income diversity, age dependency ratio, age dependence and unemployment (Araya-Muñoz et al., 2016; S. Juhola and Kruse, 2015; Sietchiping, 2006; Swanson et al., 2007; Vincent, 2007);
- *Infrastructures:* Transport (roads, railways, etc.), informal networks (households with telephone, mobile phone or internet connections), physical housing condition, access to water (water infrastructure), internet use, electricity usage, remoteness, and health (hospital beds, physicians, etc.) (Araya-Muñoz et al., 2016; De Groeve et al., 2015; S. Juhola and Kruse, 2015; Sietchiping, 2006; Swanson et al., 2007);
- *Knowledge and technology:* literacy rate, tertiary qualification, capacity to undertake research and patents (Araya-Muñoz et al., 2016; De Groeve et al., 2015; S. Juhola and Kruse, 2015);
- *Institutions:* corruption, municipal budget, master plan updates, community activities, voice and accountability (social cooperatives, associations, etc.), government effectiveness (endowment of social and economic facilities, etc.), regulatory quality (economic openness, local government employee, etc.), rule of law (tax evasion, submerged economy, etc.) (Araya-Muñoz et al., 2016; De Groeve et al., 2015; Nifo and Vecchione, 2014; Sietchiping, 2006).

Table 1.1 Indicators of AC considered for the analysis

Criteria	Code	Indicator	Unit	Source	Scale	Year
Economic resources	RE1	Gross Domestic Product (GDP)	Euros per capita	EUROSTAT	NUTS2, NUTS3	2013
	RE3	Distribution of the household income	GINI Index	ISTAT	NUTS2	2013
	RE4	Household relative poverty incidence	% of families	ISTAT-DPS	NUTS2	2013
	RE6	At-risk-of-poverty rate (before housing costs)	% of population in households with less than 60% of the median equalized household income	ESPON	NUTS2, NUTS3	2008-2011
	RE7	Unexpected expenses (families unable to face unexpected financial expenses)	% of families	ISTAT	NUTS2, NUTS3	2014
	RE9	Families living below the poverty line	% of families	ISTAT-DPS	NUTS2	2013
	RE10	Unemployment rate	%	ISTAT	NUTS2, NUTS3	2015
Infrastructures	IN1	Extension of the infrastructure (road and railways) as a share of the total area	Km per km2	Manually computed	NUTS2, NUTS3	2017
	IN3	Water use from the public water supply as a share of the water input to a distribution network	%	ISTAT	NUTS2, NUTS3	2012
	IN5	Irrigated and Irrigable land over the total utilized agricultural area	%	ISTAT-DPS	NUTS2	2013
	IN6	Share of the protected lands from the total area	%	Manually computed	NUTS2, NUTS3	2017
Knowledge and Technology	KT1	Electricity consumption of agricultural enterprises	GWh for 100 x 106 Euro of agricultural added value	ISTAT-DPS	NUTS2	2014
	KT2	Total expenditure for R&D	% of GDP	ISTAT -DPS	NUTS2	2013
	KT3	Personnel engaged in R&D	Full time equivalent for 100 inhabitants	ISTAT -DPS	NUTS2	2013
	KT4	Patent applications to European patent office (EPO) by priority year	Average number over a million of inhabitants	Eurostat	NUTS2, NUTS3	2008-2012
	KT5	30-34 age population having a level of education 5 and 6 (Isced97)	% of same age population (total)	ISTAT (Census)	NUTS2, NUTS3	2011
	KT6	Share of the families having internet access	% of the total families	ISTAT (Census)	NUTS2, NUTS3	2011
	KT7a	Industries and services' enterprises (with less than 10 employees) with personal computers	% of enterprises	ISTAT -DPS	NUTS2	2007
	KT7b	Industries and services enterprises (with more than 10 employees) with personal computers	% of enterprises	ISTAT -DPS	NUTS2	2015
	KT8	Index of spreading broadband in the enterprises	% of enterprises	ISTAT -DPS	NUTS2	2015
Institutions	INS1	Institutional Quality Index	Index	(Nifo and Vecchione, 2014)	NUTS2, NUTS3	2012

Table 1.1 shows the initial set of AC indicators. A detailed explanation of the indicators can be found in the supplementary material. The data were obtained from multiple sources but primarily from the database of territorial indicators for the development policies (ISTAT, 2015a), developed as part of the sectoral territorial statistical information on structural policies 2010-2014. Additional data were obtained from ESPON (2012), Eurostat (2017) and ISTAT (2017). The share of the protected lands from the total area (IN6) was estimated on the basis of the extension of the Special Protection Areas (SPA) and the Sites of Community Importance (SCIs) under the Natura 2000 Network (EEA, 2017a, 2017b).The composite Institutional Quality Index (IQI) (Nifo and Vecchione, 2014) was used as a sole indicator (INS1) of the institutional dimension.

The detailed geographical maps of the Italian administrative units are provided in supplementary electronic material. Each of the 20 Italian administrative regions (NUTS2), except for the Aosta Valley, is sub-divided into provinces. The Alto Adige/Südtirol and Trentino are autonomous provinces, which means that they have the same legislative powers as regions and are not subordinated to the region they are part of (Trentino-Alto Adige/Südtirol). The administrative subdivision is being reorganised and in the course of this process the provinces are transformed into second-level institutional bodies, the so-called Metropolitan cities (MC). Within the statistical framework of the European Union (NUTS - Classification of Territorial Units for Statistics), regions and provinces correspond to NUTS2 and NUTS3 levels.

1.2.2 Multivariate analysis

To choose a representative set of indicators, we analysed the rank correlations (Nardo et al., 2005; OECD, 2008) and performed a principal component analysis (PCA) to transform correlated variables into a set of principal components or factors (Aroca-Jimenez et al., 2017; Fekete, 2009; Mazumdar and Paul, 2016). PCA explores the variance of variables $x_1,\ldots, x_n$ through linear combinations of the original data called principal components $p_1,\ldots, p_n$, which are uncorrelated measuring different statistical dimensions in the data set (Equation 1).

$$p_1 = a_{11}x_1 + a_{12}x_2 + a_{1n}x_n$$
$$p_2 = a_{21}x_1 + a_{22}x_2 + a_{2n}x_n$$
$$\ldots$$
$$p_n = a_{n1}x_1 + a_{n2}x_2 + a_{nn}x_n \qquad \text{(Equation 1)}$$

The weights a_{ij} are called factor loadings and indicate to what level the variance of original variables is explained by each factor. Accordingly, the first principal component p1 explains the largest share of variance, the second accounts for the largest share of the remaining variance, and so on. The variances of principal components correspond to eigenvalues $\lambda_j, j = 1, .. n$ of the sample covariance matrix CM (Equation 2), in which the diagonal and off-diagonal elements are formed by a variance and a covariance of the original variables.

$$CM = \begin{pmatrix} cm_{11} & cm_{12} & \cdots & cm_{1n} \\ cm_{21} & cm_{22} & \cdots & cm_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ cm_{n1} & cm_{n2} & \ldots & cm_{nn} \end{pmatrix} \qquad \text{(Equation 2)}$$

To avoid the undue influence of any single variable on the principal components, the variables have been standardized by using z-scores. Afterwards, PCA was performed on z-standardised values, which is explained in *data and transformation* (section 2.3) with acceptable Kaiser-Mayer-Olkin (KMO) sampling adequacy (KMO > 0.6) and Bartlett's test of sphericity values ($p < 0.05$). We have chosen a subset of the indicator based on factor loadings and the correlation matrix (see tables SM4 and SM5 in electronic supplementary material). The indicators with higher factor loadings were preferred (OECD, 2008).

As for the category *economic resources*, household relative poverty incidence (RE4), at risk of poverty rate (RE6) and unemployment rate (RE10), are the most preferable due to higher factor loadings. However, given that RE4 is not available at both the regional and provincial levels, we chose GDP per capita (RE1) instead, as it is closely correlated to RE4. As for the *infrastructures* category, extension of infrastructures (IN1), water use from public water supply (IN3) and irrigated and irrigable land (IN5) were chosen in an analogous way. IN5 is replaced by share of protected lands (IN6) because of the data limitations. As for the category *knowledge and technology*, personnel engaged in R&D (KT3), patent application (KT4) and share of the families having internet access (KT6) would have been preferred, but because of limited availability of the data at lower administrative levels, we used KT5 (30-34 age population having a 5 and 6 level of education) instead of KT3. Finally, as for institutions, the Institutional Quality Index (IQI) has been chosen as the input of the analysis, which contains all the necessary elements regarding the governance and institutional quality.

1.2.3 Data transformation and analysis

Indicators have been standardized by using z-scores to make them comparable (OECD, 2008). There are several alternative methods of data normalisation (e.g. min-max, z-scores, distance to a benchmark, balance of opinions, etc.) which are more or less suitable, depending on the typology of data and the intended aggregation. While using the PCA, it is recommended to apply z-scores standardization. This method preserves range (maximum and minimum) and introduces the dispersion of the series (standard deviation / variance). The scales of indicators with inverse effect on the output (such as RE6 and RE10) were reverted before standardization.

We applied three sets of weights in our analysis. For a preliminary screening, we applied equal weights. In the next step, we used the same set of weights as in ESPON (2011), adapted to our assessment design (see Table SM3 in electronic supplementary material). The last set of weights was estimated by using PCA, which depicts the highest possible variability in the indicator set by using the smallest possible number of uncorrelated factors based on the statistical dimensions of the data (Tapia et al., 2017). The steps we took to calculate PCA weights are explained in the supplementary electronic material. Simple additive aggregation was applied to determine the final performance and rankings. Weights express trade-offs between indicators, and subsequently a deficit in one dimension could be compensated by a surplus in another. In order to consider some degree of non-compensability, some other aggregation operators can be applied, such as generalized mean, fuzzy gamma, as well as non-additive measures such as fuzzy-based integrals (Fernandez et al., 2017; Lewis et al., 2014; OECD, 2008; Pinar et al., 2014a).

Finally, we analysed the consistency of the results across the geographic scales. To this end, the provincial ACI scores were aggregated and compared with the ACI scores obtained at the regional level. To control the trade-offs during the aggregation, we applied fuzzy gamma function (FGF) (Araya-Muñoz et al., 2016). This function is a combination of fuzzy SUM (which is fully compensatory) and fuzzy PRODUCT (which does not allow for compensation). Fuzzy SUM (Equation 3) yields larger aggregate outcomes from any single input. Fuzzy PRODUCT (Equation 4), on the other hand, yields outcomes that are equal to or lower than those of any single input. Hence fuzzy product is strictly non-compensatory.

$$Fuzzy\ SUM = 1 - \prod_{i=1}^{n}(1 - \mu_i) \qquad \text{(Equation 3)}$$

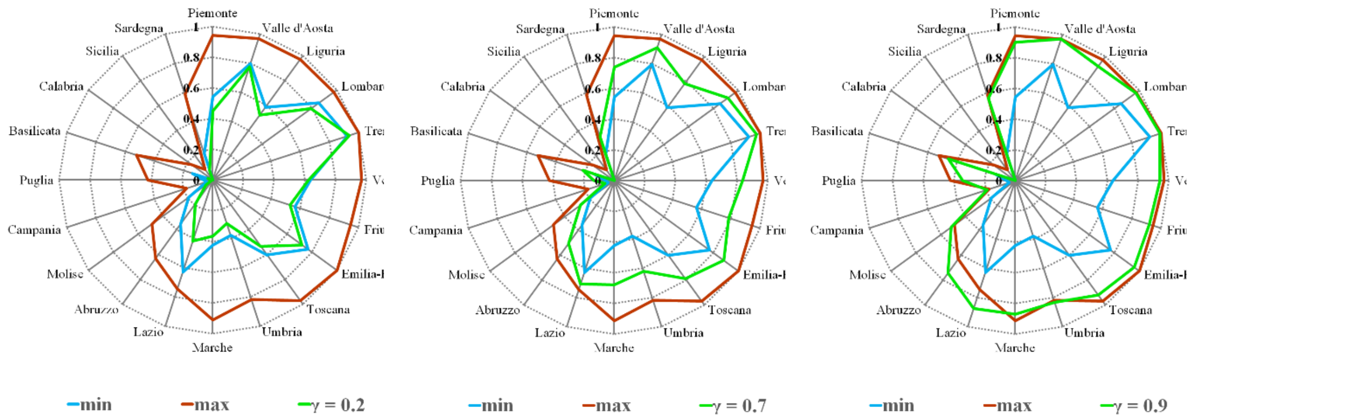
$$Fuzzy\ PRODUCT = \prod_{i=1}^{n}(\mu_i) \qquad \text{(Equation 4)}$$

where n denotes the number of the aggregated indicators and μ stands for membership values.

Fuzzy gamma method (equation 5) controls the level of compensation by means of γ parameter. High values of gamma correspond to a higher degree of compensation and the results are closer to Fuzzy SUM. In contrary, low values of gamma represent a lower compensation level and the Fuzzy PRODUCT dominates in this case (Herath and Prato, 2016; Nardo et al., 2005). FGF helps to prevent returning maximum or minimum values of the whole membership set (fuzzy OR and fuzzy AND functions), and attribution of a higher weight to a single variable (fuzzy SUM and fuzzy PRODUCT) (Araya-Muñoz et al., 2016; Lee, 2007; Sema et al., 2017a). More information on Fuzzy overlay functions is included in the supplementary electronic material.

$$Fuzzy\ Gamma = (Fuzzy\ SUM)^{\gamma}.(Fuzzy\ PRODUCT)^{1-\gamma} \qquad \text{(Equation 5)}$$

To choose γ, we performed a sensitivity analysis, using multiple γ values in the range of [0,1] with increment by 0.1 (Araya-Muñoz et al., 2016). For γ < 0.6, FGF results in lower aggregated scores than minimum input values, which means that the fuzzy PRODUCT prevails (restrictive behaviour) (Figure 1.2-a). With γ greater than 0.6, the FGF yields outcomes larger than the min input values, until the max input values are exceeded with γ close to 1 (Figure 1.2-c). In this situation, fuzzy SUM dominates. We have chosen γ (equal to 0.7), balancing the restrictive and expansive behaviours. In this case, FGF yields outcomes exactly between maximum and minimum input values (Figure 1.2-b), which creates a balance between two functions and avoids dominance of either them.



a) γ < 0.6 b) 1 > γ > 0.6 c) γ ~ 1

Figure 1.2 Fuzzy Gamma values, along with minimum and maximum values of the first criteria (economic resources), for the 1st Fuzzy aggregation with three different gamma values calculated as part of the sensitivity analysis on Gamma coefficient.

The FGF has been applied both to aggregate the individual indicators of all criteria as well as to combine these in a final aggregate ACI as shown in Figure 1.3. The data has been normalized using linear min-max function.

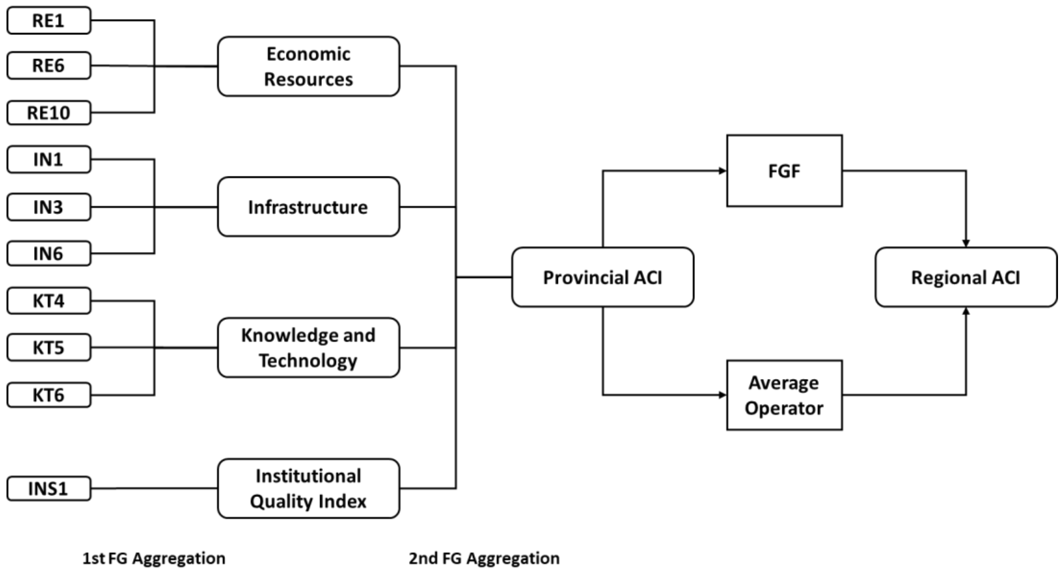


Figure 1.3 Fuzzy Gamma aggregation. Modified from Araya-Muñoz et al. (2016)

After the final aggregate ACI for each province was calculated by means of FGF, the regional ACI was regenerated through two different aggregation procedures (Figure 1.3). In the first procedure, the final aggregates ACI were considered as membership values for each province and afterwards combined through FGF. In the second procedure, the regional ACI were calculated by averaging the final aggregate ACI of the provinces in each region. Applying the "Average Operator" compensates the consequent rank reversals and anomalies caused by FGF implementation and diminishes the effect of non-compensatory PRODUCT operator. For comparison, we also aggregated the scores of ACI at provincial scale using the PCA weights (as shown in Figure 1.1).

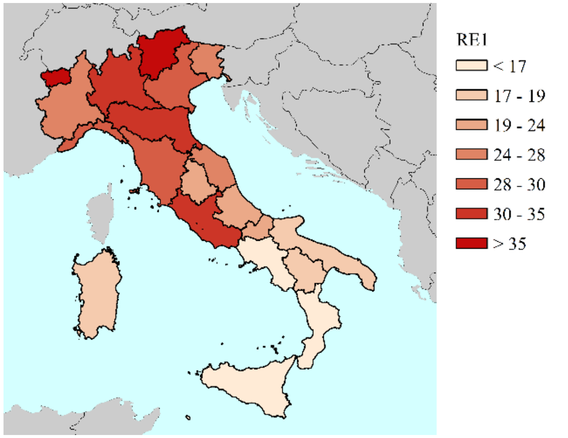
1.3 Results and discussion

1.3.1 ACI at regional scale

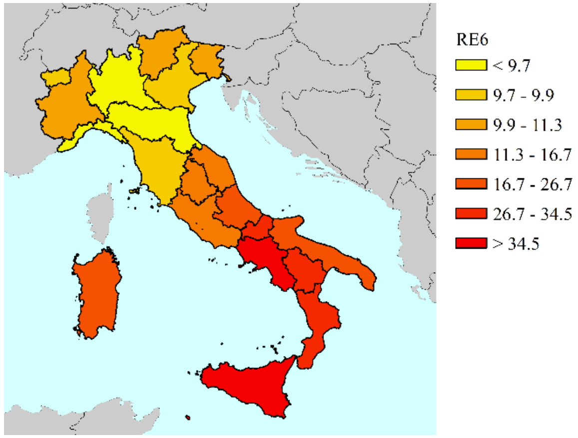
Figure 1.4 shows the raw scores of all indicators. Most of the maps indicate that the northern and central regions have higher potentials in terms of economy, infrastructure, technology, institutional quality and education. However, this gap is lower in determinants of infrastructure and knowledge-technology criteria. The level of education is very high in central and also some southern regions, but the number of patents is higher in northern regions. This may be explained with higher R&D endowments and migration of highly skilled workers. The correlation between migration and innovations approximated by patent intensity was analysed by Di Berardino et al. (2017), who found that emigration flows from southern regions have a positive impact on the quality of economic institutions of central and northern regions.

The scores derived from all aggregation methods (if we consider equal weights, ESPON weights and the weights evaluated from PCA) are illustrated in Table SM6 in the supplementary electronic material. Table 1.2 shows the ranking position of regions, indicating the relative regional adaptation capacity. Regions are classified into four groups, based on their ranking positions. The ranking in the first and last classes are consistent across the aggregation methods, and the position of individual regions changes only slightly. The two intermediate classes comprise regions that lag behind in some indicators (category 2) and regions that are better than the worst ones in some terms (category 3)

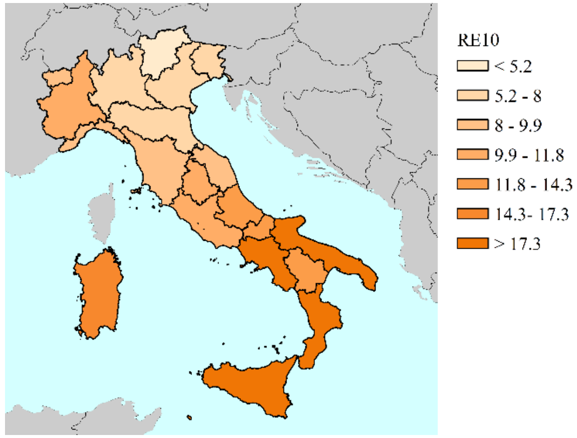
1.4-a Economic Resources



RE1- Gross Domestic Product (GDP) [1000 Euros per capita]

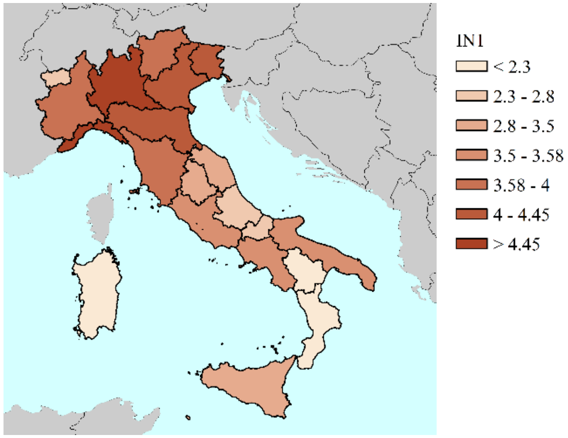


RE6- At-risk-of-poverty rate before housing costs (% of population in households)

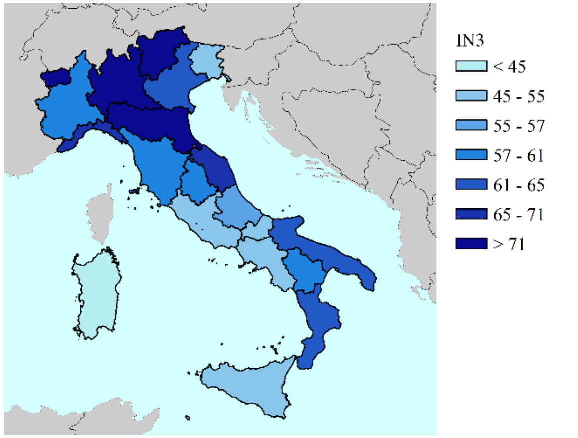


RE10- Unemployment rate (%)

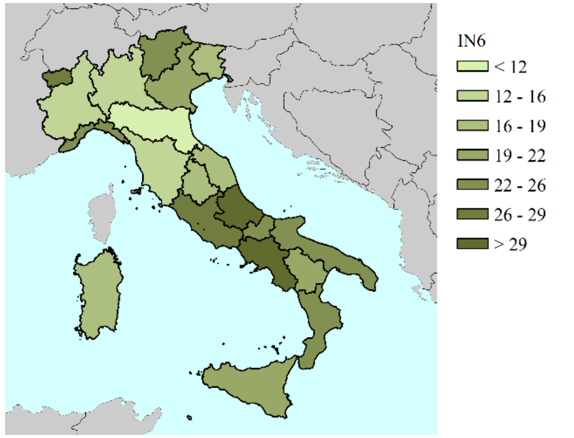
1.4-b Infrastructures



IN1- Extension of the infrastructure (roads and railways) as a share of total area (Km per km2)

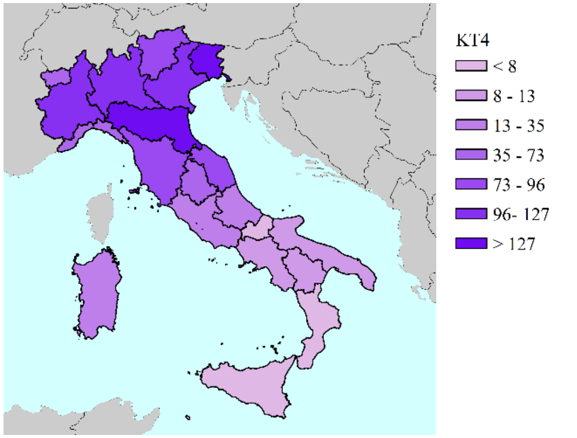


IN3- Water use from the public water supply as a share of the water input to a distribution network (%)

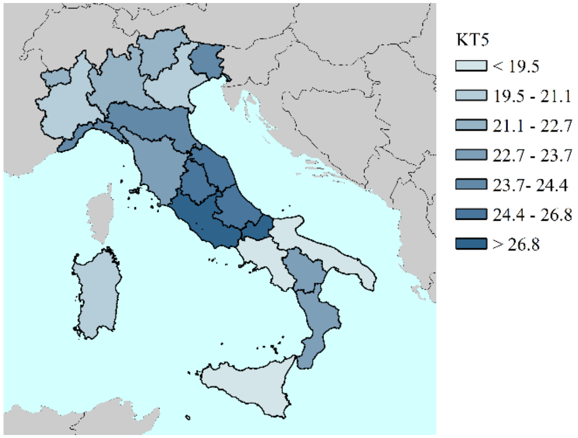


IN6- Share of the protected lands from total area (%)

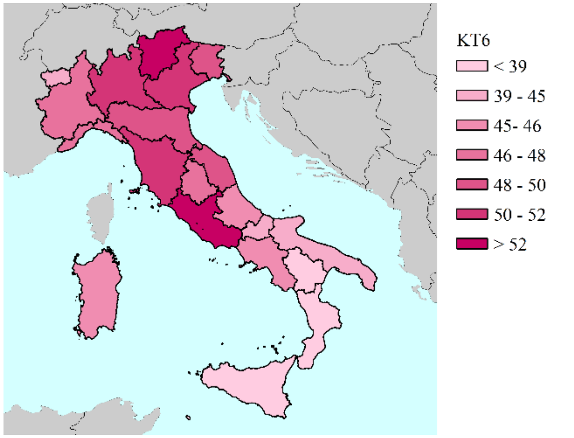
1.4-c Knowledge and Technology



KT4- Patent applications to European patent office (EPO) by priority year (number over a million of inhabitant)

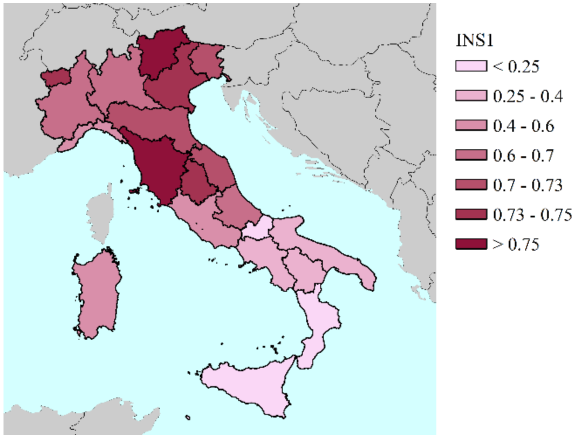


KT5- 30-34 age population having a level of education 5 and 6 (Isced97) (% of same age total population)



KT6- Share of the families having internet access (% of the total families)

1.4-d Institutions



INS1- Institutional Quality Index (IQI)

Figure 1.4 Mapping the original data regarding to indicators' se

Table 1.2 Regional rankings obtained by different set of weights (equal weights; weights from ESPON, 2011; and weights retrieved from the PCA)

Region	**Rank positions**			**CATEGORY**
	Equal W	**ESPON**	**PCA**	
Trentino-Alto Adige	1	1	1	1
Lombardia	2	3	2	1
Emilia-Romagna	3	2	3	1
Friuli-Venezia Giulia	5	4	4	1
Veneto	7	6	5	2
Liguria	4	9	6	2
Valle d'Aosta/Vallée d'Aoste	6	10	7	2
Lazio	8	5	9	2
Marche	9	8	10	2
Toscana	10	7	8	2
Abruzzo	11	11	13	3
Piemonte	12	12	11	3
Umbria	13	13	12	3
Molise	14	14	14	3
Basilicata	17	15	15	3
Puglia	15	18	17	3
Campania	16	17	18	4
Sardegna	18	16	16	4
Calabria	19	19	19	4
Sicilia	20	20	20	4

Figure 1.5 shows the ACI results based on PCA weights (aggregated scores and ranking positions by classes as in Table 1.2). The rankings obtained using equal and ESPON weights were estimated for comparison only.

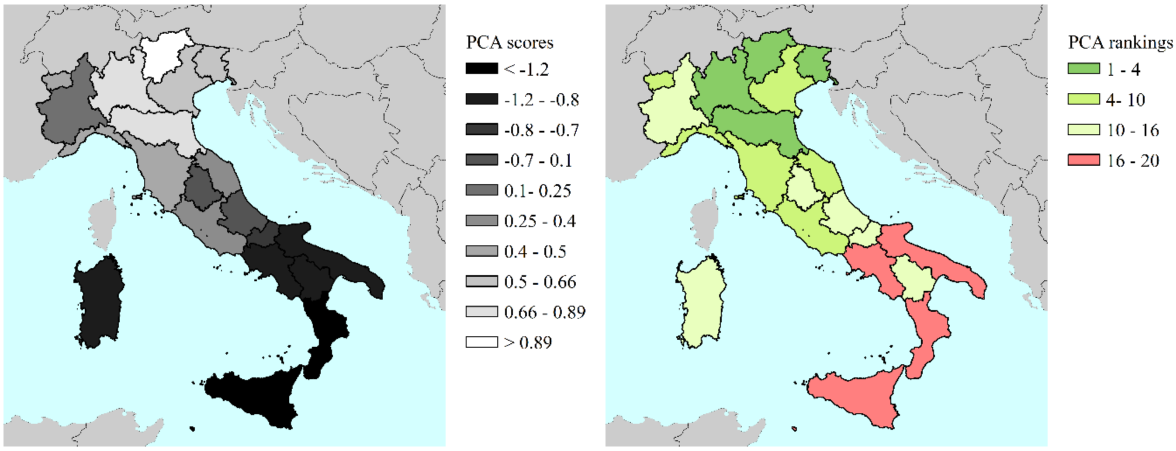


Figure 1.5 Scores and rankings derived by implementing PCA weighting

Figure 1.6 shows the previously explained regional classification for all underlying indicators, to illustrate the group-means differences. The scatter plots show to what extent the implicit order in the original data was preserved during the aggregation. As shown in Figure 1.6-a, the group-means differences are preserved in the regional classifications. For instance, with respect to GDP per capita (RE1) and at-risk-of-poverty-rate (RE6), the best-off regions

(Cat1) are densely clustered on the top-left of the scatterplot in Figure 1.6-a. Similar patterns can be observed in Figure 1.6-c for knowledge and technology criteria. This indicates that the aggregation had minor influence on the implicit order of the initial data. Figure 1.6-b shows a greater dispersion in clusters. The dispersion is caused by non-linear trade-offs between the underlying indicators. In a nutshell, Figure 1.6 shows that some indicators (e.g. those related to economic resources) are less sensitive to ranking reversal than some others (such as the indicators related to the infrastructure).

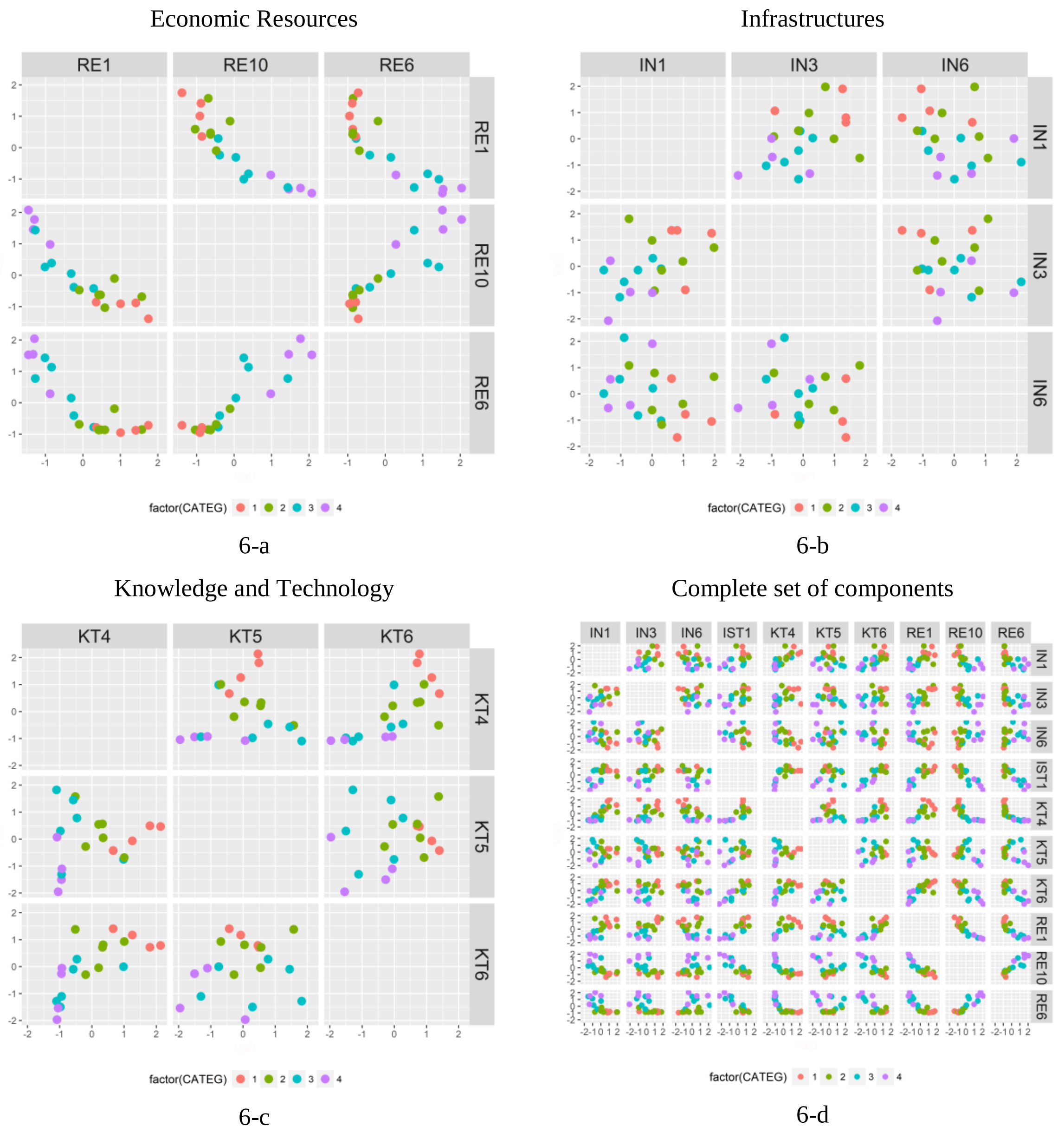


Figure 1.6 Group-means distributions regarding the best, worst and intermediate category of the regions

1.3.2 ACI at provincial scale

Figure 1.7 shows the aggregation results at the provincial (NUTS3) scale, based on PCA weights. The raw scores derived from each of the aggregation procedures (if we consider equal weights, ESPON weights and the weights evaluated from PCA) have been illustrated in the electronic supplementary material Table SM7. An analysis at this scale is instrumental for exploring the intra-regional' variability of the adaptive capacity.

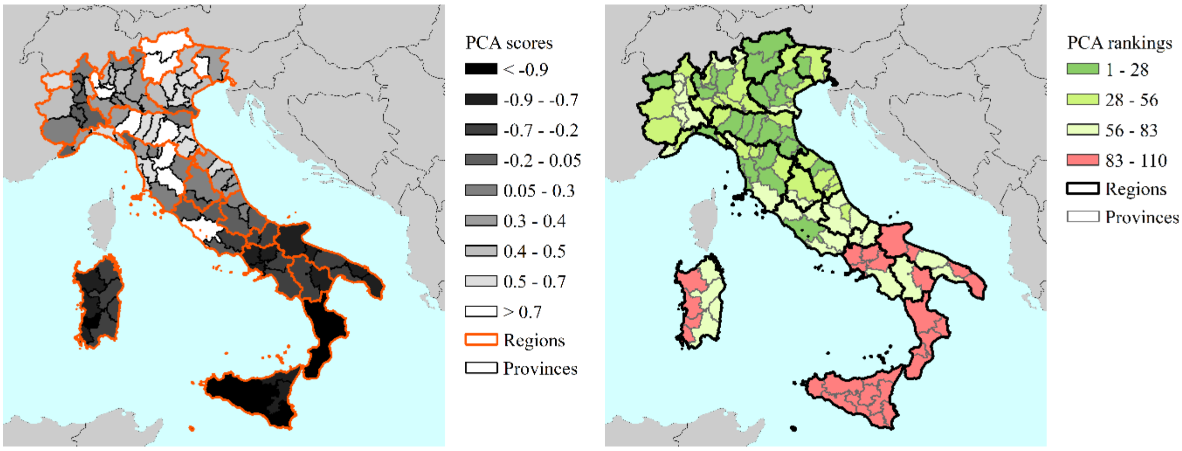


Figure 1.7 Provincial scores and rankings derived by implementing PCA weighting

As an example, a sizeable variability can be observed across the provincial PCA scores in Lombardy (Figure SM5 in supplementary material). Milano province holds much higher scores than the other provinces, indicating higher adaptive capacity level. This is not surprising, since its capital city is Milan, headquarters of Italy's financial sector. If the regional performance in terms of adaptive capacity is implicitly assumed homogenous across the lower administrative units, then our example shows that the assessment may lead to underestimation of the capacity gaps and eventually sub-optimal public policy choices. Consequently, it is appropriate to ask to what extent the sub-regional variability should be reflected in the regional ranking? In the case of Lombardy, there is no doubt that the regional ranking would be influenced by the capacity performance of the Milano province, and the lower performance of the other provinces would be concealed in the regional ACI score. Lombardy is just one example for other regions, particularly those comprising larger metropolitan areas such as Emilia Romagna (Bologna) or Latium (Rome) (Figure 1.8). To explore this issue further, in the next section we reconstructed regional ACI based on the sub-regional performance and variability.

1.3.3 Regional ACI reconstructed from the provincial ACI scores

Next, we examined and reviewed the regional rankings, taking into account the sub-regional variability. To this end we applied compensatory and partially non-compensatory aggregation operators, as suggested by Fernandez et al. (2017). Table 1.3 shows the final reassessed rankings, along with the original rankings (obtained from PCA weights) for comparisons.

Table 1.3 Final regional rankings

Region	Original regional ranking	Re-assessed regional scores			CAT
	PCA	PCA average	Fuzzy gamma	Fuzzy average	
Trentino-Alto Adige	1	1	1	1	1
Lombardia	2	5	15	8	3
Emilia-Romagna	3	3	9	3	3
Friuli-Venezia Giulia	4	2	3	2	1
Veneto	5	6	8	5	1
Liguria	6	9	5	9	1
Valle d'Aosta	7	4	2	4	2
Toscana	8	7	12	6	3
Lazio	9	13	15	13	3
Marche	10	8	6	7	1
Piemonte	11	10	11	11	1
Umbria	12	11	4	12	2
Abruzzo	13	12	7	10	2
Molise	14	14	10	16	1
Basilicata	15	15	15	18	3
Sardegna	16	17	15	17	3
Puglia	17	18	14	15	2
Campania	18	16	13	14	2
Calabria	19	19	15	20	1
Sicilia	20	20	15	19	1

Table 1.3 displays considerable variability among the rankings obtained by different aggregation operators. To make interpretation easier, we applied a similar classification to the preceding one (Figure 1.8), while considering the following:

- Category 1 is composed of the regions in which the changes in ranking positions are negligible.
- Category 2 contains the regions in which the ranking positions improve in the reassessment exercise.
- Category 3 comprises the regions which have lower scores as a result of reassessment.

It is possible to observe how the manipulation of the compensation degree by using various aggregators results in considerable ranking reversals, based on the extent to which they express the existing heterogeneity among the provinces of each region. if we again take the example of

Lombardy, very low scores of some provinces lead to much lower total performance when reassessed by using the Fuzzy Gamma aggregator.

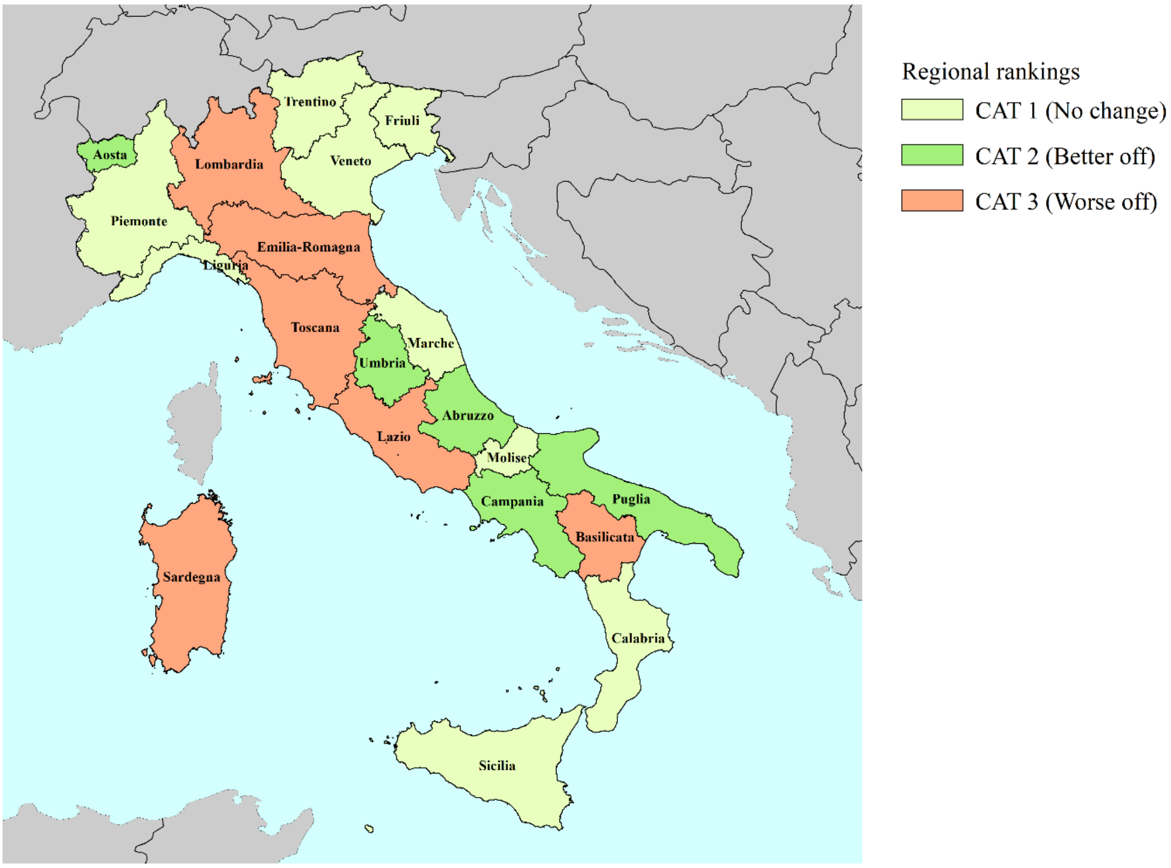
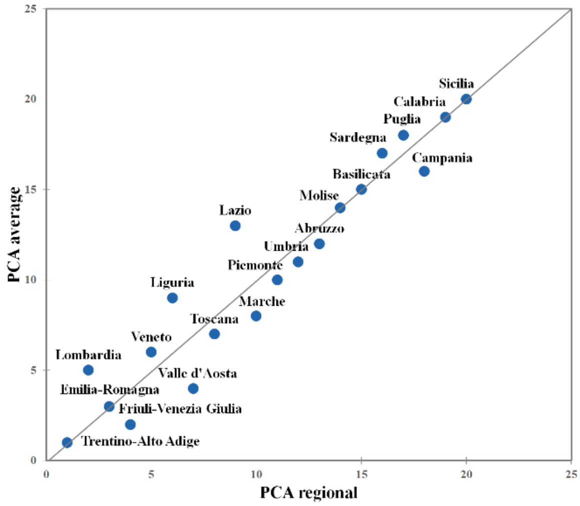
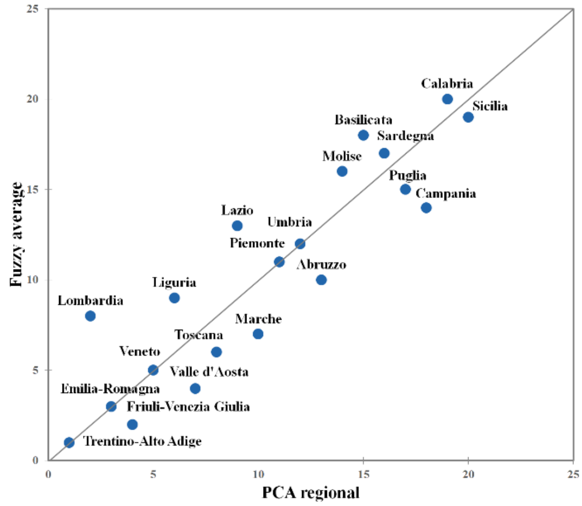


Figure 1.8 Final regional results derived by the implemented methodology

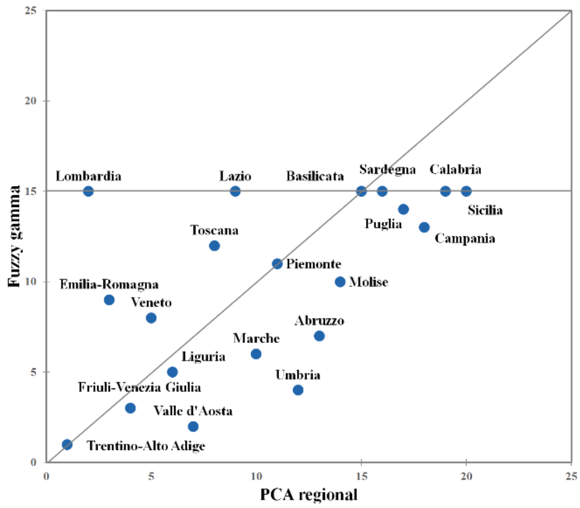
Figure 1.9 shows the pairwise comparison of the rankings obtained by using different aggregators illustrated from high to low compensation degrees.



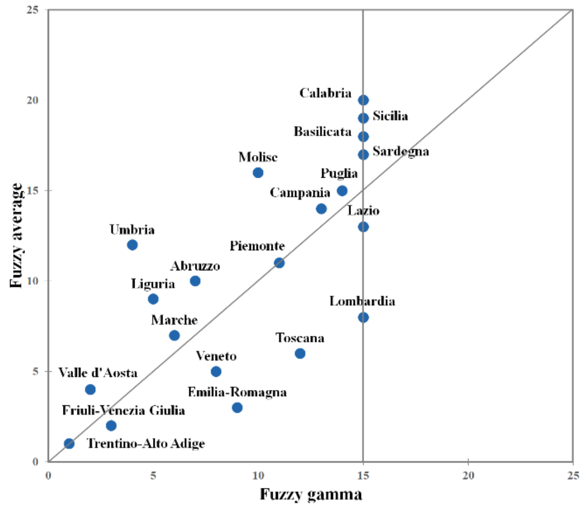
a) PCA regional vs. PCA average



b) PCA regional vs. fuzzy average rankings



c) PCA regional vs. Fuzzy Gamma rankings



d) Fuzzy Gamma vs. Fuzzy average rankings

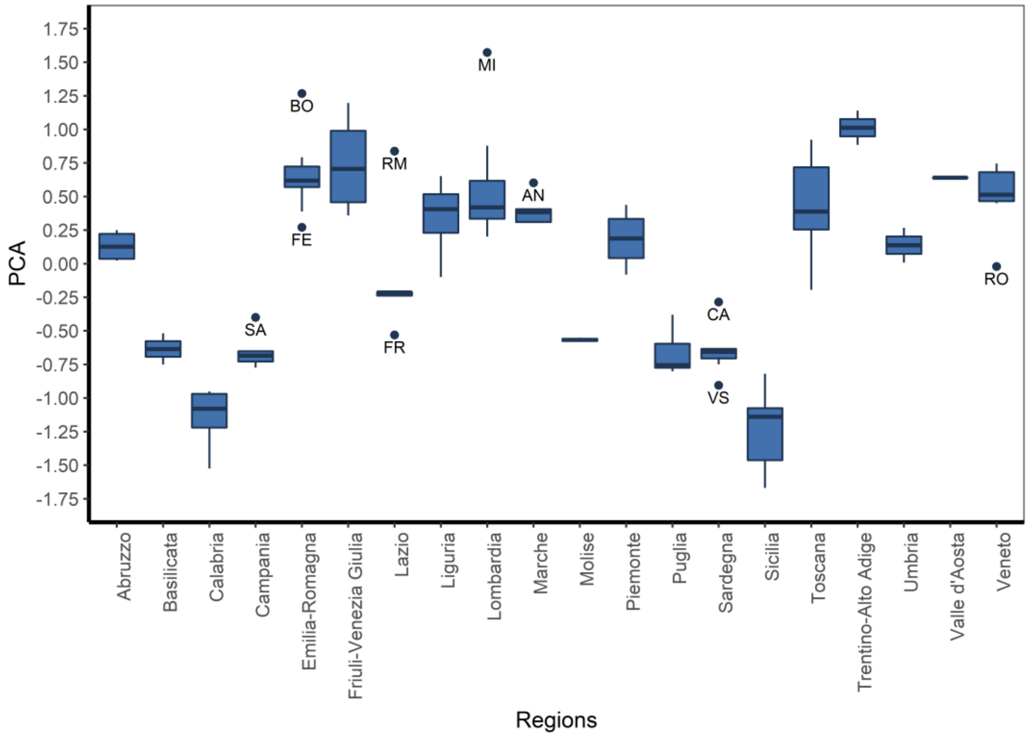
Figure 1.9 Pairwise comparisons of the rankings attained from different aggregation methods

In Figure 1.9-a, the discrepancies between the original and the reassessed rank positions are not very large because of implementing the same weights and the average aggregator. On the contrary, Figure 1.9-b and Figure 1.9-c apply a partial non-compensatory approach which leads to some shifts in ranking positions, at least for some regions. This variability can be explained in a twofold way- First, the presence of outlying areas such as Lodi Province in Lombardy and Frosinone in Latium, with very low AC levels (Figure 1.10-b), which result in lower regional rankings. Accordingly, the lower the compensation degree, the higher the shift in the rankings. Second, the numbers of provinces, which is an important element in the occurrence of such shifts. The regions with a lower number of provinces are approximately less exposed to ranking displacements by using the average aggregator, and mostly positive shifts by applying fuzzy gamma, because there is a lower AC variability among the provinces. Valle d'Aosta and Umbria regions could be named as examples of the above explanation above.

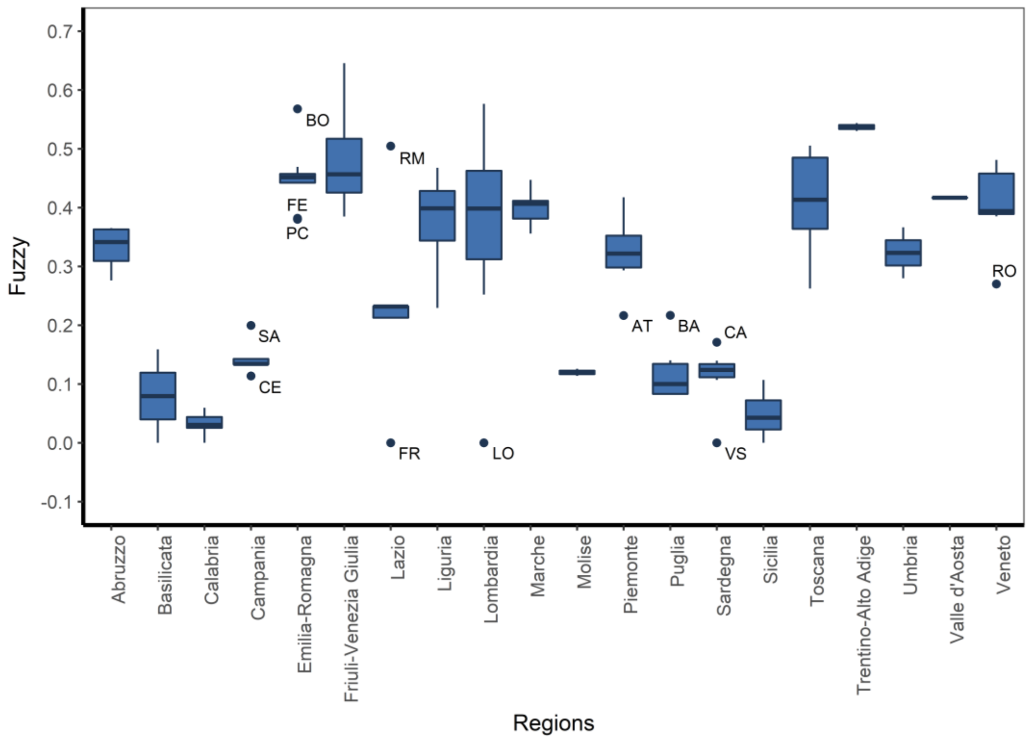
Figure 1.9-b depicts the outcomes of aggregation that allow for a medium-low degree of compensation by applying both average and fuzzy aggregators (fuzzy average) as was explained in methodology. Accordingly, the average aggregator balances the powerful effect of the multiplication part of the FGF (Fuzzy PRODUCT), which generalizes very low provincial AC values (e.g., zero for Lodi province, coming from the Min-Max normalization procedure) to the whole region. Figure 1.9-c illustrates the cross-comparison between PCA regional and Fuzzy Gamma outputs with much larger variations. As mentioned, the Fuzzy PRODUCT aggregator leads to very low ranking positions for the regions, with at least one province with very low scores in one indicator. The FG outcomes of such regions are close to zero, which leads to approximately the same positions for all of them (15^{th} position in Figure 1.9-c). In order to highlight the role of the fuzzy operators, a cross comparison analysis was performed on both fuzzy-based aggregations as the second part of the analysis (Figure 1.9-d).

By using a partial, non-compensatory approach, the discrepancies inside one region can be checked in order to attract the attention of policy makers to possible weaknesses. A glance at the above-indicated graph could show the need for heterogeneity in the regions with high discrepancies. Hence, the DM shall be also provided with some additional data which indicate the influential elements of the existing heterogeneities.

Final ranking positions are sensitive to very high and low scores of the index, which may lead to ranking reversals. The box plots in Figure 1.10 show the regional scores, including variability and outlying areas for both PCA regional (compensatory approach) and Fuzzy Gamma (partial non-compensatory) results. For a holistic regional analysis, both box plots should be considered together. For instance, in the PCA box plot, Bologna (BO) and Ferrara (FE) are shown as the outlying areas in the Emilia-Romagna region, but in the Fuzzy Gamma graph Piacenza (PC) is identified as another outlying area. Moreover, in Lombardia, only Milano province (MI) is considered as an outlying area by the PCA results, but Fuzzy Gamma singles out Lodi Province (LO) as an outlying area.



a) Variability and outliers for PCA regional results



b) Variability and outliers for Fuzzy Gamma results

Figure 1.10 PCA and Fuzzy Gamma provincial variability analysis

Fernandez et al. (2017) and O'Brien et al.(2004) obtained analogous results. Fernandez et al. (2017) showed that the final rankings are sensitive to the degree of compensation. We believe that applying different aggregation operators and degrees of compensation makes possible a deeper understanding of the adaptive capacities and more transparent solicitation of value judgements. Applying various compensation degrees illuminates the trade-offs between separate indicators and to what extent the aggregate results are sensitive to underperformance of an indicator (or group of indicators). O'Brien et al. (2004) argued that multiple-scale assessments are better suited to analyzing vulnerability and adaptive capacity. They suggest that a multiscale analysis of adaptive capacity may provide greater insights into vulnerability and adaptation, which is in line with our results.

1.4 Conclusion

Boosting adaptive capacity is an important goal of climate change adaptation policies. Greater adaptive capacity contributes to reducing vulnerability to future climate change and increasing resilience. AC is associated with a range of socioeconomic, governance and development, such as economic resources, knowledge and technology, infrastructures and institutional quality. AC should be consistent across geographical scales, otherwise policy and decision makers may be misled in adopting ill-suited adaptation strategies. Quantitative, indicator-based assessments are typically employed to measure adaptive capacity, by combining several disparate performance indicators into a composite index. The methodological and technical choices made for the construction of composite indices can have a significant impact on the resulting score (Jacobs and Goddard, 2007). Therefore, it is important to explore how robust the final scores are with respect to the choice of underlying indicators and the degree of compensation embedded in the aggregation methods.

We have described the adaptive capacity index ACI, developed at the regional (NUTS2) and provincial (NUTS3) administrative and statistical levels, to inform Italy's national climate change adaptation planning. Our analysis has explored the patterns of ACI at various scales and analysed how the degree of compensation affected the final scores of indices. The choice of indicators used in our analysis was driven by mainstream literature on adaptive capacity, multivariate statistical analysis and expert consultations. We first estimated the ACI composite indices at both the regional and the provincial scale, using a harmonised set of performance indicators, and then revised the regional index by considering the unequal distribution (performance) of the provincial ACI scores. To do so, we applied average and fuzzy gamma aggregation operators with different degrees of compensation.

The results showed, as expected, that the ACI scores are higher in the Northern, more developed regions of Italy. However, we have demonstrated that high regional scores of ACI are often driven by an above-average performance of regional capital towns and that below-average performance at the provincial level is hidden in the regional ACI assessments. This means that if ACI is estimated only at a higher administrative or statistical level, the inherent variability of performance at lower administrative levels is neglected. We argue that scale-dependent variability of adaptive capacity should be considered in the decision-making process to avoid misinformed policies. After having accounted for this variability of performance, we found substantially different patterns at the regional level. In doing so, the choice of aggregation rules plays an important role. Hence, a trade-off should be made explicit for choosing an aggregator that reflects the intended degree of compensation. Our results show that moving toward a lower degree of compensation leads to considerable rank reversals at the regional level, whereas the average operators maintain the original results from a regional analysis. This process involves a certain degree of subjectivity that can be reduced by experts' choices made on specific characteristics of the case studies. To put it in a nutshell, we suggest that multiple scale AC assessments be more informative and useful for policy makers than scale-specific ones.

The research on scale-dependency of composite indices can be further extended in several ways. High resolution statistical data collection and samplings can substantially improve data availability at lower administrative (e.g. municipal) levels. Tracking adaptive capacity from the local/municipal level up to a regional/national level can lead to further improvements. In addition, the number of indicators used may influence the final scores. Deductive methods with fewer indicators can be applied once the knowledge regarding the determinants of adaptive capacity is more consolidated. Until then, inductive methods using many indicators are more suitable. The time-series describing the recent trends in the indicators can offer better insights than a snapshot-assessment of ACI. In terms of aggregation operators, in our analysis we used two types of operators (average and fuzzy gamma) from among a large number of possible methods. Applying other aggregators, such as generalized mean, fuzzy t-norms and t-conorms, may lead to additional insights. In the future, ACI may be further developed to include actual climate change adaptation practices, documented using the appropriate monitoring, reporting and evaluation (MRE) schemes (EEA, 2015). MRE systems are currently being developed for the purpose of continuous monitoring, reporting and evaluation of the progress made in implementing climate change adaptation plans.

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2 COMPETENCE ANALYSIS FOR PROMOTING ENERGY EFFICIENCY PROJECTS IN DEVELOPING COUNTRIES: THE CASE OF OPEC

Abstract

Enhancing energy efficiency is an important goal of climate change resilient pathways and mitigation policies. Promoting energy efficiency in developing countries had faced several barriers, preventing optimal investments. One of the main barriers is the lack of internationally recognized indicators to compare projects in different countries in terms of their relative energy efficiency potentials and related investment risk. In this era of global political turbulence and a looming trade-war that will likely lead to unjustified tariffs, it is critical to provide a publicly available robust index for investors. At the same time, multinational and international corporations increasingly exposed to financial and political risks, making investment decisions more difficult than ever. We construct the Energy Efficiency Country Attractiveness Index (EECAI) developed to evaluate countries in terms of energy efficiency potentials and related investment risk. The index includes 30 indicators congregated in four pillars covering political, economic, social and technological (PEST) factors, combined by means of a mix strategy using Mean-Min function for intra-pillar aggregation and multi-attribute aggregation methodology for the pillars. We use one of the most common multi-attribute aggregation methodologies: the Choquet integral operator based on fuzzy measures and experts' elicitations collected using questionnaires. The OPEC member countries have been chosen in our analysis due to similarities regarding to energy exporting issues and the volume of the emissions in oil and gas sector. Our results show the experts' consensus over the economic and political factors as the most important elements affecting investment in the energy related projects, higher degrees of redundancy among various coalitions of pillars, and a disjunctive behavior of the experts having higher tendencies toward compensation among the PEST criteria. The highest conflict among the experts' preferences is embraced in the political pillar as well as the coalition of economic-technological and technological-political coalitions of pillars. By considering various degrees of compensation inside the Mean-Min operator, different patterns of capacities can be observed. Trade-offs should be made explicit for choosing aggregators reflecting the intended degree of compensation.

2.1 Introduction

According to the United Nations Environmental Programme (UNEP) statement, "climate change is the defining challenge of our generation" (UNEP, 2016). In order to tackle the climate change adverse impacts, diverse mitigation policies and methods have been introduced to diminish the amount of greenhouse gas emissions which directly affect natural and built environments all over the globe. Mitigation actions are the efforts intended to reduce GHG emissions along with capacity increase of Carbon Sinks (IPCC, 2014d; Morgan Stanley, 2016). GHG reduction could be performed through either energy demand or energy supply along with technological progress in energy storage devices. In SUPPLY side, utilizing alternative low carbon energy sources and fuel switch leads to a paradigm shift in fossil-based energy production. On the other hand, energy efficiency and conservation could enhance the shift toward low carbon society from both supply and demand side.

Energy efficiency practices reduce production costs, enhance competitiveness, support energy security and diminish carbon emissions per unit of production which guarantees the formation of future resilient and sustainable low carbon societies (Denton et al., 2014; EBRD, 2015). According to the IPCC fifth assessment report, annual investments in energy efficiency across the sectors would be increased dramatically from 2010 to 2029 in compare to other alternatives such as renewables (IPCC, 2014d). The aforesaid energy efficiency investments could be allocated in the most energy intensive sectors of the economy such as industrial, residential, transport and services sectors (IEA, 2014). It is also stated that 60 percent of the available cost effective opportunities to improve energy efficiency projects are located in developing countries, where the energy demand is increasing drastically (IEA, 2015; KfW, 2016). However, these opportunities are still untapped due to several financial and non-financial barriers for investors and prevent optimal investments in energy efficiency projects.

Various factors have been identified as barriers to increased energy efficiency implementation in developing countries explained in detail in supplementary material. Lack of data on energy efficiency potentials, financial barriers and economic/political uncertainties has been indicated as one the main barriers in implementing energy efficiency projects in developing countries. There are no internationally recognized indicators to compare countries in terms of the relative energy efficiency potentials and investment risks (Ryan et al., 2012). Investors are less likely to support the projects if they do not have essential data to compare projects in different countries, their relative energy efficiency potentials, existing regulatory/governance framework and macroeconomic perspective of the countries (Pitatzis, 2016; Ryan et al., 2012). The literature consists of several partial analyses on the aforesaid barriers. For instance, there are some indices which rank countries in terms of economic and political investment risk such as S&P, Moody, Fitch, World Bank doing business, Global Competitiveness Report, MARSH, Heritage and Hermes-Euler which cover economic and financial aspects (Euler Hermes, 2018; Forbes, 2018; Haspolat, 2015; MARSH, 2018; The World Bank Group, 2018). Also, it was found that some assessments have been done in the context of energy efficiency. For instance in the paper conducted by P. Kleindorfer (2011), risk management of the energy efficiency projects has been performed through the analysis of the energy intensity and complexity of the countries (Kleindorfer, 2011). Nevertheless, there is no evidence of existing indices which include indicators related to energy efficiency beside the economic and political ones that could be utilized to perform a country-based competence risk analysis. It should be added that in other sectors especially in renewable technologies, such indices are available to assist the decision makers (e.g. Renewable Energy Country Attractiveness Index) (EY, 2015). The reason could be difficulties in terms of technology and sectoral classifications (industrial, residential, etc.) of the energy efficiency topic which limits the construction of composite country-based indicators in this sector. Generally, the investments in this sector have been allocated by development banks such as KfW development bank and European Bank for Reconstruction and Development (EBRD). However, there is no public data on the criteria they have used to assess the competencies in terms of energy efficiency potentials (EBRD, 2015; KfW, 2016).

The aim of this study is to develop methods that can be used to address the gaps. We perform quantitative indicator-based assessments for analysing countries' energy efficiency potentials and investment risk. To perform such analysis, abovementioned barriers and expert-based assessments are considered implicitly as a basis to explore various indicators which cover political, economic, social and technological (PEST) dimensions of each country. Afterwards, we aggregate the indicators into a composite index to evaluate the Energy Efficiency Country Attractiveness (EECA) by means of multi-attribute value theory (MAVT). We first estimate the capacities of the countries for each dimension applying a hybrid Mean-Min aggregator with various degrees of compensation to show the trade-offs between indicators. Afterwards, we combine the aggregate results using fuzzy-based Choquet integral. The case of OPEC member countries has been chosen as the primary analysis target due to similarities regarding to energy exporting issues and the volume of the emissions in oil and gas sector.

2.2 OPEC member countries

The Organization of the Petroleum Exporting Countries (OPEC) is a permanent intergovernmental organization coordinating and unifying petroleum policies among 15 member countries namely, Iran, Iraq, Kuwait, Venezuela, Saudi Arabia, Qatar, Nigeria, Ecuador, United Arab Emirates, Algeria, Angola, Libya, Gabon, Indonesia, Congo and Equatorial Guinea (OPEC, 2017). Since our analysis is based on historical series of data between 2010 and 2017, Indonesia (suspended membership in 2009 and rejoined in 2016), Congo (joined in 2018), Equatorial Guinea (joined 2017) and Gabon (rejoined in 2016) have been excluded from the analysis. As a brief introduction on the OPEC member countries, it should be mentioned that the energy demand will experience a drastic growth in these countries due to population growth, the expansion of the more value-added industries, urbanization growth and infrastructure development which leads to higher emission rates (Al-Rashed and León, 2015). The total emission data from OPEC countries show that these countries were responsible for around 7% of global CO_2 emissions in 2010 which has been increased recently due to consumption growth of fossil-based fuels (Adetutu, 2014; Chiroma et al., 2015). Hence, these countries could be assumed as acceptable targets for the energy efficiency analysis. Whereas the most emissions in these countries are related to oil and gas sector as the major productive sector in economy (Hutt, 2018; The World Bank, 2018a), this analysis attempts to consider indicators related to this sector in addition to the general socioeconomic indicators. The energy efficiency practices in OPEC could be implemented in various stages of the production and logistics phases from upstream to downstream segments (“Oil & Gas Technologies,” 2017). Gas flaring, oil refining and transport infrastructures could be named as the most energy intensive compartments in oil and gas sector which could be analyzed in this study (Parekh and Singh, 2015).

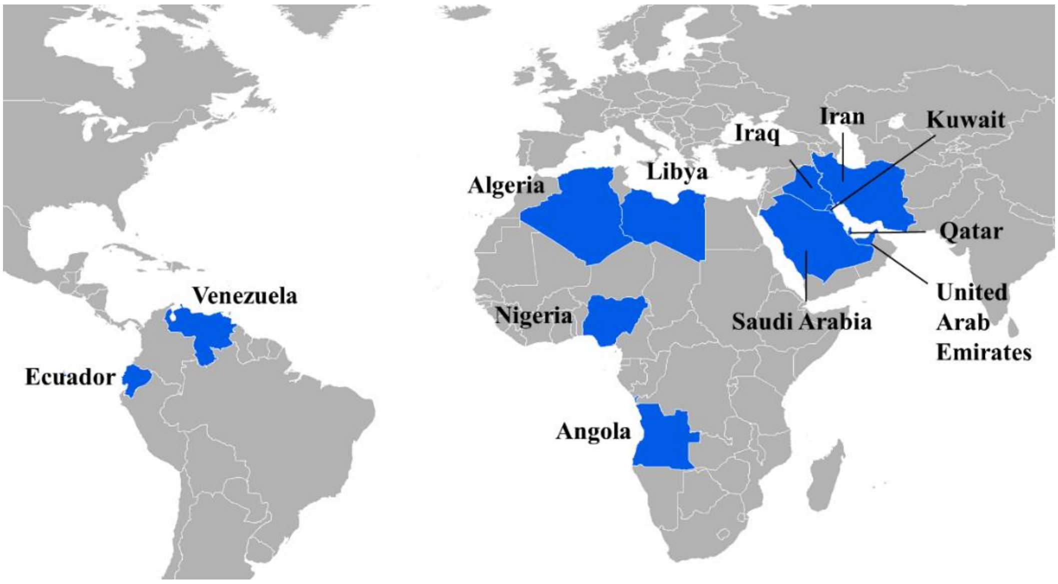


Figure 2.1 OPEC member countries considered in the analysis (OPEC, 2017)

2.3 Data and methodology

Figure 2.2 displays the main stages of the analysis. We start with a regular composition of the indices comprising the theoretical framework used, selection of indicators, data pre-processing and data transformation and analysis to estimate the EECA index.

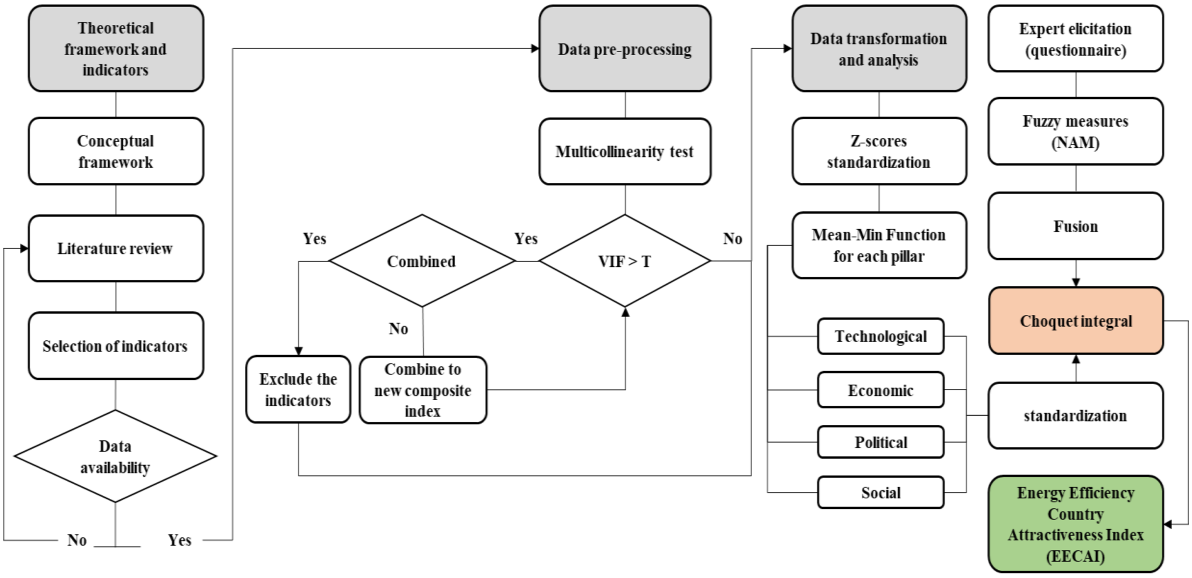


Figure 2.2 Workflow diagram of the analysis.

2.3.1 Conceptual framework and indicators used

In order to build a prosperous framework addressing the countries capacities, political, economic, social and technological factors (PEST) framework could be a convenient approach (Shilei and Yong, 2009). According to IEA, energy intensity could be considered as one the most important elements of energy efficiency. However, the socioeconomic and governance/political structure of the country also plays a crucial role that cannot be neglected (IEA, 2016). PEST analysis is a multifaceted strategic approach defined as one the most important stages of the multi-dimensional qualitative strategic analysis converting political, economic, social and technological, aspects (Song et al., 2017; Yüksel, 2012). PEST analysis helps investors to explore various macroenvironmental factors that they need to take into consideration when determining the decline or growth of a specific market and risk of investment. It is also a crucial instrument for determining business position, the potential of a business and the direction the business should be moving in to succeed in the marketplace. All large businesses such as energy sector should undertake this kind of analysis in order to evaluate the factors of external environment of the market that could influence the investments (Kolios et al., 2013; Shahid et al., 2012; Tan et al., 2018). PEST analysis has been recently identified as an important tool for country-based analysis and has been used by many companies such as MarketLine company in country analysis reports (MarketLine, 2014).

The indicators for each component of the framework have been chosen on the basis of literature review and advice from the experts in the field of energy and economics. Explanation of each pillar along with examples of frequently used indicators in the scientific literature for various components of PEST are as follows:

Economic factor: Economic factors include macro and microeconomic aspects that conjointly influence industry development (Verma, 2011). The stability of the macroeconomic environment is one of the most important factors for business and, therefore, is significant for the overall competitiveness of a country (WEF, 2017). In the context of petroleum exporting countries, these factors can be proxied by economic capital and growth, foreign direct investments, energy exports, budget balance, tax rate, electrical intensity and inflation rate (Howell, 2016; Song et al., 2017; The World Bank Group, 2018; UNIDO, 2017; WEF, 2017; Yüksel, 2012). These factors have major impacts on how businesses operate in these countries and decision-making process. For example, tax rates have been considered as an important element to attract the private sector to participate in the construction of for-profit public welfare and infrastructure projects through "individual proprietorships, joint ventures, and project financing" (Song et al., 2017). In the context of oil exporting countries, energy dependence proxied by Oil rents (as a percentage of GDP) have been also considered in our analysis. Oil rents are defined as "the difference between the value of crude oil production at regional prices and total costs of production" and determine contribution of natural resources to economic output and the liquidation of a country's capital stock (oil and gas reserves) (The World Bank, 2018b). Increase in oil rents determine the over-extraction of natural resources (oil and gas) and higher discount rates (Arezki and Brückner, 2011; Matallah and Matallah, 2016; The World Bank, 2018b).

Technological factor: Technological factors include the application conditions for various techniques and technology development trends (Song et al., 2017). Technological factors refer to technology incentives and technological change that can affect the minimum efficient production level and outsourcing decisions. In addition, they comprise the environmental factors such as emissions which can affect production levels as well (Verma, 2011). In this paper, we consider the main proxies showing the level of technological and industrial competitiveness among the countries with respect to the typology of their economy profile and energy efficiency targets. The energy intensity, electricity generation, carbon intensity, electricity loss, consumption growth rates in industry, gas flaring and refinery capacity are the most relevant proxies found in literature displaying the technological competitiveness issues in the context of energy efficiency (Al-Rashed and León, 2015; Blumberga et al., 2018; Comodi et al., 2016; IEA, 2014; Pappas et al., 2018; Parekh and Singh, 2015; Weng and Zhang, 2017; Yüksel, 2012). For instance, gas flaring as a source of greenhouse gas emissions, can be practically eliminated or recovered in oil field operations by employing of the gas for re-injection technology or enhanced oil recovery (EOR) (Comodi et al., 2016; Muggeridge et al., 2014; OPEC, 2018a; Orji, 2014). Hence, the lower the gas flared in compare to the output, the less EOR complex technologies have been employed which can be a convenient proxy for lack of technological and efficiency advancement in oil exporting countries (Comodi et al., 2016; Mullakaev et al., 2017) .

Political factor: Political factors play an immense role in determining the impacts on long term profitability of the companies in a certain country or market (Eni S.p.A., 2017). The companies benefit significantly from political stability and well-maintained rule of law (Forbes, 2018). High institutional quality can affect countries' attractiveness and foster growth by providing good governance and the correct levels of protection and incentives which are essential factors for long-term investments. Companies usually closely analyze political risks before entering or investing in a certain market (Eni S.p.A., 2017). The political factors refer to threats and uncertainties for the operational performance of the companies which are influenced by proxies such as government effectiveness, rule of law, investment profile, corruption control, political stability and regulatory quality (Euler Hermes, 2018; Forbes, 2018; Kaufmann et al., 2010; MARSH, 2018; Nifo and Vecchione, 2014; The PRS Group, 2017; The World Bank Group, 2018; Verma, 2011). As an example, regulatory quality reflects perceptions of "the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development" (Kaufmann et al., 2010; Kaufmann and Kraay, 2018).

Social factor: Social capital plays an important role in forming energy-related industries and stable business environments (Tan et al., 2018). Trends in social factors affect the operational success of a company and long-term profitability of the investments (Verma, 2011). In addition, society's culture and attitudes of the population can affect the way marketers perceive the customers of a given market and how they design the marketing message for industry consumers (specifically in major Integrated Oil and Gas sector) (Eni S.p.A., 2017). Social factors include the cultural aspects, health consciousness, demographics, population growth, urbanization, education level, human resources structure, unemployment and availability of workforce (Igliński et al., 2016; Song et al., 2017; The World Bank Group, 2018; Verma, 2011; WEF, 2017; Yüksel, 2012). As an example, better performance in "Doing Business" is highly correlated with lower levels of unemployment and poverty. "Economies with less streamlined business regulation are those with higher levels of unemployment on average" (The World Bank Group, 2018).

Table 2.1 Indicators of PEST considered for the analysis

Pillars	Criteria	Indicator	Code	Source	Year	Effect on EECAI
Economic	National income	GDP per capita, PPP (current international US$)	NI	World Bank, World Factbook, Central Bank of Libya, OPEC	2010-2016	increase
	Foreign investment	Foreign direct investment, net inflows (BoP, current US$)	FDI	World Bank	2010-2016	increase
	Budget balance	current account balance (m $)	BB	OPEC	2012-2016	increase
	Energy export	exports of petroleum products [1000b/d]	EE_1	OPEC	2011-2016	increase
		Crude oil exports [1000b/d]	EE_2	OPEC	2011-2016	increase
		Marketed natural gas production (million standard cubic meters)	EE_3	OPEC	2010-2016	increase
	Tax rate	Total tax rate (% of commercial profits)	TR	World Bank	2005-2017	decrease
	Electrical intensity	Electricity consumption (billion kilowatt-hour)/total primary energy consumption (Quadrillion Btu)	EI	EIA	2010-2015	increase
	Energy dependence	Oil rents (% of GDP)	ED	World Bank	2010-2016	decrease
	Inflation	Inflation, GDP deflator (annual %)	IN	World Bank	2010-2016	decrease
Technological	Electricity generation	Electricity generation as percentage of TPES	EG	IEA	2010-2015	increase
	Energy intensity	Energy intensity level of primary energy (MJ/$2011 PPP GDP)	ENI	World Bank	2010-2016	decrease
	Carbon intensity	CO2 over TPES (tCO2/toe)	CI	IEA	2010-2016	decrease
	Electricity loss	Electric power transmission and distribution losses (% of output)	EL	World Bank	2010-2016	decrease
	Consumption growth	Average annual growth rates of total final consumption in industry (%)	CG	OPEC, World Bank	2010-2015	increase
	Gas Flaring	Upstream gas flaring (million cubic meters) over total oil produced (1000 barrels)	GF	World Bank, IEA	2013-2016	decrease
	Refinery capacity	Refinery capacity (1,000 b/cd) over produced oil (1000b/d)	RC	OPEC	2012-2016	increase
	Infrastructure	Infrastructure expansion pillar of Global Competitiveness Index (1-7 scores)	INF	WEF	2014-2016	increase
	Technological readiness	Technological readiness pillar of Global Competitiveness Index (1-7 scores)	TRS	WEF	2014-2016	increase

Political	Government effectiveness	Quality of the civil service and the degree of its independence from political pressures, policy formulation and implementation and the credibility of the government's commitment	GE	WGI	2010-2016	increase
	Rule of law	Confidence in and abide by the rules of society, and the quality of contract enforcement, property rights, the police, and the courts and the likelihood of crime and violence.	RL	WGI	2010-2016	increase
	Investment profile	factors affecting the risk to investment such as contract variability/expropriation, profits repatriation and payment delays	IP	WGI	2010-2016	increase
	Corruption control	The extent to which public power is exercised for private gain, including both petty and grand forms of corruption	CC	WGI	2010-2016	increase
	Political stability	The likelihood of political instability and/or politically-motivated violence, including terrorism.	PS	WGI	2010-2016	increase
	Regulatory Quality	The ability of the government to formulate and implement sound policies and regulations.	RQ	WGI	2010-2016	increase
Social	Education	Education Index	EDI	UNDP	2010-2015	increase
	Health	Life Expectancy Index	LEI	UNDP	2010-2015	increase
	Unemployment	Unemployment, total (% of total labor force) (modeled ILO estimate)	UR	World Bank	2010-2017	decrease
	Urbanization level	Urban population (% of total)	UL	World Bank	2010-2016	increase
	Population	population growth (annual percent)	PG	World Bank	2010-2016	increase

Table 2.1 shows the initial set of AC indicators. The socioeconomic data for the analysis were obtained from multiple international development databases and reports such as World Bank Development Indicators (The World Bank, 2018c), UNDP Human Development Data (UNDP, 2016) and World Economic Forum (WEF, 2018). GDP data for Libya has been collected from various databases such as World Bank (The World Bank, 2018c), OPEC annual reports (OPEC, 2018b), World Factbook (CIA, 2018) and Central Bank of Libya (Central Bank of Libya, 2017). Additional data related to energy and electricity components were extracted from OPEC annual reports (OPEC, 2018b), International Energy Agency (IEA) database (IEA, 2018) and U.S. Energy Information Administration (EIA) (EIA, 2018). The data used to assess the political competitiveness were obtained from the Worldwide Governance Indicators (WGI) database gathered from a number of survey institutes, think tanks, non-governmental organizations, international organizations, and private sector firms (Kaufmann and Kraay, 2018). The data for technological readiness (TRS) and infrastructure (INF) has been extracted from the Global competitiveness Report by World Economic Forum (WEF) for 2014-2016 time period (WEF, 2018). The average annual growth rates of total final consumption in industry (CG) were calculated using the methodology proposed by Al-Rashed and León (2015). Education (EDI) and life expectancy (LEI) were extracted from Human Development Index from UNDP (UNDP, 2016). We use the average values for the available time series of the data (mostly 2010-2016) to balance the distortions caused by fluctuations in the political and socioeconomic trends in the OPEC member countries. Some of target countries such as Libya and Iraq are suffering from the impacts of external and internal conflicts, and some others such as Iran and Venezuela are supressed by sanctions which causes significant fluctuations in socioeconomic and political indicators.

2.3.2 Data pre-processing

Before data transformation and aggregation, the suitability of the data set and overall structure of the indicators should be assessed (OECD, 2008). In our study, the multicollinearity of the data in each pillar was assessed to avoid too high intercorrelation among the indicators of each segment of the decision three (Figure 2.3). When multicollinearity exceeds a certain threshold, standard errors and variances will be inflated which may bias the overall results (Avkiran and Ringle, 2018; OECD, 2008). In order to detect the multicollinearity among the variables, we calculated the Variance Inflation Factor (VIF). Various VIF threshold values have been considered for the collinearity test (Hagenlocher et al., 2016; KC et al., 2015; Makoka, 2008;

OECD, 2008). We consider VIF = 10 as the cut-off value (T) (Frigerio and De Amicis, 2016; Makoka, 2008). If the VIF values exceed the defined threshold, the corresponding indicators should be either removed or combined into a new composite indicator and checked again (Avkiran and Ringle, 2018). We calculated the VIF values using “olsrr” package (Hebbali, 2018) in an iterative process considering each indicator as a dependent variable and the rest as independent variables.

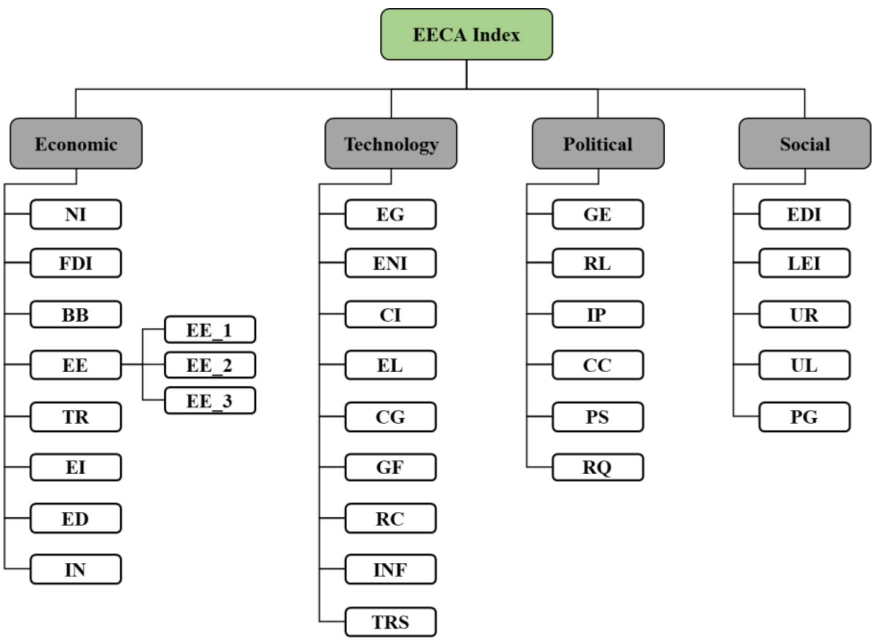


Figure 2.3 Decision Tree of the analysis.

After performing the multicollinearity test, the VIF values for government effectiveness (GE), rule of law (RL), infrastructure expansion (INF) and technological readiness (TRS) exceeded the defined threshold. First, we combined the values related to each pillar in an aggregated indicator (INF-TRS and GE-RL) and run the VIF test again. The applied aggregation methods to combine the aforesaid indicators are explained in data transformation and analysis section. In the case of GE-RL, the VIF values remained unacceptable range. Hence, we excluded these two indicators from the analysis.

2.3.3 Data transformation and analysis

Normalization

Indicators have been standardized by using z-scores to make them comparable (OECD, 2008). There are several alternative methods of data normalisation (e.g. min-max, z-scores, distance from a benchmark (indicization), balance of opinions, etc.) which are suitable, depending on the typology of data and the intended aggregation. This method preserves range (maximum and minimum) and introduces the dispersion of the series (standard deviation / variance). The formula is:

$$y_{ij} = \frac{x_{ij} - M_j}{S_j} \qquad \text{(Equation 1)}$$

where the M_j and S_j are the mean and standard deviation of indicator j. To revert the scales of indicators with negative polarity Equation 1 has been multiplied by -1 (Maggino, 2017). Since we have considerable number of indicators with negative polarity, employing the z-scores with linear transformation saves the same distance between units with a different origin which cannot be achieved using indicization methods with non-linear transformations ($x'_{ij} = \frac{1}{x_{ij}}$) (Maggino, 2017).

We applied two various aggregation methods two construct the EECA index. In the first-order aggregation stage, we aggregated the indicators under each pillar using the Mean-Min Function (MMF). Afterwards, the aggregated results of each pillar have been combined using fuzzy-based Choquet Integral in the second-order aggregation stage. A detailed explanation of the aggregation procedure is as follows:

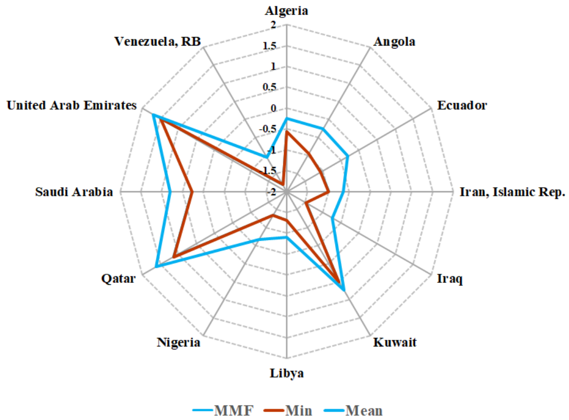
First-order aggregation

The indicators under each pillar have been aggregated using the Mean-Min Function (MMF). MMF is a two-parameter hybrid function developed by Tarabusi and Guarini (2013) incorporating two extreme cases of penalization of unbalance: the zero-penalization represented by the arithmetic mean (compensatory approach) and the maximum penalization represented by the minimum function (non-compensatory approach) (Casadio Tarabusi and Guarini, 2013; Greco et al., 2018; Maggino, 2017) while all other possible cases are intermediate. The "compensation" degree denotes trade-offs between higher performance in some indicators and lower performance in other ones. Using additive aggregators with high degree of compensation (e.g. arithmetic mean) implies that underperformance with respect to one or more indicators may not receive the adequate attention (Aggarwal, 2015; Fernandez et al., 2017; Langhans et al., 2014; Liu et al., 2014).

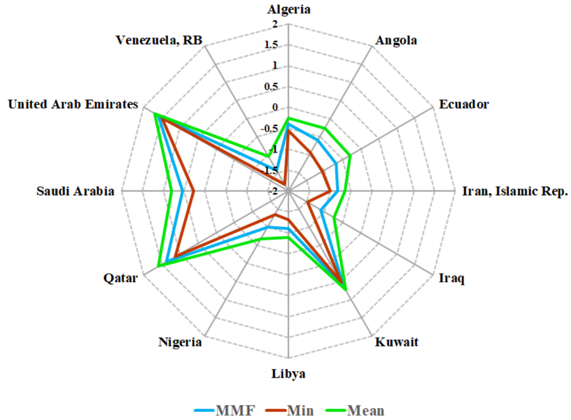
The MMF gives us the ability to construct our index using different compensation degrees. Applying various compensation degrees illuminates the trade-offs between separate indicators and to what extent the aggregate results are sensitive to underperformance of an indicator (or group of indicators) and makes possible a better understanding of each countries potentials and weaknesses (Marzi et al., 2018). The MMF is defined as:

$$MMF_i = M_{y_i} - \alpha\left(\sqrt{\left(M_{y_i} - \min_j\{y_{ij}\}^2 + \beta^2\right)} - \beta\right) \quad \text{(Equation 2)}$$

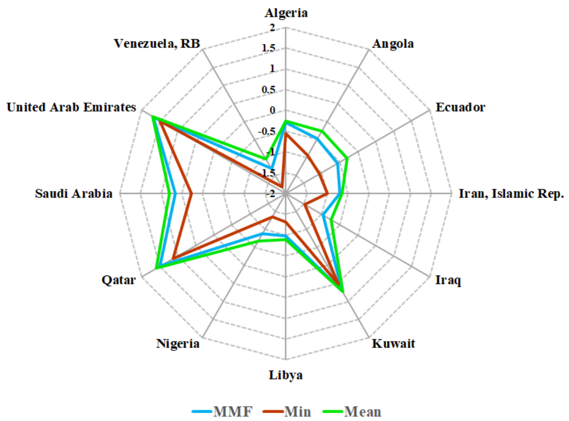
Where M_{y_i} is the mean of the normalized values for unit i, and the parameters $0 \leq \alpha \leq 1$ and $\beta \geq 0$ are respectively related to the penalization of unbalance and intensity of compensability between factors. The MMF reduces to the arithmetic mean for $\alpha = 0$ (in this case β is irrelevant) and the minimum function for $\alpha = 1$ and $\beta = 0$. Hence, β can be considered as a coefficient that determines the compensability between the arithmetic mean and the minimum function. Moreover, with $\alpha = 1$ the function yields to incomplete compensability and with $\beta = 0$ and $0 < \alpha < 1$ it has proportional compensability. With complete compensability any underperformance of any single variable can be compensated by suitable increases of the remaining variables. In the case of incomplete compensability, only decreases in one single variable that are smaller than a given amount are compensable with suitable increases of the remaining variables. On the other hand, in the case of proportional compensability, for any two variables *i*, *j* and any point *z*, the rate of compensation between z_i and z_j does not vary with the variable z_j, if *i* and the remaining variables are kept constant. It means the proportionality is not bunded to as single variable (Casadio Tarabusi and Guarini, 2013). Figure 2.4 displays the calculated MMF values for political pillar considering the aforesaid compensation possibilities.



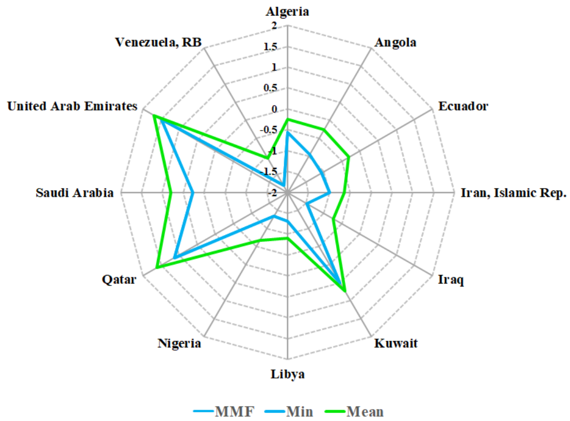
a) Arithmetic mean: $\alpha = 0$ and $\beta = 0$



b) Proportional compensability: $\alpha = 0.5$ and $\beta = 0$



c) Incomplete compensability: $\alpha = 1$ and $\beta = 1$



d) Min: $\alpha = 1$ and $\beta = 0$

Figure 2.4 Mean-Min Function values, for the political pillar of the analysis, for the different combinations of α and β calculated as part of the sensitivity analysis on MMF.

The sensitivity analysis on our data shows that in the case of incomplete compensability (Figure 2.4-c) with $\beta = 1$, the results are slightly less penalized than the proportional compensability ($\beta = 0$). (Figure 2.4-c). This occurs due to the degree of β as the compensability coefficient. However, this issue cannot be generalized to other cases and should be examined for various types of indicators and data sets. In order to aggregate the indicators under each pillar in the decision tree (Figure 2.3), the MMF was applied with the various degrees of compensation (cases shown in Figure 2.4).

Re-standardization: The variance of a pillar is proportional to the number of indicators inside the pillar. Therefore, unevenly distributed indicators among pillar implicitly create problems: pillar with higher variance (because with less indicators) will have higher influence on the composite index not because it is more important but, because there are fewer indicators inside which is undesirable. To avoid such distortion, the results of each pillar should be re-standardized before second-order aggregation.

Second-order aggregation

In the second-order aggregation stage, the aggregated results of each pillar have been combined to construct the EECAI. The PEST analysis consists of four dimension (political, economic, social and technological) which are closely interlinked with each other. Using simple linear aggregation techniques disallow the consideration of the possible interactions among the dimensions which may discard considerable amount of information from the analysis (Pinar et al., 2014). One of the most advanced algorithms to model the interactions is based on non-additive measures (or fuzzy measures) where a measure is assigned to every set that can be formed from an initial set of criteria (Farnia and Giove, 2015; Greco et al., 2011) and the Choquet integral (Grabisch, 2000). In this method, the value of fuzzy measures is elicited by experts. In this study we follow the expert elicitation methodology based on suitable questionnaires proposed by Farnia and Giove (2015). Farnia and Giove (2015) applied Least Square optimization algorithm to elicit the non-additive measures which minimizes the sum of squared distances between the answers of the experts and the solutions of the problem. Below some fundamental concepts for understanding fuzzy measures and Choquet integral are introduced:

Fuzzy measures and Choquet integral: A fuzzy measure (or NAM) is a set function $\mu: 2^N \rightarrow [0,1]$ defined over set of criteria $N = \{1,2, \dots, n\}$ which satisfies the following boundary and monotonicity conditions:

$$\mu(\varphi) = 0, \mu(N) = 1$$

$$S \subseteq T \subseteq N \Rightarrow \mu(S) \leq \mu(T) \leq 1 \; \forall S, T \subseteq N \qquad \text{(Equation 3)}$$

Fuzzy measure assigns a measure to every subset (coalition) of the criteria which shows the importance of that subset. For all disjoint subsets of $S, T \subseteq N$ a measure represents additive (linear aggregation), redundant or synergic interaction among the criteria if $\mu(S \cup T) = \mu(S) + \mu(T)$, $\mu(S \cup T) < \mu(S) + \mu(T)$ and $\mu(S \cup T) > \mu(S) + \mu(T)$ respectively. The Mobius of the set function for a given fuzzy measure μ is defined as (Farnia and Giove, 2015; Marichal, 2000; Marichal and Roubens, 2000):

$$m(S) = \sum_{T \subseteq S} (-1)^{s-t} \mu(T), \forall S, T \subseteq N \qquad \text{(Equation 4)}$$

where $s = card(S), t = card(T)$. The following boundary and monotonicity conditions are required (Farnia and Giove, 2015; Marichal, 2000; Marichal and Roubens, 2000):

$m(\emptyset) = 0$ (Equation 5)

$\sum_{T \subseteq N} \; m(T) = 1$

$\sum_{\substack{T \subseteq S \\ T \ni i}} m(T) \geq 0, \forall S \subseteq N, \forall i \subseteq S$

Let $X = \{x_1, x_2, \dots., x_n\}$ be the normalized values of the criteria belonging to N and μ as a fuzzy measure defined on N. The Choquet integral (discrete) with respect to μ is defined as (Grabisch, 2000):

$C_\mu(x_1, \dots., x_n) = \sum_{i=1}^{n} (x_{(i)} - x_{(i-1)}) \mu(A_{(i)})$ (Equation 6)

where (i) is the permutation of the indicators in a way that $x_{(1)} \leq \cdots \leq x_{(n)}$, and $A_{(i)} = \{x_{(i)}, \dots., x_{(n)}\}$ for $x_{(0)} = 0$. The Choquet integral for Mobius representation is given by (Farnia and Giove, 2015):

$C_m(x_1, \dots., x_n) = \sum_{T \subseteq N} m(T) \wedge_{i \in T} x_i$ (Equation 7)

where $\wedge$ stands for minimum operator. Fuzzy measures have been extracted from a simple questionnaire filled out by board of experts, which includes a decision matrix of the preferences for each one of the decomposition nodes of the decision tree. The board of experts were composed of 15 respondents chosen regarding their professionality in the context of energy economics from both European Union and OPEC member countries. The respondents were asked to provide an evaluation score between 0 and 100 for each combination of the criteria expect for the first and second rows containing best and worst scenarios for all criteria. Figure 5 displays a suitable questionnaire in which the respondent asked to express his/her evaluation on all possible combinations of the main four pillars (political, economic, social and technological).

Criteria					
Combination	Economic	Technological	Political	Social	Evaluation
Worst Case	Worst	Worst	Worst	Worst	0
Best Case	Best	Best	Best	Best	100
1	Best	Worst	Worst	Worst	50
2	Worst	Best	Worst	Worst	45
3	Worst	Worst	Best	Worst	65
4	Worst	Worst	Worst	Best	50
5	Best	Best	Worst	Worst	55
6	Best	Worst	Best	Worst	68
7	Best	Worst	Worst	Best	60
8	Worst	Best	Best	Worst	70
9	Worst	Best	Worst	Best	50
10	Worst	Worst	Best	Best	80
11	Best	Best	Best	Worst	80
12	Best	Best	Worst	Best	70
13	Best	Worst	Best	Best	95
14	Worst	Best	Best	Best	85

Figure 2.5 Questionnaire sample used as the decision matrix for the analysis.

Additivity: A fuzzy measure μ on N is k-additive if its mobius representation satisfies $m(T) = 0, \forall T \subseteq N$ such that $t > k$ and there exists at least one subset T with $card(T) = k$ such that $m(T) \neq 0$. In our study, we consider $k = 4$ which is called full order model (Grabisch, 1997).

Behavioral analysis: In order to interpret the results of fuzzy measures, *Shapley value*, *Interaction index* and *ORNESS* have to be calculated (Grabisch, 1997). The *Shapley value* characterizes the relative importance of each criterion attained by averaging all the marginal gains between any coalition not including the criterion, and the one which includes it. Shapley value of criterion *i* in terms of Mobius representation is given by:

$$\varphi(m; i) = \sum_{T \ni i} \frac{1}{t} m(T) \;\; \forall T \subseteq N \qquad \text{(Equation 8)}$$

Interaction index between two indicators represents their degree of synergy (perfect synergy +1) or redundancy (perfect redundancy -1); two independent indicators have interaction index equal to zero. The interaction index among a combination S of criteria in terms of Mobius representation is given by:

$$I_S(m; S) = \sum_{T \supseteq S} \frac{1}{t-s+1} m(T) \;\; \forall S \subseteq N \qquad \text{(Equation 9)}$$

The degree of ORNESS is a measure of the tolerance of the decision maker. Tolerant decision makers can accept that only some criteria are satisfied; this corresponds to a disjunctive behaviour (ORNESS(Cμ) > 0.5), whose extreme example is max. On the other hand, intolerant decision makers demand that most criteria be equally satisfied; this corresponds to a conjunctive behaviour (ORNESS(Cμ) < 0.5), whose extreme example is min. Of course, ORNESS(Cμ) = 0.5 corresponds to equitable decision makers. (Carraro and Giove, 2011; Pinar et al., 2014). In terms of Mobius representation, the ORNESS can be computed as follows:

$$ORNESS_m(i) = \frac{1}{n-1}\sum_{T\subseteq N}\frac{n-t}{t+1}a(T) \quad \text{(Equation 10)}$$

Expert preference fusion: Given that NAM (fuzzy measure) approach is sufficiently general to cover many preference structures, Expert's preference has been weighted according to his/her overall consistency in judging the alternatives proposed in the Choquet context. We measure Expert's consistency as a function of the sum of squared distances, in such a way that the greater (smaller) this sum, the smaller (greater) the contribution from the relative Expert. The above conditions can be formalized as following: given v alternatives to be judged, let define the vector $\boldsymbol{\varepsilon}_j$ $(v \times 1)$ whose entries represent the differences between the overall utilities values set by the j-th Expert and the respective Choquet values (solution of problem 14)). Let g_j be the sum of squared residuals (SSR) for the j-th Expert:

$$g_j = \boldsymbol{\varepsilon}_j{}'\boldsymbol{\varepsilon}_j \quad \text{(Equation 11)}$$

For each expert j-th Expert, we compute the R^2 index:

$$R_j^2 = \frac{\sum_{i=1}^{v}\left(\hat{y}_{ji}-\bar{y}\right)^2}{\sum_{i=1}^{v}\left(y_{ji}-\bar{y}\right)^2} \quad \text{(Equation 12)}$$

where as usual $\hat{y}_{ji}$ represents the estimated value for the j-th Expert, y his/her true value and $\bar{y}$ the sample mean of true values. The weight attached to the preference of the j-th Expert is computed as follows:

$$w_j = \frac{R_j^2}{\sum_{j=1}^{d} R_j^2} \quad \text{(Equation 13)}$$

Given that a linear weighted combination of Möbius representations is a Möbius representation too, the final Möbius representation can be defined in the following:

$$m^*\{T\} = \sum_{j=1}^{d} w_j m_j\{T\} \quad \forall\, T \subseteq N \quad \text{(Equation 14)}$$

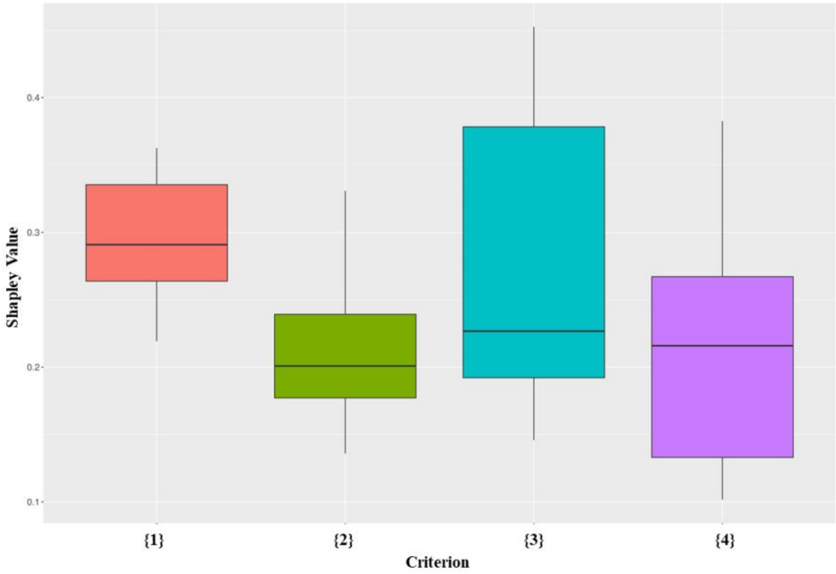
2.4 Results and discussion

In this section, we present the outcomes of the second-order aggregation phases. The results and discussions related to the first-order aggregation are provided in the supplementary material. The final EECAI rankings have been compared to available global indices to explore the robustness of the index.

2.4.1 Characteristics of the fusion measures

The characteristics of the fusion measures provide policy makers with some insight on experts' preferences and on their tendency to consider criteria as complements or substitutes as well as their relative importance (Farnia and Giove, 2015). In this section, we present the characteristics of the representative experts (respondents) using Shapley, interaction and ORNESS indices.

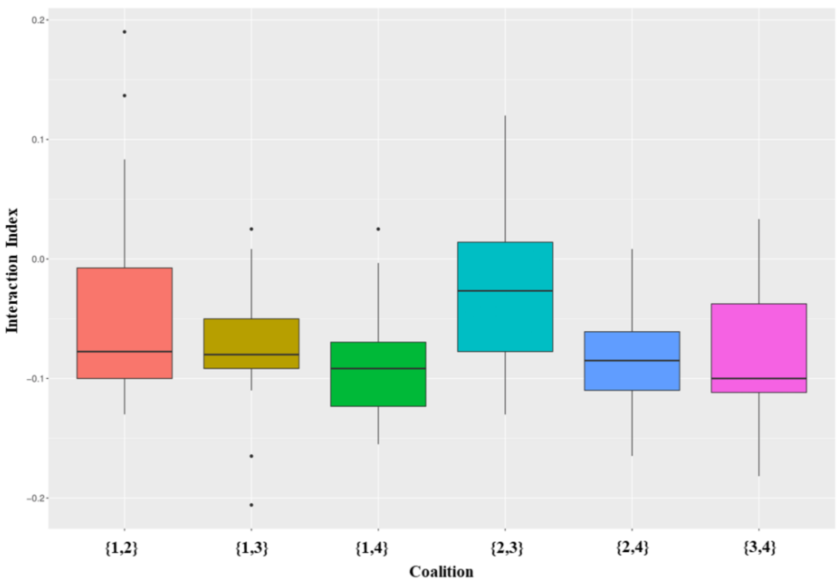
Figure 2.6 illustrates the Shapley values for each criterion derived from fusion measures. Higher Shapley values indicate higher importance of the criteria (in the range of [0,1]). According to Figure 2.6, economic and political pillars have higher relative importance median values than social and technological ones. The variability in pillars determines the variance among the experts' preferences. As it can be seen, political pillar embraces highest variability among the others which can be interpreted as a conflict among expert's preferences on this pillar (Table SM9 in supplementary material). The experts from OPEC countries assigned higher importance to political pillar, whereas the European experts considered higher weights for the social pillar instead of the political one. On the other hand, technological pillar holds lowest variability as well as smallest Shapley median value which indicates the experts' consensus on low relative importance of this pillar.



PEST factors	
Economic	{1}
Technological	{2}
Political	{3}
Social	{4}

Figure 2.6 Shapley values calculated for each pillar (criterion).

Figure 2.7 shows the interaction index values calculated for each coalition of criteria. The value of interaction index shows the average marginal interaction between two criteria in the range of [-1,1]. The interaction index equal to 1 (-1) indicates perfect complementarity/synergy (substitutability/redundancy) between two criteria (explained in fuzzy measures and Choquet integral section). For all the coalitions shown in Figure 10, interaction index median values are lower than zero which indicates a certain degree of redundancy among various coalitions of criteria. The coalitions of technological-political and political-social pillars gained highest and lowest median redundancies among all coalitions. The variability in pillars determines the variance among the experts' preferences for each coalition. Economic-technological and technological-political coalitions embrace highest variabilities among all coalitions. For these two coalitions, upper third quantiles (one fourth of the experts) have interactions larger than zero which shows higher tendencies toward synergy among a minor portion of experts. In contrary, for technological-political coalition, highest variability occurs below median value which determines higher propensities to redundancy. The lowest variability holds by economic-political coalition determining experts' consensus on the level of interactions among economic and political pillars. In this case, the largest variability is placed above the median showing higher tendencies toward synergic behavior.



PEST factors	
Economic	{1}
Technological	{2}
Political	{3}
Social	{4}

Figure 2.7 Interaction index calculated for each coalition of PEST criteria.

Figure 2.8 displays the ORNESS degrees for each expert (respondent) and the fusion of experts' preferences. The ORNESS index evaluates the extent to which the expert's preferences allow criteria to compensate each other. The ORNESS equal to 1 shows the expert's measures are fully compensative (fully disjunctive behavior). In contrary, for ORNESS equal to zero, expert's preferences are perfectly complementary (fully conjunctive behavior). In the special case of ORNESS equal to 0.5, expert has additive preferences on average. We consider ORNESS degree over 0.5 as propensity to compensability (below 0.5 as tendency to complementarity). The results show that ORNESS degrees are all in the range of 0.5 to 0.75 except Respondent_1 with ORNESS degree lower than 0.5. The derived ORNESS degrees indicate the experts' tendency toward moderate compensation (disjunctive or redundant behavior) among the criteria which is approximately comparable to incomplete compensability ($\alpha = 1$ and $\beta = 1$) using MMF. In addition, the ORNESS degrees of the analysis show that decision makers are moderately tolerant following disjunctive behavior in dealing with PEST criteria.

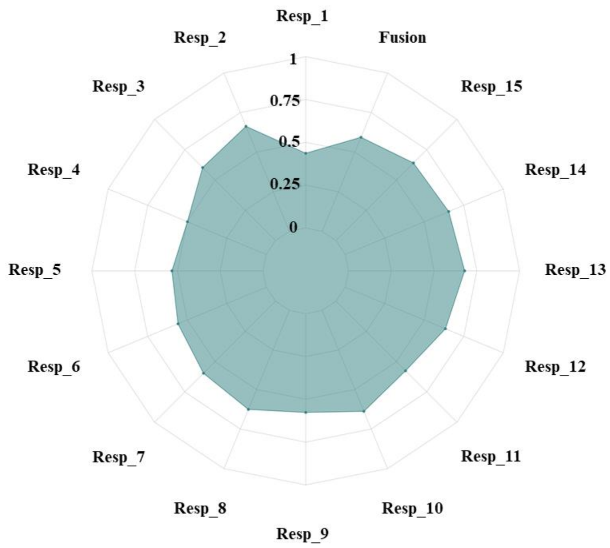
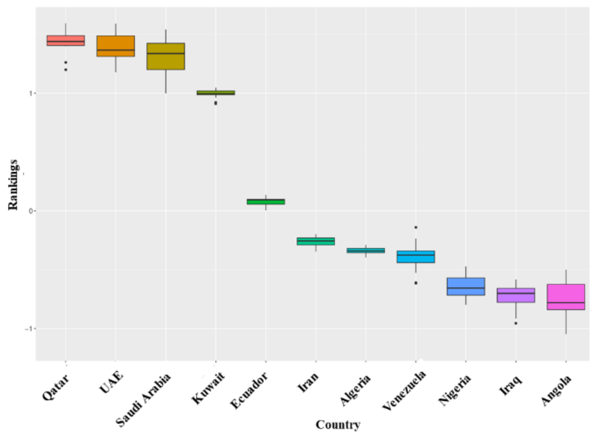


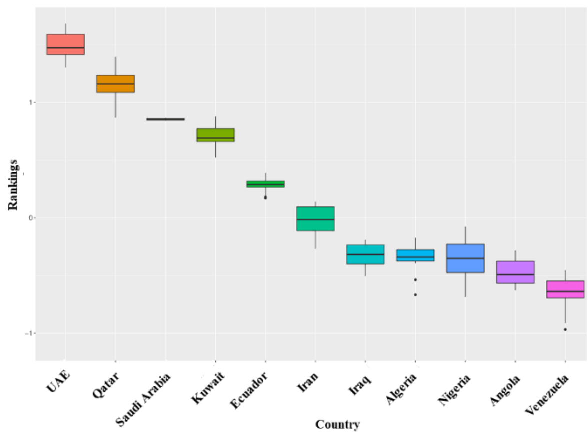
Figure 2.8 ORNESS degree of experts.

2.4.2 Results

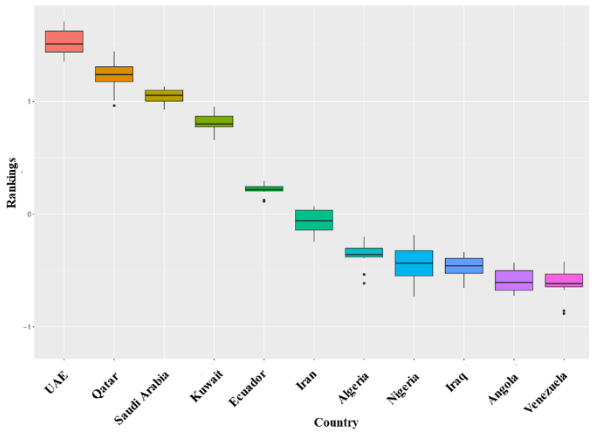
In this section, we present the results attained from application of Choquet integral as an aggregation operator which strongly depends on the subjective relative importance of coalitions among the criteria. Figure 9 illustrates EECAI Rankings for various combinations of α and β. Accordingly, Qatar and United Arab Emirates interchangeably have the highest rankings positions and various aggregations yield almost robust results for these two countries. Using the experts' preferences fusion, the results for Saudi Arabia and Kuwait are completely robust with no variations (third and fourth respectively in the final rankings derived from various aggregations). In general, four gulf countries are embraced in a cluster with robust rankings positions which has a considerable difference with the rest of countries in the case of arithmetic mean aggregation due to very high capacities in most of the indicator. Nevertheless, the gap diminishes while applying an inherent level of non-compensation. The variabilities in results determines the inherent variances among expert's preferences. The results show that the variability can be also affected by the aggregation operator. Hence, no rational trend could be found to justify the variabilities and interpretation of variabilities is limited to each aggregation results. The results for Ecuador and Iran are completely robust as well (fifth and sixth ranking positions in all cases respectively). The worst ranking position goes for Libya in all four cases (completely robust) due to very low scores in all pillars. The rankings for the rest of the countries experience moderate rank reversals which makes it impossible to create relevant clusters to ease the further interpretations.



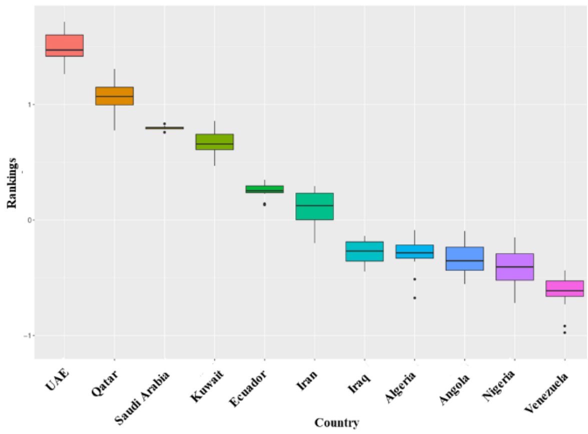
a) Arithmetic mean: $\alpha = 0$ and $\beta = 0$



b) Incomplete compensability: $\alpha = 1$ and $\beta = 1$



c) Proportional compensability: $\alpha = 0.5$ and $\beta = 0$



d) Min: $\alpha = 1$ and $\beta = 0$

Figure 2.9 EECAI Rankings for various combinations of α and β

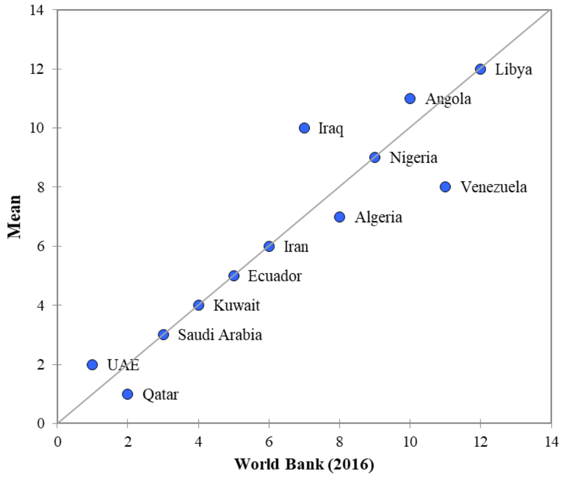
We proceed with a comparison of our rankings with the available international investment risk indices to verify the truthiness and consistency of the results. Since the final ranking are mostly affected by economic and political pillars, we compare our index with World Bank Doing Business and Marsh political risk index. Pairwise comparisons with some famous indices such as Moody is not possible due to lack of data on some of targeted countries in such indices. Doing Business Index provides quotative assessments on regulations for starting a business, dealing with construction permits, registering property, getting credit, protecting investors, paying taxes, trading across borders, enforcing contracts and resolving insolvency as well as features of labour market regulations (The World Bank Group, 2018). However, macroeconomic stability, development of the financial system, quality of the labour force, corruption, market size and lack of security (mostly related to political pillar) are not covered. To this end, Marsh political risk index has been also considered for pairwise comparisons. Marsh Political Risk Map presents a global view of issues facing multinational organizations and investors considering in-country political, economic and operational in order to assist investors in making smarter decisions about where and how to allocate their financial resources globally (MARSH & McLennan, 2016). Unfortunately, Marsh index is only available for 2018 (2016 and 2017 rankings are not provided for public use). Although both indices do not account for technological aspects regarding energy and energy efficiency, they can show general investment risk in a country. Whereas the most of foreign investments in OPEC countries are deployed in energy and petroleum technologies, thus the comparison could be relevant.

Table 2.2 show the final rankings obtained from Choquet integral for various combinations of α and β compared with World Bank Doing Business and MARSH political risk rankings. Accordingly, negligible differences can be detected between Marsh and Doing Business (2018) indices. Therefore, we continue with Doing Business rankings for pairwise comparisons. The World Bank Doing Business index shows negligible rank reversals in three consecutive years (2016-2018). As it can be seen in Table6, Iraq's ranking positions diminishes due to the internal conflicts began in 2015 and got worse every consecutive year. In the case of Venezuela, the rankings decline from 2017 to 2018 due to the recent economic crises caused by significant reductions in crude oil prices (2015). In the case of Nigeria and Libya, the rankings improve which can be related to re-establishment of relatively stable authorities in these two countries.

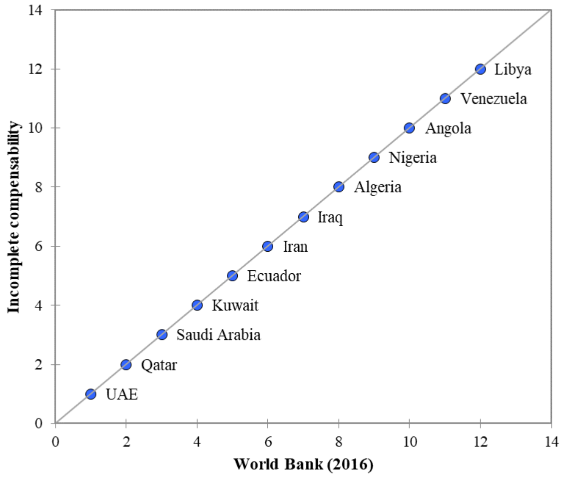
Table 2.2 EECAI Rankings with various combinations of α and β compared with World Bank Group Doing Business (WBG) (2016 and 2017), and MARSH political risk rankings

	MEAN	INCOM. COMPEN.	PROP. COMPEN.	MIN	WBG (2016)	WBG (2017)	WBG (2018)	MARSH (2018)
ALGERIA	7	8	7	8	8	7	8	7
ANGOLA	11	10	10	9	10	10	10	9
ECUADOR	5	5	5	5	5	5	5	5
IRAN	6	6	6	6	6	6	6	6
IRAQ	10	7	9	7	7	8	9	10
KUWAIT	4	4	4	4	4	4	4	4
LIBYA	12	12	12	12	12	12	11	12
NIGERIA	9	9	8	10	9	9	7	8
QATAR	1	2	2	2	2	2	2	2
SAUDI ARABIA	3	3	3	3	3	3	3	3
UNITED ARAB EMIRATES	2	1	1	1	1	1	1	1
VENEZUELA	8	11	11	11	11	11	12	11

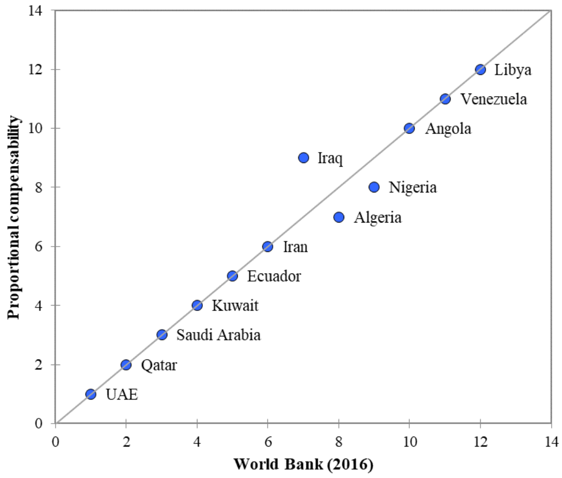
Since the analysis data is collected for the years 2010-2016, we perform the pairwise comparisons with Doing Business 2016. Figure 2.10 comprises Pairwise comparisons of the rankings attained from aggregations with various combinations of α and β with World Bank Doing Business 2016. Accordingly, the largest shifts occur in the case of Mean function with full compensation among the indicators (Figure 2.10-a). Surprisingly, in the case of incomplete compensability the rankings are fully compatible with the World Bank rankings. The shifts are negligible in the case of proportional compensability and minimum operator. The results of the pairwise comparison cannot be interpreted in terms of internal interaction between indicators and criteria. Nevertheless, it is useful for consistency verification of the analysis and testing the truthiness of the results in compare to reliable sources of information published by international organizations such as World Bank.



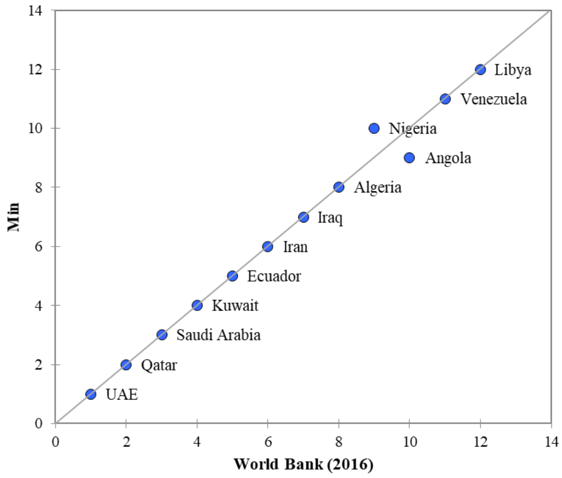
a) World Bank vs Mean operator rankings



b) World Bank vs incomplete compensability rankings



c) World Bank vs proportional compensability rankings



d) World Bank vs Min operator rankings

Figure 2.10 Pairwise comparisons of the rankings attained from aggregations with World Bank Doing Business 2016

2.4.3 Robustness analysis

The complex aggregation applied to evaluate the EECAI is strongly dependent on the attitude of the representative experts discussed in the expert preference fusion section. In order to evaluate the robustness of the index, alternative configurations of expert preferences have to be modelled to run a significant number of simulations as part of the Monte Carlo approach. Pinar et al (2014) generated various sets of measures so called “artificial decision makers (ADM)” to aggregate the indicators using Choquet integral. In their application, each ADM represents “a univocal instance of consensus among real decision makers, whose measures have been combined using random weights”. This approach results in a distribution of the final index for each country indicating the extent of the robustness of the final results. In order to describe more accurately the simulation results the relative dominance measure (ρ) has been proposed which indicates the degree of relative dominance of the i unit (country) across simulations (Pinar et al, 2014). This measure can be a useful tool to provide a robust ranking of the countries considering numerous configurations extracted from different inputs (derivation procedure has been explained in the supplementary material). In our study, by employing MMF with various degrees of compensation, the aggregation yields non-analogous results using each input (expert preference). In the end, we have 60 models derived from applying four different combinations of α and β to aggregate the fuzzy measures provided by 15 respondents (experts). Figure 2.11 shows the distribution of EECAI values for each country ordered by decreasing relative dominance measure.

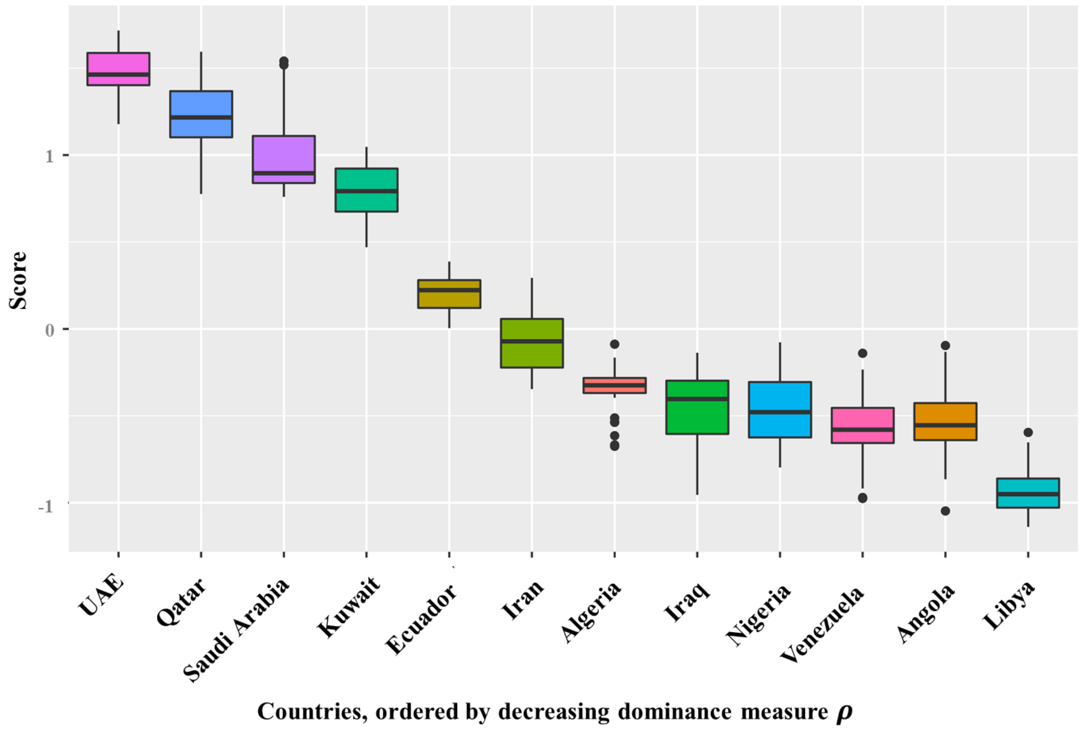


Figure 2.11 Distribution of EECAI values for 60 models based on various combinations of α and β

Accordingly, the box plots of modelled distributions ordered by the decreasing dominance measure validates some of the previous interpretations in results section. The high-ranking cluster containing UAE, Qatar, Saudi Arabia and Kuwait are quite set apart from the rest of the countries. However, the variabilities are overlapping specially for the first and forth quartiles. The results of this cluster are closely aligned with results explained in the section 2.4.2 with a robust ranking for Saudi Arabia and Kuwait. This cluster of countries has been followed by Ecuador and Iran having moderate distance to the rest of the countries excluding the first and forth quartiles in the distributions. The rankings associated with these two countries are robust in all the combinations taken into account (2.4.2 and 2.4.3 sections). The rest of the countries except Libya are clustered in a group with considerable overlaps for the second and third quartiles, suggesting that statistical inferencing is made with caution. This cluster has been followed by Libya which has the lowest ranking among the OPEC group. In the case of Libya, the distribution values excluding first and forth quartile are completely detached from the previous cluster of countries. By comparing the results of both sections (robustness and results), the ranking assigned to Libya can be assumed robust as well. Figure 2.11 rankings can be used as the final policy making tool in which the all the possible alternative configurations are modelled. These rakings can be improved by generating significant number of simulations using ADMs as a future research topic.

2.5 Conclusion and policy implications

Boosting energy efficiency is a critical goal to achieve climate change resilient pathways and mitigation policies. Energy efficiency facilitates a shift toward low carbon society and guarantees energy conservation as a crucial element of sustainable development. With significant energy demand in developing countries, energy efficiency offers the opportunity to amend the trajectory of energy consumption growth that would be crucial to enhance the sustainability and reducing the environmental impacts and GHG emissions. Promoting energy efficiency in developing countries faces several barriers preventing optimal investments. One of the main barriers for the investors is the lack of internationally recognized indices/indicators to compare countries in terms of energy efficiency potentials and related investment risk.

In this paper, we construct the Energy Efficiency Country Attractiveness Index for OPEC member countries (which have a considerable share of global GHG emissions), to inform decision making of businesses and investors on energy efficiency potentials and the related investment risk. We utilize an indicator-based assessment using PEST (political, economic, social and technological) factors as the framework of the analysis. The choice of indicators in our analysis was driven by mainstream literature and expert elicitations. First, we estimate the capacities of the countries for each pillar of the framework applying a hybrid Mean-Min aggregator with various degrees of compensation (from full compensation (mean) to non-compensation (minimum)) to illustrate the trade-offs between these indicators. Secondly, the aggregate results of each pillar were combined using fuzzy-based Choquet integral by which the interactions between pillars can be incorporated in the analysis. Fuzzy measures were extracted from a questionnaire filled out by board of experts, which demonstrated the experts' preferences regarding the importance of each coalition of the PEST pillars. Expert's preference has been weighted according to their overall consistency in judging the alternatives as a function of the sum of squared distances. The analysis has been completed by robustness analysis of the results using a combination of the results derived from diverse assumptions and relative dominance measures.

The main findings from the experts' elicitations are represented by means of Shapley value, interaction index, and ORNESS degrees among the PEST criteria. The results from Shapley values indicate the experts' consensus over the economic and political factors as the most important determinants of the attractiveness of the countries in terms of investment in the energy related projects. Nevertheless, there is a significant variability regarding the experts' preferences on the importance of the political pillar. The calculated values for interaction index show higher degrees of substitutability (redundancy) among various coalitions of criteria rather than complementarity (synergy). The highest and lowest redundancies can be observed among technological-political and political-social coalitions respectively. In addition, the economic-technological and technological-political coalitions embrace highest variabilities, showing higher degree of conflict among experts' preferences for these two coalitions. Finally, the results regarding the ORNESS degrees show that the experts are moderately tolerant and follow a disjunctive behavior with higher tendencies toward compensation among PEST criteria.

The final results derived from Choquet integral show that the four OPEC members' Gulf countries (United Arab Emirates, Saudi Arabia, Kuwait, and Qatar) are at top of the ranking list with slight shifts for various combinations of the penalization parameters. Ecuador and Iran are placed in fifth and sixth with no shifts in the rankings. Finally, Libya and Angola are placed in the last Worst cluster of the countries with no shift in ranking positions in all the combinations. The rest of the countries experience various rankings with different degrees of compensation. Whereas the final rankings are mostly inclined toward the economic and political factors, we compare our results with World Bank Doing Business report and Marsh Political Risk Index to verify the consistency of the final rankings. Pairwise comparisons illustrate approximately negligible discrepancies in the ranking positions in the case of employing an intended degree of non-compensation among indicators. The robustness analysis resulted in a distribution of the final EECAI scores for each country ranked by the relative dominance measure. The results extracted from the robustness analysis validated the rankings associated with the previously clustered groups of countries considering the variabilities generated by diverse compensation assumptions.

In summary, applying various degrees of compensation demonstrates the trade-offs between the indicators and the criteria, and the extent to which the results are sensitive to under-performance of an indicator (or group of indicators). By using the minimum operator, the discrepancies in PEST factors between countries can be examined in order to attract the attention of investors to possible weaknesses for each country (as argued in first-order results and discussion section). The interpretation of trade-offs between proxy indicators incorporates higher degree of uncertainty which cannot be attained easily from solicitations of value judgements. For instance, the interaction and importance degree between upstream gas flaring and refinery capacity is difficult to achieve using value judgements. Hence, it is more convenient to apply data driven techniques such as Mean-Min function, Fuzzy Gamma or generalized mean to evaluate such trade-offs. In the case of the PEST pillars, the interactions and importance of the individual pillars can be achieved using value judgements obtained from expert's preferences and aggregation through fuzzy-based techniques such as the Choquet integral. Nevertheless, applying methods based on experts' elicitation is rather time consuming and usually depends on the willingness of the experts to participate in such surveys.

In this era of global political turbulence and a looming trade-war that will likely lead to unjustified tariffs, it is critical to provide a publicly available robust index for investors. At the same time, multinational and international corporations increasingly exposed to financial and political risks, making investment decisions more difficult than ever. The two most well-known risk indices, the World Bank Doing Business Index and the Marsh Political Risk do not consider technological aspects of a country, as a result they are unable to provide a complete set of information for investment decision-making. Our index accounts for political, economic, social and technological factors within countries and combines expert elicitation with fuzzy measure based Choquet integral to rank countries according to various criteria. Along with investors, policymakers could also utilize our index to identify sectors and pillars that are lagging behind.

The EECAI presents a useful tool for energy policy management by which experts solicitations are explicitly involved in the construction process of the index. The policy makers are often involved in a multi-criteria decision-making process to assess fit-for-purpose energy and economic assessments. Using simple additive measures to combine the multi-faceted criteria may lead to misinformed policies and inefficient allocation of financial resources. Applying advanced non-additive measures which consider the experts' preferences encompasses higher degree of reliability and robustness. The future use of our index will be beneficial to OPEC industrial sector. The most important policy implication of our study is promoting energy efficiency projects in the countries with higher possibility of returning desired outcomes in terms of mitigation targets and sustainable development.

The research on competence analysis for promoting energy efficiency projects can be further extended in several ways. The choice of indicators can be modified to cover other energy intensive sectors such as residential and transportation to provide better insight of the capacities and weaknesses for policy makers and investors. The number of alternative countries can be expanded as well. In terms of methodology, we used Mean-Min function to aggregate the intra-pillar indicators among a large spectrum of aggregators. Applying other aggregators such as Fuzzy Gamma, generalized mean, and OWA types may lead to additional insights. In addition, various types of weights extracted from either panel of experts or data driven techniques (e.g. PCA) can be assigned to proxy indicators to improve the accuracy of the index. The analysis can be further updated using the most recent data in the future to monitor, report, and evaluate possible improvements or deteriorations for targeted countries.

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3 CONSTRUCTING A COMPREHENSIVE DISASTER RESILIENCE INDEX: THE CASE OF ITALY

Abstract

Measuring disaster resilience is a key component towards successful disaster risk management and climate change adaptation. Quantitative, indicator-based assessments are typically applied to estimate resilience for specific geographical units by combining several disparate performance indicators into a composite index. Building upon research on social vulnerability and incorporating features describing coping and adaptive capacity (such as novel distance-decay based attributes), this paper explores how methodological and technical choices made for the construction of composite indices can impact on the outcomes of composite disaster resilience indices. The analysis is divided into two parts: first, we develop an innovative composite disaster resilience index (DRI) at the municipality level for whole Italy to address disaster resilience and to support the implementation of the Sendai Framework for Disaster Risk Reduction (SFDRR). Then, we apply advanced normalization and aggregation procedures accompanied by sensitivity and robustness analysis to assess how different procedures in designing composite indicator can influence the resulting index. The results show different patterns of social vulnerability and resilience in Italy with higher variabilities identified in different clusters, such as the northern Italian regions of Lombardy and Trenitno, and the Sardegna, Basilicata and Puglia regions. The results derived from the sensitivity analysis show that the coupling of the various procedures for normalization and aggregation, and in particular different weight configurations for the aggregation process, yield in somewhat varied outcomes. Depending on the type of policy application and the interest of decision makers, certain set of solutions are available which are introduced in this study. We conclude that policy-makers must to pay close attention to the methodology used for the development of composite indices in order to avoid inefficient disaster risk management and maladaptation.

3.1 Introduction

Climate-related disasters can affect the economy, security and well-being of communities. In recent years, climate-related disaster risks have increased as a result of changing climate, urbanization, demographic pressures, land-use and land-cover change, biodiversity loss, and eco-system degradation (European Commission, 2014, 2013; Poljanšek et al., 2017). Reducing climate-related risks and strengthening natural disasters resilience are currently major societal challenges, demanding a comprehensive understanding of the complex interactions among societies, ecosystems and natural hazards, also with respect to climate change. Implementation of strategic and instrumental measures for supporting disaster risk reduction and enhancing resilience are defined as the core elements of disaster risk management and climate change adaptation (IPCC, 2014a, 2012; UNISDR, 2015b; World Bank, 2012).

The UN Sendai Framework for Disaster Risk Reduction (UNISDR, 2015b) adopted in 2015, called for fostering disaster resilience at all levels through “the implementation of integrated and inclusive economic, structural, legal, social, health, educational, environmental, technological, political and institutional measures” that reduce hazard exposure and vulnerability and reinforce resilience. The Sendai Framework prioritizes investing in disaster risk reduction for resilience to enhance preparedness for effective response, recovery, rehabilitation and reconstruction with the aid of a strong interface between science and policy to empower disaster risk governance to manage to disaster resilience. (Poljanšek et al., 2017; UNISDR, 2015b). The main focus of the Sendai Framework is on addressing the cohesion of disaster risk management actions with sustainable development policies in the context of hazard exposure and vulnerability information to boost disaster resilience (Breil et al., 2018; UNISDR, 2015b).

The EU strategy on adaptation to climate change calls for the integration of adaptation actions and disaster risk management policies to promote sustainable growth and disaster resilience at all levels (EC, 2013). In 2015, a conference entitled “Building a resilient Europe in a globalized world” was held by the Joint Research Centre (JRC) and the European Political Strategy Centre (EPSC) to discuss different aspects of disaster resilience among European institutions and member states. As a result, the Disaster Risk Management Knowledge Centre was launched to reinforce the science policy interface to enhance the contribution of science in disaster risk management policymaking (DRMKC, 2017; EC, 2015).

Previous attempts to measure resilience (Bakkensen et al., 2017; Cutter et al., 2014; Frazier et al., 2013; Parsons et al., 2016) addressed resilience as networked social and economic capacities which comprise attributes of different dimensions such as infrastructures, economy, governance and environment (Alawiyah et al., 2011; Aldrich, 2012; Bates et al., 2014; Khazai et al., 2018; Rose, 2007; Sherrieb et al., 2012, 2010; Tierney, 2012). In general, resilience is a construct of preparedness and strengthened social and economic cohesion and trust before disaster plus promoting adaptive capacity and sustainability considering resource availability and demographic characteristics to deal with post-disaster era (Beccari, 2016; Cutter et al., 2014; Poljanšek et al., 2017). Cutter et al. (2014, 2010, 2008) classifies resilient components under ecological, social, economic, organizational, infrastructure and community competence pillars. The resilience of ecological systems can be associated with various factors related to biodiversity, redundancies, response diversity, governance and management policies (Adger, 2006; Adger and Vincent, 2005; Brenkert and Malone, 2005; Folke, 2006). The social pillar of resilience is influenced by factors related to communications, risk awareness and preparedness which are closely correlated to demographic characteristics of the community and its access to resources. Post- disaster property loss and effects of business disruption have been stated as the components of economic pillar revealing the operational role of businesses, organizational and institutional entities (Rose, 2006). Organizational resilience comprises the physical properties of organizations and emergency assets which guarantee and manage a proper response to disasters (Tierney and Bruneau, 2007). The infrastructure pillar includes the characteristics of physical systems as well as the degree of interdependency of the infrastructure construct. Finally, the community competence captures the population wellness, quality of life and emotional health which show the community performance before and after disaster strikes (Norris et al., 2008). Recently, Parsons et al. (2016) conducted a research on disaster resilience in Australia focusing on coping and adaptive capacity as the main dimensions of resilience. Accordingly, social and economic capital, infrastructure and planning, emergency services, community cohesion, remoteness, information and engagement and governance have been considered as the main components of coping and adaptive capacity for assessing the disaster resilience in Australia.

Indicator-based assessments are widely used to assess the relative resilience of geographic units by aggregating separate indicators into one composite index (Bakkensen et al., 2017). Place-based Composite resilience indices can capture a snapshot of the most important facets involved in promoting resilience (Cutter et al., 2014). Baseline resilience indicators for communities (BRIC), disaster resilience of place (DROP), community disaster resilience index (CDRI) and Foster's resilience capacity index (RCI) could be mentioned as the most known resilience indices throughout the literature assessing resilience at provincial administrative level and have been used as a basis to build upon by various scholars and international agencies (Bakkensen et al., 2017; Cutter et al., 2014, 2008; Foster, 2012; Peacock et al., 2010). Despite Italy being one of the countries highly exposed to natural hazards, there are very few studies focusing on disaster resilience indices. Recently, Graziano and Rizzi (2016) have explored the resilience of the local systems for Italian provinces using an indicator-based assessment following the theoretical frameworks conducted by Dallara and Rizzi (2012), Graziano and Provenzano (2014) and Rizzi and Graziano (2013). It has been stated that to reach more robust resilience assessments, multi-scalar measures including various collective levels (e.g. regional, provincial and municipal levels) are preferable (Birkmann, 2007; Frazier et al., 2013; Neil Adger et al., 2005). Marzi et al. (2018) argues that if a composite index is estimated only at a higher administrative or statistical level, the inherent variability of performance at lower administrative levels will be neglected. Hence, the variability of resilience measures at lower scales (e.g. municipal level) should be considered in the decision-making process to avoid misinformed policies (Marzi et al., 2018). At municipal administrative level, most of the indicator-based assessments targeted social vulnerability instead of resilience including only socioeconomic and demographic features of resilience (Frigerio et al., 2018, 2016; ISTAT, 2018; Roder et al., 2017). Some elements of coping and adaptive capacity such as distance-based accessibility measures as well as infrastructure and economic resources variables are excluded from the aforesaid indices which are considered as the core elements of disaster resilience.

In this paper, we propose an innovative composite disaster resilience index (CDRI) at the municipal level for whole Italy that builds upon research on social vulnerability and disaster resilience (ISTAT, 2017b). Subsequently, the analysis is extended by means of sensitivity analysis so to provide a wide range of results to policy makers and to make possible the identification of the trade-offs between different normalization and aggregation choices, and their influences on alternatives with different resilience capacities. The work developed in this article is structured as follows: Section 2 explains the methodological framework, data preparation and the multivariate analysis performed to narrow down the choice the indicators for the composite index. Section 3 describes results at the municipal scale and presents the outcomes for sensitivity and robustness analysis of the results. Section 4 consists of the discussion of the results obtained and section 5 concludes with the main findings.

3.2 Data and methodology

3.2.1 Conceptual framework and indicators used

The framework for the development of the composite disaster resilience index CDRI as proposed in this paper is inspired by Cutter et al. (2014, 2008) and Parsons et al. (2016), whose resilience index comprises services, cohesion, economic resources, housing conditions, education, environmental status and institutions. The resilience framework proposed in this paper considers indicators to describe social vulnerability, while including additional indicators covering accessibility, environment and institutions. The full range of indicators considered in our framework has been chosen on the basis of literature review and is listed as follows.

Access to services: The accessibility (or remoteness) can be interpreted both in terms of coping and adaptive capacities. Distance-decay accessibility (travel time and distance) to emergency services such as hospitals, fire & rescue stations has been extensively considered in previous studies (Aroca-Jimenez et al., 2017; Carreño et al., 2007; Fekete, 2009; Fernandez et al., 2016; Haddow et al., 2011; Kienberger et al., 2014). Accessibility can also be embedded in the context of adaptive capacity and sustainable development. Access to health, education services and other assets play a crucial role in reducing inequalities and climate resilient pathways (Denton et al., 2014; ESPON, 2011; UNDP, 2017). In Italy, accessibility to essential services such as education, health and mobility is a defying feature of disadvantaged (also called internal) areas (Barca et al., 2014). In our analysis, we use two distance decay indicators to service centres, and fire and rescue units.

Cohesion: Cohesion increases ability of communities to 'bounce back' in an aftermath of a disaster strike (Patel and Gleason, 2018; Townshend et al., 2015). Cohesion refers to "bond that keeps societies integrated" (Larsen, 2014). Cohesion comprise economic and social factors such as inclusion, membership and participation in society. Factors driving disparities reduce cohesion and consequently resilience. Cohesion may comprise demographic elements of disparity, dependencies, turnover and commuting rates (Appleby-Arnold et al., 2018; Beccari, 2016; Thomas et al., 2013; Vandermotten and Van Hamme, 2017). We considered family structure, age dependencies, gender equality and commuting as the indicators for cohesion.

Education: Level of education is often used as a proxy degree of preparedness for dealing with shocks and reinforces responses (Beccari, 2016; Frigerio and De Amicis, 2016; Parsons et al., 2016; Poljanšek et al., 2017; Thomas et al., 2013). Higher education levels has been considered as elements of adaptive capacity which can affect the productivity yields in R&D and innovation sectors (Annoni et al., 2017; Araya-Muñoz et al., 2016; De Groeve et al., 2015; S. Juhola and Kruse, 2015; World Economic Forum, 2017).

Economic resources: Economic resources play an important role for boosting resilience and adaptive capacity (Bowen et al., 2012; ESPON, 2011; Sietchiping, 2006). Per capita income, income distribution, poverty rates and unemployment have been employed to assess economic resources (Annoni et al., 2017; Barr et al., 2010; Smit and Pilifosova, 2003; Tol and Yohe, 2007; World Economic Forum, 2017). In our study, we also considered land valuation which can support emergency response, recovery and reconstruction after disaster shock (Bakkensen et al., 2017; Mitchell et al., 2014; Roy and Ferland, 2015).

Environment: Environmental and ecosystem aspects of resilience has been embedded inside the ecological/ecosystem dimension in previous studies (Cutter et al., 2014, 2008). According to IPCC report, conservation of protected areas and ecological corridors can be important for ecosystem-based climate adaptation and disaster risk reduction strategies (IPCC, 2014a). Expansion and conservation of protected areas and ecological corridors leads to preservation of ecosystem services and ecological resilience which are the core elements of green infrastructures planning in Europe (Suckall et al., 2018; Vallecillo et al., 2018).

Housing conditions: Housing conditions and dwellings are referred to infrastructure (Beccari, 2016; Cutter et al., 2014, 2008; Parsons et al., 2016). The quality and occupancy rate of dwellings can affect the degree of physical damage and vulnerability of the residents in time of disaster shock (Aroca-Jimenez et al., 2017; Flanagan et al., 2011; Frigerio et al., 2018; Ludy and Kondolf, 2012). Hence, empowering the elements regarding the housing and dwellings can promote coping capacity and consequently resilience.

Institutions: High institutional quality and governance can ensure effective implementation of the of emegency planning as well as climate change adaptation and resilience policies (Bowen et al., 2012; Cutter et al., 2008; ESPON, 2011; Smit and Pilifosova, 2003). Accountability and trust in institutions and officials has been mentioned as an important element of organizational resilience which can empower the risk perception of the society and boost the social cohesion (Cutter et al., 2008; Larsen, 2014; Rufat et al., 2015). According to Larsen (2014), well-functioning democracy is positively correlated to level of social trust in the system. Hooghe and Stiers (2016) argues that the participation in elections as a representative element of democracy increases the social and political trust regardless of being winner or loser of the elections. In the case of Italy, despite being disappointed with the past, recent trends show that the participation generates trust and as consequence the confidence in institutions is increasing significantly among the population showing higher participation rates (Diamanti, 2017). In our study, we consider the participation rates in election as a proxy to evaluate the trust in institutions.

Table 1 shows the initial set of resilience indicators classified at individual, household and community levels. A detailed explanation of the indicators can be found in the supplementary material.

Table 3.1 Full list of disaster resilience indicators considered for the analysis

Category	Sub-Category	Code	Indicators	Unit	Source	Year	sub-scale	Impact on Resilience
Access to Services	Public infrastructures	ACC_1	Distance and travel time to service centers	Meters-Minutes	Inner Areas-ISTAT-Manual	2012	community	decrease
		ACC_2	Distance and travel time to fire brigades	Meters- Minutes	Dipartimento dei Vigili del Fuocco -Manual	2009	community	decrease
Housing Conditions	Housing	HC_1	Quality rate of dwellings	%	ISTAT-Census	2011	community	increase
		HC_2	Rate of empty dwellings over total	%	ISTAT-Census	2011	community	increase
		HC_3	Index of overcrowded residences	%	ISTAT-8Mila	2011	household	decrease
		HC_4	Residential buildings over total	%	ISTAT-Census	2011	community	decrease
Cohesion	Family structure	COH_1	Index of single parent families	%	ISTAT-Census	2011	household	decrease
		COH_2	Index of large families	%	ISTAT-Census	2011	household	decrease
		COH_3	Index of small families	%	ISTAT-Census	2011	household	decrease
	Dependencies	COH_4	Index of elderly dependence	%	ISTAT-8Mila	2011	individual	decrease
		COH_5	Old age index	%	ISTAT-8Mila	2011	individual	decrease
		COH_6	Index of minor dependence	%	ISTAT-8Mila	2011	individual	decrease
		COH_7	Share of the families with assistance need	%	ISTAT-8Mila	2011	household	decrease
	Population	COH_8	Population density	Inhabitants/KM2	ISTAT-Census	2011	individual	decrease
	Commuters	COH_9	Commuting rate for study or work	%	ISTAT-8Mila	2011	individual	decrease
		COH_10	Containment index	%	ISTAT-Census	2011	individual	decrease
		COH_11	Attraction index	%	ISTAT-Census	2011	individual	decrease
	Gender	COH_12	Participation in the labor market - female	%	ISTAT-8Mila	2011	individual	increase
Institutions	Trust in Government and authorities	INS_1	Election participation	%	Ministero dell'Interno	2016	community	increase
Education	Education	EDU_1	Illiteracy	%	ISTAT-8Mila	2011	individual	decrease
		EDU_2	Low education index	%	ISTAT-Census	2011	individual	decrease
		EDU_3	High education index	%	ISTAT-Census	2011	individual	increase

Environment	Environmental status/ecosystem protection	ENV_1	Share of the protected lands	%	Natura 2000 Network	2017	community	increase
		ENV_2	Share of ecological corridors	%	Copernicus-Manual	2017	community	increase
Economic Resources	Economic capacity and distribution	RE_1	Income	Euros	Ministry of finance	2011	individual	increase
		RE_2	GINI index	GINI	Manual	2011	community	decrease
		RE_3	Unemployment rate	%	ISTAT-Census	2011	community	decrease
		RE_4	Cadastral stock (property value)	1000 Euros	Agenzia Entrate	2013	community	decrease
	Poverty	RE_5	Share of the families with potential economic hardship	%	ISTAT-8Mila	2011	household	decrease

3.2.2 Data used

Data collected was performed from multiple data sources, while the main data source is the national 2011 Italian census (ISTAT, 2015b). Another important data source is the 8milacensus database (ISTAT, 2015c), comprising 99 indicators disposed in historical series from 1951 to 2011. Income data was obtained from the Department of Finance (2018) and was used to calculate inequality in income distribution according to the GINI coefficient. In particular, we used the GiniWegNeg R package (Raffinetti and Aimar, 2016) that allows for the estimation of Gini-based coefficients for cases which include also negative incomes. Land value were estimated as cadastral stock and obtained from the Agenzia Entrate database (2013) at the municipal level and covering all Italian territory.

The distance and travel time to service centres has been estimated by using matrices of distance between all municipalities (ISTAT, 2013). Service centres are defined as municipalities that have: a) full range of secondary schools; b) at least first level DEA hospital, and; c) at least a “silver-type” railway station. Data on municipalities hosting essential services were obtained from (Barca et al., 2014). The distance between municipalities is measured from municipality centroids (2013), while travel time is estimated using TomTom MultiNet road network (2013). We applied an analogous procedure to estimate distance and travel time to fire stations and rescue service units. Location of fire stations stem from Dipartimento dei Vigili del Fuocco (2009). Attraction index (COH_11) is defined as the capability of the municipalities to appeal the commuters (Frigerio and De Amicis, 2016).

The share of the protected lands from the total area (ENV_1) was estimated on the basis of the extension of the Special Protection Areas (SPA) and the Sites of Community Importance (SCIs) under the Natura 2000 Network (EEA, 2017a, 2017b). For the ecological corridors, we used the database developed by European Environment Agency in the frame of the EU Copernicus programme (Copernicus, 2018). The database contains Green Linear Elements (GLE) and structural landscape elements which act as important dispersion vectors of biodiversity.

The missing data was less than 5 percent of the overall sample size (59 out of 8092 municipalities encompassed missing completely at random (MCAR) values). Hence, we employed the case deletion method suggested by OECD (2008).

We have identified and removed outliers based *n skewness-kurtosis* measures (García-Sánchez et al., 2015; JRC, 2018; Nardo et al., 2005; OECD, 2008; Yale University, 2016).

Outliers lead to heavy-tailed distributions and may distort basic descriptive statistics such as mean, standard deviation and correlation (Damioli, 2017; OECD, 2008; Saisana et al., 2018). Recent studies consider indicators with absolute skewness greater than 2.25 and kurtosis greater than 3.5 as problematic (Saisana et al., 2018). The descriptive statistics can be found in Table SM1 in supplementary material. Some of the indicators, 12 in total and listed in Table 2, did not meet the skewness-kurtosis criterion and have been transformed by means of Box-Cox transformation. Transformation procedures are widely used in the literature and employed to construct the most cited global indices such as Environmental Performance Index (EPI) and EU Regional competitiveness Index (RCI) conducted by Yale University (2016) and European Commission (2017) respectively. We adopted the Box-Cox transformation to adjust for outliers in the same way as in Annoni et al. (2017) to construct the EU Regional competitiveness Index (RCI). Box-Cox transformations are continuous and monotonously increasing generalized power transformations including logarithmic one as a special case which were originally proposed by Box and Cox (1964) and defined as follows:

$$x^{(\lambda)} = \begin{cases} \frac{x^{\lambda}-1}{\lambda} & if\ \lambda \neq 0 \\ \log(x) & if\ \lambda = 0 \end{cases} \qquad \text{(Equation 1)}$$

Depending on the power parameter λ usually defined in the interval of [0,1], the transformation is the identity for $\lambda = 1$, the logarithmic for $\lambda = 0$ and square root for $\lambda = 0.5$ (Bergmeir et al., 2016; Bicego and Baldo, 2016; Lai, 2010; Proietti and Lütkepohl, 2013). Estimation of the optimal λ has been argued in various statistical literature (e.g. Box and Cox (1964) and Sakia (1992)). We adopted the Box-Cox function based on maximization of the rank correlations proposed by Han (1987). We chose a λ value corresponding to maximum correlation coefficient of the transformed normal probability plot for each indicator (Han, 1987; NIST/SEMATECH, 2013). The analysis was conducted using R “ppcc” package (Pohlert, 2017) (see supplementary material). The data that has not been transformed due to out-of-range λ values has been winsorized. The indicators that have been transformed are listed in Table 2, with the corresponding λ value used for transformation process. In all the cases listed in Table 2, the transformation was successful in adjusting the skewness-kurtosis values and no subsequent winsorization was performed. The descriptive statistics of the final set of indictors containing transformed ones and density plots portraying the original and transformed indicators are shown in Table SM2 and Table SM3 in supplementary material.

Table 3.2 Indicators transformed to correct the outliers

Indicators	Code	Transformation	λ	Winsorized
Quality rate of dwellings	HC_1	Box-Cox	0.2	Not-applicable
Rate of empty dwellings over total	HC_2	Box-Cox	0.1	Not-applicable
Index of overcrowded residences	HC_3	Box-Cox	0.6	Not-applicable
Index of old single parent families	COH_1	Box-Cox	0.2	Not-applicable
Index of elderly dependence	COH_4	Box-Cox	0.1	Not-applicable
Old age index	COH_5	Box-Cox	0.2	Not-applicable
Population density	COH_8	Box-Cox	0.1	Not-applicable
Attraction index	COH_11	Box-Cox	0.2	Not-applicable
Illiteracy	EDU_1	Box-Cox	0.4	Not-applicable
Share of ecological corridors	ENV_2	Box-Cox	0.3	Not-applicable
Cadastral stock (property value)	RE_4	Box-Cox	0.1	Not-applicable
Share of the families with potential economic hardship	RE_5	Box-Cox	0.4	Not-applicable

Multicollinearity of the data was assessed to avoid too high intercorrelation. When multicollinearity exceeds a certain threshold, standard errors and variances are inflated, possibly biasing the overall results (Avkiran and Ringle, 2018; OECD, 2008). In order to detect multicollinearity among the variables, we calculated the Variance Inflation Factor (VIF), defined as:

$$VIF_i = \frac{1}{(1-R_i^2)} \quad \text{(Equation 2)}$$

Where R_i^2 is the proportion of variance of indicator *i* associated with the other indicators in the data set (Avkiran and Ringle, 2018; Makoka, 2008). Various VIF threshold values have been considered for the collinearity test (Hagenlocher et al., 2016; KC et al., 2015; Makoka, 2008; OECD, 2008). Researchers working on risk, vulnerability and resilience have been considering the VIF = 10 as the cut-off value (Frigerio and De Amicis, 2016; Makoka, 2008). We calculated the VIF values using "olsrr" package in R (Hebbali, 2018) in an iterative process considering each indicator as a dependent variable and the rest as independent variables. After performing the multicollinearity test, travel time indicators (ACC1_TT and ACC2_TT), old age index (COH_5) and containment index (COH_10) were excluded from the analysis. The choice of excluding COH_10 instead of COH_9 (commuting rate) has been made with regards to previously conducted indices available in literature. Table SM4 in supplementary material displays the VIF values for the first analysis cycle before and after elimination of the problematic indicators.

3.2.3 Analysis

The selected indicators as described in Section 2.2. have to be normalized to make them comparable among each other (OECD, 2008). In order to analyse how different normalization procedures can affect the final results of index composition, we evaluated three types of normalization methods, namely Adjusted Mazziotta-Pareto (AMP), Topsis, and z-scores standardization. Since the AMP normalization technique has been used to in the social vulnerability index provided by ISTAT, it is considered as the baseline in our analysis. The three types of normalization techniques are described below:

The AMP normalization is given by:

$$r_{ij} = \frac{(x_{ij} - Min_{xj})}{(Max_{xj} - Min_{xj})} 60 + 70 \qquad \text{(Equation 3)}$$

where x_{ij} is the value of the indicator j for the municipality i and Min_{xj} and Max_{xj} are the goalposts for the indicator j. To revert the scales of indicators with negative polarity, the complement of Equation 3 with respect to 200 has been calculated (Lucarelli et al., 2014; Mazziotta and Pareto, 2014).

The Topsis normalization takes into account the shortest distance from the positive benchmark for the best alternative the farthest distance from the negative benchmark. Given the matrix $X = \{x_{\text{ij}}\}$ with m rows (municipalities) and n columns (indicators), the normalized matrix can be computed as follows:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} r_{ij}{}^{2}}}\ ; j = 1,2, \ldots, n; i = 1,2, \ldots., m \qquad \text{(Equation 4)}$$

The scales were reverted using the complement of the Equation 4 (1- r_{ij}) for the indicators with negative polarity (Biswas et al., 2016; Shanian and Savadogo, 2006).

Finally, the z-scores is one of the most common standardization method and preserves range (maximum and minimum) and introduces the dispersion of the series (standard deviation / variance). The formula is:

$$r_{ij} = \frac{x_{ij} - M_{xj}}{S_{xj}} \qquad \text{(Equation 5)}$$

where the M_{xj} and S_{xj} are the mean and standard deviation of indicator j. To revert the scales of indicators with negative polarity Equation 1 has been multiplied by -1 (Maggino, 2017).

In order to compare the results with social vulnerability index, we first construct the resilience index using Adjusted Mazziotta-Pareto method. Denoting with M_{r_i} and S_{r_i}, respectively, the mean and the standard deviation of the normalized values of the unit i, the generalized form of the adjusted MPI can be computed using following formula:

$$AMPI^{+/-} = M_{r_i} \pm S_{r_i} cv_i \qquad \text{(Equation 6)}$$

where $cv_i = \frac{S_{r_i}}{M_{r_i}}$ is the variation coefficient of the unit i and the sign ± depends on the kind of the phenomenon to be measured (Lucarelli et al., 2014; Mazziotta and Pareto, 2014). Since the increasing values of the index correspond to an improvement of the resilience, a downward penalization has been used ($AMPI^{-}$) (Maggino, 2017).

AMPI is a hybrid non-compensatory aggregation method penalising the compensability among indicators in order to incorporate the possible trade-offs. In the AMPI, the penalization is addressed by subtracting a component (cv_i) from a non-weighted arithmetic mean (subtraction in the case of resilience index) (Greco et al., 2018). Nevertheless, by using AMPI, the degree of penalization is not explicit and trade-offs among the indicators cannot be clearly portrayed in terms of degree of compensation. To display unequivocally the trade-offs with respect to compensability, a spectrum of hybrid methods can be deployed such as Fuzzy Gamma, Mean-Min function, generalized mean, etc. Since, we are incorporating simultaneously various normalization procedures as part of the sensitivity analysis, the aggregation must be independent from the type of normalization. To control the trade-offs during the aggregation, we applied ordered weighted average (OWA) operator introduced by Yager (1988) which provides a circumstance in which the degree of compensation can be adjusted and modified. The OWA operator is defined as follows:

$$OWA(x_1, \dots, x_n) = \sum_{i=1}^{n} w_i . x_{\sigma(i)} \qquad \text{(Equation 7)}$$

where σ is a permutation ordering the elements as $x_{\sigma(1)} \leq \cdots \leq x_{\sigma(n)}$, with associated non-negative weights in the range of [0,1] summing up to one ($\sum_{i=1}^{n} w_i = 1$) (Jin et al., 2017; Yager, 1988; Zabeo, 2011). OWA operator provides a family of operators including maximum (1,0, 0,…,0), minimum (0,0,…,1), k-order statistics (kth weight equal to 1 and the rest zero), the arithmetic mean ($\frac{1}{n}, \frac{1}{n} \ldots, \frac{1}{n}$) and window type OWA taking the average of m components in the center (Fullér, 1996; Zabeo, 2011).

The weights can be ordered in different ways and can be distributed either using linear or uniform patterns, as graphically depicted in Figure 3.1 (Jin et al., 2017; Jaroslav Mysiak et al., 2018). In order to evaluate how different weights distributions can affect OWA, different combinations of weights have been created following either a linear or uniform distribution. In total, 128 different weights combinations have been tested, 65 of which following a linear functions distribution, while the remaining 63 follow uniform weights distributions patterns. For the 65 weight combinations following a linear function, 26 results from descending linear functions (example shown in top left of Figure 3.1), 13 of central linear distributions (example shown in top middle of Figure 3.1), and another 26 of ascending linear functions (example shown in top right of Figure 3.1). Similarly, For the 63 weight combinations following a uniform distribution, 25 consist of left side biased distributions (example shown in bottom left of Figure 3.1), 13 of central uniform distributions (example shown in bottom middle of Figure 3.1), and another 25 of right side biased distributions (example shown in bottom right of Figure 3.1).

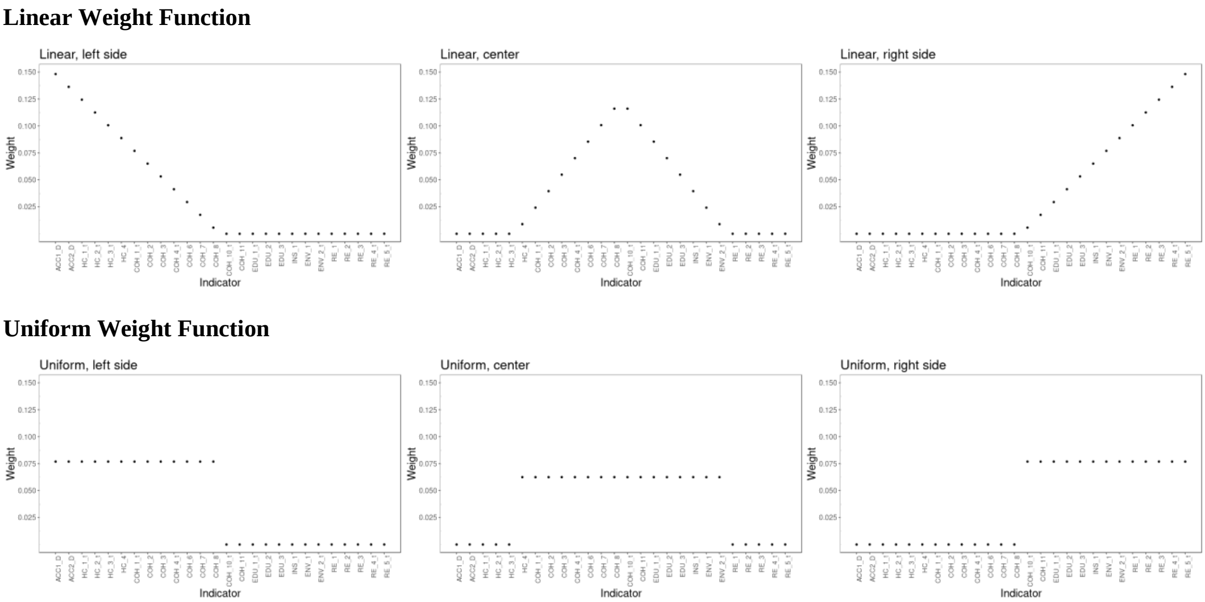


Figure 3.1 Example of six different distributions of OWA weights. Top part: Linear weight function. Bottom part: Uniform weight function.

In order to examine the trade-offs, Yager (1988) introduced the degree of ORNESS determining the proximity to the maximum operator for a particular set of weights (Chaji et al., 2018; Zabeo, 2011). The ORNESS index is given by:

$$ORNESS(w_1, \dots, w_n) = \frac{1}{n-1}\sum_{i=1}^{n} w_i.(n-i) \qquad \text{(Equation 8)}$$

The ORNESS index evaluates the extent to which the indicators compensate each other. The ORNESS equal to 1 shows the highest proximity to maximum operator indicating full compensative trade-offs (optimistic approach). In contrary, ORNESS equal to zero, indicates the highest propensity to minimum operator reflecting perfect complementary behavior (pessimistic approach). The special case of ORNESS equal to 0.5, determines the highest proximity to average (arithmetic mean) operator (additive approach) (Pinar et al., 2014b). Figure 3.2 shows the ORNESS trends using the 128 different combinations of weights for both linear and uniform patterns. The OWA operator controls the level of compensation using different order of weights. The order of weights corresponding to higher ORNESS levels indicates higher degree of compensation and proximity to maximum operator and vice versa.

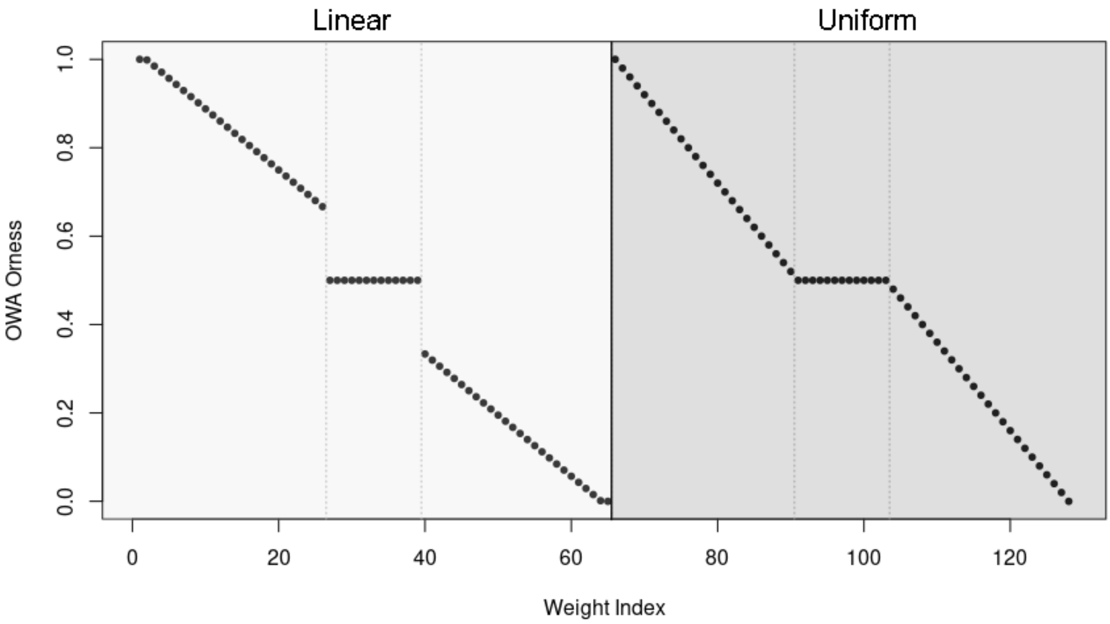


Figure 3.2 Degree of ORNESS following a Linear (left), and a Uniform (right) distribution of OWA weights for all 128 different weights distributions.

We use the designed combinations to perform sensitivity analysis on resilience index. The sensitivity analysis is performed considering the different normalization and aggregation procedures. To this end, we analyze the resilience data normalized with three different methods, using various combination of OWA weights (both linear and uniform distributions) reflecting the ORNESS in the range of [0,1]. In addition, the original data (i.e. the data that feeds the transformation procedure) is also considered in order to identify possible effects of the Box-Cox transformation. In order to extract robust rankings out of various OWA configurations, we employ the relative dominance measure(ρ) proposed by Pinar et al. (2014) which indicates the extent of relative dominance of the ith administrative unit across simulations (derivation procedure has been explained in the second article supplementary material). The ρ measure takes into account the relationship between administrative units across the simulated combinations to investigate to what extent each unit either dominates or being dominated by other units considering the overall variability in the resilience results imposed by diverse inputs.

3.3 Results and discussion

3.3.1 Resilience at municipal scale

The results of the CDRI at the municipal scale are shown in Figure 3.3 together with the official SVI results published by ISTAT. SVI results illustrate a trend in the spatial distribution of the standard deviation from the southern to northern areas in Italy, with higher values in north, moderate values in centre and low values in south. In general, the CDRI results indicate that northern and central areas of Italy have higher resilience scores if compared to the SVI results. Figure 3.4 illustrates the differences among the scores between ISTAT and CDRI derived from AMP analysis. The differences are categorized in three groups: i) negative differences correspond to municipalities worse-off, shifting from social vulnerability (i.e. SVI) to resilience (i.e. CDRI); ii) moderate differences show not significant changes, and; iii) positive differences show the areas better-off in terms of resilience. Some negative difference clusters can be identified in Figure 3.4, namely the northern Italian regions of Lombardy and Trenitno, and Sardegna, Basilicata and Puglia regions.

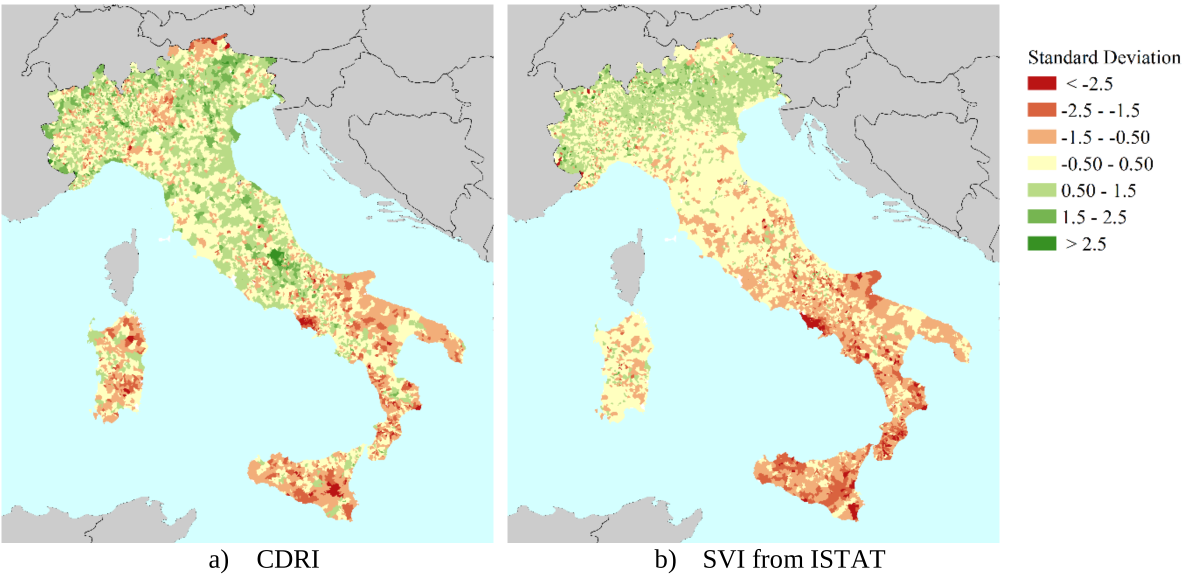


Figure 3.3 Comparisons between SVI from ISTAT and CDRI derived from AMP analysis. SVI results are inverted (i.e. opposite signal) so to facilitate the visual comparison between the results.

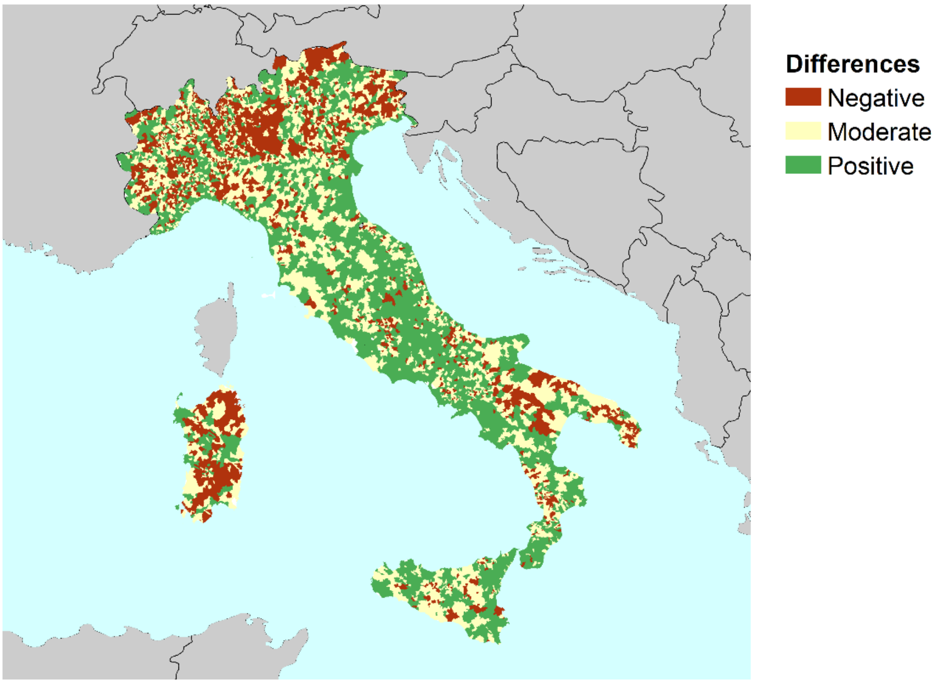


Figure 3.4 Degree of differences between SVI from ISTAT and CDRI derived from AMP analysis.

Whereas part of the differences between SVI and CDRI indicators are embodied in adaptive capacity dimension, we use Marzi et al. (2018) adaptive capacity index to interpret the results. Accordingly, in spite of sizeable intra-regional variabilities, the northern and central regions have higher potentials in terms of economy, infrastructures, technology, level of education and institutional quality regarding the original data (before aggregation). Hence, by adding adaptive capacity elements to the social vulnerability dimension, we can observe higher scores in central and northern Italian territories with respect to the SVI. Since the AMP is a non-compensatory approach, the level of under-performance indicators is a determinant factor for the outcome of the aggregation process. Hence, to clarify the differences, we examine the indicators which may embody lower performance in the areas with higher score variabilities. To do so, we map the distance-decay based attributes (travel distance to service centers and fire brigades) to investigate the variabilities. Figure 3.5 shows the mapping of the original data regarding to distance-decay based attributes. Accordingly, it can be observed that the variabilities among two maps are compatible to sizeable differences in northern territories and Sardegna region, as illustrated in Figure 3.5. Hence, it can be inferred that the differences between SVI and CDRI may be more sensitive to variations in distance-decay based attributes, as illustrated by the "travel distance to fire brigades" indicator and shown in the right side of Figure 3.5.

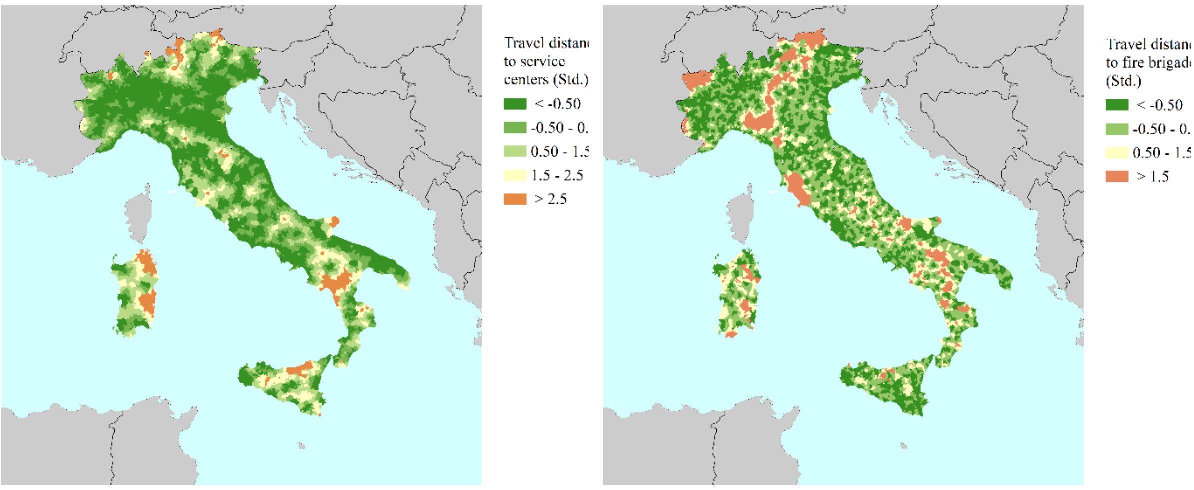
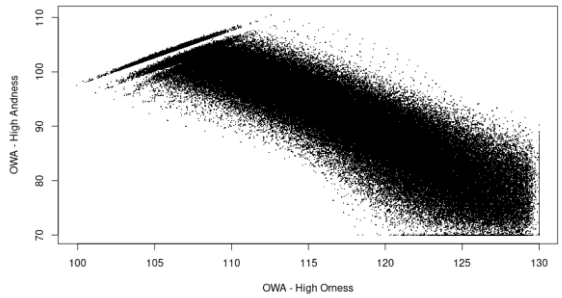


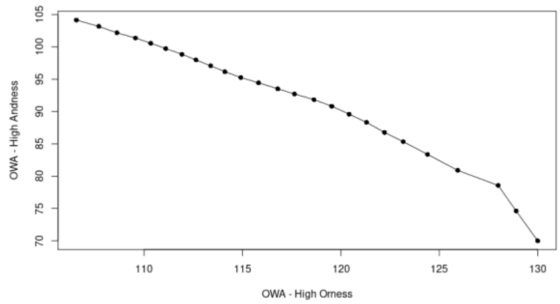
Figure 3.5 Mapping the original data regarding to distance-decay based attributes.

3.3.2 Sensitivity and robustness analysis

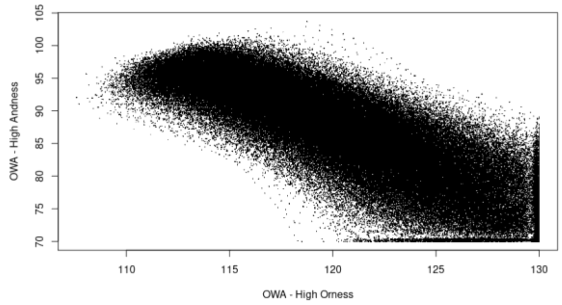
In order to test the distribution of OWA weights and the corresponding ORNESS and ANDNESS values, we plotted the scores derived from the OWA using the transformed data normalized by means of AMP method for all the municipalities (Figure 3.6). The results show approximately a linear trend from high ORNESS to high ANDNESS values for both linear and uniform distribution of the weights. As explained in the methodology section, there is a complementary trade-off between ORNESS and ANDNESS values ($ANDNESS + ORNESS = 1$). The first combination has the largest weight assigned to minimum value corresponding to largest ANDNESS (Lowest ORNESS). By shifting the proximity from minimum to maximum value, the ANDNESS degree diminishes while the ORNESS increases. The graphs validate the assigned spectrum of OWA weights which are employed to perform the sensitivity analysis.



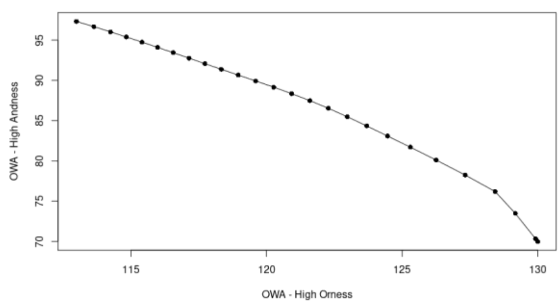
a) Uniform – all the municipalities



b) Uniform – municipality 1001



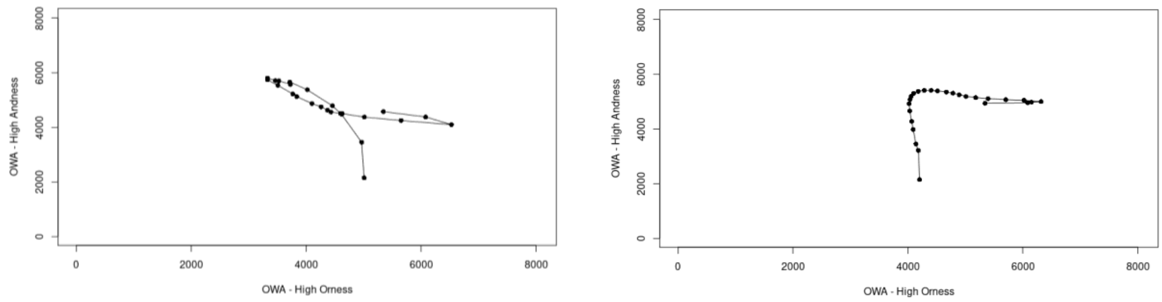
c) Linear – all the municipalities



b) Linear – municipality 1001

Figure 3.6 ORNESS vs ANDNESS degrees for all the municipalities using OWA-AMP.

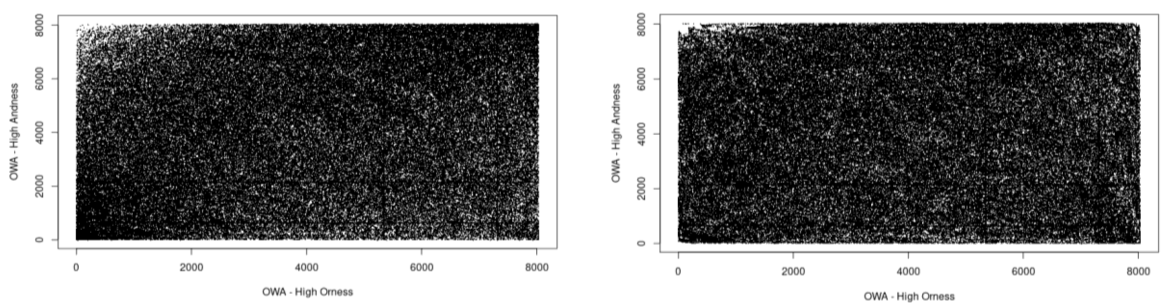
Next, we applied the same procedure to examine to what extent rankings derived from the same scores plotted in Figure 3.6 follow the same trend. Figure 3.7 displays the ORNESS vs ANDNESS degrees for the rankings related to municipality 1001 derived from OWA-AMP scores. The results show that the rankings follow a non-linear spiral trend which makes it difficult to interpret the trade-offs between the rankings and the degree of ORNESS as different weight configurations are used for the computation of OWA-AMP scored. These results suggest a strong variability of OWA-AMP scores with respect to weights, and thereby low robustness of the rankings.



a) Uniform distribution b) Linear distribution

Figure 3.7 Rank reversals corresponding to ORNESS variations for various OWA weights derived from OWA-AMP method for municipality 1001.

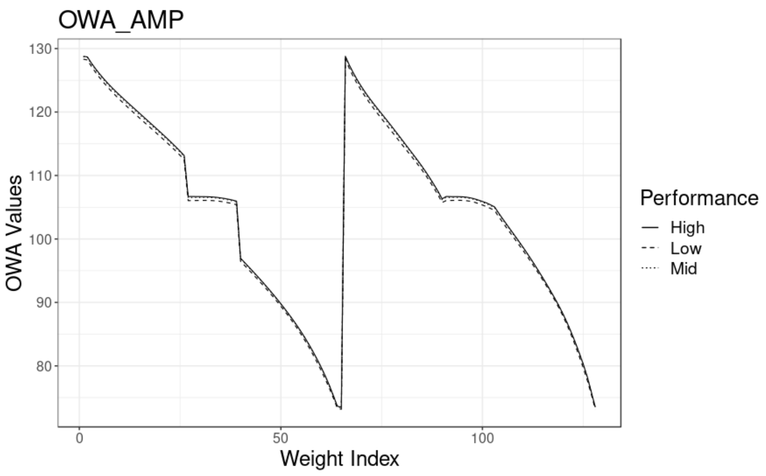
As explained before, by varying the proximity from minimum to maximum values, the ANDNESS values decreases, and the aggregation imposes higher degree of compensation (additivity) among the indicators. Using additive aggregators with high degree of compensation implies that underperformance with respect to one or more indicators may not be penalised. However, the level of unbalances plays an important role in the amount of imposed penalization. The decreasing trend observed in Figure 3.6 is similar for all the OWA combinations, but even a slight variation in the slope for different municipalities may result in variant rank reversals depending on the endogenous level of unbalances among the indicators for each municipality. This complexity arises from the iterative variations of score exposed to different OWA weights for different municipalities and results in completely chaotic trend shown in Figure 3.8.



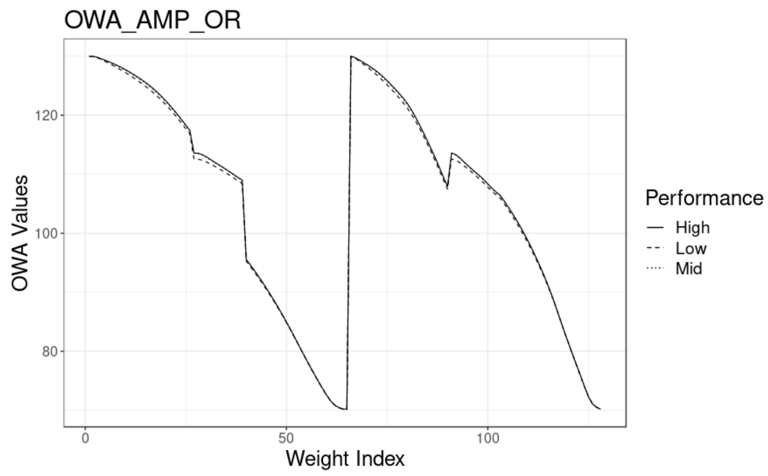
a) Uniform distribution b) Linear distribution

Figure 3.8 Rank reversals corresponding to ORNESS variations for various OWA weights derived from OWA-AMP method for all municipalities

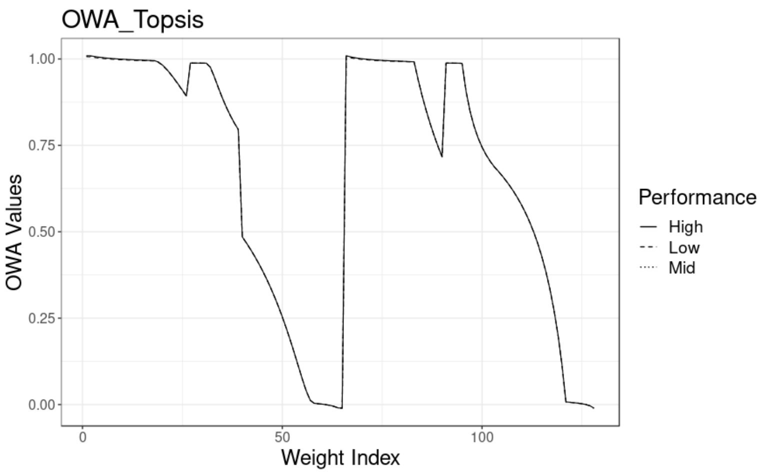
In the next step, we plot the results derived from OWA aggregation using all the possible combinations of OWA weights (Figure 3.9) to analyze the sensitivity of the aggregation procedure to normalization methods. High, medium and low performances represent the alternatives having scores corresponding to median values of 95^{th}, 50^{th} and 5^{th} percentiles of CDRI respectively, calculated using AMP aggregation. In this way, we can simultaneously involve the alternative's performance in the analysis.



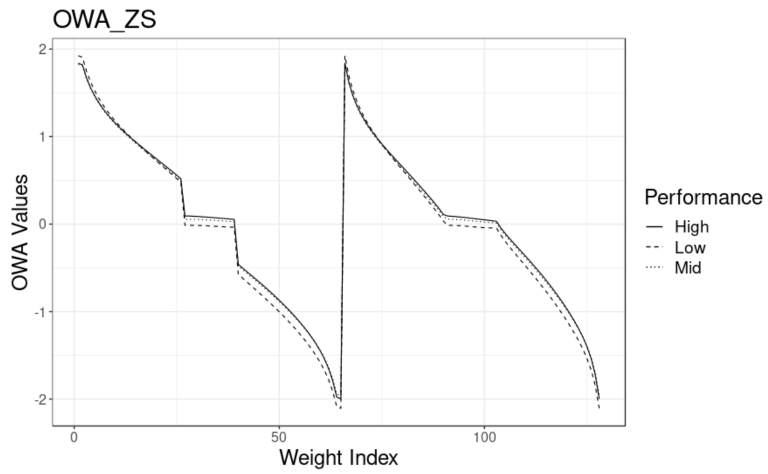
a) Box-Cox transformed data normalized using AMP



b) Original data normalized using AMP



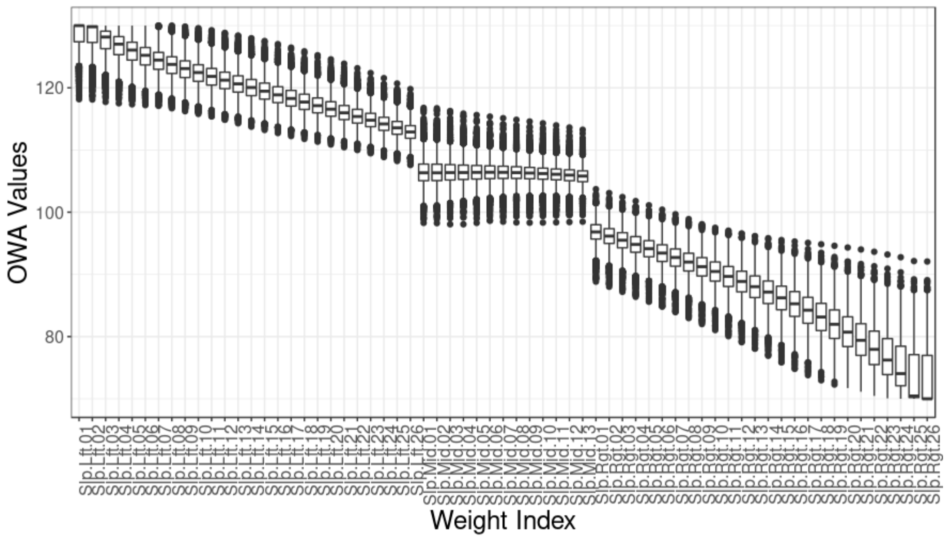
c) Box-Cox transformed data normalized using Topsis



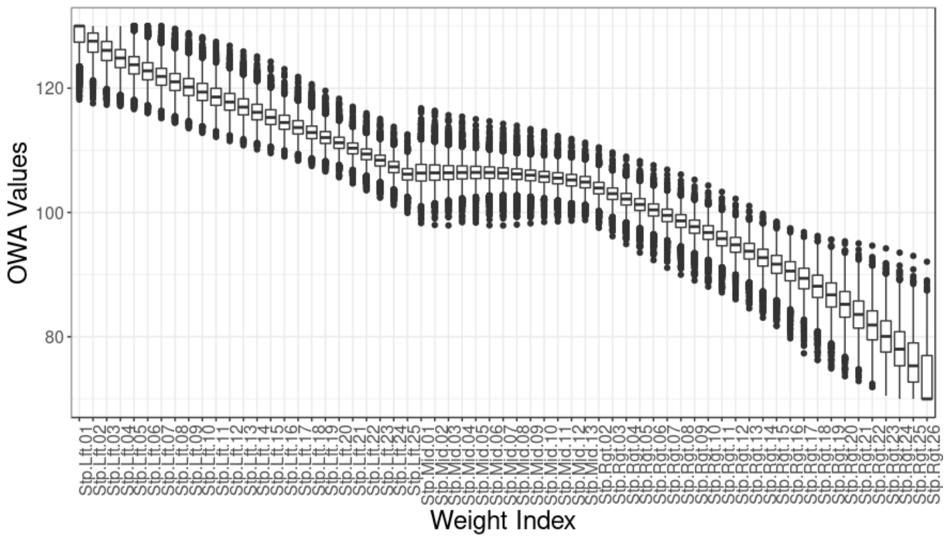
d) Box-Cox transformed data normalized using Z-score

Figure 3.9 OWA scores derived from various types of normalized data for different combination of weights (ORNESS variations

Figure 3.10, instead, displays the boxplot for only a segment of the OWA-AMP data (3.9-a), considering the variations among all the municipalities for both linear (top plot) and uniform (bottom plot) distributions. More cross-sections from various normalizations are provided in the supplementary material.



a) Linear



b) Uniform

Figure 3.10 Section of OWA scores derived from AMP normalized data for different combination of weights for all the municipalities (linear and uniform)

According to Figure 3.9, applying various normalization methods and transformation yield different results. Cross-comparisons between AMP-BoxCox and AMP-original (Figure 3.9-a and 3.9-b) show how the transformation flattens the anomalies (jumps and sudden declines) exist in the window type OWA section by equalizing the outliers. The OWA results derived from AMP and z-score normalized (linear methods) data almost follow the same trend; linearly decreasing from high ORNESS to high ANDNESS (except in the range of window type OWA). Nevertheless, z-score results show higher variance among OWA scores between low and high-performance alternatives in compare to both AMP and Topsis. This characteristic can be either advantageous or disadvantageous, as in some cases, lower variance among the results may be preferable. Having results with higher variance makes it easier to present explicitly the existing differences to policy makers. The OWA aggregation using non-linear Topsis normalized data yields a low-pass filter shape signal, having constant results up to a local cut-off with some fluctuations in the middle and decreasing more or less linearly after passing the cut-off. This property may be interesting for the policy makers dealing with extreme cases with high range of con-compensability. Topsis provides policy makers with more precise and meaningful information on discontinuities and local minima. Nevertheless, the variance among the low, medium and high performances are very low (Figure SM2 in supplementary material) which makes it difficult to visually detect the variabilities. In summary, the sensitivity and robustness analysis show that the coupling of the variations in normalization and aggregation methods, and different weight configurations, results in outcomes that may be significantly different amongst themselves, a result that pinpoints the importance of policy-makers to pay close attention to the methodology used for the development of composite indices. Moreover, depending on the type of policy application and the interest of decision makers, certain set of solutions are available which are introduced in this study. However, even if the results presented and discussed in this paper are so far interesting and promising, further investigation is needed so to provide robust rankings of the municipalities estimated by means of OWA, considering the relative dominance of the municipalities across the simulation. The results of dominance analysis could be more informative and bring additional insight to identify relative resilience measures across the municipalities. Unfortunately, due to time restrictions it was not possible to run the analysis for the whole Italian municipalities. Figure 3.11 illustrates standardized relative dominance scores for Veneto region considering the overall variability imposed by diverse configurations. The results of such analysis could be used as a reliable measure of resilience encompassing spectrum of simulations designed based on the variant OWA weights and normalization procedures. The analysis can be further extended using extra models designed by different normalization, weighting and aggregation schemes.

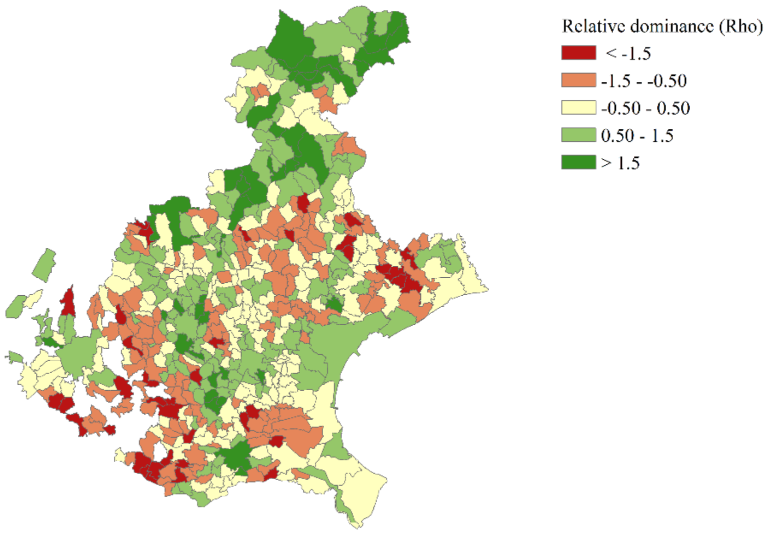


Figure 3.11 Relative dominance scores for Veneto region derived from 512 OWA configurations.

3.4 Conclusion

Enhancing disaster resilience is an important rudiment of disaster risk management and climate change adaptation, demanding a comprehensive understanding of the complex interactions among societies, ecosystems and hazards. Resilience is a construct composed of several features, ranging from preparedness to strengthened social and economic cohesion and trust before natural disasters. Quantitative indicator-based assessments are typically applied to estimate resilience for specific geographical units by combining several disparate performance indicators into composite indices. This paper has proposed an innovative composite disaster resilience index for Italy, while evaluating how methodological and technical choices made for the construction of composite indices can have a significant impact on the resulting score. The work presented here highlights the importance to explore how robust the final scores are with respect to the choice of underlying indicators and the degree of compensation embedded in the aggregation methods.

We developed a comprehensive disaster resilience index (CDRI) at municipal level for Italy. Our analysis builds upon research on social vulnerability made by ISTAT in Italy and contains features describing coping and adaptive capacity. We apply advanced normalization and aggregation procedures accompanied by sensitivity analysis. The choice of indicators used in our analysis was driven by mainstream literature on resilience, multivariate statistical analysis and expert consultations. We first estimate the resilience using an analogous method applied by ISTAT to be able to compare both indices. Afterwards, we performed sensitivity analysis by coupling various normalization schemes combined by means of OWA operators with variant set of weights corresponding to different degrees of compensability. Finally, to introduce a robust relative measure of disaster resilience across the municipalities, we computed the relative dominance measure using all the alternative configurations designed for sensitivity analysis.

The results showed that there is considerable change in the scores derived from Adjusted Mazziotta-Pareto (AMP) analysis while comparing social vulnerability and resilience indices. The most negative difference corresponding to the municipalities which worse-off shifting from social vulnerability to resilience, can be observed in northern territories and Sardegna region. Since the results are derived from a non-compensatory AMP operator, they differences are mostly rooted in the indicators with performances close to minimum. By plotting the distance-decay attributes, we observed analogous patterns in the areas having higher difference. This shows that differences among these two indices are highly correlated with distanced-based indicators. The results derived from sensitivity analysis show that the coupling of the variations in normalization and aggregation methods results in different outcomes. Depending on the type of policy application and the interest of decision makers, certain set of solutions are available which are introduced in this study. For instance, in terms of presentation the variabilities for various classes of alternatives, OWA values derived from z-score normalized data are preferable due to higher variances between different classes. On the other hand, values derived from Topsis normalized data are preferable for policy makers interested in extreme cases with high range of con-compensability. In general, this process involves a certain degree of subjectivity that can be reduced by experts' choices made on specific characteristics of the case studies. The results of dominance analysis provide robust rankings of the municipalities which could be used as a reliable decision-making benchmark for climate adaptation and sustainable development policies.

Although the results presented in this paper are promising and interesting, further research can contribute to increment the analysis. For instance, information on the robustness of the rankings can be estimated by means of OWA, considering five performance categories namely, very good, good, average, bad and very bad. The results of robustness and sensitivity analysis could be more informative and bring additional insight to identify sound and robust combination of methodological choices. In terms of aggregation operators, in our analysis we used OWA operator from among a large number of possible methods. Applying other aggregators, such as LSP, fuzzy t-norms and t-conorms, may lead to additional insights. The time-series describing the recent trends in the indicators can offer better insights than a snapshot-assessment of CDRI. The CDRI results may be further developed to include actual climate change adaptation practices, documented using the appropriate monitoring, reporting and evaluation (MRE) schemes (EEA, 2015). MRE systems are currently being developed for the purpose of continuous monitoring, reporting and evaluation of the progress made in implementing climate change adaptation plans. In addition, the index can be tested in different case studies in order to develop a reliable procedure that can be applied in different investigative contexts.

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SUPPLEMENTARY MATERIAL

COMPARING ADAPTIVE CAPACITY INDEX ACROSS SCALES: THE CASE OF ITALY

The supplementary material is composed of additional information for each section of our manuscript. The structure follows the exact order of the information in the manuscript, comprising an introduction, data and methodology, results and a discussion. To facilitate readers, this material opens with maps showing Italy's administrative units.

Study Area

First-order statistical subdivision	Second-order statistical and administrative subdivision – regions/NUTS2	Third-order statistical and administrative subdivision – provinces/NUTS3 (abbreviations as in Table SM1)

Figure SM1: Administrative units in Italy

Table SM1: Administrative units in Italy

FIRST ORDER	SECOND ORDER CODE	SECOND ORDER NAMES	THIRD ORDER CODE	THIRD ORDER NAMES	ABB
NORTHWEST	1	Piemonte	1	Torino	TO
NORTHWEST	1	Piemonte	2	Vercelli	VC
NORTHWEST	1	Piemonte	3	Novara	NO
NORTHWEST	1	Piemonte	4	Cuneo	CN
NORTHWEST	1	Piemonte	5	Asti	AT
NORTHWEST	1	Piemonte	6	Alessandria	AL
NORTHWEST	1	Piemonte	96	Biella	BI
NORTHWEST	1	Piemonte	103	Verbano-Cusio-Ossola	VB
NORTHWEST	2	Valle D'Aosta	7	Aosta	AO

NORTHWEST	3	Lombardia	12	Varese	VA
NORTHWEST	3	Lombardia	13	Como	CO
NORTHWEST	3	Lombardia	14	Sondrio	SO
NORTHWEST	3	Lombardia	15	Milano	MI
NORTHWEST	3	Lombardia	16	Bergamo	BG
NORTHWEST	3	Lombardia	17	Brescia	BS
NORTHWEST	3	Lombardia	18	Pavia	PV
NORTHWEST	3	Lombardia	19	Cremona	CR
NORTHWEST	3	Lombardia	20	Mantova	MN
NORTHWEST	3	Lombardia	97	Lecco	LC
NORTHWEST	3	Lombardia	98	Lodi	LO
NORTHWEST	3	Lombardia	108	Monza e della Brianza	MB
NORTHEAST	4	Trentino-Alto Adige	21	Bolzano	BZ
NORTHEAST	4	Trentino-Alto Adige	22	Trento	TN
NORTHEAST	5	Veneto	23	Verona	VR
NORTHEAST	5	Veneto	24	Vicenza	VI
NORTHEAST	5	Veneto	25	Belluno	BL
NORTHEAST	5	Veneto	26	Treviso	TV
NORTHEAST	5	Veneto	27	Venezia	VE
NORTHEAST	5	Veneto	28	Padova	PD
NORTHEAST	5	Veneto	29	Rovigo	RO
NORTHEAST	6	Friuli Venezia Giulia	30	Udine	UD
NORTHEAST	6	Friuli Venezia Giulia	31	Gorizia	GO
NORTHEAST	6	Friuli Venezia Giulia	32	Trieste	TS
NORTHEAST	6	Friuli Venezia Giulia	93	Pordenone	PN
NORTHWEST	7	Liguria	8	Imperia	IM
NORTHWEST	7	Liguria	9	Savona	SV
NORTHWEST	7	Liguria	10	Genova	GE
NORTHWEST	7	Liguria	11	La Spezia	SP
NORTHEAST	8	Emilia-Romagna	33	Piacenza	PC
NORTHEAST	8	Emilia-Romagna	34	Parma	PR
NORTHEAST	8	Emilia-Romagna	35	Reggio nell'Emilia	RE
NORTHEAST	8	Emilia-Romagna	36	Modena	MO
NORTHEAST	8	Emilia-Romagna	37	Bologna	BO
NORTHEAST	8	Emilia-Romagna	38	Ferrara	FE
NORTHEAST	8	Emilia-Romagna	39	Ravenna	RA
NORTHEAST	8	Emilia-Romagna	40	Forli'-Cesena	FC
NORTHEAST	8	Emilia-Romagna	99	Rimini	RN
CENTRAL	9	Toscana	45	Massa Carrara	MS
CENTRAL	9	Toscana	46	Lucca	LU
CENTRAL	9	Toscana	47	Pistoia	PT
CENTRAL	9	Toscana	48	Firenze	FI
CENTRAL	9	Toscana	49	Livorno	LI
CENTRAL	9	Toscana	50	Pisa	PI

CENTRAL	9	Toscana	51	Arezzo	AR
CENTRAL	9	Toscana	52	Siena	SI
CENTRAL	9	Toscana	53	Grosseto	GR
CENTRAL	9	Toscana	100	Prato	PO
CENTRAL	10	Umbria	54	Perugia	PG
CENTRAL	10	Umbria	55	Terni	TR
CENTRAL	11	Marche	41	Pesaro e Urbino	PU
CENTRAL	11	Marche	42	Ancona	AN
CENTRAL	11	Marche	43	Macerata	MC
CENTRAL	11	Marche	44	Ascoli Piceno	AP
CENTRAL	11	Marche	109	Fermo	FM
CENTRAL	12	Lazio	56	Viterbo	VT
CENTRAL	12	Lazio	57	Rieti	RI
CENTRAL	12	Lazio	58	Roma	RM
CENTRAL	12	Lazio	59	Latina	LT
CENTRAL	12	Lazio	60	Frosinone	FR
SOUTH	13	Abruzzo	66	L'Aquila	AQ
SOUTH	13	Abruzzo	67	Teramo	TE
SOUTH	13	Abruzzo	68	Pescara	PE
SOUTH	13	Abruzzo	69	Chieti	CH
SOUTH	14	Molise	70	Campobasso	CB
SOUTH	14	Molise	94	Isernia	IS
SOUTH	15	Campania	61	Caserta	CE
SOUTH	15	Campania	62	Benevento	BN
SOUTH	15	Campania	63	Napoli	NA
SOUTH	15	Campania	64	Avellino	AV
SOUTH	15	Campania	65	Salerno	SA
SOUTH	16	Puglia	71	Foggia	FG
SOUTH	16	Puglia	72	Bari	BA
SOUTH	16	Puglia	73	Taranto	TA
SOUTH	16	Puglia	74	Brindisi	BR
SOUTH	16	Puglia	75	Lecce	LE
SOUTH	16	Puglia	110	Barletta-Andria-Trani	BT
SOUTH	17	Basilicata	76	Potenza	PZ
SOUTH	17	Basilicata	77	Matera	MT
SOUTH	18	Calabria	78	Cosenza	CS
SOUTH	18	Calabria	79	Catanzaro	CZ
SOUTH	18	Calabria	80	Reggio di Calabria	RC
SOUTH	18	Calabria	101	Crotone	KR
SOUTH	18	Calabria	102	Vibo Valentia	VV
ISLANDS	19	Sicilia	81	Trapani	TP
ISLANDS	19	Sicilia	82	Palermo	PA
ISLANDS	19	Sicilia	83	Messina	ME
ISLANDS	19	Sicilia	84	Agrigento	AG
ISLANDS	19	Sicilia	85	Caltanissetta	CL
ISLANDS	19	Sicilia	86	Enna	EN
ISLANDS	19	Sicilia	87	Catania	CT
ISLANDS	19	Sicilia	88	Ragusa	RG

ISLANDS	19	Sicilia	89	Siracusa	SR
ISLANDS	20	Sardegna	90	Sassari	SS
ISLANDS	20	Sardegna	91	Nuoro	NU
ISLANDS	20	Sardegna	92	Cagliari	CA
ISLANDS	20	Sardegna	95	Oristano	OR
ISLANDS	20	Sardegna	104	Olbia-Tempio	OT
ISLANDS	20	Sardegna	105	Ogliastra	OG
ISLANDS	20	Sardegna	106	Medio Campidano	VS
ISLANDS	20	Sardegna	107	Carbonia-Iglesias	CI

Introduction

The scope of this section is to provide additional information on how the notion of vulnerability and adaptive capacity has been incorporated in Intergovernmental Panel on Climate Change (IPCC) reports (IPCC, 2014c, 2007) and how we conceptualize AC in our study.

Over the years the conceptualization of vulnerability has changed due to divergent scientific priorities in different communities of scholars. The most important vulnerability frameworks in the context of climate change are introduced by two different communities: (a) the disaster risk reduction (DRR) community, which conceptualizes vulnerability based on social science and considers it as the starting point of climate-related risk assessments (contextual or starting point vulnerability). The contextual vulnerability framework follows bottom-up approaches, which focus on responses in short-time frames and small spatial scales; (b) the climate change impacts community, which interprets vulnerability on the basis of natural science as the end point (outcome or end point vulnerability). Outcome frameworks are based on top-down approaches using long-term frames and larger scales specified by climate scenarios, and focus on physical impacts (impact-driven). (Breil et al., 2018; Poljanšek et al., 2017).

IPCC 2007 interprets vulnerability as the final outcome of the integration of exposure, sensitivity and adaptive capacity as shown in Figure SM1-A. This interpretation has been used by several scientific reports, such as ESPON Climate Project (ESPON, 2011), which has been considered as the basis of our study. On the other hand, in a recent IPCC report, the vulnerability definition has shifted from the impacts community to the DRR, in which vulnerability is assumed as the starting point to frame the climate change related risk which comprises “sensitivity or susceptibility to harm” and “lack of capacity to cope and adapt (adaptive capacity)” (Figure SM2-B).

In IPCC 2007, the adaptive capacity will be integrated with potential impacts (exposure and sensitivity) and may enhance or counteract the vulnerability results. In this framework, the adaptive capacity was separated from the sensitivity element. In contrast, in IPCC 2014, the vulnerability itself, as a result of adaptive capacity- sensitivity combination, will be used to assess potential impacts and risk of climate-related hazards. Hence, the adaptive capacity and sensitivity are not separated in this framework.

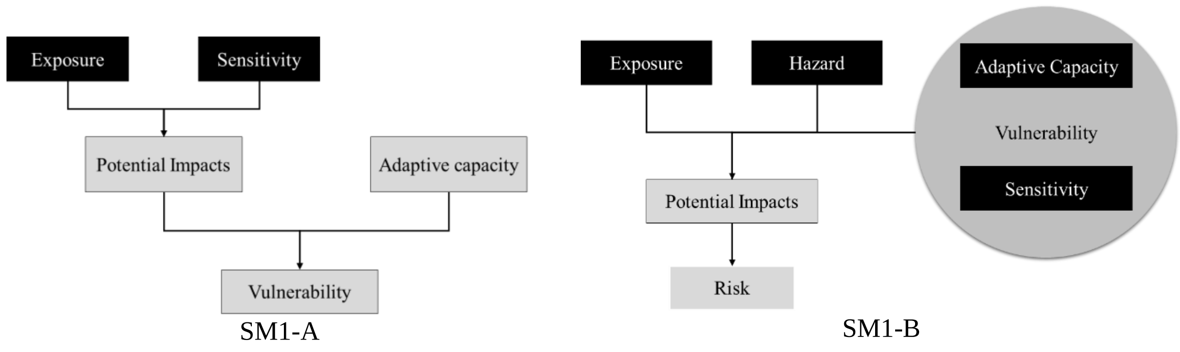

Figure SM2: Comparison of the adaptive capacity definitions in IPCC 2014 and 2007

ESPON Climate Project

The ESPON climate project developed a top-down comprehensive vulnerability assessment at the European level, based on IPCC's 2007 report (Figure SM2-A). The ESPON climate project measures the potential impacts by combining exposure and sensitivity variables. In order to evaluate exposure, 10 climatic variables have been selected, which reflect a wide range of climatic conditions, from temperature to hydraulic variables (e.g., change in annual mean temperature, relative change in annual mean precipitation in summer months, etc.). To evaluate sensitivity, ESPON defines five dimensions, namely physical, social, environmental, economic and cultural, which indicate how the overall system is affected by climatic changes. In order to measure each of these dimensions, several variables have been defined. For instance, physical sensitivity includes settlements, roads, railways, airports and harbors which are potentially affected by climate change. The measured impacts are then integrated with adaptive capacity to evaluate the vulnerability element. The ESPON adaptive capacity is defined by three dimensions, namely awareness, ability and action, and five determinants (knowledge and awareness, technology, infrastructures, institutions and economic resources). Each determinant will be assessed by several indicators, as shown in Figure SM3.

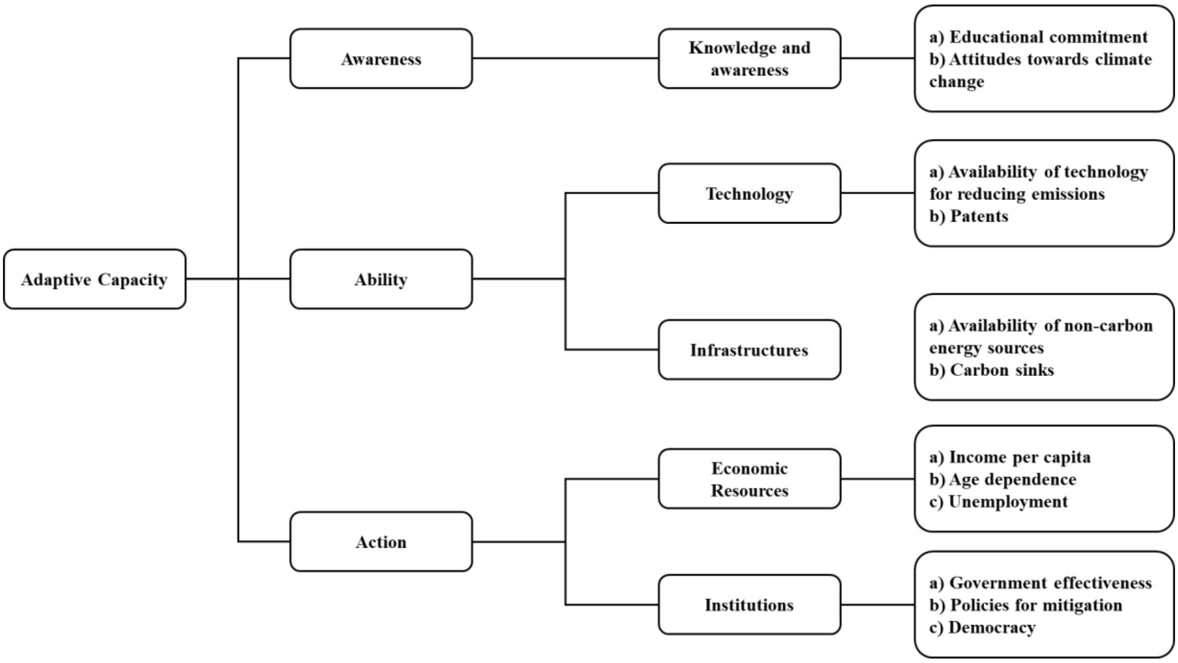

Figure SM3. ESPON adaptive capacity framework (ESPON, 2011).

In our study we focus only on adaptive capacity as a key component of vulnerability assessment. The framework we used to develop the adaptive capacity index (ACI) is composed of two dimensions (awareness-ability and action) comprising four determinants (knowledge and technology, economic resources, infrastructures and institutions), based on the framework used by ESPON's Climate Project (Figure SM4).

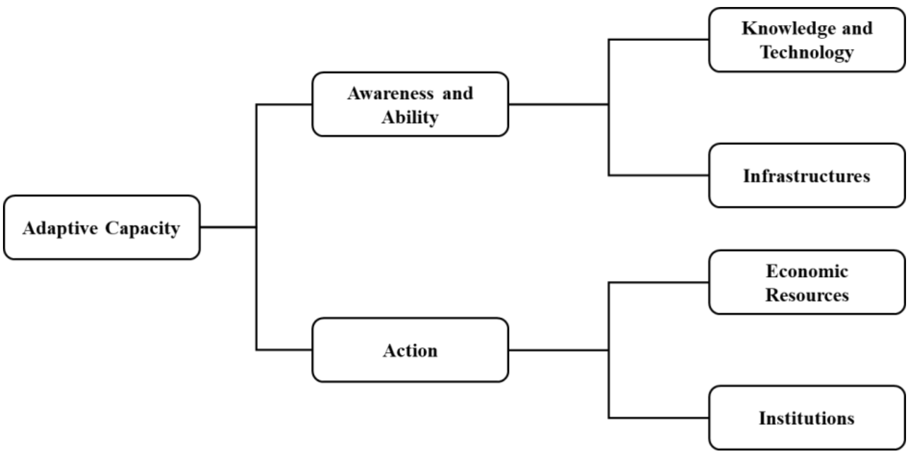

Figure SM4. ACI framework. Modified from ESPON project (ESPON, 2011).

Selection of the indicators

The indicators for each determinant of the framework have been chosen based on expert judgement and literature review. The adaptive capacity index that we describe in the manuscript has been developed for the purpose of the Italian National Climate Adaptation Plan. The methodological design and the choice of indicators were deliberated by an interdisciplinary team of experts that conducted the analysis of climate risks (Jaroslav Mysiak et al., 2018) and successively reviewed (and amended based on the feedback received) by a large-scale stakeholders' consultation that included experts and practitioners from all relevant national and regional public entities (agencies and authorities) and civil society groups. The preliminary set of the AC indicators are chosen based on literature review as explained in the following:

Economic resources: Economic resources play an important role in empowering the adaptive capacity and resilience of the regions to climate change impacts (Bowen et al., 2012; ESPON, 2011; Sietchiping, 2006). Per capita income, income distribution, poverty rates and unemployment components have been employed to assess the competitiveness of different regions in terms of economic resources (Annoni et al., 2017; Barr et al., 2010; Smit and Pilifosova, 2003; Tol and Yohe, 2007; World Economic Forum, 2017). GDP per capita (RE1), GINI index (RE3), unemployment rate (RE10) and poverty measures (RE4, RE6, RE7 and RE9) were the most cited proxy indicators covering those components throughout the adaptive capacity literature (Barr et al., 2010; Brooks et al., 2005; ESPON, 2011; Painuly et al., 2003; Sietchiping, 2006; Tol and Yohe, 2007; Gary Yohe and Tol, 2002) and confirmed by our board of experts.

Knowledge and technology: Knowledge and technology dimension of the index comprises indicators associated with education, technological innovation, and ICT (information and communication technologies). Adaptive capacity can be improved as a result of higher economic productivity (Bowen et al., 2012). According to Global Competitiveness Report (World Economic Forum, 2017), the productivity yields can be realised through efficiency-driven or innovation-driven processes. We have considered indicators associated with both options. For instance, KT1 (electricity consumption of agricultural enterprises) is related to efficiency-driven transformations and technology (Martinho, 2016). Fabiani et al. (2016) found that agriculture accounted for three percent of national Italian energy consumption and improved efficiency can lead to large transformations in this sector of economy. Technological readiness and ICT are also embedded as efficiency-driven transformations. We considered KT7 (industries and enterprises with personal computers) and KT8 (Index of spreading broadband in the enterprises) as the main ICT indicators of ISTAT database (ISTAT, 2017c). These indicator shows the level of ICT improvements in an enterprise. For the technological readiness, we chose KT6 (Share of the families having internet access) as mentioned in (Annoni et al., 2017). To fulfil the innovation-driven pillar, R&D expenditure and patent applications has been mentioned as one the main indicators which can show the performance of innovation sector and technological competitiveness (KT2, KT3 and KT4) (Annoni et al., 2017; Sirkku Juhola and Kruse, 2015; World Economic Forum, 2017).

Infrastructures: For infrastructure dimension, transportation network, water resources and protected lands has been considered regarding the literature. Transportation network has been used as one of the main constituents of infrastructure dimension in several competitiveness and adaptive capacity assessments (Annoni et al., 2017; Sirkku Juhola and Kruse, 2015; Swanson et al., 2007). Higher performance in transportation networks can ease the adaptation procedure and mobilization of economic and human capital. In addition, the transportation network is a fundamental component of the remoteness/ accessibility assessments (Parsons et al., 2016). For this criterion, we considered IN1 (Extension of the infrastructure -road and railways- as a share of the total area). Water resources can be also considered as mostly used component of infrastructure dimension in adaptive capacity literature (Juhola and Kruse, 2015; Swanson et al., 2007). We chose two different indicators to evaluate this component (IN3 and IN5). "Water use from the public water supply as a share of the water input to a distribution network" (IN3) shows the efficiency of the distribution network in sustaining the level of water savings (IPCC, 2014a; Thapa et al., 2016). On the other hand, we have "Irrigated and Irrigable land over the total" (IN5) which describes the level of water supply for agricultural purposes ensuring the food security and resilience (IPCC, 2014a). The final component of the infrastructure dimension is "the share of protected lands from total area" (IN6). According to IPCC report, conservation of protected area can be an important tool for adaptation. Expansion of protected areas leads to preservation of ecosystem services which are the core elements of green infrastructures planning in Europe (Vallecillo et al., 2018).

Institutions: High institutional quality and governance can ensure effective implementation of the adaptation policies (Bowen et al., 2012; ESPON, 2011; Smit and Pilifosova, 2003). The regions with unstable or weak institutions have very low capacities to adapt to climate-related hazards (Smit and Pilifosova, 2003). Accountability, civil liberties, corruption, democracy, economic freedom, government effectiveness and rule of law are the most cited indicators to assess the intitutions (ESPON, 2011; Tol and Yohe, 2007). Nifo and Vecchione (2014) computed the institutional quality index for Italy which comprises voice and accountability, government effectiveness, regulatory quality, rule of law and corruption as the main indicators of institutional quality. We have incorporated their index as a proxy for our analysis.

Data and methods

This section provides additional information on the data and methods used in our analysis, including explanations on the Delphi method and Principal Component Analysis (PCA). The correlation matrix and PCA factor loadings are also included.

Explanation of the Delphi survey among the members of the ESPON monitoring committee.

The Delphi method is a well-known iterative and questionnaire-based process for collecting and synthesizing the knowledge of experts on a specific topic. The advantages of the Delphi method are: (a) diminishing the influence of key experts on the results, (b) optimizing performance in terms of geographical constraints and costs, (c) anonymizing answers that give participants an acceptable degree of freedom. In the ESPON Climate Project, the weights assigned to adaptive capacity determinants have been calculated through a two round-Delphi survey among the members of the ESPON monitoring committee (ESPON, 2011). This committee has been formed by 47 members who represent various member states involved in the study. 25 members out of 47 participated in the first round and the rest in the second round of the weighting procedure. The survey itself was structured in two phases. In the first phase, all the members were asked to assign a preference percentage to each of the adaptive capacity determinants. In the second phase, they were informed about the results and were asked to redo the weights. This procedure allowed the participants to modify responses that were significantly different from the average scores. In theory, this procedure will be repeated until the scores converge with an acceptable variance. In the ESPON project, the second phase was not repeated after the acceptable score convergence. The final weights are shown in Supplementary Table SM2.

Table SM2. AC determinants' weights from Delphi survey (ESPON, 2011).

Determinants	Weight [%]
Knowledge and Awareness	23
Technology	23
Infrastructures	16
Institutions	17
Economic resources	21
Total	100

In our study, these weights were manipulated due to differentiation of the assumed criteria. Consequently, the weights concerning the combined determinant (knowledge/awareness and technology) were summed up. Additionally, the ESPON weights were divided by three for each indicator (except institutions). The weights are illustrated in Table SM3.

Table SM3. ESPON weights

	ESPON	ACI
RE1	0.2100	0.0700
RE6	0.2100	0.0700
RE10	0.2100	0.0700
IN1	0.1600	0.0533
IN3	0.1600	0.0533
IN6	0.1600	0.0533
KT4	0.4600	0.1533
KT5	0.4600	0.1533
KT6	0.4600	0.1533
IST1	0.1700	0.1700

Description of Principal Component Analysis (PCA) and how to calculate the PCA weights.

Principal Component analysis (PCA) is a statistical tool that measures the correlations between sets of variables and transforms correlated variables into a new set of uncorrelated ones by means of a correlation matrix. PCA evaluates the highest possible variability in the indicator set by means of the smallest possible number of uncorrelated factors, based on the statistical dimensions of the data. With the aid of PCA, the data could be transformed to principal components (factors) that are uncorrelated. Besides, the first principal component accounts for the maximum possible proportion of the variance of the data set. Technically speaking, PCA explores the variance of the variables $x_1,\ldots, x_n$ through a small number of linear combinations of the original data, called principal components $p_1,\ldots, p_n$, which are uncorrelated, measuring different statistical dimensions in the data set.

$$p_1 = a_{11}x_1 + a_{12}x_2 + a_{1n}x_n$$

$$p_2 = a_{21}x_1 + a_{22}x_2 + a_{2n}x_n$$

$$\dots$$

$$p_n = a_{n1}x_1 + a_{n2}x_2 + a_{nn}x_n$$

The weights a_{ij} are referred as component or factor loadings that make the principal components p_i uncorrelated. The squared factor loadings show to what extent the variance in the original variable is explained by each factor. Accordingly, the first principal component shows the maximum variance, the second one accounts for the maximum of the remaining variance, and so on. The variance of each factor can be extracted from eigenvalues λ_j , $j = 1, .. n$ of the sample covariance matrix CM , which is composed of the variance of each factor on the diagonal and covariance of other variables elsewhere, and afterwards it will take the form of the correlation matrix, as shown in the following:

$$CM = \begin{pmatrix} cm_{11} & cm_{12} & \cdots & cm_{1n} \\ cm_{21} & cm_{22} & \cdots & cm_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ cm_{n1} & cm_{n2} & \dots & cm_{nn} \end{pmatrix}$$

The eigenvalues of CM , which represent the variances of principal components, can be evaluated by solving the equation $|CM - \lambda I|$, where *I* stands for the identity matrix (*CM* size). In theory, the sum of variances of the principal components is equal to the sum of the variances of the original variables which will be utilized to construct the PCA weights.

It should be mentioned that, to avoid the influence of one variable on the principal components, the variables shall be standardized by means of z-scores standardization. In addition, the Kaiser-Mayer-Olkin (KMO) sampling adequacy test and Bartlett's sphericity test shall be applied to ensure that the variables are suitable for the PCA. The KMO sampling adequacy test result shall be over 0.6 to proceed with PCA. Values higher than 0.8 are stated to be more reliable. The Bartlett test investigates the truth of the null hypothesis that the variables in correlation matrix are uncorrelated. The values of the Bartlett test shall be smaller than 0.05.

Exploring the weights of variables by means of PCA could be considered as a pure statistical procedure investigating the overlapping information regarding correlated indicators, which is not based on the importance of the related indicators. The results of the analysis (Eigen values and factor loadings) can be used to determine the weights. The evaluated weights are the weighting average of all the calculated factor loadings. According to OECD handbook, two various methods can be used to extract the weights. The first method follows (a) to (e) steps.

- Calculating the share of each factor of the total variance (each factor's eigenvalue divided by the sum of first five factors' eigenvalues.
- Identifying the highest factor loadings among five factors.
- All the loadings should be squared to obtain the variance.
- The attained variances are divided by their related factors' eigenvalue to evaluate the share of each indicator in the eigenvalues.
- Calculating the weighting average of all the factor loadings.

In the second method, after the second step (b), the factor loadings that are not considered as the highest values would be assumed to be "zero". Afterwards the same procedure would be applied. The choice of which method to use is completely arbitrary and depends on the decision maker's point of view.

The explained PCA material has been extracted from Nardo et al. (2005), OECD (2008), Aroca-Jimenez et al. (2017) and Mazumdar and Paul (2016).

Factor loadings and correlation matrix

Table SM4. Factor loadings derived from PCA

	F1	F2	F3	F4	F5
RE1	-0.896	-0.234	0.021	0.089	0.129
RE3	0.584	0.434	0.151	0.341	0.314
RE4	0.944	0.207	0.189	-0.058	-0.062
RE6	0.932	0.194	0.077	0.006	0.022
RE7	0.728	0.143	-0.443	-0.156	0.009
RE9	0.905	0.109	0.100	-0.213	0.043
RE10	0.931	0.276	0.067	-0.041	0.077
IN1	-0.767	0.311	-0.029	-0.099	0.406
IN3	-0.528	-0.438	0.220	-0.384	0.299
IN5	-0.632	0.408	0.064	-0.414	0.260
IN6	0.441	-0.350	-0.041	0.459	0.498
KT1	-0.556	0.502	-0.209	-0.211	-0.443
KT2	-0.591	0.524	-0.299	0.075	0.319
KT3	-0.898	0.265	-0.080	0.111	0.140
KT4	-0.899	0.184	-0.016	-0.277	-0.017
KT5	-0.179	-0.469	-0.516	0.256	-0.159
KT6	-0.879	0.122	-0.178	0.345	-0.050
KT7a	-0.122	0.676	0.071	0.502	-0.193
KT7b	-0.475	-0.003	0.765	0.171	-0.182
KT8	-0.518	-0.035	0.703	0.099	-0.051
IST1	-0.884	-0.224	-0.125	0.167	-0.127

Table SM5. Correlation Matrix

Variables	RE1	RE3	RE4	RE6	RE7	RE9	RE10	IN1	IN3	IN5	IN6	KT1	KT2	KT3	KT4	KT5	KT6	KT7a	KT7b	KT8	IST1
RE1	1.00	-0.54	-0.89	-0.86	-0.75	-0.83	-0.89	0.62	0.63	0.50	-0.22	0.32	0.41	0.77	0.71	0.24	0.79	0.03	0.42	0.42	0.82
RE3	-0.54	1.00	0.63	0.61	0.45	0.46	0.71	-0.23	-0.43	-0.32	0.28	-0.31	-0.02	-0.30	-0.59	-0.28	-0.38	0.21	-0.10	-0.19	-0.61
RE4	-0.89	0.63	1.00	0.95	0.60	0.91	0.96	-0.69	-0.52	-0.47	0.31	-0.38	-0.56	-0.83	-0.79	-0.36	-0.84	0.04	-0.32	-0.38	-0.91
RE6	-0.86	0.61	0.95	1.00	0.57	0.92	0.90	-0.66	-0.52	-0.48	0.39	-0.41	-0.47	-0.79	-0.79	-0.27	-0.82	0.07	-0.43	-0.45	-0.89
RE7	-0.75	0.45	0.60	0.57	1.00	0.59	0.73	-0.44	-0.49	-0.44	0.13	-0.28	-0.19	-0.59	-0.57	0.01	-0.61	-0.17	-0.61	-0.65	-0.64
RE9	-0.83	0.46	0.91	0.92	0.59	1.00	0.86	-0.62	-0.44	-0.38	0.30	-0.47	-0.49	-0.80	-0.68	-0.22	-0.90	-0.09	-0.41	-0.39	-0.93
RE10	-0.89	0.71	0.96	0.90	0.73	0.86	1.00	-0.61	-0.52	-0.46	0.33	-0.41	-0.41	-0.75	-0.78	-0.39	-0.79	0.03	-0.38	-0.49	-0.88
IN1	0.62	-0.23	-0.69	-0.66	-0.44	-0.62	-0.61	1.00	0.44	0.75	-0.30	0.42	0.67	0.76	0.76	-0.01	0.66	0.24	0.20	0.42	0.51
IN3	0.63	-0.43	-0.52	-0.52	-0.49	-0.44	-0.52	0.44	1.00	0.34	-0.14	0.06	-0.01	0.35	0.45	0.03	0.27	-0.35	0.29	0.28	0.43
IN5	0.50	-0.32	-0.47	-0.48	-0.44	-0.38	-0.46	0.75	0.34	1.00	-0.33	0.59	0.55	0.58	0.77	-0.17	0.43	0.16	0.19	0.35	0.31
IN6	-0.22	0.28	0.31	0.39	0.13	0.30	0.33	-0.30	-0.14	-0.33	1.00	-0.62	-0.33	-0.44	-0.56	0.12	-0.28	-0.07	-0.31	-0.24	-0.28
KT1	0.32	-0.31	-0.38	-0.41	-0.28	-0.47	-0.41	0.42	0.06	0.59	-0.62	1.00	0.40	0.52	0.64	0.01	0.56	0.41	0.11	0.09	0.43
KT2	0.41	-0.02	-0.56	-0.47	-0.19	-0.49	-0.41	0.67	-0.01	0.55	-0.33	0.40	1.00	0.83	0.65	0.01	0.59	0.25	0.09	0.11	0.42
KT3	0.77	-0.30	-0.83	-0.79	-0.59	-0.80	-0.75	0.76	0.35	0.58	-0.44	0.52	0.83	1.00	0.83	0.06	0.85	0.24	0.41	0.37	0.77
KT4	0.71	-0.59	-0.79	-0.79	-0.57	-0.68	-0.78	0.76	0.45	0.77	-0.56	0.64	0.65	0.83	1.00	0.09	0.70	0.10	0.39	0.48	0.68
KT5	0.24	-0.28	-0.36	-0.27	0.01	-0.22	-0.39	-0.01	0.03	-0.17	0.12	0.01	0.01	0.06	0.09	1.00	0.21	-0.15	-0.21	-0.02	0.23
KT6	0.79	-0.38	-0.84	-0.82	-0.61	-0.90	-0.79	0.66	0.27	0.43	-0.28	0.56	0.59	0.85	0.70	0.21	1.00	0.38	0.33	0.29	0.86
KT7a	0.03	0.21	0.04	0.07	-0.17	-0.09	0.03	0.24	-0.35	0.16	-0.07	0.41	0.25	0.24	0.10	-0.15	0.38	1.00	0.14	0.12	0.00
KT7b	0.42	-0.10	-0.32	-0.43	-0.61	-0.41	-0.38	0.20	0.29	0.19	-0.31	0.11	0.09	0.41	0.39	-0.21	0.33	0.14	1.00	0.79	0.39
KT8	0.42	-0.19	-0.38	-0.45	-0.65	-0.39	-0.49	0.42	0.28	0.35	-0.24	0.09	0.11	0.37	0.48	-0.02	0.29	0.12	0.79	1.00	0.33
IST1	0.82	-0.61	-0.91	-0.89	-0.64	-0.93	-0.88	0.51	0.43	0.31	-0.28	0.43	0.42	0.77	0.68	0.23	0.86	0.00	0.39	0.33	1.00

Description of fuzzy overlay functions

Various operators can be applied to combine membership values (between 0 and 1) resulted from linear normalization functions (e.g. Min-Max normalization) (Sema et al., 2017b). Lewis et al. (2014) introduces five different operators namely fuzzy AND, fuzzy OR, fuzzy PRODUCT, fuzzy SUM and fuzzy Gamma which can be calculated by the following formulas:

$$Fuzzy\ AND = min\ (\mu_i), \quad i = 1, \dots, n$$

$$Fuzzy\ OR = max\ (\mu_i), \quad i = 1, \dots, n$$

$$Fuzzy\ SUM = 1 - \prod_{i=1}^{n}(1 - \mu_i)$$

$$Fuzzy\ PRODUCT = \prod_{i=1}^{n}(\mu_i)$$

$$Fuzzy\ Gamma = (Fuzzy\ SUM)^{\gamma}.(Fuzzy\ PRODUCT)^{1-\gamma}$$

Applying each of the abovementioned functions may result in diverse outcomes. The AND overlay function assigns the lowest performance value as the outcome considering a low compensation degree among the indicators. On the contrary, fuzzy OR overlay function chooses the highest performance value and neglects the lower performances which implies high levels of compensation. Applying either of these two functions result in considerable influence of a single variable on the final outcome of the aggregation. Using fuzzy PRODUCT overlay function gives a multiplication of the performance values which may be lower than any of them considering very low degree of compensation. Nevertheless, the interaction between indicators would be preserved in this case. An analogous interpretation can be inferred utilizing fuzzy SUM function in which the outcome is composed by summation of the performance values with high degree of compensation. In order to create a balance among multiple performance values and provide a tool to manually vary the level of compensation for decision makers, fuzzy Gamma overlay function is introduced which combines both fuzzy PRODUCT and fuzzy SUM operators. By employing fuzzy Gamma, one can assign weights to limiting factors (low performance values) while allows a liberation degree to other performance values. The Gamma values are the decision tools enabling decision makers to employ diverse degrees of compensation to the aggregator and experiment the outcomes. For high values of gamma, the fuzzy SUM dominates (high compensation level) whereas low values of gamma favor the fuzzy PRODUCT (low compensation levels). By setting a moderate value for gamma, one can balance the two aggregation operators and avoid that one of them dominates (Araya-Muñoz et al., 2016; Lewis et al., 2014).

Data and methods

This section includes additional tables illustrating the results of the regional and provincial analysis. In addition, some figures related to the discussion part have been moved to this section from the manuscript.

Table SM6. Regional AC scores

CODE	REGION	EW	ESPON	PCA
ITC1	Piemonte	0.144	0.189	0.249
ITC2	Valle d'Aosta/Vallée d'Aoste	0.521	0.337	0.510
ITC3	Liguria	0.577	0.389	0.531
ITC4	Lombardia	0.820	0.792	0.893
ITDA	Trentino-Alto Adige/Südtirol	0.932	0.871	0.980
ITH3	Veneto	0.519	0.521	0.607
ITH4	Friuli-Venezia Giulia	0.539	0.733	0.665
ITH5	Emilia-Romagna	0.702	0.797	0.811
ITI1	Toscana	0.350	0.497	0.481
ITI2	Umbria	0.046	0.179	0.116
ITI3	Marche	0.369	0.452	0.408
ITI4	Lazio	0.394	0.521	0.412
ITF1	Abruzzo	0.154	0.223	0.075
ITF2	Molise	-0.607	-0.595	-0.690
ITF3	Campania	-0.717	-0.847	-0.888
ITF4	Puglia	-0.704	-0.858	-0.826
ITF5	Basilicata	-0.733	-0.745	-0.802
ITF6	Calabria	-1.084	-1.224	-1.277
ITG1	Sicilia	-1.339	-1.444	-1.432
ITG2	Sardegna	-0.884	-0.788	-0.823

Table SM7. Provincial AC results

CODE	PROVINCE	EW	ESPON	PCA
ITC11	Torino	0.387391	0.51325	0.436418
ITC12	Vercelli	-0.06658	-0.1031	0.000304
ITC13	Biella	0.106211	0.040856	0.155311
ITC14	Verbano-Cusio-Ossola	0.136227	0.004021	0.218873
ITC15	Novara	0.360625	0.443757	0.416
ITC16	Cuneo	0.176921	0.124274	0.306451
ITC17	Asti	-0.12871	-0.17985	-0.08249
ITC18	Alessandria	0.006764	0.000929	0.054756
ITC20	Valle d'Aosta/Vallée d'Aoste	0.555323	0.416192	0.639703
ITC31	Imperia	-0.12236	-0.38063	-0.09962
ITC32	Savona	0.328714	0.171081	0.339208
ITC33	Genova	0.693517	0.653014	0.651492
ITC34	La Spezia	0.505654	0.311996	0.473517
ITC41	Varese	0.769887	0.829313	0.747189
ITC42	Como	0.407608	0.517916	0.449662
ITC43	Lecco	0.52134	0.618002	0.573488

ITC44	Sondrio	0.104461	-0.04407	0.201362
ITC46	Bergamo	0.480766	0.443898	0.568093
ITC47	Brescia	0.242246	0.189245	0.338142
ITC48	Pavia	0.437212	0.352325	0.388384
ITC49	Lodi	0.232837	0.241712	0.279511
ITC4A	Cremona	0.241243	0.264345	0.324393
ITC4B	Mantova	0.245844	0.229305	0.363759
ITC4C	Milano	1.650189	1.586379	1.572448
ITC4D	Monza e della Brianza	1.031798	0.970536	0.87685
ITH10	Bolzano-Bozen	0.960118	0.926443	1.139396
ITH20	Trento	0.824529	0.842175	0.884829
ITH31	Verona	0.401417	0.443163	0.5134
ITH32	Vicenza	0.635356	0.636257	0.71608
ITH33	Belluno	0.422998	0.323173	0.482906
ITH34	Treviso	0.537059	0.667166	0.645588
ITH35	Venezia	0.369367	0.399577	0.448863
ITH36	Padova	0.719036	0.832657	0.74447
ITH37	Rovigo	-0.11139	-0.09529	-0.02119
ITH41	Pordenone	0.844043	1.161522	0.920151
ITH42	Udine	0.282059	0.412604	0.358626
ITH43	Gorizia	0.467025	0.49168	0.490317
ITH44	Trieste	1.420218	1.379111	1.195797
ITH51	Piacenza	0.323431	0.306717	0.38793
ITH52	Parma	0.742496	0.917453	0.791377
ITH53	Reggio nell'Emilia	0.595738	0.58424	0.678866
ITH54	Modena	0.666651	0.767197	0.723838
ITH55	Bologna	1.23666	1.439537	1.266542
ITH56	Ferrara	0.257147	0.386587	0.270639
ITH57	Ravenna	0.539263	0.544163	0.60298
ITH58	Forlì-Cesena	0.558874	0.534748	0.617783
ITH59	Rimini	0.566975	0.565572	0.57111
ITI11	Massa-Carrara	-0.19921	-0.20361	-0.19472
ITI12	Lucca	0.306874	0.317098	0.327644
ITI13	Pistoia	0.197064	0.15105	0.244727
ITI14	Firenze	0.798222	1.047834	0.922208
ITI15	Prato	0.372463	0.343701	0.449568
ITI16	Livorno	0.606218	0.674832	0.660251
ITI17	Pisa	0.650813	0.926639	0.737264
ITI18	Arezzo	0.198954	0.29303	0.285004
ITI19	Siena	0.701374	0.892724	0.76764
ITI1A	Grosseto	-0.04685	0.021455	0.078261
ITI21	Perugia	0.223544	0.342547	0.266665
ITI22	Terni	-0.03724	0.066452	0.00815
ITI31	Pesaro e Urbino	0.345256	0.417138	0.383757
ITI32	Ancona	0.553272	0.714856	0.601742
ITI33	Macerata	0.276921	0.334169	0.310734
ITI34	Ascoli Piceno	0.44311	0.469266	0.405259
ITI35	Fermo	0.270288	0.312156	0.309793
ITI41	Viterbo	-0.21955	-0.22878	-0.21395
ITI42	Rieti	-0.18586	-0.21317	-0.21141
ITI43	Roma	0.816001	0.905136	0.838339
ITI44	Latina	-0.2603	-0.27452	-0.23742
ITI45	Frosinone	-0.58327	-0.47425	-0.53068
ITF11	L'Aquila	0.10607	0.130077	0.04029
ITF12	Teramo	0.202482	0.22921	0.212902
ITF13	Pescara	0.260535	0.38196	0.248629
ITF14	Chieti	-0.00389	0.199521	0.022073
ITF21	Isernia	-0.40254	-0.46269	-0.55113
ITF22	Campobasso	-0.51487	-0.49523	-0.58437

ITF31	Caserta	-0.70153	-0.77642	-0.77503
ITF32	Benevento	-0.62969	-0.56075	-0.68515
ITF33	Napoli	-0.54023	-0.66218	-0.72826
ITF34	Avellino	-0.59974	-0.56561	-0.6516
ITF35	Salerno	-0.32897	-0.37516	-0.39951
ITF43	Taranto	-0.47201	-0.65842	-0.54615
ITF44	Brindisi	-0.68746	-0.80309	-0.77813
ITF45	Lecce	-0.61743	-0.62679	-0.80143
ITF46	Foggia	-0.65414	-0.84803	-0.762
ITF47	Bari	-0.30966	-0.34505	-0.38069
ITF48	Barletta-Andria-Trani	-0.66566	-0.88246	-0.74861
ITF51	Potenza	-0.44151	-0.50067	-0.51894
ITF52	Matera	-0.69595	-0.62634	-0.75144
ITF61	Cosenza	-0.80061	-0.85272	-0.96934
ITF62	Crotone	-1.31975	-1.54713	-1.52534
ITF63	Catanzaro	-0.95463	-0.98711	-1.07975
ITF64	Vibo Valentia	-1.03555	-1.22721	-1.22035
ITF65	Reggio di Calabria	-0.78156	-0.98126	-0.9523
ITG11	Trapani	-0.98371	-1.20755	-1.07637
ITG12	Palermo	-1.0463	-1.1079	-1.15011
ITG13	Messina	-0.6368	-0.78869	-0.81905
ITG14	Agrigento	-1.52461	-1.56211	-1.66962
ITG15	Caltanissetta	-1.31798	-1.47297	-1.47737
ITG16	Enna	-1.36099	-1.37119	-1.46335
ITG17	Catania	-0.81851	-0.89866	-0.86618
ITG18	Ragusa	-1.00509	-1.11346	-1.07525
ITG19	Siracusa	-1.06767	-1.04901	-1.14008
ITG25	Sassari	-0.70548	-0.56601	-0.66675
ITG26	Nuoro	-0.64797	-0.65069	-0.62722
ITG27	Cagliari	-0.37147	-0.24384	-0.28578
ITG28	Oristano	-0.76231	-0.6472	-0.75076
ITG29	Olbia-Tempio	-0.7539	-0.7334	-0.64639
ITG2A	Ogliastra	-0.57083	-0.65511	-0.63681
ITG2B	Medio Campidano	-0.90286	-0.93048	-0.90613
ITG2C	Carbonia-Iglesias	-0.72754	-0.67513	-0.68947

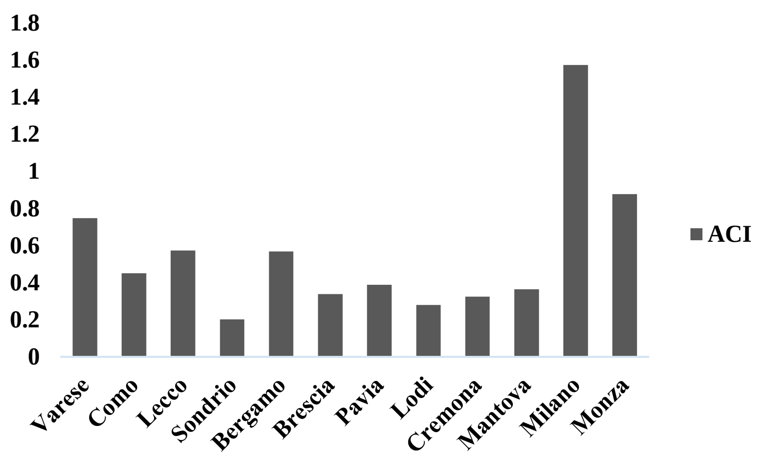

Figure SM5. ACI scores based on PCA weighting across the provinces of Lombardia

Comparison Between PCA and ESPON provincial results

In order to verify our provincial results, we compared it with ESPON provincial results, as shown in Figure SM6. As can be observed, there is a sizeable discrepancy between the ESPON and the PCA results. This may have been caused by applying different methodologies for normalization and aggregation, and also different proxy indicators. It should be mentioned that ESPON used data from 2006 to 2011, which are relatively outdated in comparison with the data we used for our analysis. Therefore, some dynamic changes in capacities are probably due to the advancements or decline of the AC components in some provinces. However, both results prove that there is a considerable intra-regional variability which is higher in our analysis than the ESPON one.

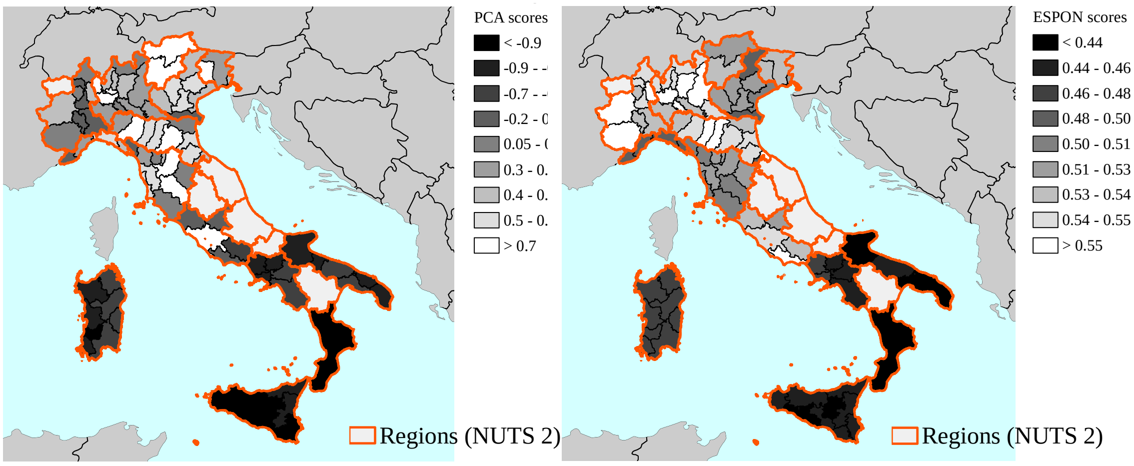

Figure SM6. Comparison between ESPON and PCA provincial scores

Figure SM7 is added to show the pattern of ranking reversals between ESPON and PCA. Accordingly, three types of clusters can be observed. The first cluster is composed of provinces with high AC rankings facing very high ranking reversals. The second cluster comprises the provinces with moderate AC rankings experiencing no change in rankings. And, finally, the third cluster is formed by provinces with low AC rankings experiencing slight ranking reversals. The comparison shows that the rate of ranking reversals is higher among the high AC provinces than the lower AC ones. Hence, since 2011, the high AC provinces have experienced a higher rate of improvements or decline than the lower AC provinces.

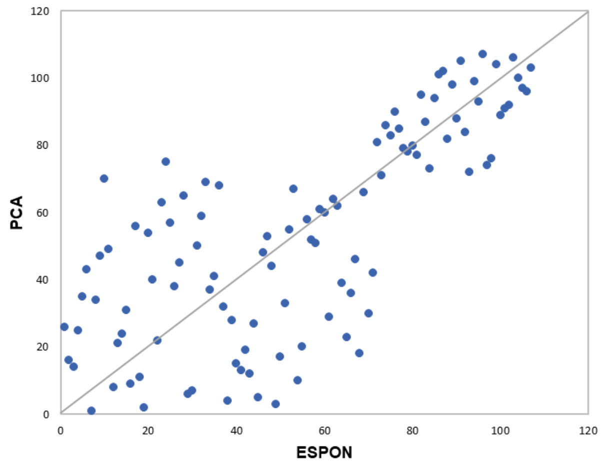

Figure SM7. Comparison between ESPON and PCA provincial rankings

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COMPETENCE ANALYSIS FOR PROMOTING ENERGY EFFICIENCY PROJECTS IN DEVELOPING COUNTRIES: THE CASE OF OPEC

Barriers to increased energy efficiency implementation in developing countries

Informational Barriers: Lack of data on relative energy efficiency levels/potentials and energy efficiency financial flows, Lack of information on technical and financial issues and on available technical support, including uncertainties about the performance and reliability of energy saving technologies, Institutional barriers to knowledge, communication and technology flows (Kleindorfer, 2011; Ryan et al., 2012; UNIDO, 2011).

Technological Barriers: Unavailability of efficient equipment, Misapplication of efficient technologies, Shortage of trained technical personnel to maintain/install new equipment, Shortage of human capacity (UNIDO, 2011).

Financial Barriers: Credit and budget constraints which imply short-term payback requirements, Lack of credit markets, High capital costs (Gillingham and Palmer, 2014; Kleindorfer, 2011; UNIDO, 2011)

Economic and Market Barriers: Uncertainty about future energy prices/economic uncertainty, High user discount rates, Slow rate of capital turnover/infrequency of capital investments, High transaction costs (Gillingham and Palmer, 2014; UNIDO, 2011)

Policy/political Barriers: Political uncertainty, Policy instability, Contracting barriers/weak contracting institutions, Absence of effective energy efficiency policy at national level, Inappropriate energy pricing and cross-subsidizing, Intra and inter-governmental coordination, Lack of integration strategies such as standardization (Kleindorfer, 2011; Maghazei et al., 2014; Ryan et al., 2012; UNIDO, 2011)

First-order aggregation results

The rankings derived from MMF aggregation for each pillar of the PEST decision tree are discussed separately to provide decision makers with a detailed explanatory data of the countries' endogenous potentials and weaknesses. To make interpretations easier, Countries are classified into three groups, based on their ranking positions considering the following:

- Category 1 is composed of countries in which the changes in ranking positions are negligible (less than 2 rank reversals)

- Category 2 contains the regions in which the rankings positions improve from no penalization (arithmetic mean) to full penalization (minimum) approaches.
- Category 3 comprises the regions in which the rankings positions diminish from no penalization (arithmetic mean) to full penalization (minimum) approaches.

Political pillar

Table SM1 shows the ranking position of countries, indicating the relative political capacities. The scores derived from aggregation with various combinations of α and β for political pillar are illustrated in Table SM2. All the countries are classified under Category 1 which indicates the consistency and robustness of the rankings obtained from various combinations of α and β. In this case, penalization of the indicators yields approximately analogous outcomes which determines a low degree of unbalances among variables of political pillar. In addition, the countries can be grouped in three clusters namely best (1), intermediate (2) and worst (3) which can be a useful determinant of the political risk among the target countries for investors.

Table SM1. Rankings for the political pillar calculated with various combinations of α and β

RANKINGS	ALFA=0, BETA=0	ALFA=BETA=1	ALFA=0.5, BETA=0	ALFA=1, BETA=0	CAT	CLUSTER
ALGERIA	5	5	5	5	1	2
ANGOLA	6	6	6	6	1	2
ECUADOR	7	7	7	8	1	2
IRAN, ISLAMIC REP.	8	8	8	7	1	2
IRAQ	10	10	10	11	1	3
KUWAIT	4	3	3	3	1	1
LIBYA	11	11	11	9	1	3
NIGERIA	9	9	9	10	1	3
QATAR	2	2	2	2	1	1
SAUDI ARABIA	3	4	4	4	1	1
UNITED ARAB EMIRATES	1	1	1	1	1	1
VENEZUELA, RB	12	12	12	12	1	3

Table SM2. The scores derived from aggregation with various combinations of α and β for political pillar.

COUNTRY NAME	ALFA=0, BETA=0	ALFA=1, BETA=1	ALFA=0.5, BETA=0	ALFA=1, BETA=0
ALGERIA	-0.24905	-0.29697	-0.40568	-0.56232
ANGOLA	-0.26271	-0.47587	-0.60614	-0.94956
ECUADOR	-0.30539	-0.55895	-0.68335	-1.06132
IRAN, ISLAMIC REP.	-0.64092	-0.70104	-0.81688	-0.99284
IRAQ	-0.73446	-0.97418	-1.10083	-1.4672
KUWAIT	0.731421	0.70784	0.622199	0.512977
LIBYA	-0.89942	-0.9817	-1.10639	-1.31335
NIGERIA	-0.67734	-0.88005	-1.01144	-1.34555
QATAR	1.604868	1.497754	1.367328	1.129788
SAUDI ARABIA	0.79496	0.666082	0.53306	0.27116
UNITED ARAB EMIRATES	1.69209	1.672261	1.592026	1.491962
VENEZUELA, RB	-1.05405	-1.31035	-1.43428	-1.81451

Economic pillar

Table SM3 comprises the ranking positions of countries, indicating the relative economic capacities. The scores derived from aggregation with various combinations of α and β for economic pillar are illustrated in Table SM4. The results show considerable rank reversals in compare to political pillar. The most noticeable rank reversals occur in the case of Iran, Nigeria and Kuwait. Figure 6 comprises normalized values of the indicators with positive polarity for aforesaid countries.

Table SM3. Rankings for the economic pillar calculated with various combinations of α and β

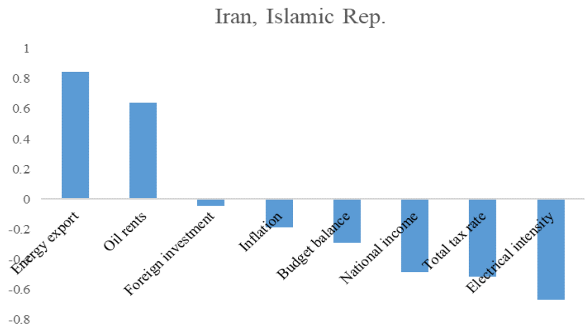
RANKINGS	ALFA=0, BETA=0	ALFA=BETA=1	ALFA=0.5, BETA=0	ALFA=1, BETA=0	CAT
ALGERIA	9	11	11	11	3
ANGOLA	12	8	9	7	2
ECUADOR	5	5	6	5	1
IRAN, ISLAMIC REP.	6	3	3	2	2
IRAQ	8	6	8	6	2
KUWAIT	4	9	7	10	3
LIBYA	11	10	10	9	2
NIGERIA	7	4	5	4	2
QATAR	3	7	4	8	3
SAUDI ARABIA	1	2	2	3	3
UNITED ARAB EMIRATES	2	1	1	1	1
VENEZUELA, RB	10	12	12	12	3

Table SM4. The scores derived from aggregation with various combinations of α and β for economic pillar.

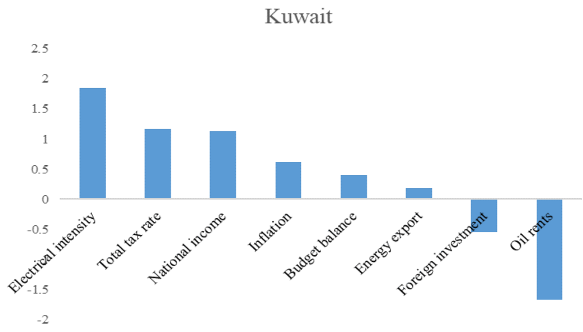
COUNTRY NAME	ALFA=0, BETA=0	ALFA=BETA =1	ALFA=0.5, BETA=0	ALFA=1, BETA=0
ALGERIA	-0.37329	-1.22674	-1.17461	-1.92744
ANGOLA	-0.62909	-0.74406	-0.88154	-1.11479
ECUADOR	0.006777	-0.37796	-0.49878	-1.05025
IRAN, ISLAMIC REP.	-0.0874	-0.2773	-0.41362	-0.66924
IRAQ	-0.22379	-0.56356	-0.6826	-1.10551
KUWAIT	0.393043	-0.89875	-0.66263	-1.66453
LIBYA	-0.62602	-1.0036	-1.10385	-1.57296
NIGERIA	-0.13069	-0.3572	-0.49673	-1.03327
QATAR	0.45166	-0.58442	-0.46781	-1.31066
SAUDI ARABIA	1.131368	-0.03513	0.13552	-0.78011
UNITED ARAB EMIRATES	0.622034	0.468332	0.313399	-0.05443
VENEZUELA, RB	-0.5346	-2.32091	-1.84789	-3.13449

In the case of Iran and Nigeria, the rankings improve after penalization. This fact can be explained by exploring the degree of unbalances among separate indicators shown in Figure SM1. According to Figure SM1-a, high performance in energy exports and oil rents do not fully compensate for the lower performance of the rest of the indicators. By moving toward no compensatory status, the level of under-performance indicators determine the outcome of the aggregation. In the case of Iran, the minimum value among all the indicators (electrical intensity) is relatively higher than the minimum values of other indicators for the rest of countries. Hence, Iran's ranking position has been improved substantially using non-compensatory approach. In other words, although Iran has low and moderate performance in most of the indicators, but the under-performance indicators are higher than the minimum baseline of other countries (higher performance in minimum indicators). This interpretation can assist the policy makers to distinguish the level of unbalances among the indicators and grab their attention to the most important capacities and weaknesses. Countries such as Iran show low and moderate performance in most of the economic indicators in compare to the high rank countries but on the other hand they do not show extremely low capacities for any of the indicator. The same explanation is applicable for Nigeria (Figure SM1-c). Figure SM1-b shows high and moderate performance for most of the indicators in the case of Kuwait. Therefore, by using compensatory approach, those high and moderate performance indicators compensate the unbalances caused mostly by FDI and oil rents indicators. Nevertheless, moving toward the minimum, extremely low performance in oil rents yields considerable low-ranking positions for Kuwait.

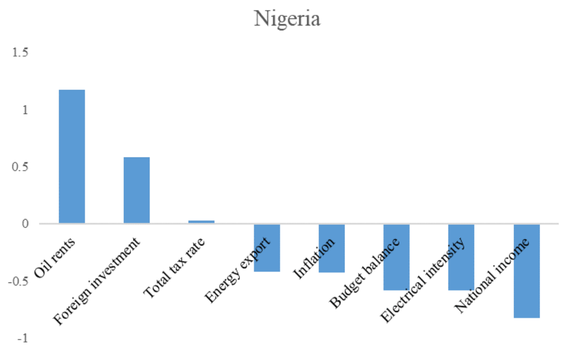
It should be mentioned that the clustering of the countries was not possible due to high ranking reversals among various aggregation methods.



SM1-a



SM1-b



SM1-c

Figure SM1. Normalized values of economic indicators for each country.

Technology pillar

Table SM5 comprises the ranking positions of countries, indicating the relative technological capacities. The scores derived from aggregation with various combinations of α and β for economic pillar are illustrated in Table SM6. The most noticeable rank reversals occur in the case of Iran, Algeria and Iraq. Figure 7 comprises normalized values of the indicators with positive polarity for aforesaid countries.

Table SM5. Rankings for the technology pillar calculated with various combinations of α and β

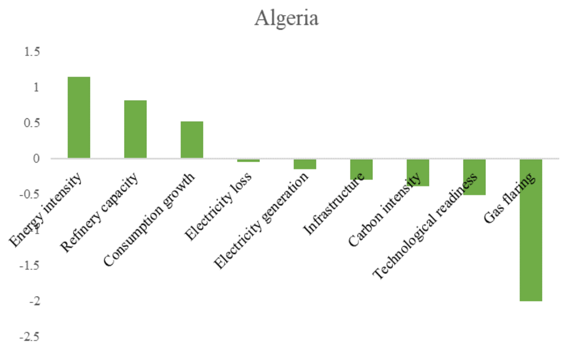
RANKINGS	ALFA=0, BETA=0	ALFA=BETA=1	ALFA=0.5, BETA=0	ALFA=1, BETA=0	CAT
ALGERIA	8	10	8	10	3
ANGOLA	9	8	9	9	1
ECUADOR	5	5	5	5	1
IRAN, ISLAMIC REP.	6	7	7	8	3
IRAQ	12	9	10	7	2
KUWAIT	2	1	1	1	1
LIBYA	11	12	12	12	1
NIGERIA	10	11	11	11	1
QATAR	3	3	3	4	1
SAUDI ARABIA	4	4	4	3	1
UNITED ARAB EMIRATES	1	2	2	2	1
VENEZUELA, RB	7	6	6	6	1

Table SM6. The scores derived from aggregation with various combinations of α and β for technology pillar.

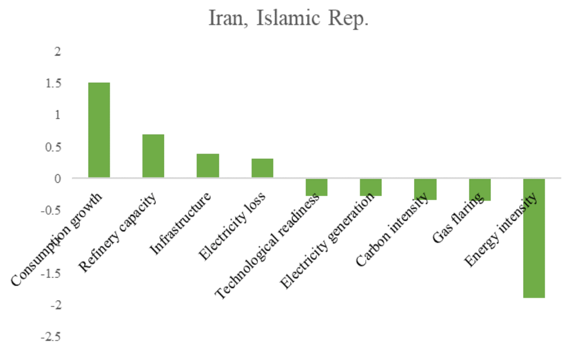
COUNTRY NAME	ALFA=0, BETA=0	ALFA=BETA=1	ALFA=0.5, BETA=0	ALFA=1, BETA=0
ALGERIA	-0.10091	-1.24994	-1.05201	-2.0031
ANGOLA	-0.28656	-1.19133	-1.09714	-1.90772
ECUADOR	0.17264	-0.21948	-0.31161	-0.79587
IRAN, ISLAMIC REP.	-0.02694	-1.13951	-0.95739	-1.88784
IRAQ	-0.64449	-1.20042	-1.2405	-1.83652
KUWAIT	0.547536	0.161079	0.067363	-0.41281
LIBYA	-0.51835	-1.56781	-1.41281	-2.30728
NIGERIA	-0.39766	-1.38648	-1.25722	-2.11679
QATAR	0.478385	-0.0998	-0.13208	-0.74254
SAUDI ARABIA	0.237802	-0.15638	-0.24793	-0.73367
UNITED ARAB EMIRATES	0.56868	0.05386	-0.00024	-0.56916
VENEZUELA, RB	-0.03014	-0.29723	-0.41921	-0.80829

In the case of Iraq, the rankings also improve after penalization. According to Figure SM2-c, high performance in energy intensity cannot fully compensate for the lower performance of the rest of the indicators. By moving toward no compensation, the level of under-performance indicators determine the outcome of the aggregation. For Iraq, the minimum value among all the indicators (electrical loss) is relatively higher than the minimum values of other indicators for the rest of countries. Hence, Iraq's ranking position has been improved substantially using minimum function. In the case of Algeria and Iran (Figure SM2-a and SM2-b), extremely low performance in gas flaring and energy intensity yields considerable negative rank reversals. Applying minimum aggregator leads to very low-ranking positions for the countries, with at least one indicator with very low scores.

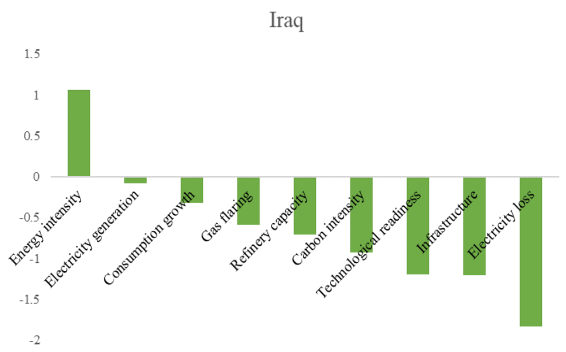
It should also be mentioned that the clustering of the countries was not possible due to high ranking reversals among various aggregation methods.



SM2-a



SM2-b



SM2-c

Figure SM2. Normalized values of technology indicators for each country.

Social pillar

Table SM7 contains the ranking positions of countries, indicating the relative social capacities. The scores derived from aggregation with various combinations of α and β for economic pillar are illustrated in Table SM8. We applied similar cluster classifications (best (1), intermediate (2) and worst (3)) for easier interpretation. The most noticeable rank reversals occur in the case of Kuwait, Libya, Saudi Arabia and Venezuela. Figure SM3 comprises normalized values of the indicators with positive polarity for aforesaid countries.

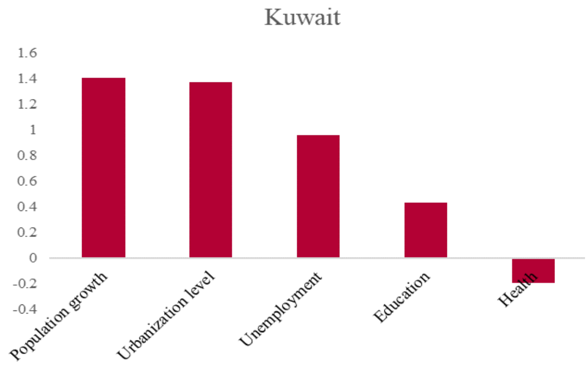
Table SM7. Rankings for the social pillar calculated with various combinations of α and β

RANKINGS	ALFA=0, BETA=0	ALFA=BETA=1	ALFA=0.5, BETA=0	ALFA=1, BETA=0	CAT	CLUSTER
ALGERIA	7	7	7	6	1	2
ANGOLA	12	11	12	11	1	3
ECUADOR	6	6	6	5	1	2
IRAN, ISLAMIC REP.	8	8	8	8	1	2
IRAQ	9	9	9	9	1	3
KUWAIT	2	3	2	4	3	1
LIBYA	10	12	10	12	3	3
NIGERIA	11	10	11	10	1	3
QATAR	1	1	1	1	1	1
SAUDI ARABIA	4	4	4	2	2	1
UNITED ARAB EMIRATES	3	2	3	3	1	1
VENEZUELA, RB	5	5	5	7	3	2

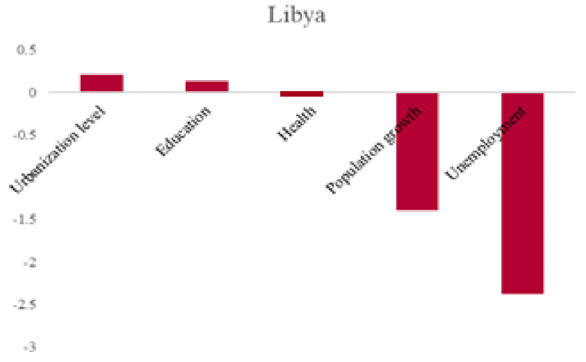
Table SM8. The scores derived from aggregation with various combinations of α and β for social pillar.

COUNTRY NAME	ALFA=0, BETA=0	ALFA=BETA=1	ALFA=0.5, BETA=0	ALFA=1, BETA=0
ALGERIA	-0.143	-0.29465	-0.42861	-0.71422
ANGOLA	-1.10918	-1.5866	-1.65296	-2.19673
ECUADOR	0.042438	-0.20895	-0.33372	-0.70987
IRAN, ISLAMIC REP.	-0.17402	-0.50889	-0.61614	-1.05826
IRAQ	-0.37214	-0.73399	-0.83437	-1.29661
KUWAIT	0.796114	0.388298	0.300648	-0.19482
LIBYA	-0.68313	-1.65109	-1.53061	-2.37808
NIGERIA	-1.02173	-1.51617	-1.57701	-2.13229
QATAR	1.348814	1.138203	1.007648	0.666481
SAUDI ARABIA	0.491219	0.365358	0.232587	-0.02605
UNITED ARAB EMIRATES	0.575697	0.403422	0.269826	-0.03604
VENEZUELA, RB	0.248919	-0.19503	-0.2719	-0.79271

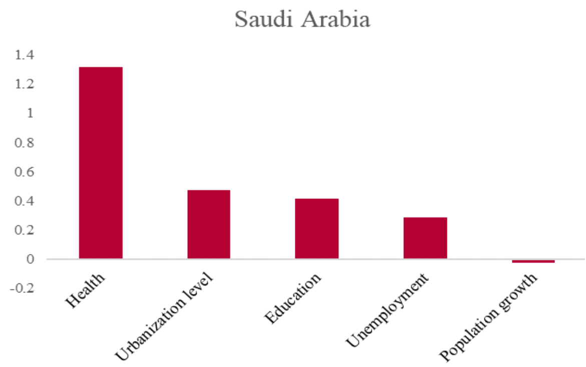
In the case of Saudi Arabia, the rankings improve slightly after full penalization. By moving toward minimum, population growth with a value close to mean determines the final score (Figure SM3-c). However, no variations can be seen in the cluster position of Saudi Arabia with various aggregations which determines the robustness of the results. In the case of Kuwait, Libya and Venezuela, the rankings decline slightly after increasing the degree of penalization. The minimum values of the indicators are illustrated in Figures SM3-a, SM3-b and SM3-d respectively. In an analogous way, no variations can be seen in the cluster position of these countries with various aggregations. This shows that rank reversals are negligible, and results are proportionally robust.



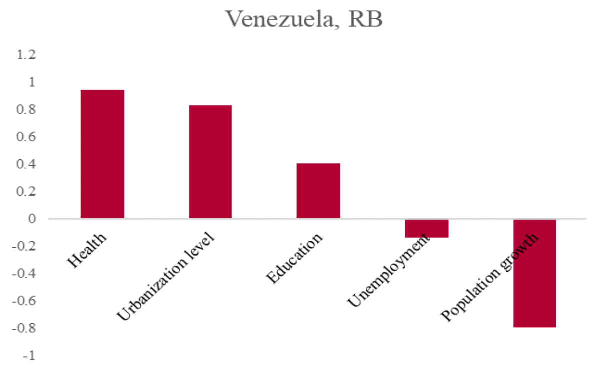
SM3-a



SM3-b



SM3-c



SM3-d

Figure SM3. Normalized values of social indicators for each country.

Table SM9. Mobius representation of respondents' preferences over each fuzzy set.

SET	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9	R_10	R_11	R_12	R_13	R_14	R_15	FUSION
{}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
{1}	0.25	0.50	0.55	0.35	0.25	0.29	0.40	0.50	0.38	0.60	0.42	0.50	0.60	0.55	0.60	0.45
{2}	0.20	0.45	0.45	0.20	0.20	0.31	0.35	0.40	0.35	0.35	0.30	0.30	0.40	0.50	0.45	0.35
{3}	0.05	0.65	0.40	0.30	0.22	0.20	0.50	0.65	0.39	0.40	0.32	0.40	0.75	0.65	0.60	0.43
{4}	0.15	0.50	0.58	0.10	0.40	0.31	0.25	0.30	0.48	0.57	0.46	0.65	0.30	0.40	0.35	0.38
{1,2}	0.15	-0.40	-0.40	-0.05	0.25	0.16	-0.17	-0.36	-0.21	-0.35	-0.14	-0.25	-0.36	-0.45	-0.40	-0.20
{1,3}	0.05	-0.47	-0.40	-0.05	0.01	0.05	-0.13	-0.40	-0.18	-0.35	-0.17	-0.30	-0.46	-0.40	-0.40	-0.24
{1,4}	0.00	-0.40	-0.38	0.10	-0.10	0.01	-0.20	-0.29	-0.24	-0.44	-0.22	-0.30	-0.27	-0.37	-0.33	-0.23
{2,3}	0.00	-0.40	-0.40	-0.05	0.15	-0.02	-0.15	-0.35	-0.21	-0.12	-0.03	-0.15	-0.38	-0.43	-0.40	-0.19
{2,4}	0.00	-0.45	-0.45	0.10	-0.09	-0.09	-0.05	-0.28	-0.33	-0.35	-0.24	-0.30	-0.25	-0.35	-0.30	-0.23
{3,4}	0.00	-0.35	-0.40	0.00	-0.09	0.08	-0.10	-0.27	-0.36	-0.35	-0.22	-0.40	-0.28	-0.35	-0.34	-0.23
{1,2,3}	0.20	0.47	0.55	0.20	-0.18	-0.06	0.15	0.51	0.28	0.33	0.04	0.20	0.40	0.48	0.50	0.27
{1,2,4}	0.10	0.50	0.45	-0.10	-0.06	-0.10	0.02	0.29	0.45	0.41	0.28	0.25	0.26	0.36	0.31	0.23
{1,3,4}	0.15	0.52	0.42	0.05	-0.14	-0.33	0.05	0.41	0.27	0.41	0.22	0.34	0.25	0.37	0.34	0.22
{2,3,4}	0.35	0.45	0.40	0.00	0.00	0.02	0.05	0.40	0.40	0.21	0.08	0.25	0.26	0.30	0.32	0.23
{1,2,3,4}	-0.65	-0.57	-0.37	-0.15	0.18	0.17	0.03	-0.51	-0.47	-0.32	-0.10	-0.19	-0.22	-0.26	-0.30	-0.25

*The respondents in red color are the experts chosen from OPEC countries.

Dominance analysis

The following formulas have been employed to calculate the relative dominance measure comparing units (countries, municipalities,etc.) *i* and *j* included in the ranking (explained in 2.4.3 and 3.4.3 sections). First of all, the "average cardinal dominance of unit *i* on unit *j* has to be calculated which is given by:

$$\Delta(i,j) = \frac{1}{N}\sum_{k=1}^{K} F[R_k(i) - R_k(j)]$$

where N is the number of units considered in the analysis, K represents the number of models generated for the analysis, $R(i)$ and $R(j)$ are the EECAI scores for i^{th} *and* j^{th} units respectively, and $F(x)$ is given by:

$$F(x) = \begin{cases} 0 & if \quad x < 0 \\ x & if \quad x \geq 0 \end{cases}$$

The "average cardinal dominance shows the extent the i^{th} unit dominates the j^{th} unit on average. Afterwards, the total dominance measure of unit *i* on every other unit can be computed as follows:

$$\rho^{+}(i) = \frac{1}{N-1}\sum_{j=1}^{N} \Delta(i,j)$$

The degree to which unit *i* is dominated by every other unit is given by:

$$\rho^{-}(i) = \frac{1}{N-1}\sum_{j=1}^{N} \Delta(j,i)$$

Finally, the relative dominance measure can be calculated as follows:

$$\rho(i) = \frac{\rho^{+}(i)}{\rho^{+}(i) + \rho^{-}(i)}$$

This measure is defined within the range of [0,1] where measure 1 indicates the unit *i* fully dominates all other units and measure 0 depicts that unit *i* has been thoroughly dominated by all other units.

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CONSTRUCTING A COMPREHENSIVE DISASTER RESILIENCE INDEX: THE CASE OF ITALY

Background on resilience and vulnerability

The term *resilience* has been debated as a cross-disciplinary concept and defined in different ways among different scientific disciplines (Bogardi and Fekete, 2018; Brand and Jax, 2007). Early concept of resilience comes from the ecology and engineering science, being generally understood as the behavior of a dynamic system while exposed to external disturbances (Brand and Jax, 2007; Fletcher and Sarkar, 2013). Engineering resilience refers to the time required for a system to *bounce back* to an equilibrium steady state in dynamics close to equilibrium and is focused on stability of the state within the systems' attraction domain (local stability) (Gallopín, 2006; Grimm and Wissel, 1997; Holling, 1996; Pimm, 1984; Tu, 1994). On the other hand, the ecological (ecosystem) resilience has been explained in a system detached from any equilibrium state and defined as the amount of disturbance a system is able to absorb prior to being transformed to another steady state dynamics outside of the system's attraction domain. In this case, the stability of the system within the attraction basin in the face of perturbation is not of interest (Folke, 2006; Folke et al., 2004; Gallopín, 2006; Gunderson and Holling, 2002; Gunderson and Pritchard, 2002; Walker et al., 2004).

In recent years, the ecological construct of resilience has been incorporated in the context of social sciences at broader scale with the focus on disaster risk reduction and climate change adaptation disciplines in order to capture the behavioral dynamics of the socio-ecological systems being exposed to natural hazards (Bakkensen et al., 2017; Bogardi and Fekete, 2018; Cutter et al., 2010; Folke, 2006). Resilience in the context of disaster risk reduction has been described as "the ability of a system, community or society exposed to hazards to resist, absorb, accommodate to and recover from the effects of a hazard in a timely and efficient manner" (UNISDR, 2016). In the field of climate change, the latest IPCC report defines resilience as "the capacity of social, economic and environmental systems to cope with a hazardous event or trend or disturbance, responding or reorganizing in ways that maintain their essential function, identity and structure, while also maintaining the capacity for adaptation learning and transformation" (IPCC, 2014b). The IPCC definition addresses the importance of the capacity building for post-disaster period and climate change adaptation. The necessecity of coupling capacity building and bounce back notions has been previously introduced in the context of disaster resilience as “bounce forward” ability explained as a tranformational processes within the context of newly formed dynamics after disater shock (Manyena et al., 2011; Paton and Johnston, 2006). In general terms, resilience is a comprehensive characteristic of complex systems capable of explaining a systems’ ability to deal with disturbances and the effect of stressors (Birkmann et al., 2013).

Resilience is strongly tangled with concept of vulnerability containing similar consideration for assessment design (Fekete, 2018; Parsons et al., 2016; Turner, 2010). There are Some studies considering resilience and vulnerability as counterparts belonging to the same continuum on the opposite poles (Bogardi and Fekete, 2018; Cutter et al., 2008; Manyena et al., 2011; Manyena, 2006). On the contrary, some other studies argue that resilience and vulnerability are strictly related but cannot be used interchangeably as the opposite terms. Gallopín (2006) addresses resilience as the response capacity component of vulnerability and explains fundamental differences using the behavior of dynamic systems being exposed to external perturbations. Accordingly, resilience refers to a state remaining within the considered domain of attraction which result in structural changes in overall system stability. On the other hand, vulnerability expresses the transformations which can traverse a single domain leading to temporary shift in functional state of the system and can be counted as a pre-event characteristic of a system (Adger, 2006; Bakkensen et al., 2017; Cutter et al., 2008; Gallopín, 2006). According to Fekete (2018), resilience in the context of disaster risk reduction, includes certain array of capabilities to compensate vulnerability and mainly regards to the processes experienced when a disaster strikes. Accordingly, vulnerability portrays a broader vision of the degree of susceptibility and coping capacity than resilience. In this sense, a system might be vulnerable to a range of natural hazards and climate related impacts, but it’s not necessary “to possess all types of resiliencies to tackle all those vulnerabilities”. In addition, vulnerability is considered as an internal risk factor mostly assessed through static approaches while the dynamic approaches are usually used in the resilience context (Dixon and Stringer, 2015; Miola et al., 2015). With regards to static approach, vulnerability is the measure of the potential loss at one point in time (pre-disaster) whereas the dynamic approach addresses the integral resilience across all time steps (before, during and after crisis) (Cutter et al., 2003; Linkov et al., 2014). Climate change involves in long term causative processes changing constantly in nonlinear dynamic ways with high degree of uncertainty (Rodin, 2014; Tyler and Moench, 2012; Weichselgartner and Kelman, 2015a). Therefore, resilience discourse can be more appropriate to be employed in the context of climate change than vulnerability (Meerow et al., 2016; Weichselgartner and Kelman, 2015b). It should be mentioned that IPCC (2014a) exhibits the concept of vulnerability as the social and societal construction of the climate risk and describes it as "the propensity or predisposition to be adversely affected". Hence, vulnerability can be associated with socio-economic and demographic determinants (societal aspects of disaster) previously introduced as "social vulnerability" which influence societies' preparedness, response and recovery (Birkmann et al., 2013; Cutter et al., 2013, 2003; Fekete, 2018; Terti et al., 2015).

Data and methodology

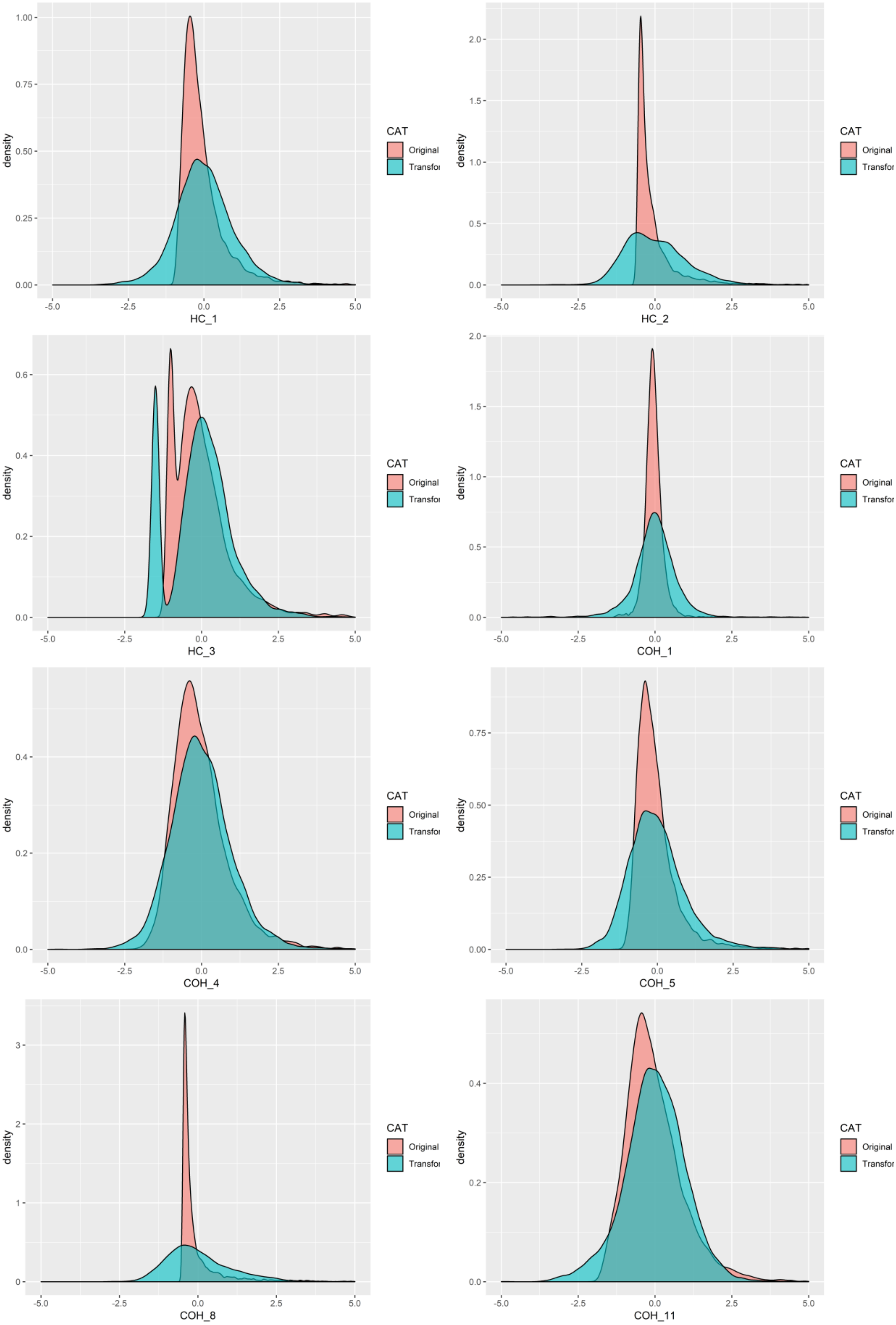
Table SM1: Descriptive statistics of the original variables

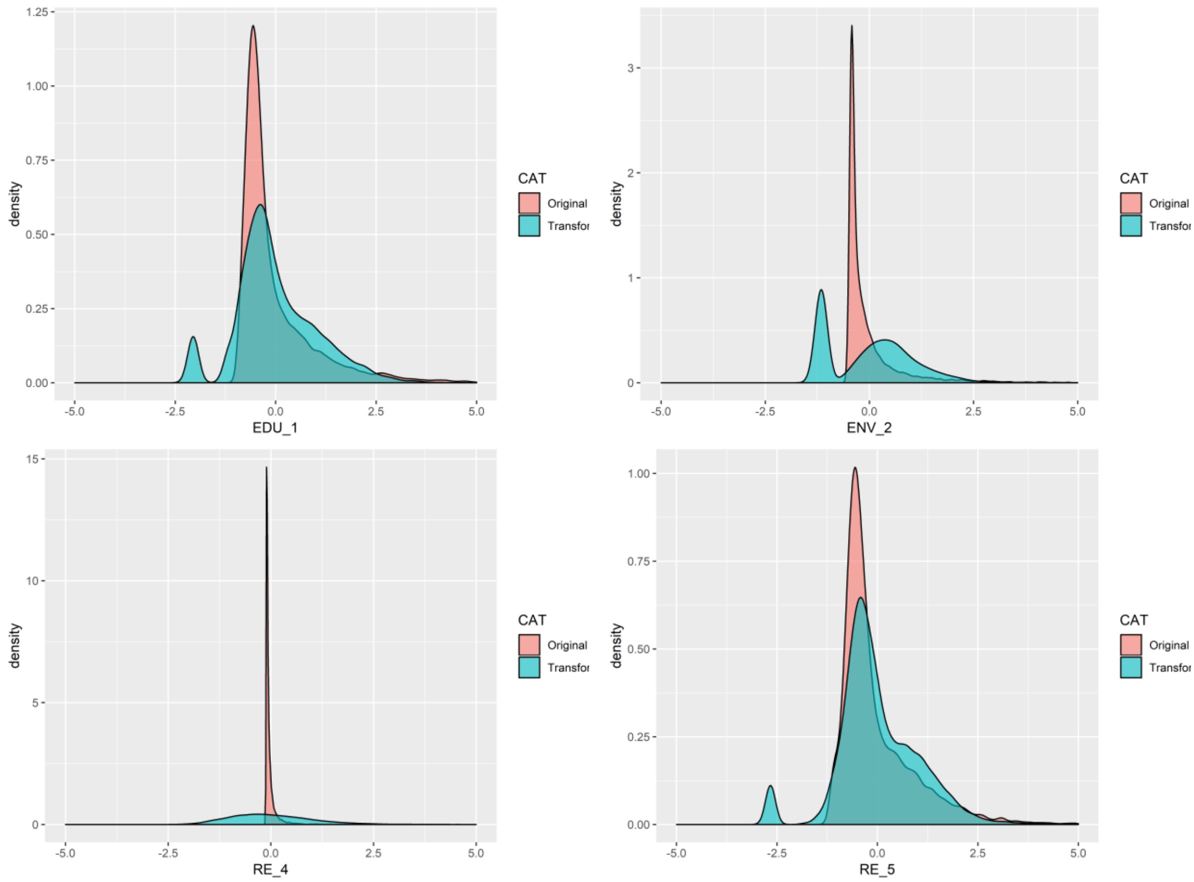
INDICATOR	MEAN	MEDIAN	MODE	STD.	VARIANCE	SKEWNESS	KURTOSIS	MINIMUM	MAXIMUM
ACC1_TT	10.976	4.810	0.000	14.398	207.308	1.462	1.953	0.000	88.580
ACC1_D	12089.885	4154.340	0.000	17088.257	292008543.600	1.815	3.702	0.000	117902.050
ACC2_TT	15.010	13.300	0.000	10.087	101.742	1.135	2.128	0.000	82.890
ACC2_D	15657.810	12873.450	0.000	12530.066	157002563.546	1.923	6.560	0.000	111083.730
HC_1	23.791	17.188	0.000	26.549	704.844	7.584	122.527	0.000	657.265
HC_2	70.108	33.500	15.600	118.311	13997.435	6.430	72.850	0.000	2630.000
HC_3	1.003	0.800	0.000	0.989	0.978	2.684	17.245	0.000	16.700
HC_4	85.568	86.996	100.000	8.021	64.331	-1.525	4.545	23.126	100.000
COH_1	10.210	9.731	9.091	7.762	60.246	27.783	992.263	0.000	354.839
COH_2	8.434	7.250	0.000	6.125	37.516	2.041	10.228	0.000	76.800
COH_3	33.014	31.157	33.333	8.979	80.626	1.222	2.304	11.232	85.542
COH_4	36.012	33.800	31.000	12.281	150.816	2.375	13.834	7.500	178.100
COH_5	195.672	166.667	200.000	141.870	20127.143	7.085	86.577	0.000	2850.000
COH_6	20.366	20.587	16.667	3.852	14.835	-0.374	1.200	0.000	38.725
COH_7	3.219	3.000	2.800	1.325	1.756	1.113	3.054	0.000	13.800
COH_8	454.872	149.256	9.776	936.687	877381.797	5.580	47.570	1.494	15185.973
COH_9	35.219	36.100	42.500	12.557	157.684	-0.187	-0.684	1.500	73.200
COH_10	19.127	18.644	20.000	7.805	60.918	0.448	0.354	0.000	56.961
COH_11	34.501	31.613	28.989	17.678	312.517	2.930	32.328	1.205	376.000
COH_12	40.514	41.200	44.800	7.601	57.776	-0.251	-0.180	10.400	71.700
EDU_1	1.197	0.600	0.300	1.427	2.036	2.587	9.241	0.000	15.000
EDU_2	22.369	21.689	22.222	4.757	22.630	1.332	4.061	7.143	57.000
EDU_3	7.274	6.910	10.300	2.702	7.300	1.301	4.013	0.000	27.500
INS_1	0.686	0.710	0.730	0.088	0.008	-1.041	2.104	0.000	0.950
ENV_1	25.907	11.793	0.000	31.043	963.677	1.012	-0.240	0.000	100.000
ENV_2	0.078	0.021	0.000	0.181	0.033	8.902	139.312	0.000	4.247
RE_1	10752.159	11177.612	7682.320	3185.622	10148185.172	0.102	0.054	2076.525	32584.593
RE_2	0.266	0.305	0.315	0.083	0.007	-1.050	-0.162	0.015	0.446
RE_3	10.127	7.700	6.200	6.306	39.765	1.211	1.023	0.000	42.200
RE_4	4573.495	1274.910	67.160	40204.088	1616368669.666	62.223	4672.308	25.110	3142908.250
RE_5	2.012	1.300	1.000	1.862	3.467	2.429	9.228	0.000	17.900

Table SM2: Descriptive statistics of the data set containing transformed variables (Box-Cox)

INDICATOR	MEAN	MEDIAN	MODE	STD.	VARIANCE	SKEWNESS	KURTOSIS	MINIMUM	MAXIMUM
ACC1_TT	10.976	4.810	0.000	14.398	207.308	1.462	1.953	0.000	88.580
ACC1_D	12089.885	4154.340	0.000	17088.257	292008543.600	1.815	3.702	0.000	117902.050
ACC2_TT	15.011	13.300	0.000	10.087	101.742	1.135	2.128	0.000	82.890
ACC2_D	15657.810	12873.450	0.000	12530.066	157002563.546	1.923	6.560	0.000	111083.730
HC_1_T	3.897	3.831	-5.000	1.559	2.432	-0.034	3.305	-5.000	13.303
HC_2_T	4.387	4.207	3.162	1.668	2.783	0.261	2.358	-10.000	11.978
HC_3_T	-0.209	-0.209	-1.667	0.973	0.947	0.507	1.311	-1.667	7.359
HC_4	85.568	86.996	100.000	8.021	64.331	-1.525	4.545	23.126	100.000
COH_1_T	2.882	2.881	2.775	0.492	0.242	2.023	57.363	-5.000	11.180
COH_2	8.434	7.250	0.000	6.125	37.516	2.041	10.228	0.000	76.800
COH_3	33.014	31.157	33.333	8.979	80.626	1.222	2.304	11.232	85.542
COH_4_T	4.248	4.220	4.097	0.435	0.189	0.495	1.532	2.232	6.791
COH_5_T	9.059	8.910	9.427	1.384	1.914	1.225	6.398	-5.000	19.544
COH_6	20.366	20.587	16.667	3.852	14.835	-0.374	1.200	0.000	38.725
COH_7	3.219	3.000	2.800	1.325	1.756	1.113	3.054	0.000	13.800
COH_8_T	6.861	6.497	2.561	2.334	5.446	0.696	0.364	0.410	16.191
COH_9	35.219	36.100	42.500	12.557	157.684	-0.187	-0.684	1.500	73.200
COH_10	19.128	18.644	20.000	7.805	60.918	0.448	0.354	0.000	56.961
COH_11_T	4.963	4.976	4.804	0.981	0.963	-0.066	1.080	0.190	11.368
COH_12	40.514	41.200	44.800	7.601	57.776	-0.251	-0.180	10.400	71.700
INS_1	0.686	0.710	0.730	0.088	0.008	-1.041	2.104	0.000	0.950
EDU_1_T	-0.188	-0.462	-0.955	1.127	1.270	0.515	0.674	-2.500	4.885
EDU_2	22.369	21.689	22.222	4.757	22.630	1.332	4.061	7.143	57.000
EDU_3	7.274	6.910	10.300	2.702	7.300	1.301	4.013	0.000	27.500
ENV_1	25.907	11.793	0.000	31.043	963.677	1.012	-0.240	0.000	100.000
ENV_2_T	-2.349	-2.287	-3.333	0.851	0.725	0.410	-0.376	-3.333	1.811
RE_1	10752.159	11177.612	7682.320	3185.622	10148185.172	0.102	0.054	2076.525	32584.593
RE_2	0.266	0.305	0.315	0.083	0.007	-1.050	-0.162	0.015	0.446
RE_3	10.127	7.700	6.200	6.306	39.765	1.211	1.023	0.000	42.200
RE_4_T	10.758	10.443	5.230	2.907	8.450	0.860	2.042	3.803	34.641
RE_5_T	0.510	0.277	0.000	1.132	1.281	0.212	1.317	-2.500	5.426

Figure SM1: Density graphs (standardized)




density
EDU_1
CAT
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density
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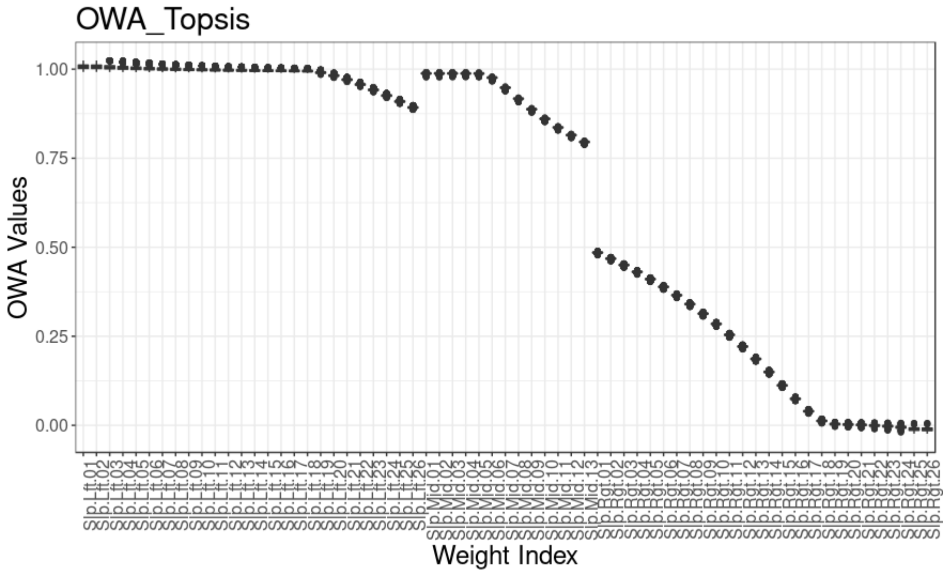
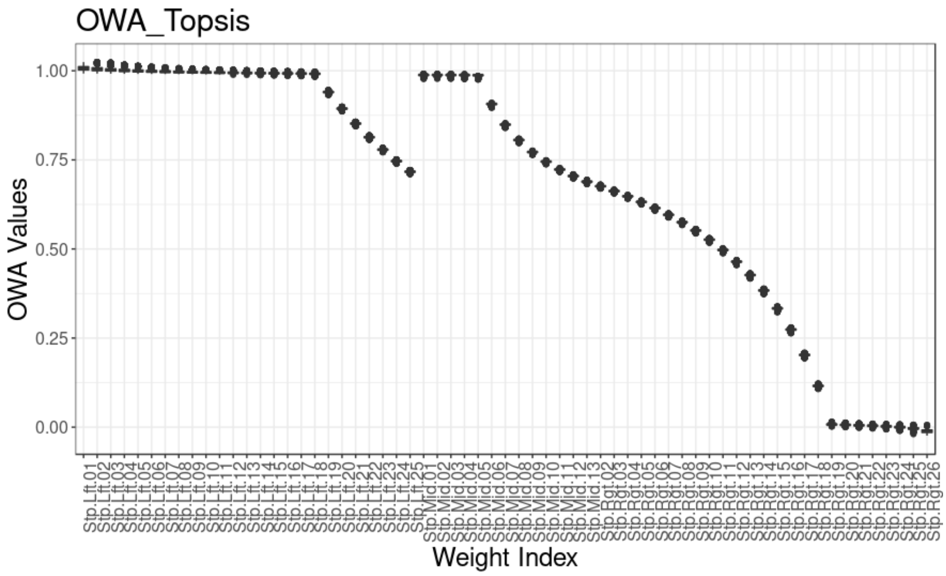
Table SM3: Multicollinearity statistics

INDICATOR	CODE	VIF (BEFORE)	VIF (AFTER)
TRAVEL TIME TO SERVICE CENTERS	ACC1_TT	1.881	excluded
TRAVEL TIME TO FIRE BRIGADES	ACC2_TT	16.081	excluded
DISTANCE TO FIRE BRIGADES	ACC2_D	15.468	1.262
QUALITY RATE OF DWELLINGS	HC_1_t	1.158	1.154
RATE OF EMPTY DWELLINGS OVER TOTAL	HC_2_t	2.59	2.533
INDEX OF OVERCROWDED RESIDENCES	HC_3_t	1.368	1.349
RESIDENTIAL BUILDINGS OVER TOTAL	HC_4	1.088	1.08
INDEX OF SINGLE PARENT FAMILIES	COH_1_t	1.098	1.092
INDEX OF LARGE FAMILIES	COH_2	1.743	1.68
INDEX OF SMALL FAMILIES	COH_3	4.763	4.431
INDEX OF ELDERLY DEPENDENCE	COH_4_t	13.641	6.735
OLD AGE INDEX	COH_5_t	21.322	excluded
INDEX OF MINOR DEPENDENCE	COH_6	6.156	2.25
SHARE OF THE FAMILIES WITH ASSISTANCE NEED	COH_7	2.473	2.467
POPULATION DENSITY	COH_8_t	1.941	1.917
COMMUTING RATE FOR STUDY OR WORK	COH_9	16.011	4.43
CONTAINMENT INDEX	COH_10	12.03	excluded
ATTRACTION INDEX	COH_11_t	2.745	2.433
PARTICIPATION IN THE LABOR MARKET - FEMALE	COH_12	5.054	4.248
ILLITERACY	EDU_1_t	3.135	3.132
LOW EDUCATION INDEX	EDU_2	3.892	3.814
HIGH EDUCATION INDEX	EDU_3	2.399	2.348
ELECTECTION PARTICIPATION	INS_1	3.487	3.416
SHARE OF THE PROTECTED LANDS	ENV_1	1.144	1.137
SHARE OF ECOLOGICAL CORIDORS	ENV_2_t	1.132	1.123
INCOME	RE_1	7.064	7.01
GINI INDEX	RE_2	4.248	4.166
UNEMPLOYMENT RATE	RE_3	4.051	3.72
CADASTRAL STOCK (PROPERTY VALUE)	RE_4_t	2.828	2.637
SHARE OF THE FAMILIES WITH POTENTIAL ECONOMIC HARDSHIP	RE_5_t	3.707	3.668
DEPENDENT VARIABLE: ACC1_D			

Sensitivity and robustness analysis

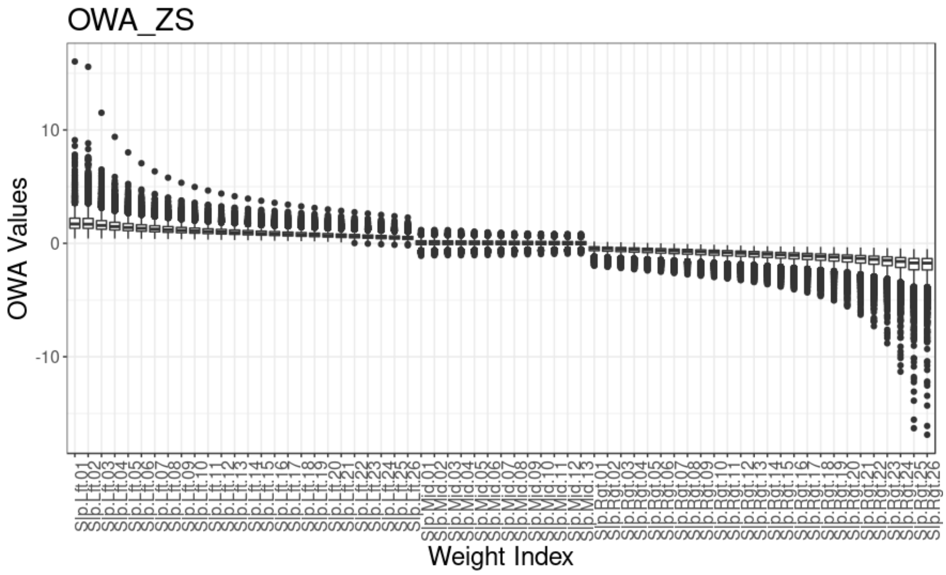


c) Linear

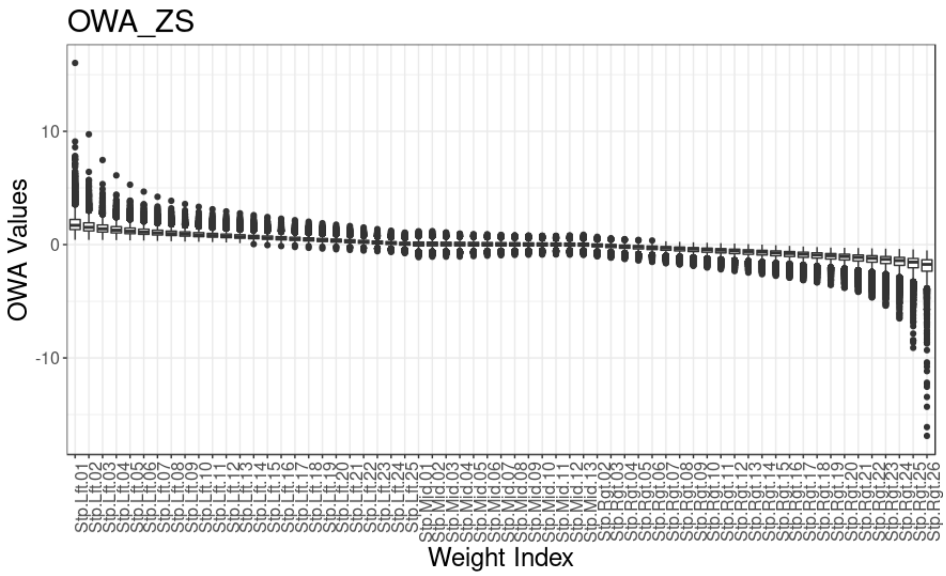


d) Uniform

Figure SM2: Section of OWA scores derived from Topsis normalized data for different combination of weights for all the municipalities (linear and uniform)

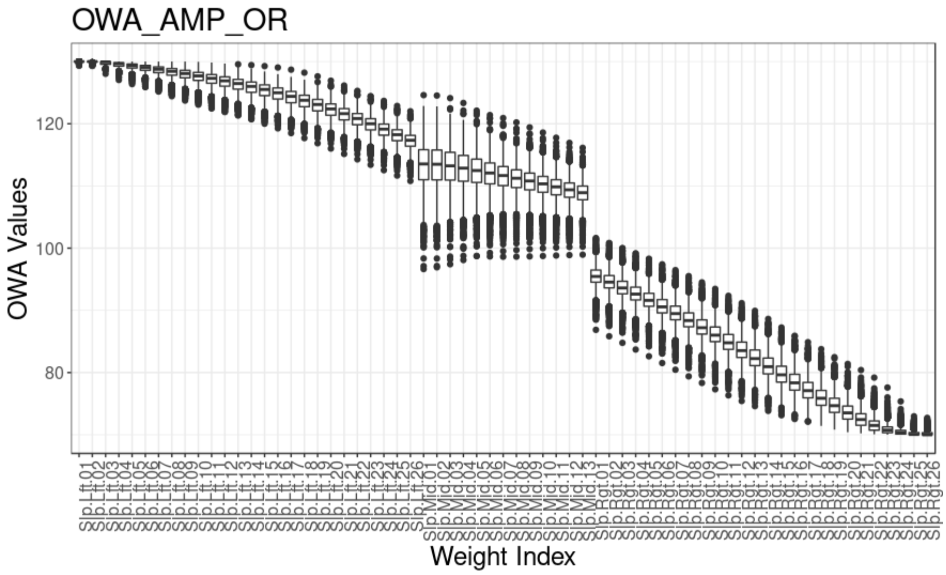


e) Linear

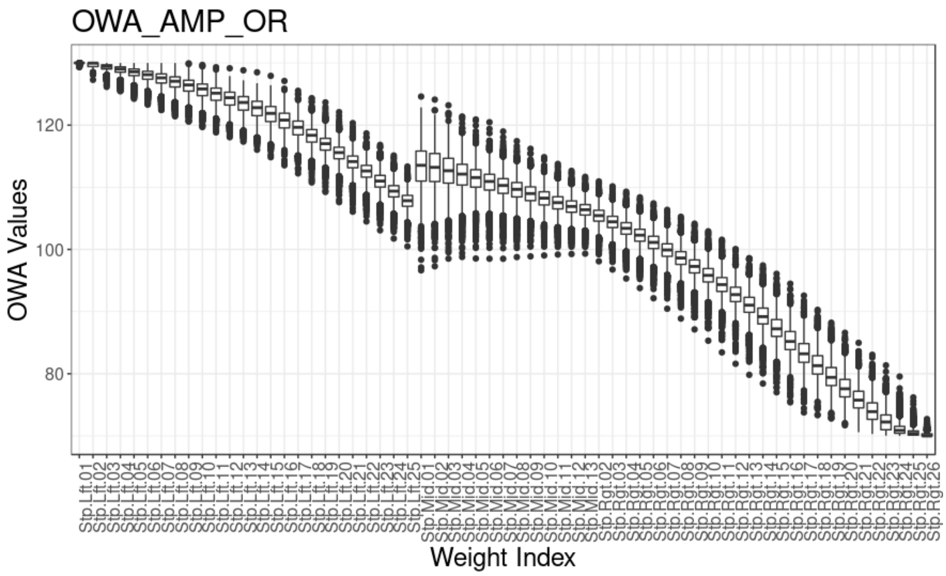


f) Uniform

Figure SM3: Section of OWA scores derived from Zscore normalized data for different combination of weights for all the municipalities (linear and uniform)



g) Linear



h) Uniform

Figure SM4: Section of OWA scores derived from AMP normalized data (with no transformation) for different combination of weights for all the municipalities (linear and uniform)

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DICHIARAZIONE SOSTITUTIVA DELL'ATTO DI NOTORIETA'
(Art. 47 D.P.R. 445 del 28/12/2000 e relative modifiche)

Io sottoscritto Sepehr Marzi

nat o a Tehran, Iran (prov. THR) il 16/09/1986

residente a Venezia in Via Col di Lana n. 19/5

Matricola (se posseduta) 956254 Autore della tesi di dottorato dal titolo:

Role and development of composite indicators for climate change and sustainable development policies and practices

Dottorato di ricerca in Scienza e Gestione dei Cambiamenti Climatici

(in cotutela con ...)

Ciclo XXXI

Anno di conseguimento del titolo 2019

DICHIARO

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L'estratto (max. 1000 battute) deve essere redatto sia in lingua italiana che in lingua inglese e nella lingua straniera eventualmente indicata dal Collegio dei docenti.
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Studente: Sepehr Marzi matricola: 956254

Dottorato: Scienza e Gestione dei Cambiamenti Climatici

Ciclo: XXXI

Titolo della tesi[1] : Role and development of composite indicators for climate change and sustainable development policies and practices

Abstract:

The thesis is a collection of three research articles in which I developed and applied indicator-based assessments to various policy areas. The first article explores how to conceptualize and measure adaptive capacity at various administrative levels, and how to factor-in the variability at a lower administrative level in the assessment of the next higher levels. The second article describes the energy efficiency country attractiveness index, developed to boost efficient and effective resource allocations and to promote energy efficiency as part of the climate mitigation policies. The index combines political, economic, social and technological factors using complex fuzzy-set techniques. The third article addresses disaster resilience and is meant to inform the implementation of the Sendai Framework for Disaster Risk Reduction 2015-2030 (SFDRR) in Europe. It reconciles various indicators used for describing "resilience", including innovative distance-decay based attributes using a range of advanced statistical techniques employed to normalize, transform and combine the variables.

Firma dello studente
Sepehr Marzi

[1] Il titolo deve essere quello definitivo, uguale a quello che risulta stampato sulla copertina dell'elaborato consegnato.