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Methodological Considerations on Regional Sustainability Assessment based on Multicriteria and Sensitivity Analysis

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Abstract: This paper proposes the use of a non-compensatory multicriteria approach combined with sensitivity analysis for constructing composite indicators of sustainability. An illustrative example on Spanish and selected Mediterranean regions is used. The sensitivity analysis shows that excluding an indicator from a 29-indicator dataset (which represents in principle a small structural change) has a much lower impact on the regional ranking if that is based on a non-compensatory multicriteria approach than on the classical linear aggregation, for example the weighted arithmetic average. An alternative approach that employs endogenous weighting (region-specific weights) and is based on data envelopment analysis is discussed.

Key Words: Regional Sustainability, Composite Indicators, Multi-Criteria Evaluation, Sensitivity Analysis

JEL Classification Numbers: A12, C43, Q01, R11

1. Introduction

The world population increase and the rapid development of economic activity are the main causes of the environmental tensions that exist in all socio-economic systems. Problems such as the greenhouse effect and climatic change, the depletion of the ozone layer, acid rain, the loss of biodiversity, and the pollution and depletion of renewable and non-renewable natural resources are clear symptoms of a possible environmental unsustainability (e.g. Allen et al., 2002; Barbier and Markandya, 1990; Yahe and Schlesinger, 2002).

Awareness of the real and potential conflicts between economic growth and the environment has paved the way for the concept of *sustainable development*, which is highly attractive in part because unlike Daly's idea of "zero growth" (Daly, 1977), it does not pit economic growth against environmental conservation, rather it defends the idea of harmonisation between or *simultaneous realisation* of economic growth and environmental concerns.

The objective of “green accounting” is to furnish information on the sustainability of the economy, but there is no established doctrine on how the different, and at times even contradictory, variables and indicators are to be combined so that they are made immediately useful for policy making in the same way that GDP or other macroeconomic statistics are. How can the destruction of resources be accounted for if they are not inventoried or if there are no property rights? How can monetary values be included along with intangible impacts (due to trade or international externalities such as exports of carbon dioxide) beyond borders? Setting aside monetary values, how can physical indicators be included? Different physical indicators can show contradictory tendencies, and as a result “aggregating” them (in order to classify the situation) becomes difficult due to the subjective nature of the problem.

Our starting point is the broadly accepted notion that sustainability is a multidimensional concept. In the majority of research proposals or projects aimed at developing sustainability indicators, this multidimensional character is present, although it is not always included in the same way nor with the same interpretation (e.g., Faucheux and O’Connor, 1998; Gibbs, 2006; Musu and Siniscalco, 1996; Pearce et al., 1996).

It is precisely the existence of multiple dimensions, along with that of their multiple interrelationships, that explains the difficult task of analysing sustainability. Taken as a whole, there is no generally accepted way of framing the analysis within which a study of sustainability should be performed. However, the common feature of all the proposals reviewed is the three dimensional structure of sustainability encompassing social, economic/institutional and environmental aspects. A second important issue, still controversial in the literature, is how to reduce or synthesise the number of relevant indicators. Moreover, the existence of different levels and scales at which a hierarchical system can be analyzed implies the unavoidable existence of non-equivalent descriptions of it (Giampietro, 1994).

By understanding, sustainable development has a global dimension. However, the existence of mutual interaction between local and global processes is also increasingly recognised. In particular, regions and cities are open systems impacting on all other areas and on the earth as a whole. In this paper, we adopt the geographical scale of a regional level; thus its peculiarities have to be considered (see e.g. Munda, 2006; Nijkamp and Giaotzi, 1993, Wallis et al., 2007)..

Quantitative measurement is needed to create a context for sound policy-making. Indicators that permit cross-region comparisons provide a further foundation for evaluating results, benchmarking performance and clarifying what might be achieved in particular circumstances. In this paper, we use an illustrative numerical example to demonstrate how few statistical approaches that are versatile and deal with different methodological assumptions can gauge the technical quality of a ranking system.

We propose a methodological framework based on a non-linear/non-compensatory multicriteria approach (Munda, 2005; Munda and Nardo, 2009) and combined with sensitivity analysis (Saisana et al., 2005; Saltelli et al. 2000; 2004; 2008). The approach we present here can be used as a policy guide to:

- identify priority sustainability issues;
- determine where current policies are producing good results or where they are insufficient;
- provide a baseline for cross-region performance comparisons;
- identify leaders and laggards on an issue-by-issue basis; and
- identify best practices and successful policy models.

Since the importance of combining sensitivity analysis with the non-compensatory approach can be best gauged by means of numerical examples, we start by explaining in Section 2 how dimensions and indicators have been chosen in a hypothetical framework of sustainability developed for Spanish and selected Greek and Italian regions. Section 3 describes methodological issues of the nonlinear/noncompensatory multicriteria ranking system and sketches upon an alternative approach that employs data envelopment analysis. Section 4 presents the regional rankings obtained by means of the multicriteria approach. The impact of excluding an indicator at-a-time from the framework under the non-compensatory multicriteria approach is assessed and confronted with that of the classical linear (and compensatory) aggregation. The ranking produced by the multicriteria approach is finally compared to the ranking produced by Data Envelopment Analysis. Section 5 summarises the main conclusions of the study.

2. An illustrative example

We start from the assumption that on-the-ground conditions are the ultimate gauge of sustainability performance, thus measurable outcomes that can be linked to policy targets and, in principle, tracked over time are needed.

In our study, we will use a hypothetical example to illustrate that even few statistical approaches that are versatile and entail different methodological assumptions can gauge the technical quality of a ranking system. The illustrative framework is built around the three main dimensions of sustainability - environment, society, economy- and has been based on 29 indicators from the regional database REGIO of Eurostat and the Spanish National Statistical Office. The choice of the indicators was based on: (a) relevance to the issue of sustainability, (b) reliable measurement data, (c) few or no missing values (2004, or nearest year) for the Spanish regions and selected Greek and Italian regions that have similar climatic and economic conditions with the Spanish regions. Table 1 presents the list of the indicators considered in the illustrative example. The full data set for the Spanish regions, together with the relevant data sources can be found in the Annex.

Table 1: Dimensions, Indicators and Optimal performance

We discuss next a few directional issues for some of the indicators, so as to make explicit the assumptions made in this analysis. *Agricultural land use* has less impact on the environment than urbanized area, thereafter the higher the indicator value the better the region’s performance from a sustainability point of view. In fact, the building industry in Spain has been the most important source of negative environmental impact in recent years. *Municipal waste collected* is used as an indicator of overall waste production and should thus be minimised. *Aging population* is expressed as percentage on the total population, thus it is considered as a minimization problem since high percentages of aging population may be considered a socio-economic source of un-sustainability in most European countries (as a result of the low birth rates and not of a longer life of people, which of course is a positive feature). *Population density* has to be minimized in the current context since it is considered as a quality of life indicator. As an ecological indicator, on the contrary, it should be maximized.

3. The Measurement Framework

3.1 A Regional Sustainability Composite Indicator Based on Non-compensatory Multicriteria Evaluation

Although various functional forms for the aggregation of indicators into a composite indicator (here the term composite indicator is used as synonymous of index) have been developed in the literature (e.g. Journal of Economic and Social Measurement, 2002; Saisana and Tarantola, 2002), in the standard practice, a composite indicator CI_n for a given country n , can be considered a weighted linear aggregation function applied to a set of m ($m = 1, 2, \dots, M$) normalised variables:

$$CI_n = \sum_{m=1}^M w_m y_{mn} \quad (1)$$

where y_{mn} is usually a scale adjusted variable (e.g. GDP per capita) normalized between zero and one, and w_m a weight attached to y_{mn} , with $\sum_{m=1}^M w_m = 1$ and $0 \leq w_m \leq 1$.

Munda and Nardo (2005) analyse the formal axioms behind linear aggregation (e.g., the weighted arithmetic average) and its operational implications and conclude that the use of nonlinear aggregation rules to construct composite indicators is compulsory for reasons of theoretical consistency when weights have the meaning of importance coefficients (i.e. the higher the weight the more important the individual indicator) or when the assumption of preferential independence among indicators does not hold. Moreover, in case of linear aggregation, compensability among the underlying indicators is always assumed, which implies complete substitutability among the indicators considered. For example, in a composite indicator of sustainability, economic growth can always substitute any environmental destruction or within a given dimension, e.g., the environmental dimension, clean air can compensate for a loss of potable water (Munda, 2005). From a normative point of view, such a complete compensability is often not desirable (see Munda, 2008 for a thorough discussion). For all these reasons, here we use a nonlinear/noncompensatory Condorcet consistent aggregation rule for computing the regional sustainability composite

indicator (Condorcet, 1785). When various individual indicators are used to compare the overall performance of two regions, some indicators are in favour of one region and some of the other region. As a consequence a conflict among the indicators exists. How can this conflict be treated in the light of a nonlinear/noncompensatory logic? This is the classical multicriteria discrete problem (Munda, 1995, 2008).

With this analogy in mind, Munda and Nardo (2009) present an aggregation convention for (nonlinear and noncompensatory) composite indicators able to rank different countries (or regions, cities and so on). We will use this approach in the present paper. The discrete multicriteria problem is based on the information included in the impact matrix of N regions (or alternatives in general) $\times M$ indicators (or criteria in general). The type of information needed to solve the so-called multi-criterion problem is:

- Intensity of preference (when quantitative indicator scores are present).
- Number of indicators in favour of a given region.
- Weight attached to each indicator.
- Relationship of each region with all the other regions.

Combinations of these pieces of information generate different aggregation conventions, i.e. manipulation rules of the available information to arrive at a preference structure. The aggregation of several indicators implies taking a position on the fundamental issue of compensability (Bouyssou, 1986; Bouyssou and Vansnick, 1986). Compensability refers to the existence of trade-offs, i.e. the possibility of offsetting a disadvantage on some indicators by a sufficiently large advantage on another indicator, whereas smaller advantages would not do the same. Thus a preference relation is noncompensatory if no trade-off occurs and vice versa. The use of weights combined with intensity of preference in the indicator values originates compensatory multi-criteria methods and gives the meaning of trade-offs to the weights. On the contrary, the use of weights combined with ordinal indicator values originates noncompensatory aggregation procedures and gives the weights the meaning of importance coefficients.

To give an example of how compensability works, we assume that a composite indicator is formed by four indicators: inequality, environmental degradation, GDP per capita and unemployment. Two regions A and B have respective values A: (21, 1, 1, 1) and B: (6, 6, 6,

6). These regions have equal composite indicator scores ($CI_A = CI_B = 6$) if the aggregation is additive, i.e. fully compensatory. Yet, these regions represent very different social conditions that are not reflected in the additive form of the composite indicator. If the aggregation rule is only partially compensatory, the use of a geometric aggregation, where $CI_n = \prod_{m=1}^M y_{nm}^{w_m}$ is a solution. Under the assumption of the multiplicative form of aggregation, region A has much lower composite indicator score than region B ($CI_A = 2.14, CI_B = 6.00$). Summing up, an additive aggregation implies full compensability among the indicators, whilst a multiplicative aggregation entails partial compensability.

In this paper, we employ a fully noncompensatory aggregation rule (Munda and Nardo, 2009) that is not assuming either additive or multiplicative aggregation and can be synthesised as follows. Given a set of individual indicators $G = \{g_m\}$, $m = 1, 2, \dots, M$ and a finite set $A = \{a_n\}$, $n = 1, 2, \dots, N$ of regions, let's assume that the indicator value of each region a_n with respect to an indicator g_m is based on an *ordinal, interval or ratio* scale of measurement. For simplicity of exposition, we assume that a higher indicator value is preferred to a lower one, that is:

$$\begin{cases} a_j P a_k \Leftrightarrow g_m(a_j) > g_m(a_k) \\ a_j I a_k \Leftrightarrow g_m(a_j) = g_m(a_k) \end{cases} \quad (2)$$

where P and I indicate a preference or an indifference relation respectively, both fulfilling the transitive property. Let's also assume further the existence of a set of indicator weights $W = \{w_m\}$, $m = 1, 2, \dots, M$ with $\sum_{m=1}^M w_m = 1$ that are derived as importance coefficients. The mathematical problem to be dealt with is how to use the available information to rank in a complete pre-order (i.e. without any incomparability relation) all the regions from best to worst. The mathematical aggregation convention proposed can be divided into two main steps:

1. Pair-wise comparison of regions according to the whole set of indicators used.

2. Ranking of regions in a complete pre-order.

An $N \times N$ matrix, E , called outranking matrix (Arrow and Raynaud, 1986) can be built, in which any generic element, e_{jk} , $j \neq k$ is the result of the pair-wise comparison, according to all the M indicators, between regions j and k . Such a global pair-wise comparison is obtained by means of equation (2) and the value of the e_{jk} is calculated by:

$$e_{jk} = \sum_{m=1}^M \left(w_m(P_{jk}) + \frac{1}{2} w_m(I_{jk}) \right) \quad (3)$$

where $w_m(P_{jk})$ and $w_m(I_{jk})$ are the weights of indicators presenting a preference or an indifference relation respectively. It clearly holds

$$e_{jk} + e_{kj} = 1 \quad (4)$$

Property (4), although obvious, is very important since it allows us to consider the outranking matrix E as a voting matrix i.e., a matrix where instead of using indicators, alternatives are compared by means of voters' preferences (with the principle one agent one vote). This analogy between a multi-criterion problem and a social choice one, as noted by Arrow and Raynaud (1986), is very useful for tackling the step of ranking the N regions in a consistent axiomatic framework.

The maximum likelihood principle selects as a final ranking the one with the maximum pair-wise support, which also involves the minimum number of pair-wise inversions. The adaptation of the maximum likelihood ranking procedure to the ranking problem we are dealing with is reasonably simple. The maximum likelihood ranking of regions is the ranking supported by the maximum number of individual indicators for each pair-wise comparison, summed over all pairs of regions considered. More formally, all the $N(N-1)$ pair-wise comparisons compose the outranking matrix E , where $e_{jk} + e_{kj} = 1$, with $j \neq k$. Call R the set of all $N!$ possible complete rankings of regions, $R = \{r_s\}$, $s = 1, 2, \dots, N!$ For each r_s ,

compute the corresponding score φ_s as the summation of e_{jk} over all the $\binom{N}{2}$ pairs j, k of regions, i.e.

$$\varphi_s = \sum e_{jk} \quad \text{where } j \neq k, s = 1, 2, \dots, N! \text{ and } e_{jk} \in r_s \quad (5)$$

The final ranking (r^*) is the one which maximises equation (6), which is:

$$r^* \Leftrightarrow \varphi^* = \max \sum e_{jk} \quad \text{where } e_{jk} \in R. \quad (6)$$

3.2 An alternative weighting and aggregation scheme based on Data Envelopment Analysis

In absence of reliable information about the true weights to be attached to the underlying indicators of sustainability, one can endogenously assign region-specific weights that maximize the composite indicator score for a given region using the Data Envelopment Analysis (DEA) method and a distance to best performer scaling (Melyn and Moesen, 1991; Cherchye et al., 2004). This gives the following linear programming problem for each region n in the dataset:

$$CI_n = \max_{w_{mn}} \frac{\sum_{m=1}^M y_{mn} w_{mn}}{\max_{y_c \in \{dataset\}} \sum_{m=1}^M y_{cn} w_{mn}} \quad (\text{bounding constraint}) \quad (7)$$

Subject to

$$w_{mn} \geq 0 \quad (\text{non-negativity constraint}) \quad (8)$$

where $m = 1, \dots, M$ and $n = 1, \dots, N$

In this basic programming problem, the weights are non-negative and a region's score is between 0 (worst) and 1 (best). The non-negativity restriction on the weights, however, allows for extreme scenarios. If a region has a value in a given indicator that dominates the values of other regions, this region would always obtain a score of 1.0 even if it has very low

values in many other indicators. Furthermore, it may lead to a situation where a large number of regions score 1.0, rendering the benchmarking exercise meaningless. Therefore, some additional constraints on the weights are needed, as recommended by several DEA supporters (see Thanassoulis *et al.* (2004) for a survey). We preferred to attach restrictions on the shares (instead of the weights), because shares (i) do not depend on the measurement unit of the indicators and (ii) directly reveal the contribution of an indicator to the composite indicator score (Cherchye et al., 2008; Wong and Beasley, 1990). Formally, the m -th share for a region n is given as the product $y_{mn} w_{mn}$. Clearly, the sum of the shares equals the CI_n . The constraints placed on the shares are thus expressed as:

$$L_m \leq \frac{y_{mn} w_{mn}}{\sum_{m=1}^M y_{mn} w_{mn}} \leq U_m \quad (\text{share constraint}) \quad (9)$$

with L_m and U_m the respective lower and upper bounds for the pie-shares.

4. Results and Sensitivity Analysis

In this section we discuss the results of the multicriteria ranking system and assess the impact on the benchmarking results of three main assumptions in the development of the regional composite indicator of sustainability: (a) number of indicators included in the framework, (b) aggregation function, (c) weights assigned to the indicators.

4.1. Results using the noncompensatory multicriteria approach

In our example, we assume that all indicators within each dimension receive equal weights and that all three dimensions are equally weighted, too. Table 2 presents the overall noncompensatory ranking and the ranking for each of the three sustainability dimensions. Among the 17 Spanish regions, the top five are Madrid, Navarra, Catalonia, Rioja and the

Balearic islands. The lowest five ranked regions are Asturias, Andalucia, Castilla la Mancha, Extremadura and Galicia. Mid-ranked performers include the remaining seven regions - Pais Vasco, Murcia, Valencia, Aragon, Cantabria, Castilla y Leon and Canary Islands. The geographic pattern of sustainability, as measured by the proposed framework, confronts the more sustainable north-east Spanish regions, with the less sustainable south and west regions.

It is interesting to note that the top performing regions do not necessarily have top performance in all three dimensions. In fact, Catalonia has middle performance in two dimensions (Environment and Society), whilst the Balearic Islands have middle performance in Economy and low performance in Society. On the other hand, the bottom-five performing regions do not necessarily have the lowest performance in all three dimensions. To make an example, Extremadura has a top-five performance in Society, while Andalucia and Castilla la Mancha have middle performance in two dimensions (Environment and Society). For the middle-rank regions, performance is medium in all three sub-dimensions for Aragon and Cantabria. Exceptionally, Murcia, despite its top-five performance in two dimensions (Environment and Society), it is ranked among the mid- performers. The opposite is noticed for three regions - Castilla y Leon, Canary Islands and Asturias.

Table 2: Rank of the Spanish regions in sustainability and its three dimensions based on the non-compensatory multicriteria approach

While each region has unique socio-economic and geographic characteristics, environmental policy priorities and development goals, cross-regional comparisons between different countries can nevertheless yield useful insights. To this end, we selected 4 Italian and 4 Greek regions that are similar to the Spanish regions regarding socio-economic development, climate, land area, and population density. Table 3 shows the ranking of the Spanish regions before and after the inclusion of the Italian and Greek regions.

Among the twenty-five regions studied, Lombardy (the Italian region which hosts Milan) performs best in overall sustainability. Madrid and Catalonia follow, with Tuscany (IT)

arriving at the 4th place. In general, three of the four Italian regions we analysed are among the top eight. Sicily (IT) performs lower than the other three Italian regions, although it has a middle rank (14th) in the overall sustainability ranking. All four Greek regions, including Attiki (the most urbanised region of Greece which hosts Athens, recognised as the “business capital” of the country), rank 19th or lower.

It is interesting to note that once Italian and Greek regions enter in the non-compensatory ranking system the order of the Spanish regions is only slightly affected. Catalonia and Navarra shift between 2nd and 3rd rank, and Aragon and Murcia shift between 7th and 9th rank. This result can be in part explained by the fact that the non-compensatory algorithm depends on the set of regions compared. As a consequence, this ranking procedure may not always respect the axiom of independence of irrelevant alternatives (Arrow, 1963). However, the literature suggests that a Condorcet consistent rule, such as the one we used here, has the lowest probability of occurrence of a rank reversal compared to any of the Borda consistent rules (Moulin, 1988; Young, 1988). A further explanation of why the relative position of the Spanish regions changes when the Italian and Greek regions are introduced in the analysis is related to the different number of indicators available for the Greek and Italian regions (22 indicators) compared to the 29 indicators considered for the Spanish regions.

No particular pattern is revealed between the population density in the regions and their level of sustainability. In fact, the most populated region, Attiki (GR), ranks 20th, whilst the least populated region, Castilla la Mancha, ranks 17th. This result makes it clear that population density is not determining sustainability. This argument is of course linked to the validity of the theoretical framework and the selection of the indicators, but as discussed in Section 2, the case study is illustrative. However, the argument whether population density undermines sustainability can be in principle studied in a similar way as proposed here, provided that a peer-reviewed theoretical framework has been chosen.

Table 3: Sustainability Ranking of the Spanish and Selected Italian and Greek Regions based on the non-compensatory multicriteria approach

4.2 Sensitivity Analysis Results

Every aggregate measure or ranking system has a subjective nature related, for example, to the selection of indicators, the choice of aggregation rule, or the weights attached to the indicators. Because the quality of a ranking system depends on the soundness of its assumptions, good practice requires assessment of the uncertainties in the development process. By acknowledging a variety of methodological assumptions that are intrinsic to policy research, sensitivity analysis can determine whether the main results of a ranking system change substantially when those assumptions are varied over a reasonable range of possibilities (Saisana et al. 2005, Saltelli et al. 2008; Saisana 2008; Brand et al. 2007).

The validity of the ranking system developed here is assessed by studying its sensitivity to three main sources of uncertainty (or decisions): (a) number of indicators in the dataset, (b) aggregation rule, and (c) weights of the indicators.

To begin with, we compare the impact on the ranking of excluding a single indicator from the framework and using either a linear/compensatory or a non-linear/non-compensatory multicriteria aggregation rule, while maintaining equal weights for the indicators within each dimension and equal weights for the three main dimensions. Normalisation is not needed in case of the multi-criteria approach (only ordinal information is used), while a min-max scaling in (0, 1) was undertaken prior to the linear aggregation. There were thus 30 scenarios analysed for each type of aggregation, one with the entire set of twenty-nine indicators, and 29 sets of twenty-eight indicators each. Table 4 provides statistics for the regions rank range, i.e. the difference between the worst and the best case scenario, in either the linear or the multicriteria approach. An interesting feature revealed by Table 4 is the sensitivity of the linear-based ranking system to the exclusion of a single indicator. Instead, the results based on the non-compensatory multicriteria approach are much more stable. The significant impact of such a small structural change on the regional ranking based on the linear aggregation rule is due to the compensation effects among indicators. In fact, in the linear system only 2 regions are not sensitive to the exclusion of a single indicator (shift ≤ 2 positions), whilst 20 regions shift more than (\geq) 5 positions. On the contrary, in the nonlinear/noncompensatory multicriteria system 10 regions are not sensitive, whilst only 5 regions (as opposed to twenty under the linear-based system) shift more than 5 positions in the overall 25-rank classification. To complement these results, Figure 1 and Figure 2 present the median, best and worst rank across the 30 scenarios in the multicriteria

or the additive aggregation, respectively. The four regions whose multicriteria derived rank is affected by the selection of indicators are Veneto (IT), Tuscany (IT), Sicily (IT) and Catalonia. The wide rank range for Veneto and Catalonia is due to several indicators, whilst only two indicators influence the rank of Tuscany and Sicily. To be more specific, Sicily's rank is sensitive to "Infant mortality rate" and "Patent Application", while Tuscany's rank is sensitive to "Employment" and "Foreigners with tertiary education". In the linear ranking system, the regions that present the widest rank range (more than 10 positions) are Attiki (GR), Sicily (IT) and Canary Islands. These results have shown that the nonlinear/noncompensatory ranking system is robust to small changes in the indicators' set (exclusion of one indicator at-a-time in a 29-indicator dataset), which provides a further argument in favour of a regional sustainability ranking system based on a noncompensatory multicriterion approach.

Table 4: Statistics for the rank range (difference between best and worst case scenario) of the twenty five regions studied.

Figure 1: Multi-criteria based ranking

Figure 2: Additive (linear) based ranking

After having studied the impact of the exclusion of a single indicator on the multicriteria ranking and confronted it with that of the linear-based ranking, we next analyse which regions and why would be affected by the choice of the aggregation rule when all indicators are included. Figure 3 plots the multicriteria ranks versus those of the linear aggregation. This graph allows one to see immediately which regions are compensating their deficiencies in some indicators with a relatively good performance in other indicators under a linear/compensatory logic. All those regions are found at the bottom-right part of Figure 3, e.g. Attiki, Kriti, Extremadura and Thessalia. Another apparent feature is that the aggregation method primarily affects the middle rank regions and, to a lesser extent, the most

or least sustainable regions. The two aggregation approaches have a Spearman correlation coefficient $r = 0.643$.

Figure 3: Non-Compensatory Multi-Criteria Aggregation (MCA) of Indicators v. Linear Aggregation of Indicators

We finally study the impact on the ranking of the weights to be assigned to the indicators. We employ data envelopment analysis (DEA) as discussed in Section 3.2 (Charnes *et al.*, 1978; Charnes and Cooper, 1985) which uses linear optimisation rules to calculate region-specific weights for the indicators, accepting that there is no (expert) consensus on the appropriate set of weights for the indicators. Moreover, several authors have argued that differential weighting may be desirable in composite indicators, e.g. because of different environments or political attitudes in different countries or regions (e.g. Veenhoven, 1996) or because the very idea of imposing weights may be inconsistent with the subsidiarity principle (Cherchye *et al.*, 2004). Basically, such worries are then overcome by rendering the weight selection problem endogenous for each observation. That is, the relative weight assigned to each indicator is endogenously determined in this type of performance evaluation models, so as to reflect the associated relative performance for the region under evaluation (Melyn and Moesen, 1991). In practice, endogenous weighting is attaching the higher weights to the indicators that show the best performance for a given region; thus if this region is still occupying a low position in the ranking, it is possible to state that this poor performance is reliable.

Figure 4 plots the multicriteria based ranking versus the DEA-based ranking. In our DEA application we require that the relative share of each indicator (i.e. product of indicator value and the respective weight) is between 3% and 20% of the total aggregate score. We added these constraints to avoid allowing regions to achieve a high score simply by assigning zero weight to those indicators for which they have low performance, or by assigning an unreasonably high weight to a single indicator (Cherchye *et al.*, 2007; Brand *et al.*, 2007). The rank order correlation coefficient between the two rankings is slightly lower than before, $r = 0.564$. The four Italian regions are those that are most affected by the DEA system, and

placed in a much lower rank than their multicriteria equivalent. Again, given the resemblance of the data envelopment analysis to a linear aggregation system, the impact on the regions ranks of excluding a single indicator from the dataset when using DEA is pronounced and similar to the one presented in Figure 3.

Figure 4: Non-Compensatory Multi-Criteria Aggregation (MCA) of Indicators v. Data Envelopment Analysis (DEA) Aggregation of Indicators

In our opinion, sensitivity analysis helps to gauge the robustness of the results obtained, to increase the transparency of the ranking system, to identify the regions that improve or decline under certain assumptions, and to help the framing of the debate around the use of a conceptual framework.

4.3. Correlation with the GDP

Having assessed the sensitivity of the regional sustainability ranking system to methodological assumptions, we finally come to tackle the question whether sustainability must necessarily be sacrificed to achieve economic success. The possible compatibility between economic growth and environmental protection is the core assumption of the so-called environmental Kuznets curve hypothesis (e.g., Andreoni and Levinson, 2001; Arrow et al., 1995; Deacon and Norman, 2006; Plassmann and Khanna, 2006). Figure 5 shows that there is a statistically significant and high correlation between GDP per capita and the regional sustainability rank ($r = -0.834$). The higher a region's GDP per capita, the more sustainable it is (of course by using our data and thus with all the limitations we already pointed out). Nevertheless, at every income level there is variation in the ranks, which is greatest at the lower income level. For example, Aragon does far better than St. Ellada (GR) at a similar level of income 20,000 EUR/cap. The most economically developed regions with GDP per capita above 20,000 EUR consistently score in the top ten of regional

sustainability. Exceptionally, St. Ellada (GR) is close to this turning point but its sustainability performance is one of the lowest in the dataset.

Figure 5: Non-Compensatory Multi-Criteria Aggregation (MCA) of Indicators v. GDP per capita

5. Conclusions

The study aimed primarily to present a methodological framework for assessing regional sustainability and benchmarking relative performance of the regions considered. In a realm plagued by uncertainty and often dominated by rhetoric rather than systematic analysis, this paper aims at showing how data-driven policymaking at regional level might enable movement towards a more fact-based, empirical, and analytically rigorous approach to sustainability.

The application proposed here is based on a nonlinear/noncompensatory multicriteria approach of the Condorcet type applied to an illustrative example of 29 indicators grouped in three dimensions: Environment, Society, and Economy. The sensitivity analysis results show that impact on the ranks of the exclusion of an indicator, which represents a small structural change in a 29-indicator dataset, is significantly lower in the case of the noncompensatory approach than in the case of a linear aggregation or data envelopment analysis. Thus, we can be reasonably confident in the robustness of the multicriteria rankings and the indication they provide about which regions are performing well in response to the challenges of pursuing sustainability objectives. Analysis of the results obtained and underlying data reveal a number of key points:

- Despite some data shortcomings and the conceptual complexity of bringing the range of issues that fall under the sustainability rubric into a single ranking system, this application shows that sustainability performance can be tracked in rigorously and quantitatively.
- The cross-region comparisons provide a useful way to identify leaders, laggards, and best practices on an issue-by-issue and aggregate basis. Every region lags in performance on some issues on which it can learn from the success of peer regions

either within Spain or in other Mediterranean countries (e.g., Italy and Greece in our illustrative application).

Our analysis has shown that, at least in the Mediterranean regions studied, there might be a simultaneous realisation of economic growth and sustainability concerns encompassing all three dimensions of sustainability (economy, environment, society). Furthermore, no particular pattern is revealed between the population density and the level of sustainability in the 25 Mediterranean regions studied, which may support the argument that population density is not necessarily undermining sustainability. According to the data we used, it seems that: economic growth tends to alleviate sustainability problems once a region's per capita income exceeds 20,000 EUR. But of course this result has to be taken with a lot of prudence. The results obtained depend heavily on the problem's structuring phase (Munda, 2004). In the application presented here, main delicate issues are:

1. Quality of the information available (in our case the REGIO database of Eurostat was used).
2. Choice of indicators (i.e. which representation of reality we are using considering that a set of indicators is simply a descriptive model of it. In our case the choice of the indicators served for illustration purposes only).
3. Direction of each indicator (i.e. the higher the better or vice versa. This choice is not always obvious).
4. Relative importance of the indicators (in our case region-specific weights estimated by data envelopment analysis were also used),
5. Ranking method used (in our case linear aggregation or fully noncompensatory rules).

This paper has discussed methodological issues on the development of a regional ranking system of sustainability and thus it is not meant to suggest real-world policy lessons. When composite indicators are used for policy consumption, the structuring process should heavily be based on social preferences, thus public participation becomes an essential ingredient (see e.g. Munda, 2008).

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3 Finally it is important to remember that there is no “optimal level of sustainability”, thus
4 precise benchmarks cannot be set. This limits the interpretation of findings for the relative
5 performance of regions. In fact even regions in the bottom part of the ranking might have
6 satisfactory levels of sustainability in absolute terms or vice versa top performing regions
7 might indeed be very far from sustainability in absolute ideal reference values.
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Table 1: Dimensions, Indicators and Optimal performance

<i>Dimensions</i>	<i>Indicators</i>	<i>Optimal performance</i>
Environment	Agricultural area	max
	Forest area	max
	Distances driven by trucks	min
	Municipal waste collected	min
	Forest area affected by fires	min
	Non-differentiated urban waste	min
	Differentiated urban waste	max
	Cement (consumption & sales)	min
	Abstraction of total fresh water by public water supply	min
	Investments in waste water collection and treatment facilities	max
	Population affected by diseases of the respiratory system	min
Society	Aging population	min
	Infant mortality rate	min
	Population density	min
	Crude birth rate	max
	Number of hospital beds	max
	Number of physicians /doctors	max
	Population affected by mental and behavioural disorders	min
	Population affected by alcoholic abuse	min
	Participation in General Elections	max
	Population in prison	min
Economy	Employment	max
	Gross Domestic Product	max
	Households with minimum subsidy or no income	min
	Foreigners with tertiary education	max
	Life long learning	max
	Population employed in Hi-Tech	max
	Patent application to the EPO	max
	Total intramural R&D expenditure (GERD)	max

Table 2: Rank of the Spanish regions in sustainability and its three dimensions based on the non-compensatory multicriteria approach

	<i>Overall Rank</i>	<i>Environment Rank</i>	<i>Society Rank</i>	<i>Economy Rank</i>
Madrid	1	5	4	1
Navarra	2	1	1	2
Catalonia	3	7	7	3
Rioja	4	3	5	4
Balearic islands	5	2	14	9
Pais Vasco	6	6	8	5
Murcia	7	4	3	11
Valencia	8	17	6	6
Aragon	9	10	12	7
Cantabria	10	9	10	12
Castilla y Leon	11	15	13	8
Canary Islands	12	13	15	10
Asturias	13	14	17	14
Andalucia	14	11	9	16
Castilla la Mancha	15	12	11	15
Extremadura	16	8	2	17
Galicia	17	16	16	13

Table 3: Sustainability Ranking of the Spanish and Selected Italian and Greek Regions based on the non-compensatory multicriteria approach

	<i>All Regions studied</i>	<i>Only Spanish Regions</i>
	<i>Rank</i>	<i>Rank</i>
Lombardy (IT)	1	
Madrid	2	1
Catalonia *	3	3
Tuscany (IT)	4	
Navarra *	5	2
Rioja	6	4
Balearic Islands	7	5
Veneto (IT)	8	
Pais Vasco	9	6
Aragon **	10	9
Valencia	11	8
Murcia **	12	7
Cantabria	13	10
Sicily (IT)	14	
Castilla y Leon	15	11
Andalucia	16	14
Castilla la Mancha	17	15
Canary Islands	18	12
Kriti (GR)	19	
Attiki (GR)	20	
Asturias	21	13
Extremadura	22	16
Galicia	23	17
St. Ellada (GR)	24	
Thessalia (GR)	25	

Note the rank reverse in the cases of :

* Catalonia and Navarra (shift between 2nd and 3rd rank), and

**Aragon and Murcia (shift between 7th and 9th rank).

Table 4: Statistics for the rank range (difference between best and worst case scenario) of the twenty five regions studied.

	Multi-criteria	Additive (linear)
Minimum	0 (St. Ellada, Galicia, Thessalia)	2 (Galicia, Navarra)
Average	3	7
Maximum	10 (Tuscany)	14 (Canary Islands)
Standard deviation	2.4	3.0
Less than (\leq) 2 positions	10	2
More than (\geq) 5 positions	5	20

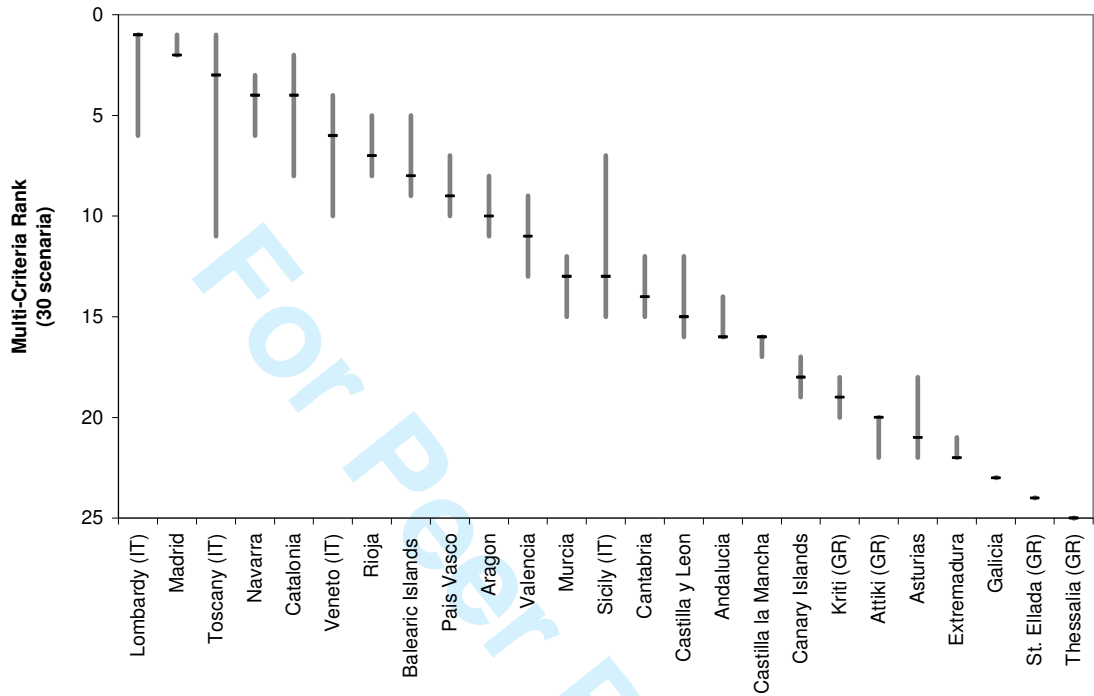


Figure 1: Multi-criteria based ranking *

*Black marks correspond to the median of the simulated ranks. Whiskers show best and worst rank across 30 scenarios produced either by considering all twenty-nine indicators, or by excluding one indicator at-a-time.

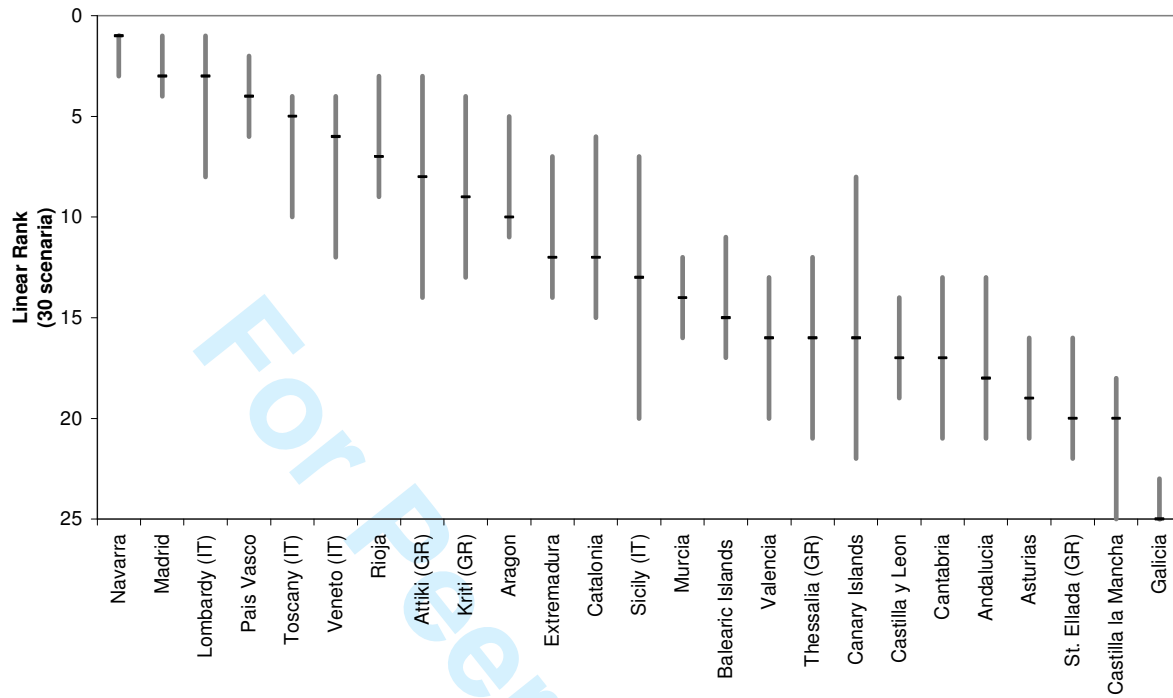


Figure 2: Additive (linear) based ranking*

*Black marks correspond to the median of the simulated ranks. Whiskers show best and worst rank across 30 scenarios produced either by considering all twenty-nine indicators, or by excluding one indicator at-a-time.

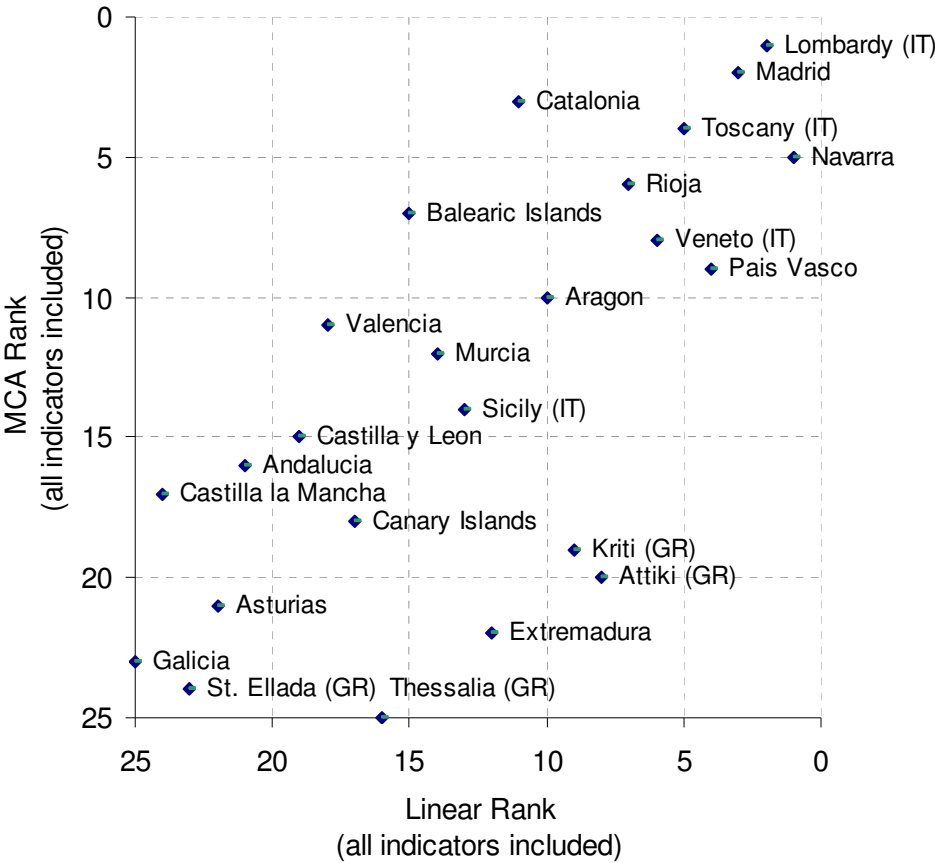


Figure 3: Non-Compensatory Multi-Criteria Aggregation (MCA) of Indicators v. Linear Aggregation of Indicators

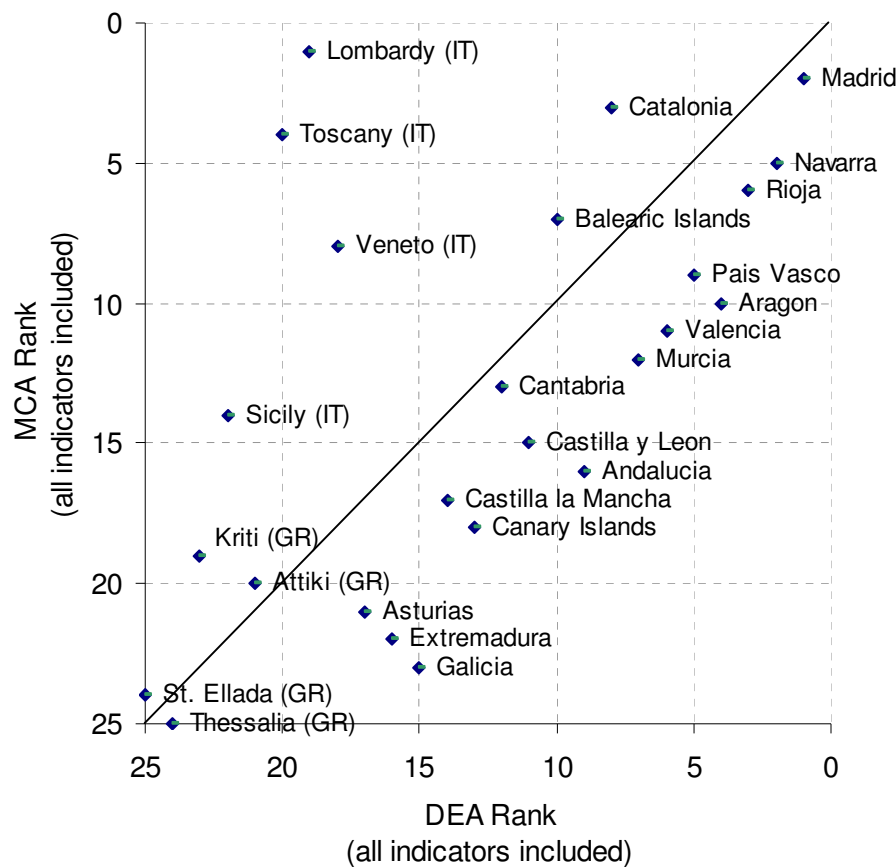


Figure 4: Non-Compensatory Multi-Criteria Aggregation (MCA) of Indicators v. Data Envelopment Analysis (DEA) Aggregation of Indicators

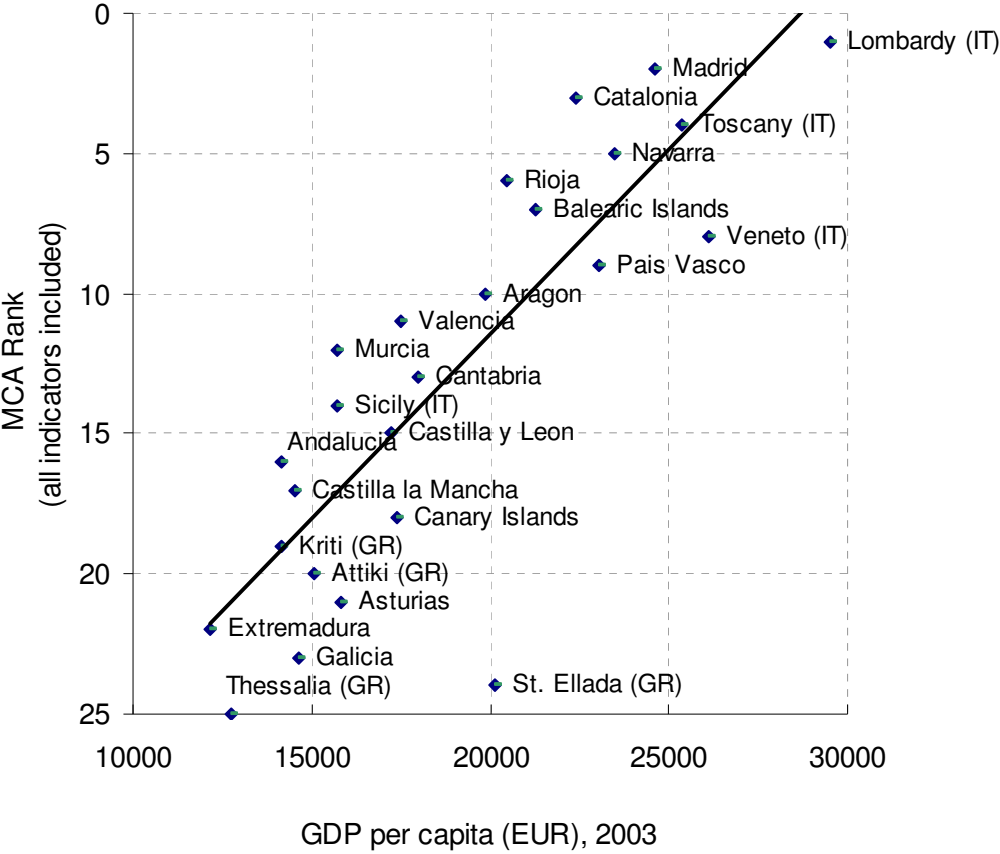


Figure 5: Non-Compensatory Multi-Criteria Aggregation (MCA) of Indicators v. GDP per capita

Annex

EVALUATION MATRIX WITH INDICATOR SCORES, DATA SOURCES AND YEAR

Dimension: Environment	Agricultural area ¹	Forest area ²	Distances driven by trucks ³	Municipal waste collected ⁴	Forest area affected by fires ⁵	Non-differentiated urban waste ⁶	Differentiated urban waste ⁷	Cement (consumption & sales) ⁸	Abstraction of total fresh water by public water supply ⁹	Investments in waste water collection and treatment facilities ¹⁰	Population affected by diseases of the respiratory system ¹¹
Direction of indicator (°)	1	1	-1	-1	-1	-1	1	-1	-1	1	-1
Galicia	30.15	59.69	1,412,161	1,568	0.55	191.9	5.6	1,031	12.652	33.185	185.5
Asturias	32.62	42.13	888,031	626	1.16	0.5	23.7	822	11.225	NaN	207.4
Cantabria	38.92	53.17	733,166	225	1.48	117.3	15.2	930	14.013	NaN	155.9
Pais Vasco	33.51	53.88	2,798,799	1,014	0.11	4.6	40.4	654	26.967	111.502	135.3
Navarra	59.64	29.89	682,716	329	0.00	1.2	20.8	1,239	11.779	36.918	130.7
Rioja	54.37	27.79	421,038	150	0.01	3.1	17.3	1,362	14.024	36.111	144.6
Aragón	50.67	27.73	1,966,061	786	0.01	38.6	17.2	1,013	14.560	8.016	160.8
Madrid	43.12	24.28	1,456,527	2,875	0.01	0.5	13.9	700	9.061	42.291	122.1
Castilla y Leon	54.42	28.77	6,112,246	1,064	0.25	117.7	10.8	1,231	11.218	4.511	169.4
Castilla la Mancha	59.55	25.51	3,111,736	829	0.01	167.3	6.3	1,115	10.406	16.383	166.7
Extremadura	53.64	38.38	998,282	531	0.06	31.1	3.9	1,050	12.315	NaN	154.1
Catalonia	36.86	44.06	8,556,978	3,652	0.05	1.3	23.7	1,003	8.058	1.127	136.6
Valencia	35.67	48.05	5,009,795	2,458	0.03	219.7	10.7	1,449	9.259	26.924	148.5
Balearic Islands	45.57	32.72	21,879	690	0.02	186.9	16.2	812	12.187	153.311	114.0
Andalucia	55.09	29.35	4,578,740	5,031	0.08	21.2	8.0	1,324	9.343	46.209	125.6
Murcia	55.54	24.33	679,370	635	0.02	122.1	10.6	1,794	7.523	157.105	134.9
Canary Islands	11.01	20.41	31,247	1,271	0.14	156.7	5.3	1,201	4.663	45.550	82.5

Sources: (A) Eurostat- General and Regional Statistics – Regions, <http://ec.europa.eu/eurostat/>

(B) Instituto de Estadística, Com. de Madrid, <http://www.madrid.org/iestadis/fijas/otros/estructu.htm>

(*) Direction of indicator: 1 indicates that higher values are desirable, -1 indicates the opposite

^{1,2} Area calculated over total land area (%). Eurostat, most recent data: 2002 (GR), 2003 (ES), 2004 (IT).

³ Total number of km driven within each region by all trucks, including intra-regional trips (1000 km/day). Eurostat, most recent data: varying.

⁴ Total amount of municipal waste collected by or on behalf of municipalities (1000 t/capita). Eurostat, most recent data: 1998 (GR, IT), 2000 (ES).

⁵ Forest area affected by fires over total forest area (%). Instituto de Estadística, most recent data: 1997.

⁶ Non differentiated urban waste (kg per capita). Instituto de Estadística, most recent data: 1998

⁷ Differentiated urban waste in the form of glass, paper, other (kg per capita). Instituto de Estadística, most recent data: 1998

⁸ Consumption and sales of cement (kg per capita). Instituto de Estadística, most recent data: 2005

⁹ Abstraction of total fresh water (ground+surface) by public supply (mio m³/yr per 100,000 inhabitants). Eurostat, most recent data: 1998

¹⁰ Total investments in waste water collection and treatment facilities (public + private sectors) (Mio € per 100,000 inhabitants). Eurostat, most recent data: 1998

¹¹ Diseases include those of the respiratory system (J00-J99) and chronic lower respiratory diseases (J40-J47) (per 100.000 inhabitants). Eurostat, most recent data: varying

Dimension: Society	Aging population ¹	Infant mortality rate ²	Population density ³	Crude birth rate ⁴	Number of hospital beds ⁵	Number of physicians/doctors ⁶	Population affected by mental and behavioural disorders ⁷	alcoholic abuse ⁸	Participation in General Elections ⁹	Population in prison ¹⁰
Direction of indicator (°)	-1	-1	-1	1	1	1	-1	-1	1	-1
Galicia	21.13	4.2	91.4	7.6	358.8	262.9	32.4	1.3	69.48	164
Principado de Asturias	21.89	3.4	100.0	6.8	376.2	387.0	48.3	1.3	69.33	122
Cantabria	18.99	2.1	101.9	9.2	388.1	222.6	30.0	0.2	73.32	134
Pais Vasco	18.18	3.1	289.1	9.3	389.5	368.7	33.5	0.2	64.48	63
Comunidad Foral de Navarra	17.86	4.0	54.7	10.9	406.0	548.7	21.6	0.9	67.60	28
La Rioja	19.09	3.8	56.5	10.1	320.9	390.2	24.0	0.4	75.43	142
Aragón	21.15	6.0	25.6	9.3	417.7	485.2	38.8	0.2	72.19	196
Comunidad de Madrid	14.51	4.1	702.5	12.0	335.7	322.5	19.4	0.4	73.33	133
Castilla y León	22.62	4.0	26.1	7.7	421.5	362.2	28.2	0.9	74.37	258
Castilla-la Mancha	19.40	4.0	22.7	10.1	278.5	201.1	30.9	1.1	77.01	115
Extremadura	19.01	4.9	25.6	9.3	366.4	397.1	18.2	1.3	76.67	105
Cataluña	17.12	3.5	204.4	11.5	466.4	317.0	46.7	0.6	64.73	124
Comunidad Valenciana	16.17	3.5	186.7	11.0	272.3	319.8	26.7	0.6	73.38	131
Illes Balears	14.09	4.7	184.1	11.4	399.2	274.0	23.8	NaN	61.91	149
Andalucía	14.63	5.0	85.6	11.7	281.9	329.0	17.6	0.7	69.76	165
Región de Murcia	14.15	6.8	110.4	13.0	318.3	438.2	22.0	0.7	74.48	67
Canarias (ES)	11.91	6.4	247.6	10.2	448.1	282.0	18.1	0.9	61.64	159

Sources: (A) Eurostat, Database: REGIO, <http://ec.europa.eu/eurostat/>

(B) Instituto de Estadística, Com. de Madrid, <http://www.madrid.org/iestadis/fijas/otros/estructu.htm>

(*) Direction of indicator: 1 indicates that higher values are desirable, -1 indicates the opposite

¹ Population aged over 65y (% total population). Eurostat, most recent data: 2003

² Infant mortality rate. Eurostat, most recent data: 2000

³ Population density. Eurostat, most recent data: 2003

⁴ Crude birth rate. Eurostat, most recent data: 2003

⁵ Number of hospital beds (per 100.000 inhabitants). Eurostat, most recent data: 2000 (GR), 2002 (ES, IT)

⁶ Number of physicians/doctors (per 100.000 inhabitants). Eurostat, most recent data: 2001 (GR), 2003 (ES, IT)

⁷ Population affected by mental and behavioural disorders (crude death rate). Eurostat, most recent data: 2002 (GR, IT), 2003 (ES)

⁸ Population affected by alcoholic abuse, including alcoholic psychosis (crude death rate). Eurostat, most recent data: 2002 (GR, IT), 2003 (ES)

⁹ Participation in General Elections (%). Instituto de Estadística, most recent data: 2000

¹⁰ Population in prison (per 100.000 inhabitants). Instituto de Estadística, most recent data: 2004

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Dimension: Economy	Employment ¹	Gross Domestic Product ²	Households with minimum subsidy or no income ³	Foreigners with tertiary education ⁴	Life long learning ⁵	Population employed in Hi-Tech ⁶	Patent application to the EPO ⁷	Total intramural R&D expenditure (GERD) ⁸
Direction of indicator (*)	1	1	-1	1	1	1	1	1
Galicia	37.41	14,619	3.54	0.070	88.9	0.40	2.10	0.69
Principado de Asturias	36.41	15,843	1.24	0.055	22.6	0.37	6.08	0.68
Cantabria	41.45	17,986	3.68	0.075	8.0	0.42	8.12	0.55
País Vasco	46.71	23,028	6.08	0.096	80.5	0.44	19.05	1.34
Comunidad Foral de Navarra	52.07	23,481	2.21	0.159	12.6	0.45	35.03	1.03
La Rioja	47.47	20,464	1.16	0.197	3.2	0.45	23.76	0.46
Aragón	46.93	19,841	2.93	0.083	27.0	0.44	16.57	0.70
Comunidad de Madrid	49.21	24,584	2.51	0.193	122.5	0.48	17.17	1.73
Castilla y León	41.25	17,217	2.08	0.141	85.0	0.39	9.78	0.80
Castilla-la Mancha	39.18	14,513	2.57	0.067	45.5	0.39	5.13	0.32
Extremadura	34.00	12,173	3.64	0.050	18.4	0.34	2.91	0.59
Cataluña	48.50	22,415	2.58	0.129	109.4	0.47	35.06	1.11
Comunidad Valenciana	42.40	17,517	3.29	0.142	165.5	0.45	14.15	0.70
Illes Balears	46.06	21,290	1.83	0.137	29.4	0.49	5.69	0.23
Andalucía	34.66	14,135	5.29	0.153	183.4	0.36	6.86	0.61
Región de Murcia	39.32	15,694	3.44	0.068	39.3	0.43	7.11	0.64
Canarias (ES)	39.38	17,371	0.00	0.105	71.0	0.43	4.59	0.51

Sources: (A) Eurostat- General and Regional Statistics – Regions, <http://ec.europa.eu/eurostat/>

(B) Instituto de Estadística, Com. de Madrid, <http://www.madrid.org/iestadis/fijas/otros/estructu.htm>

(*) Direction of indicator: 1 indicates that higher values are desirable, -1 indicates the opposite

¹ Employment (% total active population). Eurostat, most recent data: 2003

² GDP (€ per capita). Eurostat, most recent data: 2003

³ Households with minimum subsidy or with no income (% total). Instituto de Estadística, most recent data: 1998

⁴ Foreigners with tertiary education (% total population). Eurostat, most recent data: 2003

⁵ Life long learning. Eurostat, most recent data: 2004

⁶ Population employed in Hi-Tech (%). Eurostat, most recent data: 2004

⁷ Patent application to the EPO (per mio inhabitants). Eurostat, most recent data: 2003

⁸ Total intramural R&D expenditure – GERD (%GDP). Eurostat, most recent data: 2003

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