Journal of Environmental Management 223 (2018) 1023–1036

Contents lists available at ScienceDirect

Journal of Environmental Management

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

Research article

Comparing adaptive capacity index across scales: The case of Italy

Sepehr Marzi[a,b,*], Jaroslav Mysiak[a,b], Silvia Santato[a,b]

[a] Euro-Mediterranean Center on Climate Change, Via della Libertà, 12 - 30175 Venice, Italy
[b] Ca' Foscari University of Venice, Dorsoduro, 3246 - 30123 Venice, Italy

ARTICLE INFO

Keywords:
Indicators-based assessment
Principal component analysis
Sub-regional variability
Fuzzy aggregation

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 adaptive capacity can be observed at regional level as a result of the aggregation choices. Trade-offs should be made explicit for choosing aggregators that reflect 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. 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, 2014a). 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, 2014b). 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;

* Corresponding author. CMCC Foundation - Euro-Mediterranean Center on Climate Change and Ca'Foscari University of Venice, Via della Libertà, 12 - 30175 Venice, Italy.

E-mail address: sepehr.marzi@unive.it (S. Marzi).

https://doi.org/10.1016/j.jenvman.2018.06.060
Received 17 January 2018; Received in revised form 18 May 2018; Accepted 18 June 2018
0301-4797/

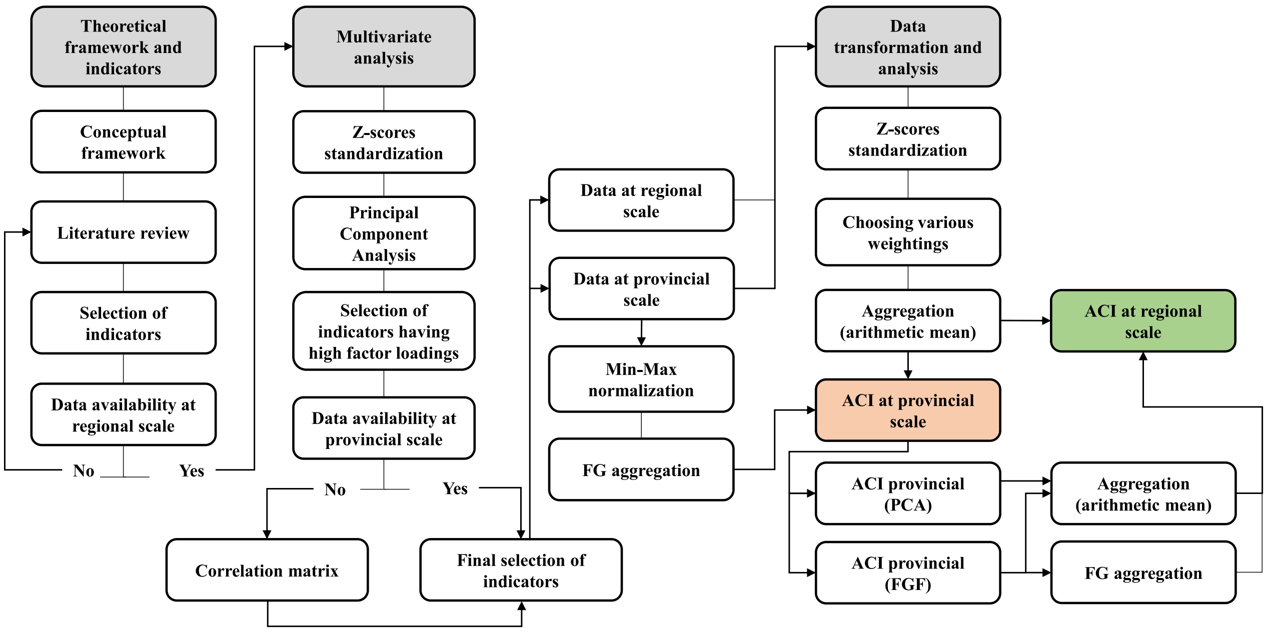


Fig. 1. Workflow diagram of the analysis.

Pelling and High, 2005; Vincent, 2007; 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 adaptive capacity 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 affects 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 (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) (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 of 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.

2. Data and methodology

2.1. Conceptual framework and indicators used

Fig. 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 ACI at both the regional and provincial levels.

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 (Fig. 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 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; 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; 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; 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 shows the initial set of AC indicators. A detailed explanation of the indicators can be found in the electronic supplementary material. The data were obtained from multiple sources but primarily from the database of territorial indicators for the development policies (ISTAT, 2015), 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 Valle d'Aosta, is sub-divided into provinces. The Alto Adige 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). 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.

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)).

$$\begin{aligned} p_1 &= a_{11}x_1 + a_{12}x_2 + a_{1n}x_n \\ p_2 &= a_{21}x_1 + a_{22}x_2 + a_{2n}x_n \\ &\ldots \\ p_n &= a_{n1}x_1 + a_{n2}x_2 + a_{nn}x_n \end{aligned} \tag{1}$$

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 p_1 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 λ_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.

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

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-standardized 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 indicators 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.

Table 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 × 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

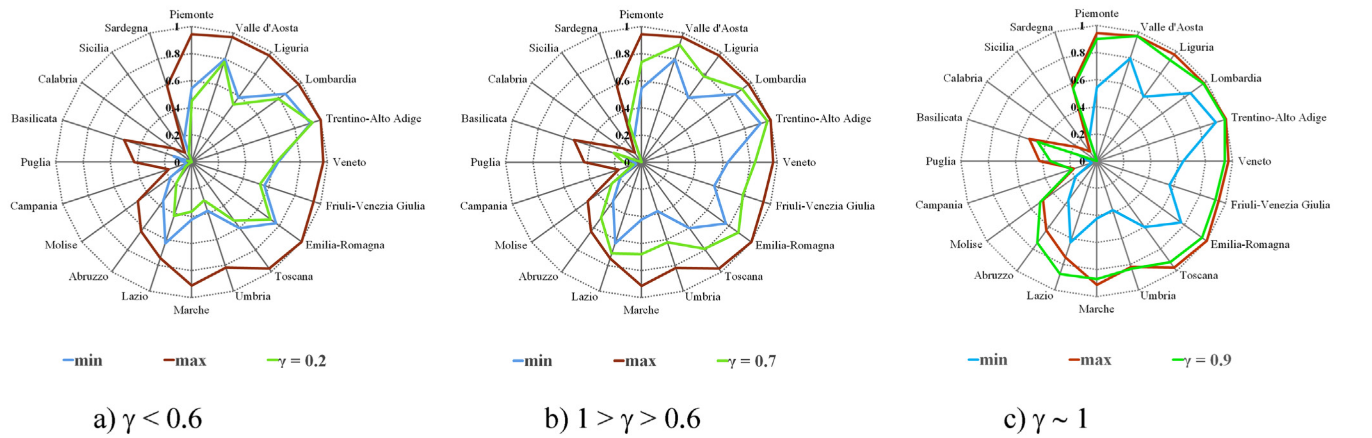


Fig. 2. Fuzzy Gamma values, along with minimum and maximum values of the first criteria (economic resources), for the 1st Fuzzy aggregation with three different gamma values calculated as part of the sensitivity analysis on Gamma coefficient.

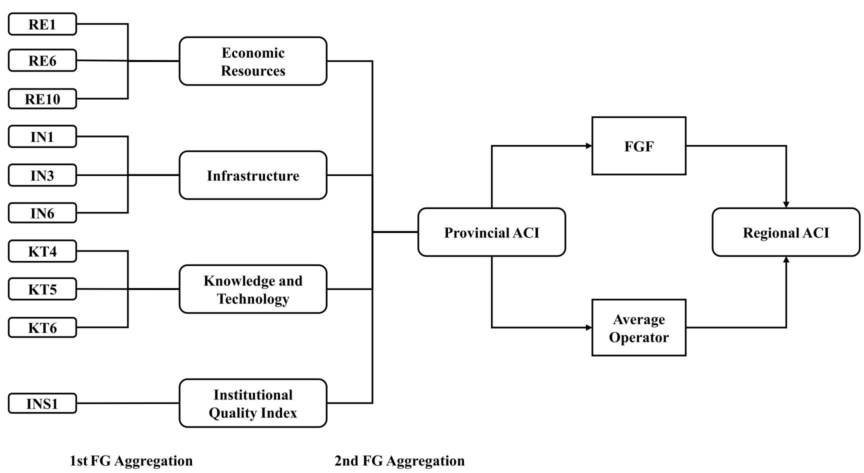


Fig. 3. Fuzzy Gamma aggregation. Modified from Araya-Munoz et al. (Araya-Muñoz et al., 2016).

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 normalization (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., 2014).

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.

$$\mathit{Fuzzy\ SUM} = 1 - \prod_{i=1}^{n} (1 - \mu_i) \tag{3}$$

$$\mathit{Fuzzy\ PRODUCT} = \prod_{i=1}^{n} (\mu_i) \tag{4}$$

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

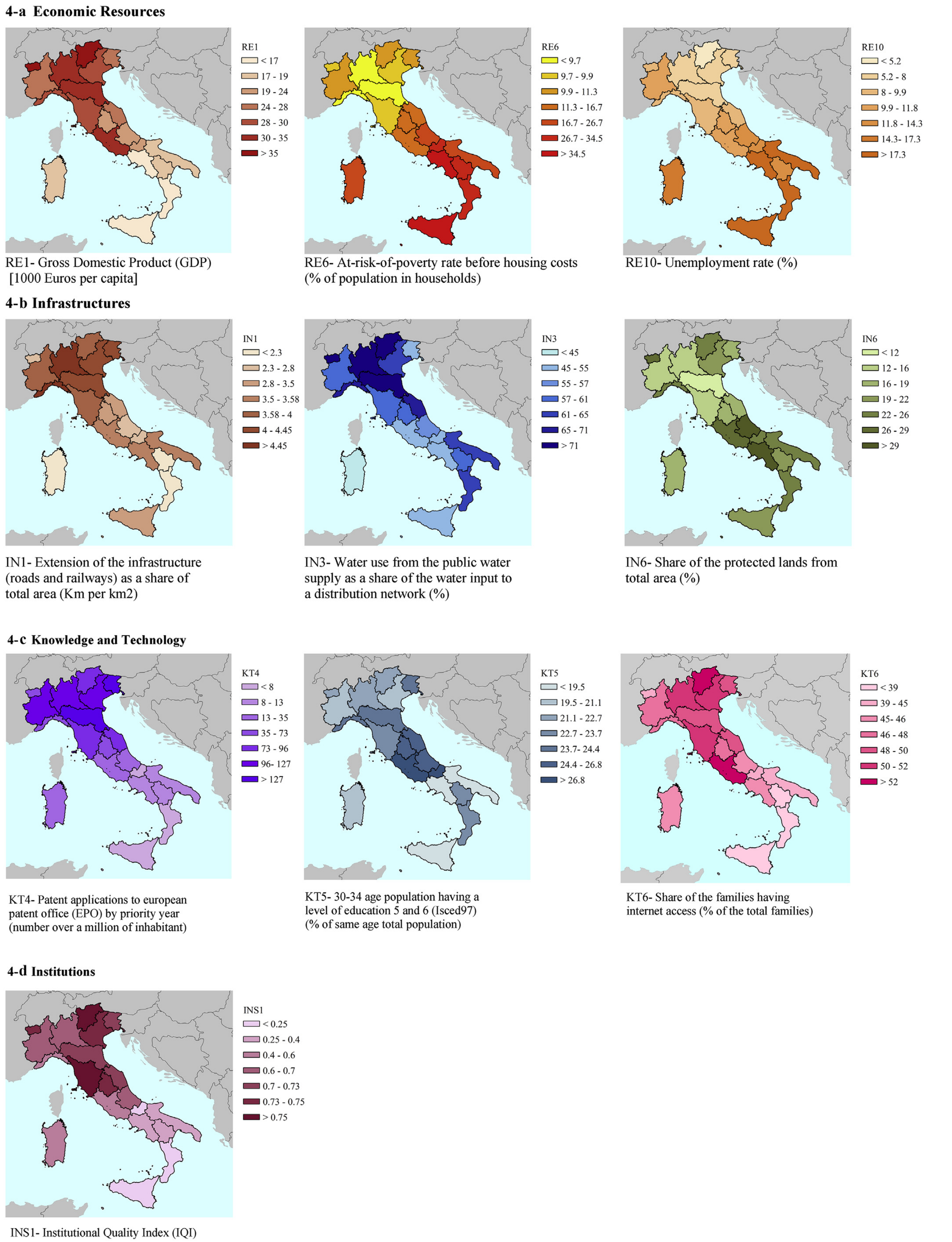


Fig. 4. Mapping the original data regarding to indicators' set.

Table 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	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

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., 2017). More information on Fuzzy overlay functions is included in the supplementary electronic material.

$$Fuzzy\ Gamma = (Fuzzy\ SUM)^{\gamma} \cdot (Fuzzy\ PRODUCT)^{1-\gamma} \tag{5}$$

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 $\gamma < 0.6$, FGF results in lower aggregated scores than minimum input values, which means that the fuzzy PRODUCT prevails (restrictive behaviour) (Fig. 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 (Fig. 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 (Fig. 2-b), which creates a balance between two functions and avoids dominance of either them.

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 Fig. 3. The data has been normalized using linear min-max function.

After the final aggregate ACI for each province was calculated by means of FGF, the regional ACI was regenerated through two different aggregation procedures (Fig. 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 Fig. 1).

3. Results and discussion

3.1. ACI at regional scale

Fig. 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 are 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 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).

Fig. 5 shows the ACI results based on PCA weights (aggregated scores and ranking positions by classes as in Table 2). The rankings obtained using equal and ESPON weights were estimated for comparison only.

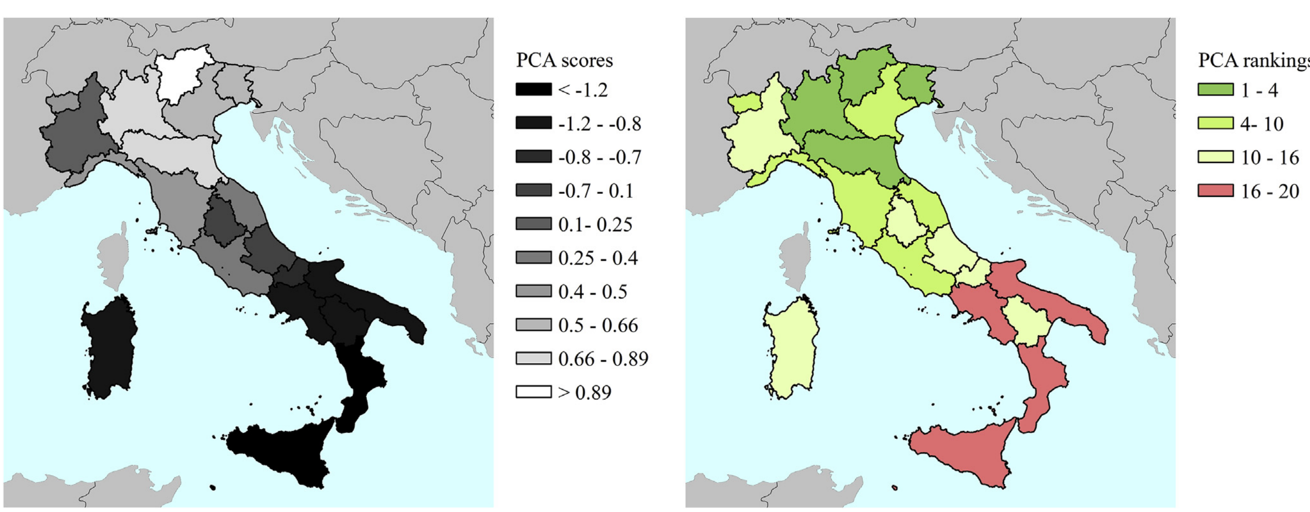


Fig. 5. Scores and rankings derived by implementing PCA weighting.

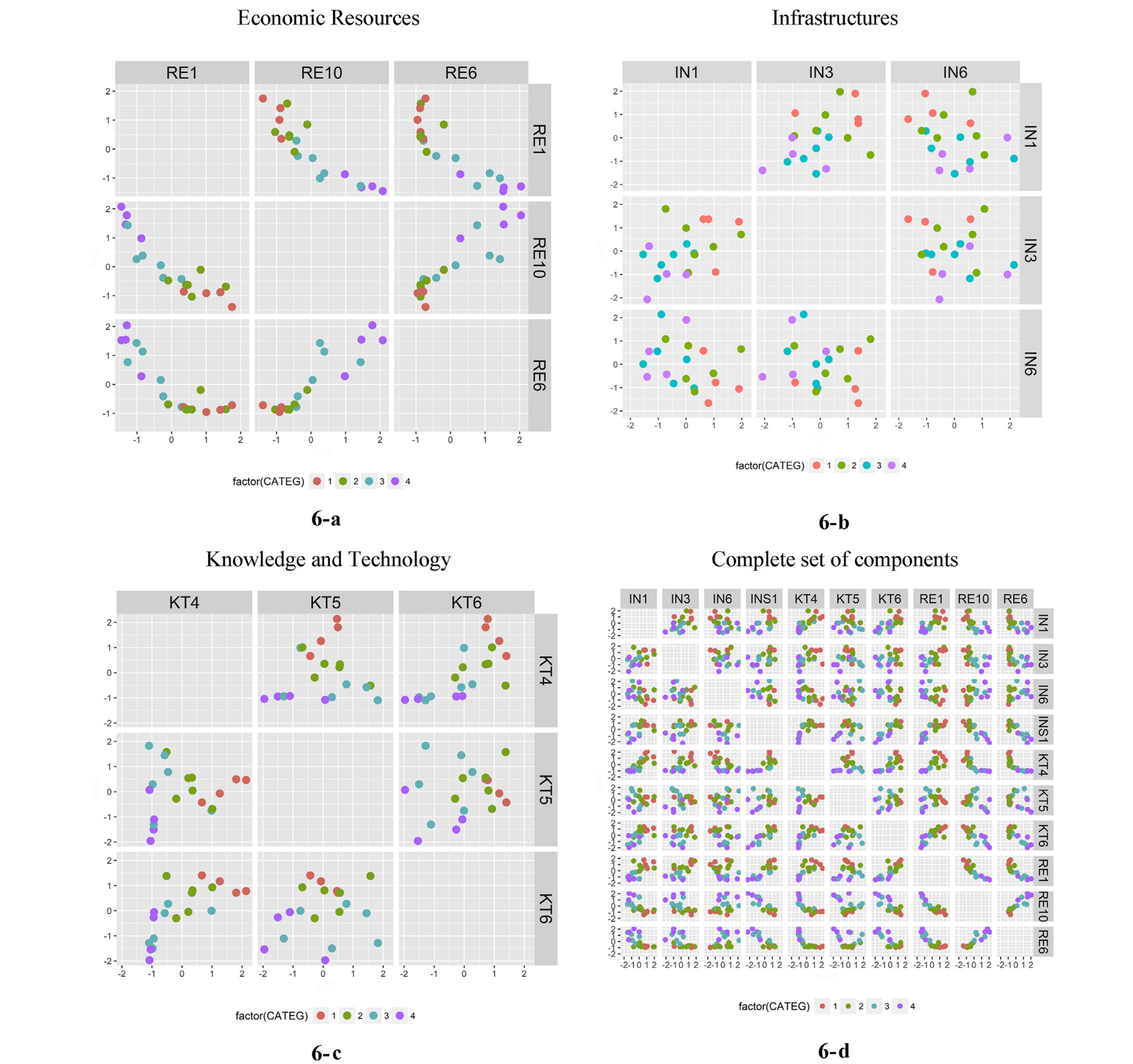


Fig. 6. Group-means distributions regarding the best, worst and intermediate category of the regions.

Fig. 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 Fig. 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 Fig. 6-a. Similar patterns can be observed in Fig. 6-c for knowledge and technology criteria. This indicates that the aggregation had minor influence on the implicit order of the initial data. Fig. 6-b shows a greater dispersion in clusters. The dispersion is caused by non-linear trade-offs between the underlying indicators. In a nutshell, Fig. 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).

3.2. AC at provincial scale

Fig. 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.

As an example, a sizeable variability can be observed across the provincial PCA scores in Lombardia (Fig. 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 Milano, 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

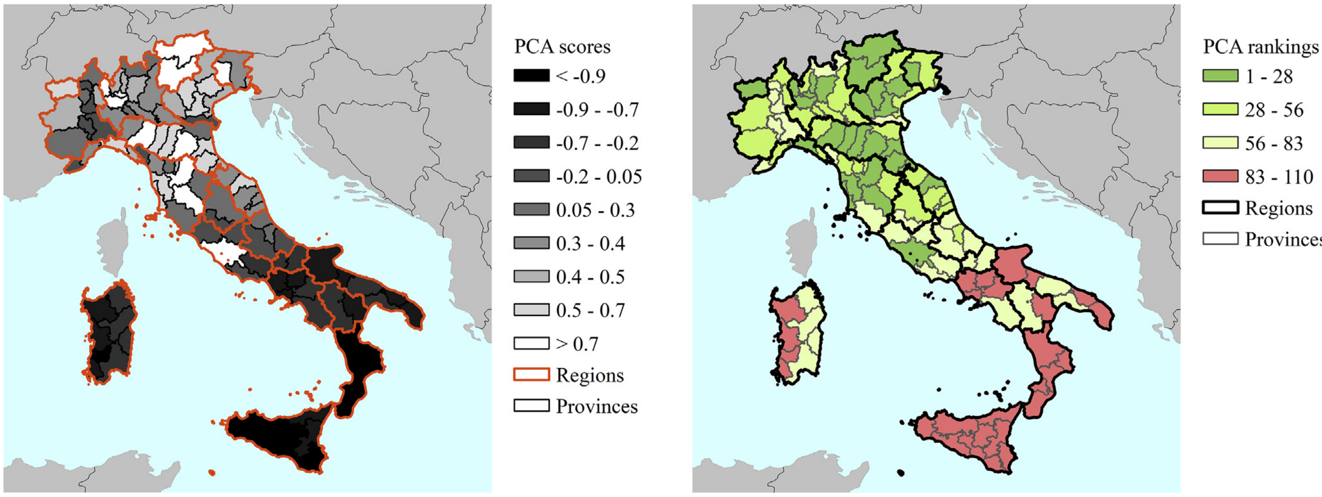


Fig. 7. Provincial scores and rankings derived by implementing PCA weighting.

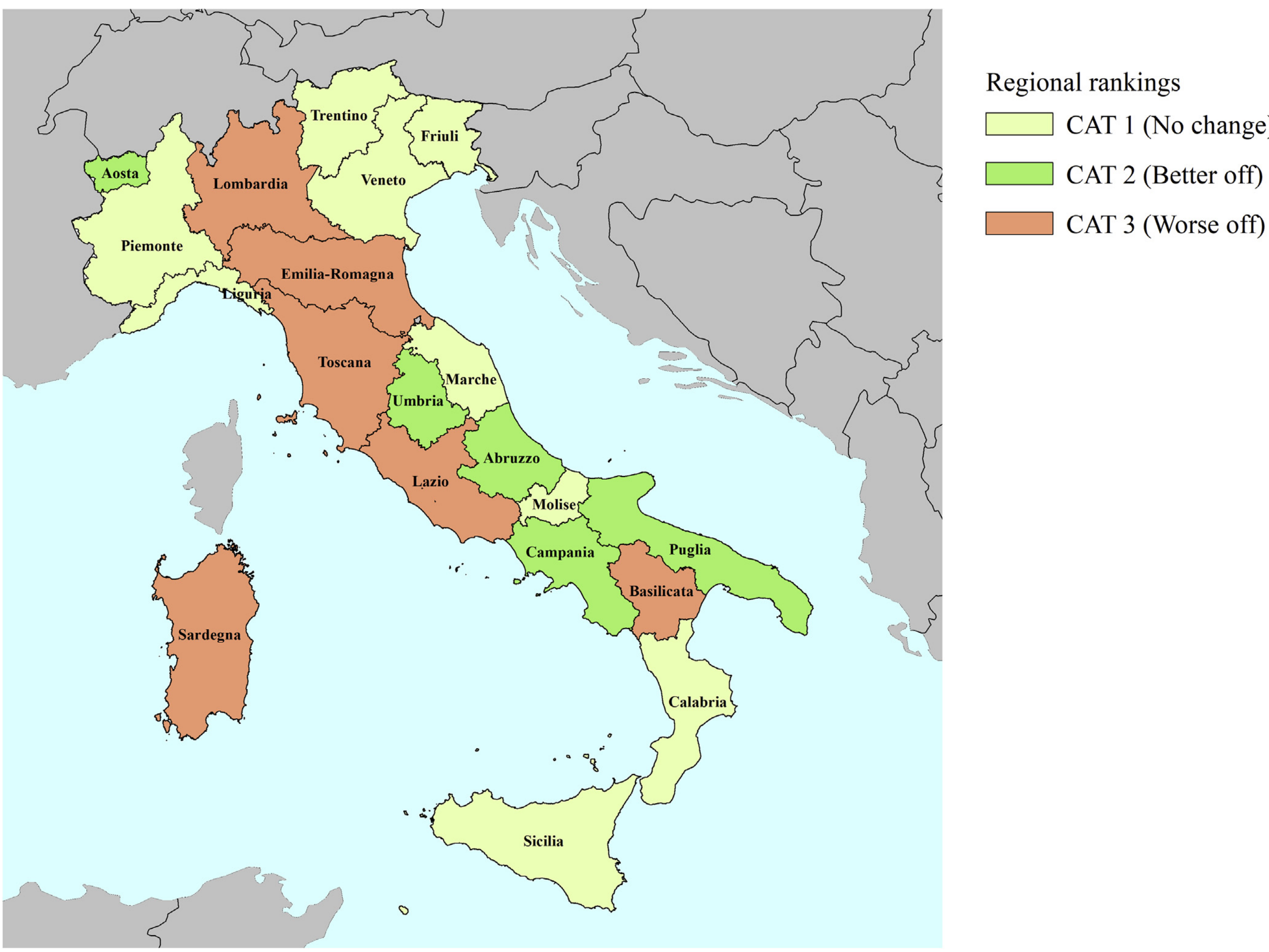


Fig. 8. Final regional results derived by the implemented methodology.

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 Lombardia, 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. Lombardia is just one example for other regions, particularly those comprising larger metropolitan areas such as Emilia-Romagna (Bologna) or Lazio (Rome) (Fig. 8). To explore this issue further, in the next section we reconstructed regional ACI based on the sub-regional performance and variability.

Table 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

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 3 shows the final reassessed rankings, along with the original rankings (obtained from PCA weights) for comparisons.

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

Fig. 9 shows the pairwise comparison of the rankings obtained by using different aggregators illustrated from high to low compensation degrees.

In Fig. 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, Fig. 9-b and Fig. 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 Lombardia and Frosinone in Lazio, with very low AC levels (Fig. 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.

Fig. 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. Fig. 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 FGF outcomes of such regions are close to zero, which leads to approximately the same positions for all of them (15th position in Fig. 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 (Fig. 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 Fig. 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.

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.

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

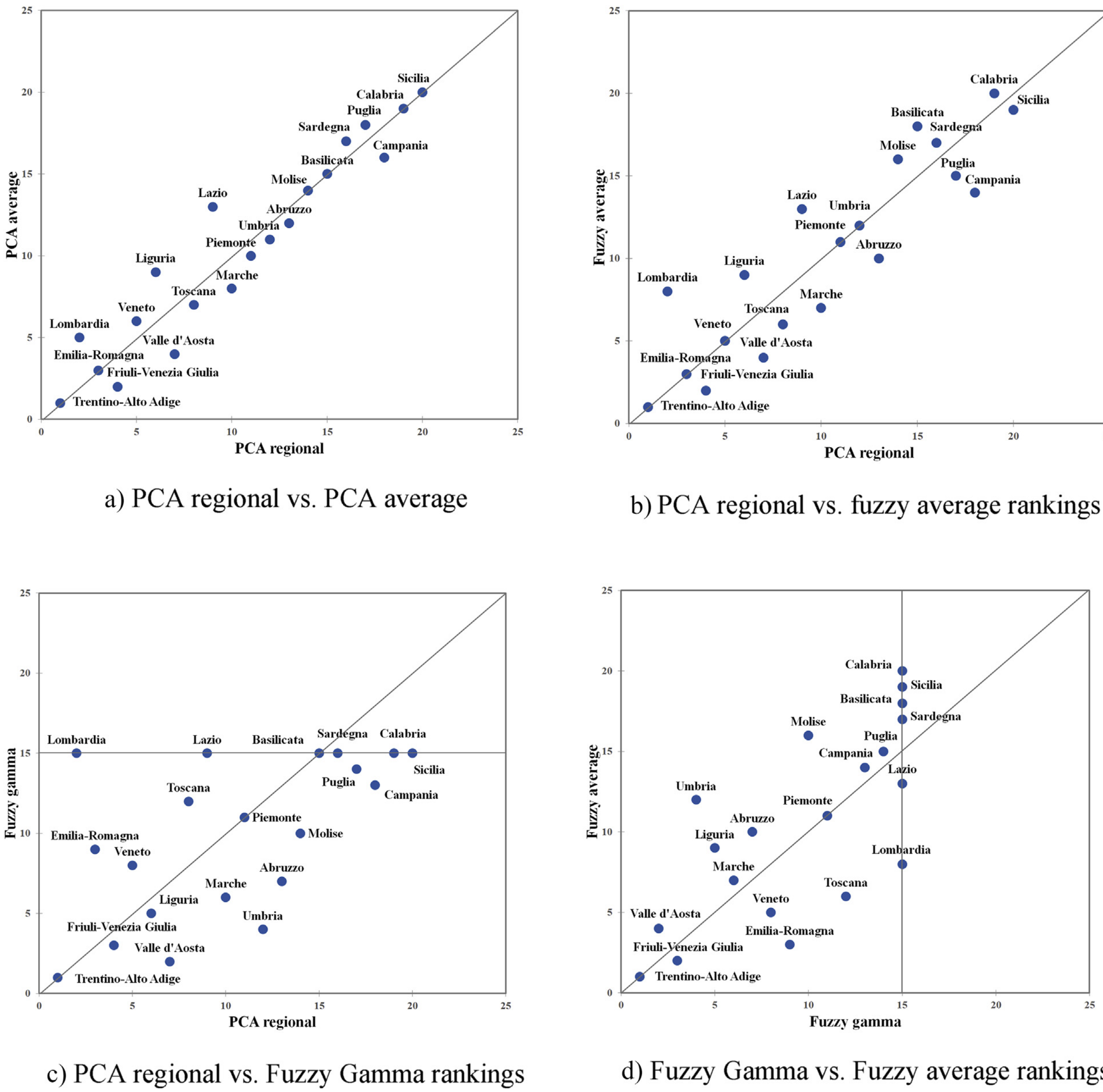
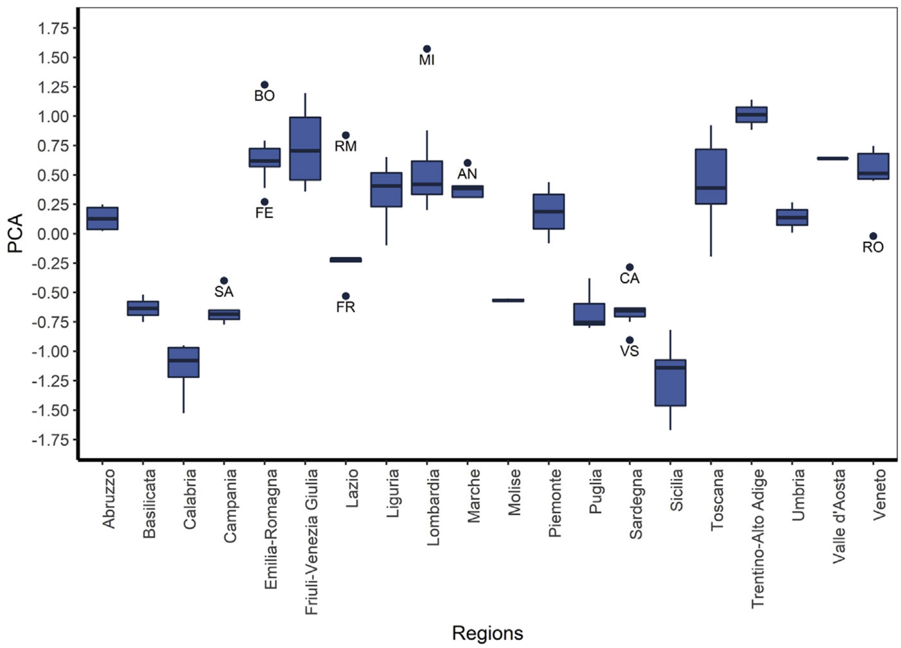


Fig. 9. Pairwise comparisons of the rankings attained from different aggregation methods.

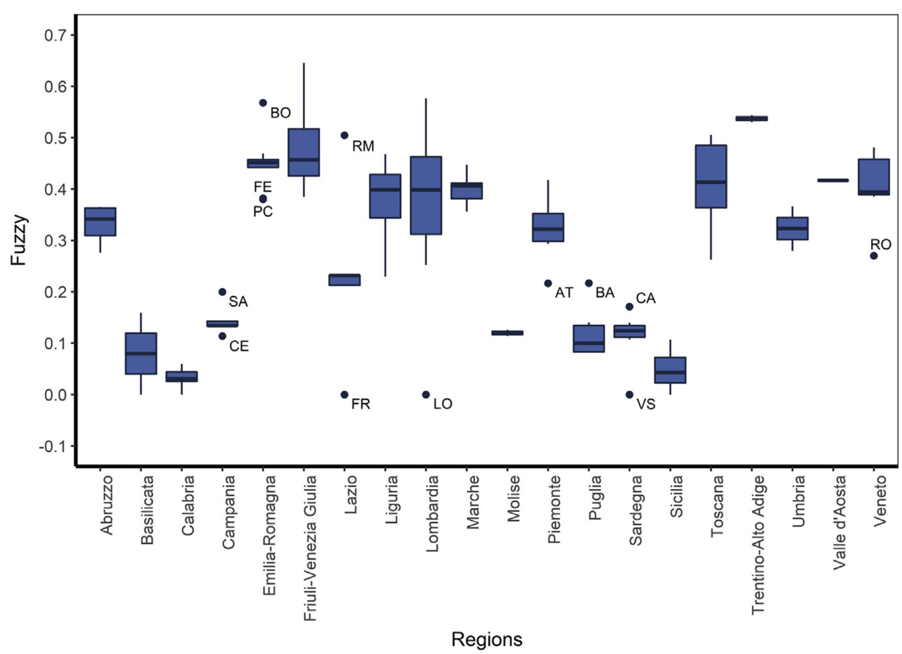
geographical scales, otherwise policy and decision makers may be misled in adopting ill-suited adaptation strategies. Quantitative, indicator-based assessments are typically employed to measure adaptive capacity, by combining several disparate performance indicators into a composite index. The methodological 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, 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



a) Variability and outliers for PCA regional results



b) Variability and outliers for Fuzzy Gamma results

Fig. 10. PCA and Fuzzy Gamma provincial variability analysis.

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 snapshotassessment 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.

Acknowledgements

This publication is part of the project CLARA "Climate forecast enabled knowledge services" that has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No 730482.

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.jenvman.2018.06.060.

References

Acosta, L., Klein, R.J.T., Reidsma, P., Metzger, M.J., Rounsevell, M.D.A., Leemans, R., Schröter, D., 2013. A spatially explicit scenario-driven model of adaptive capacity to global change in Europe. Global Environ. Change 23, 1211–1224. https://doi.org/10.1016/j.gloenvcha.2013.03.008.

Adger, W., Agrawala, S., Mirza, M., Conde, C., 2007. Assessment of adaptation practices, options, constraints and capacity. Climatic Change 200, 719–743.

Adger, W., Brooks, N., Bentham, G., Agnew, M., Eriksen, S., 2004. New indicators of vulnerability and adaptive capacity. Tyndall Cent. Clim. Chang. Res. 122.

Aggarwal, M., 2015. Compensative weighted averaging aggregation operators. Appl. Soft Comput. 28, 368–378. https://doi.org/10.1016/J.ASOC.2014.09.049.

Araya-Muñoz, D., Metzger, M.J., Stuart, N., Wilson, A.M.W., Alvarez, L., 2016. Assessing urban adaptive capacity to climate change. J. Environ. Manag. 183, 314–324. https://doi.org/10.1016/j.jenvman.2016.08.060.

Aroca-Jimenez, E., Bodoque, J., Garcia, J., 2017. Construction of an Integrated Social Vulnerability Index in urban areas prone to flash flooding. Nat. Hazards Earth Syst. Sci. 17, 1541. https://doi.org/10.5194/nhess-17-1541-201.

Bizikova, L., Bellali, J., Habtezion, Z., Diakhite, M., Pinter, L., 2009. IEA Training Manual Volume Two: Vulnerability and Impact Assessment for Adaptation to Climate Change (VIA Module). United Nations Environ. Program.

Brooks, N., Adger, W., 2005. Assessing and enhancing adaptive capacity. In: Adaptation Policy Frameworks for Climate Change: Developing Strategies, Policies and Measures. UNDP-GEF, Cambridge University Press, Cambridge, pp. 165–181.

Cutter, S.L., Boruff, B.J., Shirley, W.L., 2003. Social vulnerability to environmental hazards. Soc. Sci. Q. 84, 242–261. https://doi.org/10.1111/1540-6237.8402002.

De Groeve, T., Poljansek, K., Vernaccini, L., 2015. Index for risk management - inform. JRC Sci. Policy Reports - Eur. Comm. 96.

Di Berardino, C., D'Ingiullo, D., Quaglione, D., Sarra, A., 2017. The effect of skilled migration on institutional quality of Italian provinces. In: ERSA (European Regional Science Association) Social Progress for Resilient Regions. Groningen, Netherlands.

EEA, 2017a. Nationally Designated Areas (CDDA). Eur. Environ. Agency [WWW Document]. https://www.eea.europa.eu/data-and-maps/data/nationally-designated-areas-national-cdda-12, Accessed date: 4 August 2018.

EEA, 2017b. Natura 2000 Data - the European Network of Protected Sites. Eur. Environ. Agency [WWW Document]. https://www.eea.europa.eu/data-and-maps/data/natura-9, Accessed date: 4 August 2018.

EEA, 2015. National Monitoring, Reporting and Evaluation of Climate Change Adaptation in Europe (No. 20/2015). European Environment Agency, Luxembourg. https://doi.org/10.2800/629559.

Engle, N., 2011. Adaptive capacity and its assessment. Global Environ. Change 21, 647–656. https://doi.org/10.1016/j.gloenvcha.2011.01.019.

ESPON, 2012. The Territorial Dimension of Poverty and Social Exclusion in Europe (TiPSE).

ESPON, 2011. ESPON CLIMATE-climate Change and Territorial Effects on Regions and Local Economies.

Eurostat, 2017. Eurostat Database. [WWW Document]. http://ec.europa.eu/eurostat/data/database, Accessed date: 10 February 2017.

Fekete, A., 2009. Validation of a social vulnerability index in context to river-floods in Germany. Nat. Hazards Earth Syst. Sci. 9, 393–403. https://doi.org/10.5194/nhess-9-393-2009.

Fernandez, M., Bucaram, S., Renteria, W., 2017. (Non-) robustness of vulnerability assessments to climate change: an application to New Zealand. J. Environ. Manag. 203, 400–412. https://doi.org/10.1016/j.jenvman.2017.07.054.

Herath, G., Prato, T., 2016. Using Multi-criteria Decision Analysis in Natural Resource Management. Routledge, New York.

Hinkel, J., Bharwani, S., Bisaro, A., Carter, T., Cull, T., Davis, M., Klein, R., Lonsdale, K., Rosentrater, L., Vincent, Katharine, 2013. PROVIA Guidance on Assessing Vulnerability, Impacts and Adaptation to Climate Change. United Nations Environmental Programme (UNEP), Nairobi, Kenya.

Huynh, L.T.M., Stringer, L.C., 2018. Multi-scale assessment of social vulnerability to climate change: an empirical study in coastal Vietnam. Clim. Risk Manag 20, 165–180. https://doi.org/10.1016/J.CRM.2018.02.003.

IPCC, 2016. IPCC. Intergov. Panel Clim. Chang [WWW Document]. http://www.ipcc.ch/ipccreports/tar/wg2/index.php?idp=650.

IPCC, 2014. Annex II: Glossary. In: Mach, K.J., Planton, S., von Stechow, C. (Eds.), Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, pp. 117–130 Geneva, Switzerland.

IPCC, 2014b. Summary for policymakers. In: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group I I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 1–32.

IPCC, 2007. In: Parry, M.L., Canziani, O.F., Palutikof, J.P., van der Linden, P.J., Hanson, C.E. (Eds.), Climate Change 2007: Impacts, Adaptation and Vulnerability: Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press.

ISTAT, 2017. ISTAT Database. [WWW Document]. http://dati.istat.it/?lang=en (accessed 10.23.17).

ISTAT, 2015. Indicatori territoriali per le politiche di sviluppo. [WWW Document] (accessed 9.JanuaryMay.2017). http://www.istat.it/it/archivio/16777.

Jacobs, R., Goddard, M., 2007. How do performance indicators add Up? An examination of composite indicators in public services. Publ. Money Manag. 27, 103–110. https://doi.org/10.1111/j.1467-9302.2007.00565.x.

Juhola, S., Kruse, S., 2015. A framework for analysing regional adaptive capacity assessments: challenges for methodology and policy making. Mitig. Adapt. Strategies Glob. Change 20, 99–120. https://doi.org/10.1007/s11027-013-9481-z.

KC, B., Shepherd, J.M., Gaither, C.J., 2015. Climate change vulnerability assessment in Georgia. Appl. Geogr. 62, 62–74. https://doi.org/10.1016/j.apgeog.2015.04.007.

Kenney, M.A., Chen, R.S., Maldonado, J., Quattrochi, D., 2012. NCA Report Series. Climate Change Impacts and Responses Vol. 5c Societal Indicators for the National Climate Assessment, Washington, D.C.

Lai, Y.-L., Lin, F.-J., 2012. The effects of knowledge management and technology innovation on new product development performance an empirical study of Taiwanese machine tools industry. Procedia - Soc. Behav. Sci. 40, 157–164. https://doi.org/10.1016/J.SBSPRO.2012.03.176.

Langhans, S.D., Reichert, P., Schuwirth, N., 2014. The method matters: a guide for indicator aggregation in ecological assessments. Ecol. Indicat. 45, 494–507. https://doi.org/10.1016/J.ECOLIND.2014.05.014.

Lee, S., 2007. Application and verification of fuzzy algebraic operators to landslide susceptibility mapping. Environ. Geol. 52, 615–623. https://doi.org/10.1007/s00254-006-0491-y.

Lemos, M.C., Agrawal, A., Eakin, H., Nelson, D.R., Engle, N.L., Johns, O., 2013. Building adaptive capacity to climate change in less developed countries. Clim. Sci. Serv. Soc. 437–457. https://doi.org/10.1007/978-94-007-6692-1_16.

Lewis, S.M., Fitts, G., Kelly, M., Dale, L., 2014. A fuzzy logic-based spatial suitability model for drought-tolerant switchgrass in the United States. Comput. Electron. Agric. 103, 39–47. https://doi.org/10.1016/J.COMPAG.2014.02.006.

Liu, Y., Zhou, J., Chen, Y., 2014. Using fuzzy non-linear regression to identify the degree of compensation among customer requirements in QFD. Neurocomputing 142, 115–124. https://doi.org/10.1016/J.NEUCOM.2014.01.053.

MATTM, 2017. Piano Nazionale di Adattamento ai Cambiamenti Climatici PNACC. Minist. dell'Ambiente e della Tutela del Territ. e del Mare.

Mazumdar, J., Paul, S., 2016. Socioeconomic and infrastructural vulnerability indices for cyclones in the eastern coastal states of India. Nat. Hazards 82. https://doi.org/10.1007/s11069-016-2261-9.

Mclaughlin, S., Cooper, J.A.G., 2010. A multi-scale coastal vulnerability index: a tool for coastal managers? Environ. Hazards 9, 233–248. https://doi.org/10.3763/ehaz.2010.0052.

Metzger, M., Leemans, R., Schröter, D., 2005. A multidisciplinary multi-scale framework for assessing vulnerabilities to global change. Int. J. Appl. Earth Obs. Geoinf. 7, 253–267. https://doi.org/10.1016/j.jag.2005.06.011.

Metzger, M.J., Schröter, D., Leemans, R., Cramer, W., 2008. A spatially explicit and quantitative vulnerability assessment of ecosystem service change in Europe. Reg. Environ. Change 8, 91–107. https://doi.org/10.1007/s10113-008-0044-x.

Mysiak, J., Torresan, S., Bosello, F., Mistry, M., Amadio, M., Marzi, S., Furlan, E., Sperotto, A., 2018. Climate risk index for Italy. Philos. Trans. R. Soc. London. Ser. A Math. Phys. Eng. Sci. 376 (2121). https://doi.org/10.1098/rsta.2017.0305.

Nardo, M., Saisana, M., Saltelli, A., Tarantola, S., 2005. Tools for composite indicators building. Eur. Comm. Jt. Res. Cent. EUR 21682 EN.

Nifo, A., Vecchione, G., 2014. Do institutions play a role in skilled migration? The case of Italy. Reg. Stud. 48, 1628–1649. https://doi.org/10.1080/00343404.2013.835799.

O'Brien, K., Sygna, L., Haugen, J.E., 2004. Vulnerable or Resilient? A multi-scale assessment of climate impacts and vulnerability in Norway. Climatic Change 64, 193–225. https://doi.org/10.1023/B:CLIM.0000024668.70143.80.

OECD, 2008. Handbook on Constructing Composite Indicators. OECD Publ.

Pelling, M., High, C., 2005. Understanding adaptation: what can social capital offer assessments of adaptive capacity? Global Environ. Change 15, 308–319. https://doi.org/10.1016/j.gloenvcha.2005.02.001.

Pinar, M., Cruciani, C., Giove, S., Sostero, M., 2014. Constructing the FEEM sustainability

index: a Choquet integral application. Ecol. Indicat. 39, 189–202. https://doi.org/10.1016/j.ecolind.2013.12.012.
Preston, B., Stafford-Smith, M., 2009. Framing Vulnerability and Adaptive Capacity Assessment: Discussion Paper.
Sema, H.V., Guru, B., Veerappan, R., 2017. Fuzzy gamma operator model for preparing landslide susceptibility zonation mapping in parts of Kohima Town, Nagaland, India. Model. Earth Syst. Environ. 3, 499–514. https://doi.org/10.1007/s40808-017-0317-9.
Sietchiping, R., 2006. Applying an index of adaptive capacity to climate change in north-western Victoria, Australia. Appl. GIS 2, 1–16.
Smit, B., Pilifosova, O., 2003. Adaptation to climate change in the context of sustainable development and equity. Sustain. Dev. 8.
Smit, B., Wandel, J., 2006. Adaptation, adaptive capacity and vulnerability. Global Environ. Change 16, 282–292. https://doi.org/10.1016/j.gloenvcha.2006.03.008.
Sullivan, C., 2002. Calculating a water poverty index. World Dev. 30, 1195–1210. https://doi.org/10.1016/S0305-750X(02)00035-9.
Swanson, D., Hiley, J., Venema, H., Grosshans, R., 2007. Indicators of Adaptive Capacity to Climate Change for Agriculture in the Prairie Region of Canada: an Analysis Based on Statistics Canada's Census of Agriculture. Working Paper for the Prairie Climate Resilience Project. Winnipeg.
Tapia, C., Abajo, B., Feliu, E., Mendizabal, M., Antonio Martinez, J., Fernández, J., Laburu, T., Lejarazu, A., 2017. Profiling urban vulnerabilities to climate change: an indicator-based vulnerability assessment for European cities. Ecol. Indicat. 78, 142–155. https://doi.org/10.1016/j.ecolind.2017.02.040.
Tate, E., 2012. Social vulnerability indices: a comparative assessment using uncertainty and sensitivity analysis. Nat. Hazards 63, 325–347. https://doi.org/10.1007/s11069-012-0152-2.
Vincent, K., 2007. Uncertainty in adaptive capacity and the importance of scale. Global Environ. Change 17, 12–24. https://doi.org/10.1016/j.gloenvcha.2006.11.009.
Vincent, K., 2004. Creating an Andex of Social Vulnerability to Climate Change for Africa (No. 56). Tyndall Centre for Climate Change Research.
Yohe, G., Tol, R., 2002. Indicators for social and economic coping capacity—moving toward a working definition of adaptive capacity. Global Environ. Change 12, 25–40. https://doi.org/10.1016/S0959-3780(01)00026-7.