LENKA HUDRLÍKOVÁ[a] – JANA KRAMULOVÁ[b] – JAN ZEMAN[c]

Measuring Sustainable Development at the Lower Regional Level in the Czech Republic based on Composite Indicators

Measuring Sustainable Development in Czech LAU 1 Regions using Composite Indicators

Abstract

Measuring sustainable development is a highly significant issue as there is neither a unified set of indicators nor any preferred methodology on how to do it. This is despite continual attempts to evaluate entities from the point of view of sustainable development. The most problematic level according to sustainable development assessment seems to be the "lower" regional levels, such as LAU 1 (former NUTS 4) level. On one hand, there are usually at this level already serious problems with data availability, on the other, it is almost impossible to regularly perform detailed questionnaire surveys in all LAU 1 regions (77 districts in case of the Czech Republic), as it is done in cities. The aim of the paper is to decide how to assess sustainability at this level.

Relevant indicators, although different from indicators used at the national or NUTS 3 level, with data available for all LAU 1 regions were selected. We succeeded in filling all the three pillars of sustainable development (economic, social and environmental) with a sufficient number of suitable indicators. For the first phase, cluster analysis was applied to find coherences among regions that are affected by similar problems. Composite indicators were then constructed in order to create a ranking of all 77 districts. Ranking was derived from this composite indicator approach. Ten composite indicators were constructed to test different methods of normalisation, weighting and aggregation. The results show the ranking of LAU 1 regions in the Czech Republic from the sustainability perspective, both including and excluding the capital city of Prague as an outlying district. A good interconnection between cluster analysis and constructed composite indicators can be seen; this is also supported by the discussion of the results.

Keywords: Sustainable development indicators, normalisation, weighting and aggregation methods, composite indicators, Czech LAU 1 regions, cluster analysis.

a Department of Economic Statistics, University of Economics in Prague, Nám. W. Churchilla 4, Praha 3, CZ 130 67, Czech Republic. E-mail: lenka.hudrlikova@vse.cz

b Department of Regional Studies, University of Economics in Prague, Nám. W. Churchilla 4, Praha 3, CZ 130 67, Czech Republic. Author is also working in the Czech Statistical Office. E-mail: jana.kramulova@vse.cz

c Department of Economic Statistics, University of Economics in Prague, Nám. W. Churchilla 4, Praha 3, CZ 130 67, Czech Republic. E-mail: janzeman06@gmail.com

REGIONAL STATISTICS, 2013, VOL. 3: 117–140

Introduction

Measuring sustainable development seems to be a major issue (see e.g. Parris et al., 2003) as there is neither unified set of indicators nor any preferred methodology as to how to do it. However, attempts to evaluate entities according to sustainable development regularly occur. Particularly at the national level, various indicators set are being created (see EUROSTAT 2013), as well as at the lowest level for cities (ECI - European Commission 2013, used in the Czech Republic by TIMUR 2012) or even enterprises. Similarly, at the "higher" regional levels (NUTS 2 and in case of the Czech Republic also NUTS 3 level) there are also attempts to evaluate sustainability using a set of indicators (Progress Reports on the Czech Republic's Strategic Framework for Sustainable Development). The most problematic level, according to sustainable development assessment, seems to be "lower" regional level, such as LAU 1 (former NUTS 4) level. At this level, there are already serious problems with data availability (i.e. methodological problems of regional GDP estimate or simply non-availability of reliable data). On the other hand, it is almost impossible to regularly perform detailed questionnaire surveys in all regions at this level (77 in case of the Czech Republic), as it is carried out for example in the case of ECIs. For these reasons, it is not possible to use a similar approach as in the case of "higher" regional level or local level.

This paper is part of the project, which deals with the analysis of sustainable development in the Czech Republic at the regional level (NUTS 3, see Fischer et al., 2013). In this paper, we decided to focus also on the lower level of administrative division – on the district level (LAU 1, formerly labelled NUTS 4) – as this level is also important (compare Lengyel et al., 2012). The main aim of the paper is to decide how to assess sustainability at LAU 1 level. Unfortunately, this level has not been a subject to extensive research in the Czech Republic so far. An interesting approach is applied by Mederly et al. (2004) who analysed sustainability and quality of life in the Czech Republic at three different levels – regional, national and global; however, the regional level was limited exclusively to NUTS 3 level. They chose a very large number of 111 indicators that were initially analysed using correlation analysis and further deeper analysis. Another important approach was employed by the Czech Statistical Office (2010), again at the NUTS 3 level. Together with the Charles University in the Prague Environment Centre, they analysed indicators in a time series divided into three common pillars of sustainable development – economic, social and environmental. Some of these indicators were also used in a strategic document – Progress Reports on the Czech Republic's Strategic Framework for Sustainable Development in the year 2009 (Government Council for Sustainable Development et al. 2009). The new version of this document, published in 2012 (Government Council for Sustainable Development et al. 2012), already works with slightly different indicators in a different structure.

As there have been no attempts at the LAU 1 level, this paper attempts to illustrate some opportunities for assessing sustainability at this level. The paper is divided into several sections. The first one deals with data availability and the indicators finally included in the analysis (together with analysis of their correlations). The second section deals with potential coherences among Czech LAU 1 regions, i.e. those affected by similar problems. Cluster analysis covering all selected indicators was applied to examine this. The third section introduces a brief overview of the methodology of composite indicators.

REGIONAL STATISTICS, 2013, VOL. 3: 117–140

Later, the methods of normalisation, weighting and aggregation are used for composite indicators construction as well as for subsequent rankings creation. In the fourth section, the results are presented and discussed. In the final section, the main conclusions are outlined.

Sustainable development and set of indicators

The main idea of sustainable development lies in searching for a balance among economic development, social progress and equity, and environmental responsibility. The Brundtland Commission definition (WCED, 1987, p. 8) is usually considered to be the main definition broadly accepted. It especially emphasizes people's needs while expressing that "*Humanity has the ability to make development sustainable – to ensure that it meets the needs of the present without compromising the ability of future generations to meet their own needs*". Many other definitions can be found that add to the discussions on how to fully understand sustainable development, its targets and measurement (Marsden et al. 2010, Byrch et al. 2009, Ciegis et al. 2009, Rassafi et al. 2006, Macháček 2004, p. 28–29 or Nováček et al. 1996, p. 16–19).

We focused on the Czech Republic as a case study. There are 77 districts (i.e. LAU 1 regions) in the Czech Republic including the capital Prague, which is very specific among other districts because it is not only a district (LAU 1), but at the same time also a region (NUTS 3) and even NUTS 2 unit. This is not so common in other countries, although capital cities often form a specific region with unusual characteristics. Usually the higher the level of classification, the broader area of the city is included (i.e. with suburban areas, which have different characteristics from the core city). Cambridge Econometrics (2013) state that "In general, NUTS 3 regions are used to define cities, in recognition of the fact that many cities are essentially spatially-concentrated cores of economic interaction that are smaller than NUTS 2 regions, with the important exceptions of the major conurbations such as Paris and London". For example, London[1] as NUTS 1 is divided into Inner London and Outer London (NUTS 2 regions) and further into five NUTS 3 regions and then into 33 LAU 1 regions. In the case of Prague, the areas included in NUTS 2, NUTS 3 and LAU 1 classifications are exactly the same[2]. Therefore, we decided to perform two types of analysis – including and excluding Prague – and compare the results obtained.

From a statistical point of view and due to the need to meet certain conditions for the use of multivariate methods, the number of 77 units seems to be much more appropriate than the number of 14 regions forming the Czech Republic[3]. This was one of the reasons for focusing on this level. The disadvantage of such small territorial units (e.g. districts) is the issue of data availability. The problem lies in the fact that each district often follows its own characteristics (indicators), which may differ across districts, or indicators available for some districts are not available for other districts. These findings, meant that a set of indicators different from the one used in the analysis at the NUTS 3 level was required (Fischer et al. 2013).

1 For more details see Office for National Statistics (2013).
2 See Methodology section in Statistical Yearbook of the Czech Republic 2012 (Czech Statistical Office 2012, p. 771)
3 Appendix 1 shows map with 77 Czech LAU 1 districts.

Table 1

Correlation matrix of environmental pillar

Arable land, %	Coefficient of ecological stability	Share of broadleaved species, %	Specific emissions of solids, tonne per km^2	Specific emissions of sulphur dioxide (tonne per km^2)	Specific emissions of nitrogen oxides, tonne per km^2	Specific emissions of carbon monoxide, tonne per km^2	Number of small-scale protected areas	Share of protected areas (NP+PLA +S-SPA) in the region, %	Investment environmental protection expenditure by the investor registered office	Share of agricultural land, %	Share of agricultural holdings having the agricultural land area 500+ ha, %	Share of municipalities with established public water supply system covering all the municipality, %	Share of municipalities with established sewerage system covering all the municipality, %	Share of municipalities with established sewerage systém connected to a WWTP covering all the municipality, %	Share of municipalities with established natural gas grid covering all the municipality, %
1.000	**–0.904**	0.235	–0.098	–0.081	–0.056	–0.065	–0.154	–0.690	0.052	0.781	0.149	0.132	0.320	0.169	0.440
–0.904	1.000	–0.375	–0.050	–0.115	–0.139	–0.023	0.274	0.739	–0.090	–0.762	–0.128	–0.259	–0.375	–0.257	–0.431
0.235	–0.375	1.000	0.259	0.330	0.364	0.220	–0.158	–0.118	0.277	0.183	–0.228	0.464	0.346	0.397	0.433
–0.098	–0.050	0.259	1.000	0.706	0.810	**0.920**	–0.254	–0.046	0.216	–0.166	–0.173	0.024	–0.182	–0.082	–0.081
–0.081	–0.115	0.330	0.706	1.000	**0.942**	0.508	–0.341	–0.135	0.177	–0.276	0.050	0.173	–0.123	0.023	0.043
–0.056	–0.139	0.364	0.810	**0.942**	1.000	0.612	–0.309	–0.146	0.178	–0.207	–0.012	0.212	–0.097	0.048	0.015
–0.065	–0.023	0.220	**0.920**	0.508	0.612	1.000	–0.091	–0.006	0.246	–0.121	–0.185	–0.059	–0.193	–0.162	–0.050
–0.154	0.274	–0.158	–0.254	–0.341	–0.309	–0.091	1.000	0.361	0.091	–0.122	–0.177	0.086	0.185	0.061	0.072
–0.690	0.739	–0.118	–0.046	–0.135	–0.146	–0.006	0.361	1.000	–0.055	–0.485	–0.265	–0.109	–0.341	–0.247	–0.301
0.052	–0.090	0.277	0.216	0.177	0.178	0.246	0.091	–0.055	1.000	0.006	–0.133	0.126	0.158	0.190	0.270
0.781	–0.762	0.183	–0.166	–0.276	–0.207	–0.121	–0.122	–0.485	0.006	1.000	0.019	0.046	0.174	–0.016	0.375
0.149	–0.128	–0.228	–0.173	0.050	–0.012	–0.185	–0.177	–0.265	–0.133	0.019	1.000	–0.048	–0.073	–0.023	–0.030
0.132	–0.259	0.464	0.024	0.173	0.212	–0.059	0.086	–0.109	0.126	0.046	–0.048	1.000	0.579	0.575	0.507
0.320	–0.375	0.346	–0.182	–0.123	–0.097	–0.193	0.185	–0.341	0.158	0.174	–0.073	0.579	1.000	0.833	0.465
0.169	–0.257	0.397	–0.082	0.023	0.048	–0.162	0.061	–0.247	0.190	–0.016	–0.023	0.575	0.833	1.000	0.239
0.440	–0.431	0.433	–0.081	0.043	0.015	–0.050	0.072	–0.301	0.270	0.375	–0.030	0.507	0.465	0.239	1.000

Source: Own calculation.
Note: Grey marked indicators were discarded due to correlations. Bold underlined numbers in grey fields stand for values greater than ±0.9.

REGIONAL STATISTICS, 2013, VOL. 3: 117–140

The set of indicators for districts was carefully chosen in order to best fit the sustainable development issues. It is widely recognized that sustainable development indicators are grouped into (most commonly) three pillars (economic, social and environmental). Some of the indicators chosen for the district level are the same as those used in the analysis of regions, some of them had to be adapted to the available data sources, and the rest needed to be newly chosen after the discussions with experts. The analysis focuses on 2010, it being the most up-to-date year with data available for all selected indicators. All the relevant indicators that were available for the district level were identified.

Before starting the main analysis the correlation matrices were calculated for each of the pillars to identify and eliminate redundant indicators (it is important to pay great attention to the context and explanation of each indicator in order not to discard the indicators that have a high degree of correlation with indicators that they are not directly related to). Table 1 below shows the correlation matrix of the environmental pillar as an example. It contains 16 originally included indicators; three of them (two types of emissions and one indicator covering sewerage system) were eliminated according to the results of correlations. The highest (positive) correlation coefficients of 0.942 and 0.920, which lead to the elimination of indicators, were observed between the different types of emissions (this serves as an example of indicators that can be discarded due to their relationship). On the contrary, a high (negative) correlation coefficient of –0.904 was identified between indicators *Arable land* and *Coefficient of ecological stability*. This can be considered as an example of indicators we cannot discard due to their incoherence; both indicators were left in the analysis.

After such adjustments in all three pillars, the following set of indicators were obtained and used in the study. While Table 2 shows indicators selected for the economic pillar, tables 3 and 4 show indicators in the social and environmental pillar.

Table 2

Economic pillar indicators (13 indicators)

EC 1	Density of motorways and 1st class roads, (km per 100 km^2)
EC 2	Average value per building notification and/or permit (CZK thousands)
EC 3	Number of entrepreneurs (natural persons and legal persons) per 1000 inhabitants
EC 4	Foreign direct investment for 1000 inhabitants (CZK millions)
EC 5	Number of people receiving unemployment benefit per 100 job applicants
EC 6	Building permits per 1000 inhabitants
EC 7	Approximate value of construction projects permitted by planning and building control authorities (CZK millions)
EC 8	Domestic construction work "S" (CZK millions, current prices)
EC 9	Operated vehicles (per 1 inhabitant).
EC 10	Number of enterprises with more than 50 employees
EC 11	Share of total number of natural persons carrying out business (natural persons carrying out business in compliance with Trades Licensing Act, self-employed farmers and agricultural entrepreneurs, private entrepreneurs in business carrying out business activities governed by regulations other than the Trades Licensing Act of economically active inhabitants (%)
EC 12	Registered motor vehicles per 1 inhabitant (cars and vans)
EC 13	Share of the population living in towns (%)

Source: Own compilation based on expert discussion.

Table 3

Social pillar indicators (17 indicators)

SO 1	Total general unemployment rate (%)
SO 2	Life expectancy at birth (years)
SO 3	Civil society – political participation (turnout in elections to municipal councils %)
SO 4	Women and men in politics (share of women elected representatives in elections to municipal councils %)
SO 5	Civil society – civic participation (number of mid-year population per 1 nongovernmental non-profit organization)
SO 6	Number of job vacancies per 100 applicants
SO 7	Age index (number of inhabitants aged +65 per 100 inhabitants aged 0-14)
SO 8	Share of municipalities with medical facilities (%)
SO 9	Share of municipalities with school (%)
SO 10	Average percentage of incapacity for work
SO 11	Average length of sick leave (days)
SO 12	Number of places in social services per 1000 inhabitants
SO 13	Number of doctors per 1000 people (outpatient care)
SO 14	Number of recipients of pensions per 100 inhabitants
SO 15	Average old-age pension (CZK)
SO 16	Number of disabled people-licensee holders per 100 inhabitants
SO 17	Total paid social benefits per 1 inhabitant (CZK)

Source: Own compilation based on expert discussion.

Table 4

Environmental pillar indicators (13 indicators)

EN 1	Arable land (%)
EN 2	Coefficient of ecological stability
EN 3	Share of broadleaved species (%)
EN 4	Specific emissions of nitrogen oxides (tonne per km^2)
EN 5	Specific emissions of carbon monoxide (tonne per km^2)
EN 6	Number of small-scale protected areas
EN 7	Share of protected areas (NP + PLA + S-SPA) in the region (%)
EN 8	Investment environmental protection expenditure by the investor registered office
EN 9	Share of agricultural land (%)
EN 10	Share of agricultural holdings having the agricultural land area 500+ ha (%)
EN 11	Share of municipalities with established public water supply system covering whole municipality (%)
EN 12	Share of municipalities with established sewerage system connected to a WWTP covering whole municipality (%)
EN 13	Share of municipalities with established natural gas grid covering whole municipality (%)

Source: Own compilation based on expert discussion.

Moving to LAU 1 level means that indicators such as GDP per capita or labour productivity, which are usually an essential part of the analysis at the higher regional level (NUTS 3 or NUTS 4) cannot be used. This set of indicators represents available but also reliable and relevant data at this level.

Analysis of similarities among Czech LAU 1 regions

After selecting the most appropriate indicators, the similarities in Czech LAU 1 regions were analysed according to all 43 indicators and ignoring which pillar they are incorporated in. For this question, one of the multivariate statistical methods – cluster analysis- was used. We tried to group homogenous LAU 1 regions, and examine if such regions, with similar problems (e.g. unemployment, structurally affected regions, border regions or highly developed city regions), belong to the same cluster.

Cluster analysis (Burns et al. 2009, Mooi et al. 2011 or Hebák et al. 2007) is a method of data classification, which performs the division of data into groups that contain units having something in common. The aim of cluster analysis is to divide *n* LAU 1 regions into *k* groups, called clusters, using *p* indicators. Like other types of statistical methods, cluster analysis has several variants, which also differ in the coalescing process; in our case hierarchical clustering is used. We used the Euclidean distance (see Equation (1)) as the distance between two points in the Euclidean space. "Euclidean distance is the most commonly used type when it comes to analysing ratio or interval-scaled data." (Mooi et al. 2011, p. 245). Mimmack et al. (2001) state that when the cluster analysis is used for defining regions, which is our situation, Euclidean distance seems to be more proper than Mahalanobis distance. Furthermore, Ward's method as one of the methods of joining clusters, used as a linking clusters criterion in the sense of increase of the total intragroup sum of squared deviations of individual observations from the cluster average was applied. Increase is expressed as the sum of squares in the emerging cluster minus the sum of squares in both merging clusters as shown in Equation (2).

$$D_E(x_i, x_{i'}) = \sqrt{\sum_{j=1}^{p}(x_{ij} - x_{i'j})^2}, \qquad (1)$$

$$G = \sum_{h=1}^{k}\sum_{i=1}^{n_h}\sum_{j=1}^{p}(x_{hij} - \bar{x}_{hj})^2, \qquad (2)$$

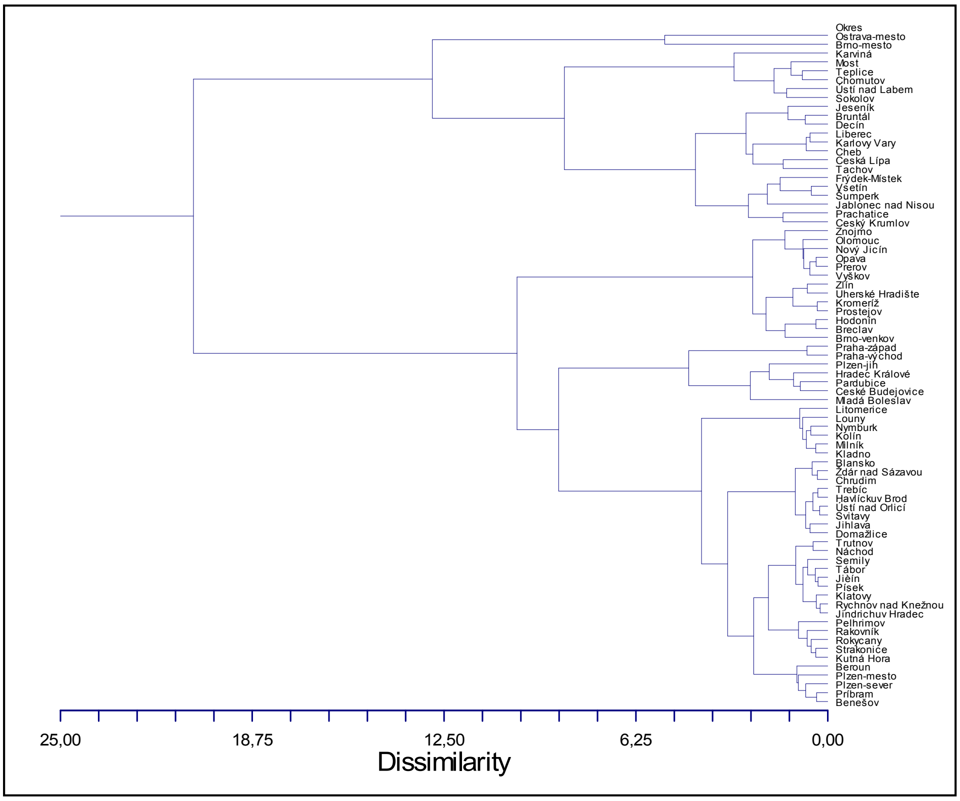
where G stands for Ward´s criterion, k for the number of clusters, n_h number of LAU 1 regions in h^{th} cluster and p for the number of indicators.

Burns et al. (2009, p. 557) emphasize about Ward's method "in general, this method is very efficient". Hebák et al. (2007, p. 135) sees another advantage of Ward's method. It forms a similarly large cluster when eliminating the small ones.

The same approach (hierarchical clustering with Euclidean distance and Ward's method) was applied by Odehnal et al. (2012) when evaluating competitiveness of Ukrainian regions. We performed hierarchical clustering within the statistical software NCSS 2007 environment. Based on the results (Figure 1), we agreed on the final number of six clusters with the degree of dissimilarity of six as a reasonable number. The results of the cluster analysis were captured into individual choropleth maps shown below. It is important to mention that after selecting the indicators and initial data analysis, we decided to remove Prague from this analysis due to its specifics and difficulty in comparing it with other districts.

Figure 1

Dendrogram from the cluster analysis



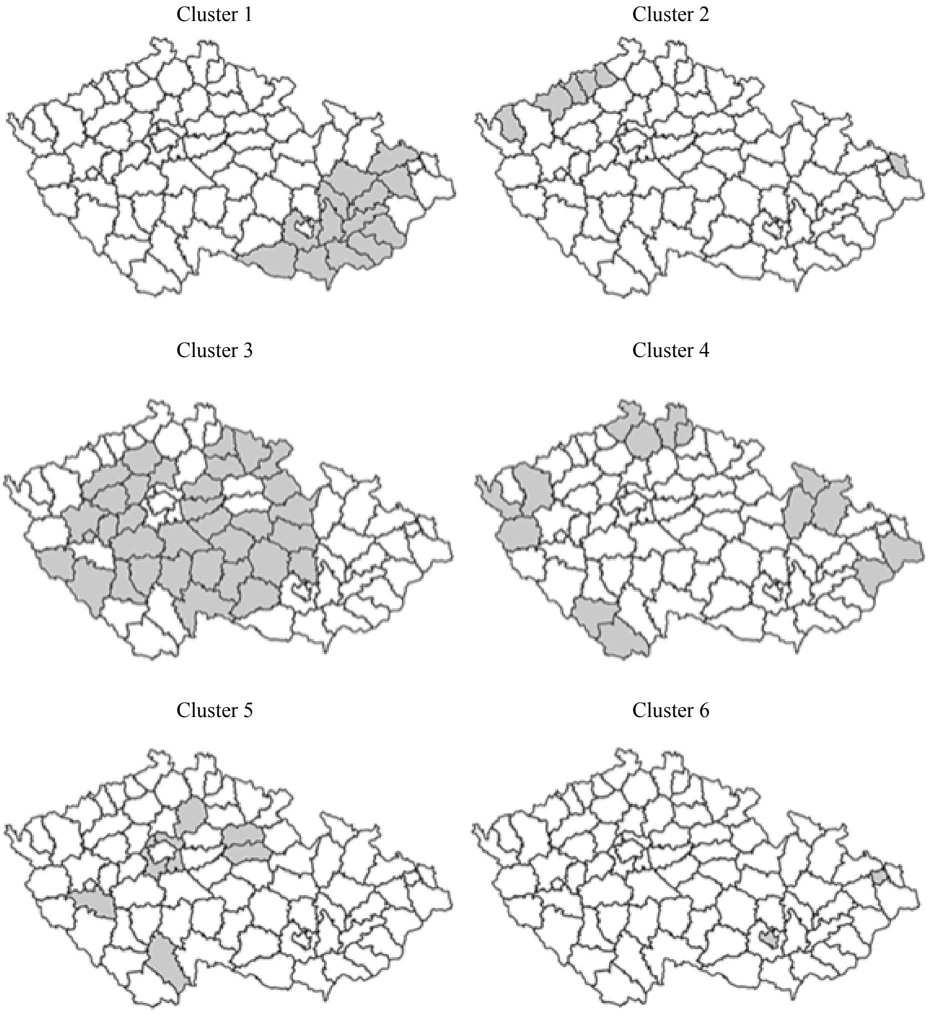
Source: NCSS 2007, own calculation.

Figure 2 shows the clusters in which many similarities can be found. Cluster 1 contains Moravian adjacent districts. Cluster 2 is formed by border districts, mostly situated to the northwest with one district situated northeast (districts with high unemployment rate). Cluster 3 is the largest cluster, made up of the majority of the Czech districts and several Moravian districts. Cluster 4 is composed of five sub-clusters, which do not have a common border; all of them are border (frontier) districts. Cluster 5 contains districts with medium-sized towns as centres, and Prague surroundings. Cluster 6 is made up from the second and the third largest cities in the Czech Republic (Brno and Ostrava). As mentioned previously, Prague as a "district-outlier" was discarded from this analysis. If left in the analysis, Prague would form a separate Cluster 7.

REGIONAL STATISTICS, 2013, VOL. 3: 117–140

Figure 2

Six clusters identified in the Czech Republic



Source: Own analysis in Maps Generator environment.

Figure 2 shows six clusters whose districts have very similar characteristics (not only in statistical sense, but also in the sense of sustainable development indicators), as Moravian districts, Czech districts, border districts, districts with big cities, or medium-sized towns. These conclusions encouraged us to continue in our analysis with the aim of evaluating all 77 Czech LAU 1 regions. In the next section, the indicators are examined divided into the three pillars.

Methodology of composite indicators

Composite indicator (CI) is considered to be a useful tool for ranking. An overview of the advantages and disadvantages of using composite indicators for sustainable development evaluation was carried out by Czesaný (2006). Examples of several CIs for assessment of sustainable development are also listed by Parris et al. (2003). It allows the expression of a multidimensional issue by one single number. We followed the generally accepted definition of sustainable development by stating three areas – economic, environmental and social. Therefore, aggregation needed to be performed in two steps. In the first step, we aggregated indicators in each separate pillar. The second step consisted of merging all three pillars into one composite indicator. This chosen approach required the solving of three central issues: method of transformation/normalization of the data, selection of a suitable weighting scheme and finally, the selection of the aggregation method.

As in most fields of economic reality, sustainable development indicators are neither measured in the same units nor have the same direction. Higher values do not always reflect better performance. In other words, the higher value of an indicator may represent a worse performance (e.g. unemployment). As a result, certain data transformation is required prior to the next analysis. The goal of the data transformation can be seen in the adjustment for different ranges, different variances and outliers. There has been considerable discussion on the range of normalization methods. Nardo et al. (2009). Choosing the most appropriate method for normalization is crucial and depends not only on the type of data, but also on weighting and subsequent aggregation. Application of normalization can result in different outcomes for the CI. This paper deals with the two most common types: min-max method and z-scores.

The first considered transformation method is min-max. Equation (3) is used for indicators when a higher value is the positive outcome, and equation (4) for indicators where the lower value is positive.

$$I_{pn} = \frac{x_{pn} - min_n(x_p)}{max_n(x_{pn}) - min_n(x_p)}, \tag{3}$$

$$I_{pn} = \frac{max_n(x_p) - x_{pn}}{max_n(x_{pn}) - min_n(x_p)}, \tag{4}$$

where x_{pn} is the value of an indicator p for district n. The min-max method is based on minimum and maximum values. The advantage lies in the fact that the boundaries can be set and all the indicators then get an identical range (0, 1). Each indicator reaches a value between 0 and 1 even if it is the extreme value. The output is dimensionless and the relative distances remain. A drawback reveals if outliers and/or extreme values are present as the computation of the min-max method is based on extreme values (the minimum and the maximum). These two values strongly influence the final output (see equations (3) and (4)). Despite this, the min-max approach is very popular and has been applied for the construction of many composite indicators, such as the well-known Human Development Index (HDI), issued by the United Nations (Klugman 2011).

The second normalization method (z-scores) converts the data in order to have a common scale with a zero mean and standard deviation of one. For each indicator x_{pn} the average across districts $x_{pn} = \bar{n}$ and standard deviation across districts $\sigma'_{pn} = \bar{n}$ are calculated and used in the formula (5).

$$I_{pn} = \frac{x_{pn} - x_{pn=\pi}}{\sigma'_{pn=\pi}}, \qquad (5)$$

This method provides no distortion from the mean; it adjusts different scales and different variance. The output is again dimensionless and because it applies a linear transformation, the relative differences are preserved. The z-scores method does not fully adjust for outliers. An indicator with an extreme value has a greater effect on a composite indicator. This is desirable if exceptional behaviour should be rewarded, i.e. if an excellent performance on a few indicators is considered to be better than a lot of average performances. This effect can be reduced by applying the correct aggregation method. Compared to the min-max method, the z-scores method is even more robust on outliers as it is based on variance instead of the range.

Weighting as the second step has a crucial effect on the outcome of the CI. With several methods in use, this part of constructing a CI is the most discussed and criticised by opponents of CIs (Freudenberg (2003). Weighting methods can be divided into two main groups: statistical approaches and participatory approaches. The most common methods are listed in Nardo et al. (2009). No results from surveys, opinion polls, questionnaires etc. are available for this analysis, thus participatory methods cannot be used. This paper deals only with the first group of weighting methods (i.e. statistical methods). These methods are only data driven, which means no subjective value judgments are needed.

Using the Equal weighting (EW) method, equal weight is assigned for each indicator (according to equation (6))

$$w_p = {}^{1}\!/_{P}, \qquad (6)$$

where w_p is a weight for p^{th} indicator (p=1,...,P) for each district. This means that all indicators are given the same weight for all LAU 1 regions. Equal weighting may be justified when there is no clear idea as to which method should be used. The main strength of the EW method is its simplicity. On one hand, this approach is easy and clear, on the other, there is a risk that a pillar with more indicators will have a higher influence on the CI.

Weighting derived from principal component analysis (PCA) and factor analysis (FA) respectively, deals with this issue. Both methods are very often used for data explanatory analysis. The PCA and FA explain the variance of the data through a few factors that are formed as a linear combinations of raw data. The original correlated set of indicators is changed into a new smaller set of uncorrelated variables. A detailed description of both methods can be found in Manly (2004), Morrison (2005), as well as in textbooks or handbooks on statistical software (e.g. StatSoft (2011). In this analysis, we carried out main components extraction and varimax rotation. Weights derived from the PCA are based on eigenvalues. After obtaining them, it is necessary to select the optimal number of components. Kaiser criterion suggests selecting all components that are associated to eigenvalues higher than one. Applying that criterion, in the economic and environmental pillars, four factors sufficed; in the social pillar, five factors were included into further computations. To obtain FA derived weights, we followed the approach proposed by

Nicoletti et al. (1999). The weights had to be normalized by squared factor loadings, which are derived as proportions of variance of the factor explained by a particular variable, then scaled to a unity sum. The main idea behind the usage of FA derived weights is correction of correlated indicators. Two highly correlated indicators are given lower weight because it is assumed that they can measure the same phenomenon. It is necessary to check the data for correlations before applying the weights on indicators, which was consistently done in section 1; this method aims at further correcting of the correlations.

The third step in the procedure of CI construction is aggregation. In practice, linear aggregation (LIN) is the most widespread. The simplest method represents the weighted average as shown in equation (7), subject to conditions (8).

$$CI_n = \sum\nolimits_{p=1}^{p} I_{pn} \cdot w_p, \qquad (7)$$

$$\sum\nolimits_{p} w_p = 1 \text{ and } 0 \leq w_p \leq 1, \qquad (8)$$

where I_{pn} is a normalized indicator p (p=1,...,P) for district n (n=1,...,N) and w_p weight for indicator p (p=1,...,P). The fundamental topic of the aggregation is compensability among indicators. Linear aggregation implies full compensability, i.e. poor performance in one indicator can be compensated by sufficiently high values of others indicators. Compensability between indicators can be desirable only if various indicators are considered as substitutes. Even if full compensability can be weakened by the weighting scheme, other aggregation rules can suppress that.

Geometric aggregation (GEO) is only partially compensable (see formula 9).

$$CI_n = \prod\nolimits_{p=1}^{p} (I_{pn})^{w_p}, \qquad (9)$$

where I_{pn} is a normalized indicator p (p=1,...,P) for district n (n=1,...,N) and w_p weight for indicator p (p=1,...,P). Geometric aggregation rewards districts with higher scores to a gretaer intensity because marginal utility of an increase in a low score is much higher than in a high score. Hence, districts with low scores should prefer a linear rather than a geometric aggregation. The drawback lies in the requirement for strictly positive values of normalised indicators (i.e. I_{pn}>1), which means it is not applicable on normalized data by means of z-scores.

As was already stated, aggregation was carried out in two steps – firstly within the pillar and then aggregation of the three pillars. By applying these techniques, we constructed ten different composite indicators. Table 5 shows all ten tested combinations.

REGIONAL STATISTICS, 2013, VOL. 3: 117–140

Table 5

List of 10 tested combinations

	Normalization	Weighting	Aggregation in pillar	Aggregation of three pillars (without weights)
CI_1	Min-max	EW	Arithmetic mean	Arithmetic mean
CI_2	Min-max	EW	Arithmetic mean	Geometric mean
CI_3	Min-max	EW	Geometric mean	Arithmetic mean
CI_4	Min-max	EW	Geometric mean	Geometric mean
CI_5	Min-max	PCA/FA	Arithmetic mean	Arithmetic mean
CI_6	Min-max	PCA/FA	Arithmetic mean	Geometric mean
CI_7	Min-max	PCA/FA	Geometric mean	Arithmetic mean
CI_8	Min-max	PCA/FA	Geometric mean	Geometric mean
CI_9	z-scores	EW	Arithmetic mean	Arithmetic mean
CI_10	z-scores	PCA/FA	Arithmetic mean	Arithmetic mean

Source: Own construction.

Note: EW stands for equal weights within the pillars, PCA/FA for weights derived from principal component analysis and factor analysis.

More techniques were used in order to assess the robustness of the ranking. We are aware that this is not the exhaustive list of techniques for normalization, weighting and aggregation. Our aim was to select only methods that are simple, easily understandable and only data driven. Applied methods cover two main issues during constructing a composite indicator – correlation and compensability between various indicators (Paruolo et al., 2013). The differences in results as well as suitability of each CI are discussed in the next section.

Computations, results and discussion

This section introduces the main results. After normalisation of an indicator, the ranking of the districts remains the same regardless of the chosen method of normalisation (min-max or z-scores). However, the values are different and further analysis will be influenced by the chosen normalisation method.

Even more important is the weighting scheme. Table 6 shows weights derived from equal weighting and PCA/FA weighting within each pillar.

Table 6

Equal and PCA/FA weights within one pillar (in %)

Economic pillar	EW	PCA/FA	Social pillar	EW	PCA/FA	Environmental pillar	EW	PCA/FA
EC1	7.69	4.10	SO1	5.88	4.53	EN1	7.69	10.82
EC2	7.69	3.27	SO2	5.88	8.36	EN2	7.69	10.42
EC3	7.69	9.71	SO3	5.88	5.83	EN3	7.69	3.85
EC4	7.69	4.94	SO4	5.88	4.15	EN4	7.69	11.60
EC5	7.69	5.23	SO5	5.88	3.39	EN5	7.69	10.41
EC6	7.69	7.24	SO6	5.88	5.32	EN6	7.69	6.16
EC7	7.69	10.00	SO7	5.88	6.73	EN7	7.69	6.81
EC8	7.69	8.86	SO8	5.88	8.45	EN8	7.69	0.64
EC9	7.69	7.05	SO9	5.88	9.48	EN9	7.69	9.68
EC10	7.69	9.73	SO10	5.88	9.46	EN10	7.69	9.82
EC11	7.69	11.09	SO11	5.88	8.69	EN11	7.69	8.75
EC12	7.69	9.55	SO12	5.88	1.47	EN12	7.69	7.98
EC13	7.69	9.21	SO13	5.88	3.75	EN13	7.69	3.05
			SO14	5.88	5.58			
			SO15	5.88	6.56			
			SO16	5.88	1.91			
			SO17	5.88	6.35			

Source: Own computation.
Note: EW stands for equal weights, PCA/FA for weights derived from principal component analysis and factor analysis.

In the third step, it was essential to decide about the most appropriate aggregation methods inside a pillar and of all three pillars. For aggregation within a pillar, we used the weights computed in Table 6. We calculated all ten CIs presented in Table 5, i.e. all possible combinations of aggregation methods; however, we concluded that geometric aggregation, in particular, at pillar level produced unreliable results. Therefore, as a final ranking, we decided to use the combination recommended by the Joint Research Centre[4]. Tarantola (2011) suggests using the arithmetic average to combine indicators within a pillar and geometric average to merge pillars into one single composite indicator. The idea is simple: within one pillar, there can be a considered trade-off between indicators but the pillars should not be fully compensable. The final ranking in Table 7 is based on min-max normalization, weighted arithmetic average at pillar level and geometric average for combining three pillars. Two combinations meet these conditions, one with equal weights (CI_2) and one with PCA/FA weights (CI_6). The results for these two CIs are shown in Table 6. Unlike in the cluster analysis in section 2, Prague is included in order to bring a complete ranking of Czech districts. The number of cluster corresponds with results in section 2 (Prague was labelled as Cluster 7).

4 Joint Research Centre provides scientific and technological support to European Union policies. Its Econometrics and Applied Statistics Unit focuses (besides other issues) on composite indicators and ranking systems (see http://ipsc.jrc.ec.europa.eu/).

Table 7

Final rankings (including Prague)

	Cluster	EW	PCA/FA		Cluster	EW	PCA/FA
Hlavní město Praha	C7	1	1	Most	C2	40	55
Brno-město	C6	2	2	Ústí nad Orlicí	C3	41	37
Ústí nad Labem	C2	3	8	Sokolov	C2	42	40
Praha-západ	C5	4	3	Náchod	C3	43	29
Nový Jičín	C1	5	6	Tachov	C4	44	50
Zlín	C1	6	5	Blansko	C3	45	54
Karviná	C2	7	12	Znojmo	C1	46	43
Plzeň-město	C3	8	7	Trutnov	C3	47	36
Olomouc	C1	9	10	Prostějov	C1	48	56
Hradec Králové	C5	10	13	Jihlava	C3	49	41
Liberec	C4	11	4	Kolín	C3	50	58
Břeclav	C1	12	18	Žďár nad Sázavou	C3	51	52
Pardubice	C5	13	14	Rychnov nad Kněžnou	C3	52	47
Česká Lípa	C4	14	19	Bruntál	C4	53	60
Uherské Hradiště	C1	15	20	Jičín	C3	54	51
Praha-východ	C5	16	11	Tábor	C3	55	44
Brno-venkov	C1	17	21	Český Krumlov	C4	56	46
Cheb	C4	18	9	Svitavy	C3	57	62
Ostrava-město	C6	19	45	Semily	C3	58	49
Litoměřice	C3	20	27	Šumperk	C4	59	61
Opava	C1	21	15	Domažlice	C3	60	63
Mladá Boleslav	C5	22	33	Benešov	C3	61	48
Vyškov	C1	23	26	Jindřichův Hradec	C3	62	57
Frýdek-Místek	C4	24	24	Louny	C3	63	66
Kladno	C3	25	35	Havlíčkův Brod	C3	64	65
Přerov	C1	26	30	Rokycany	C3	65	70
Hodonín	C1	27	38	Příbram	C3	66	59
Vsetín	C4	28	31	Třebíč	C3	67	74
Mělník	C3	29	28	Chrudim	C3	68	71
Beroun	C3	30	32	Plzeň-sever	C3	69	69
Kroměříž	C1	31	39	Klatovy	C3	70	64
Děčín	C4	32	25	Prachatice	C4	71	73
Teplice	C2	33	42	Pelhřimov	C3	72	67
Jeseník	C4	34	16	Kutná Hora	C3	73	72
Karlovy Vary	C4	35	22	Písek	C3	74	68
Chomutov	C2	36	53	Plzeň-jih	C5	75	76
České Budějovice	C5	37	23	Rakovník	C3	76	75
Nymburk	C3	38	34	Strakonice	C3	77	77
Jablonec nad Nisou	C4	39	17				

Source: Own calculation.

Note: EW stands for equal weights within the pillars, PCA/FA for weights derived from principal component analysis and factor analysis.

We can see that Prague is ranked first in both cases. This might be a little surprising, because capital cities usually perform well economically , do not have so many social problems (low unemployment, good pensions, high life expectancy etc.), but the environmental pillar may not perform as well. Brno as the second biggest Czech city occupies second place. The main surprise for us was the third place for the Ústí nad Labem district, as this district has long been connected with a damaged environment, and social problems with high unemployment. Conversely, Ostrava-město (ranked 19th and 45th), was expected to perform rather poorly being a structurally affected LAU 1 region. In case of equal weighting, probably compensability of indicators was the reason for the relatively high ranking of this district.

The remaining rankings including Prague (for CI_1, CI_5, CI_9 and CI_10), are introduced in Appendix 2. All rankings (6 CIs) excluding Prague are listed in Appendix 3.

In order to summarize all the results, we decided to evaluate 77 Czech districts from the point of view of clusters established in section 2. The median seemed to be a suitable indicator for this target as eliminates outlying values. Table 8 shows the outcomes including and excluding Prague (Cluster 7).

Table 8

Cluster medians

Cluster	Including Prague	Excluding Prague
C1	20.0	19.5
C2	40.0	39.0
C3	55.5	55.0
C4	34.5	34.5
C5	14.5	11.5
C6	10.5	6.0
C7	1.0	x

Source: Own calculation.

The resulting district rankings are not generally unexpected. Districts belonging to the same cluster very often reach similar ranking, i.e. in the overall order they are ranked close to each other. Considering cluster medians, Prague (C7) is ranked first, followed by the big cities (C6), which benefit from typically performing well in two pillars (economic and social) having slightly worse results in the third (environmental) pillar. Districts classified to cluster C5, are surroundings of big cities, districts with smaller university cities or prospering industrial branches, so there is no surprise this cluster is ranked third. The fourth place takes in Moravian districts (C1), which have a slightly better performance in the environmental pillar, there is lower share of the larger cities and they are more focused on agriculture. Clusters C2 and C4 (both border regions) have almost the same results; their common disadvantage can be seen in the distance from the centres of economic performance. The worst result achieved was cluster C3. The reason for this may lie in the fact that this cluster covers many diverse regions, i.e. when dividing the indicators into pillars this may play an important role.

Comparing the results when both including and excluding Prague brings almost no differences. Only small changes in the values can be noticed in C6 and C5 when Prague is not part of the analysis. The differences are caused by the definition of the methods used , which are endogenous.

Conclusion

For the analysis of LAU 1 regions, assessing sustainability was the key issue. Ultimately, we chose suitable indicators, although different from indicators used at the national or NUTS 3 level, with data available for all LAU 1 regions. We succeeded in filling all three pillars of sustainable development (economic, social and environmental) with a sufficient number of appropriate indicators. We found coherences among LAU 1 regions that were affected by similar problems. Using cluster analysis, six quite homogeneous clusters were identified (seven when including Prague). Following this, all 77 districts were ranked (both including and excluding Prague) according to sustainable development. Several normalisation and aggregation methods were used to compare selected indicators having diverse units of measurement. The results show the ranking of LAU 1 regions in the Czech Republic from the economic, social and environmental point of view (i.e. these three perspectives are aggregated into a composite indicator). It was demonstrated that the results obtained from cluster analysis performed in section 2 (all indicators together) correspond with the final rankings based on composite indicators computation (indicators separated into corresponding pillars).

Although we obtained exact rankings, our aim was to assess approximate rankings of the districts. The results indicate the approximate position of a particular district among all other districts. Each method gives slightly different results, the suitability should be determined according to the aim of single analysis, i.e. if equal weights are assigned to all indicators, or take into account correlations among indicators. In the same way, the compensability when choosing the appropriate aggregation method should be considered. The applicable methodological approach (i.e. proper composite indicator) should be selected according to specific requirements of the analysis.

Finally, it is necessary to add that the statistical approach to sustainable development (analysis of indicators) performed in this paper represents just one possible perspective. It may not (and usually does not) fully correspond with the feelings of people in the regions or with their subjective assessment of quality of their lives (different from sustainable development). Such analysis would exceed the scope of this paper, not only due to the financial aspects of such research, and the time required for qualitative analysis of questionnaires or in-depth interviews, but also due to uncertain data representativeness.

REFERENCES

Burns, R. B. – Burns, R. A. (2009): Additional advanced chapters, Chapter 23, Cluster Analysis In: *Business Research Methods and Statistics Using SPSS*. pp. 552–567. Sage Publications Ltd.

Byrch, C. – Kearins, K. – Milne, M. J. – Morgan, R. K. (2009): Sustainable Development: What does it really mean? *University of Auckland Business Review*, 11 (1): 1-7.

Cambridge Econometrics (2013): *Data Definitions.* [online]. Cambridge Econometrics, Cambridge. [cit. 2013-06-24]. http://www.camecon.com/Europe/Regional_Local_Cities/KnowledgeBase/Appendices/EuRegM/Data_Definitions.aspx.

Ciegis, R. – Ramanauskiene, J. – Martinkus, B. (2009): The Concept of Sustainable Development and its Use for Sustainability Scenarios. *Engineering Economics,* 62 (2): 28-37.

Czech Statistical Office (2012): *Statistical Yearbook of the Czech Republic 2012.* Český statistický úřad, Praha.

Czech Statistical Office (2010): *Vybrané oblasti udržitelného rozvoje v krajích České republiky 2010 [Selected Areas of Sustainable Development in the Regions of the Czech Republic 2010]*. Český statistický úřad, Praha.

Czesaný, S. (2006): Indikátory udržitelného rozvoje [Sustainable Development Indicators]. *Statistika*, 43 (5): 431-434.

European Commission (2013): *European Common Indicators.* [online]. European Commission, Bruxelles/ Luxembourg. [cit. 2013-06-20]. http://ec.europa.eu/environment/urban/common_indicators.htm.

EUROSTAT (2013): *Sustainable Development Indicators.* [online]. EUROSTAT, Luxembourg. [cit. 2013-06-20]. http://epp.eurostat.ec.europa.eu/portal/page/portal/sdi/indicators.

Fischer, J. – Helman, K. – Kramulová, J. – Petkovová, L. – Zeman, J. (2013): Sustainable development indicators at the regional level in the Czech Republic. *Statistika*, 93 (1): 5–18.

Freudenberg, M. (2003): Composite Indicators of Country Performance: A Critical Assessment. *OECD Science, Technology and Industry Working Papers,* 2003/16, OECD Publishing.

Government Council for Sustainable Development – Ministry of the Environment (2009): *Progress Report on the Czech Republic Sustainable Development Strategy. Summary.* Praha.

Government Council for Sustainable Development – Ministry of the Environment (2012): *Progress Report on the Czech Republic's Strategic Framework for Sustainable Development.* Praha.

Hebák, P. – Hustopecký, J. – Pecáková, I. – Plašil, M. – Průša, M. – Řezanková, H. – Vlach, P. – Svobodová, A. (2007): *Vícerozměrné statistické metody [3] [Multi-dimensional Statistical Methods [3]]*. Informatorium, Praha.

Klugman, J. (2011): *Human Development Report 2011. Sustainability and Equity: A Better Future for All.* United Nations Development Programme, New York.

Lengyel, I. – Szakálné Kanó, I. (2012): Competitiveness of Hungarian Urban Micro-regions: Localization Agglomeration Economies and Regional Competitiveness Function. *Regional Statistics*, Special Issue, 52 (2): 27–44.

Macháček, J. (2004): *Ekonomické souvislosti využívání kulturně historických lokalit [Economical Context of Taking Advantage of Cultural Historical Localities]*. Oeconomica, Praha.

Manly, B. F. J. (2004): Multivariate statistical methods: A primer. Chapman and Hall/CRC, London.

Marsden, G. – Kimble, M. – Nellthorp, J. – Kelly, C. (2010): Sustainability Assessment: The Definition Deficit. *International Journal of Sustainable Transportation*, 4 (4): 189-211.

Mederly, P. – Topercer, J. – Nováček, P. (2004): *Indikátory kvality života a udržitelného rozvoje – kvantitativní, vícerozměrný a variantní přístup [Indicators of Quality of Life and Sustainable Development – Quantitative, Multidimensional and Alternative Approach]*. UK FSV CESES, Praha.

Mimmack, G. M. – Mason, S. J. – Galpin, J. S. (2001): Choice of Distance Matrices in Cluster Analysis: Defining Regions. *Journal of Climate*. 14 (12): 2790–2797.

Mooi, E. – Sarstedt, A. (2011): Cluster Analysis: 237-284. In: *A Concise Guide to Market Research.* Springer-Verlag, Berlin Heidelberg.

Ministry of Environment – Czech Statistical Office – CENIA (2006): *Statistical Environmental Yearbook of the Czech Republic 2006*. Praha.

Morrison, D. F. (2005): *Multivariate Statistical Methods.* Thompson Brooks, California.

Nardo, M. – Saisana, M. – Saltelli, A. – Tarantola, S. – Hoffman, H. – Giovannini, E. (2009): *Handbook on constructing composite indicators: methodology and user guide.* OECD, Paris.

Nicoletti, G. – Scarpetta, S. – Boylaud, O. (1999): Summary indicators of product market regulation with an extension to employment protection legislation. *Economic Department Working Papers*. No. 226. OECD, Paris.

Nováček, P. – Mederly, P. (1996): *Strategie udržitelného rozvoje [Sustainable Development Strategy]*. G plus G, Praha.

Odehnal, J. – Sedlaik, M. – Michalek, J. (2012): A Competitiveness Evaluation of the Ukrainian Regions – Empirical Study. *Engineering Economics*. 23 (4): 406–413.

Office for National Statistics (2013): *NUTS: London Directory.* [online]. Office for National Statistics, UK. [cit. 2013-06-24]. http://www.ons.gov.uk/ons/guide-method/geography/beginner-s-guide/eurostat/london/index.html.

Parris, T. M. – Kates, R. W. (2003): Characterizing and measuring sustainable development. *Annual Review of environment and resources*. 28 (1): 559-586.

Paruolo, P. – Saisana, M. – Saltelli, A. (2013): Ratings and rankings: voodoo or science? *Journal of the Royal Statistical Society: Series A (Statistics in Society).* 176 (3): 609–634.

Rassafi, A. A. – Poorzahedy, H. – Vaziri, M. (2006): An alternative definition of sustainable development using stability and chaos theories. *Sustainable Development*, 14 (1): 62-71.

StatSoft, Inc. (2011): *Electronic Statistics Textbook.* (Electronic Version). StatSoft. Available at: www.statsoft.com/textbook

Tarantola, S. (2011): *Aggregation rules.* Lecture at JRC Seminar on Composite Indicators and Rankings. Ispra, Italy.

TIMUR. (2012): *Týmová iniciativa pro místní udržitelný rozvoj [Team Initiative for Local Sustainable Development]*. [online]. Timur, Praha. [cit. 2012-09-30]. http://www.timur.cz/.

WCED. (1987): *Our Common Future*. Oxford University Press, Oxford.

Acknowledgements

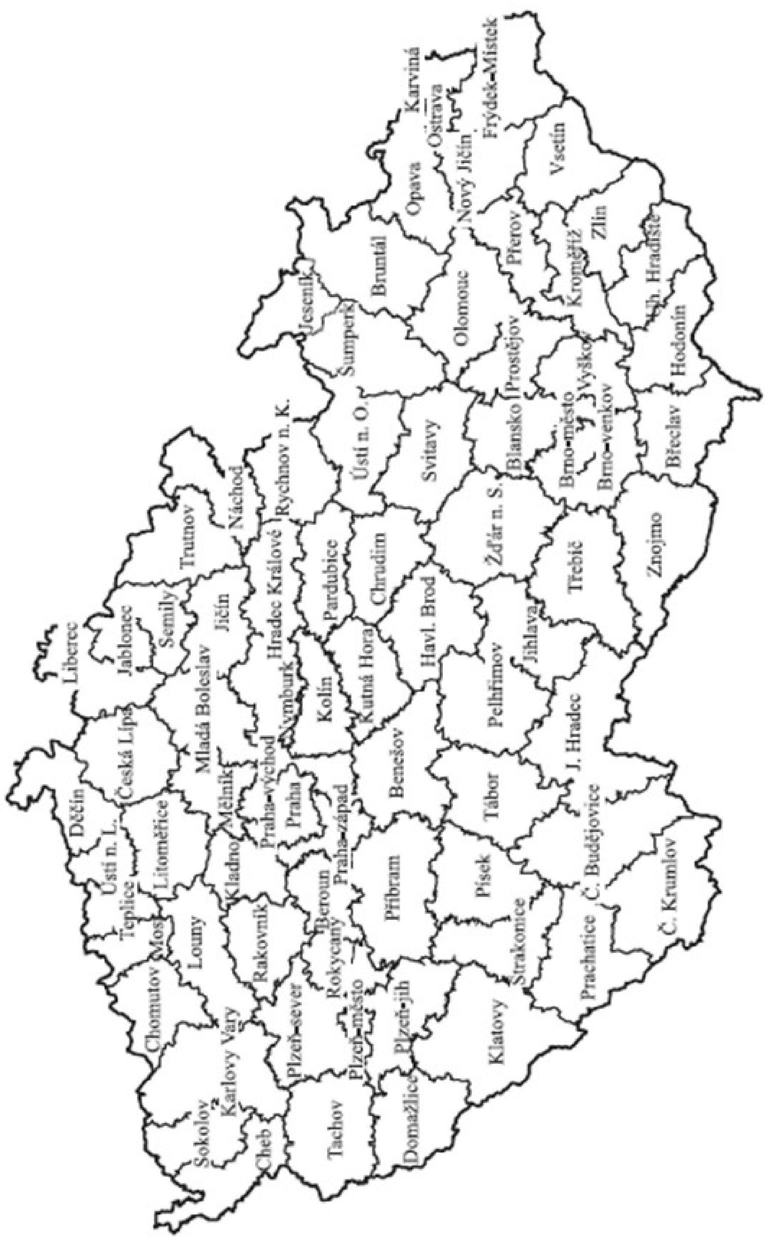
This paper was prepared with the support of the University of Economics in Prague, project No. 11/2012 “Construction and verification of sustainable development indicators in the Czech Republic and its regions”.

REGIONAL STATISTICS, 2013, VOL. 3: 117–140

Appendix

Appendix 1

77 Czech LAU 1 districts



Source: Ministry of Environment et al. (2006).

REGIONAL STATISTICS, 2013, VOL. 3: 117–140

Appendix 1

Final results of analysis of 77 Czech LAU 1 regions (including Prague)

Cluster	LAU 1 Region	CI_9	CI_10	CI_1	CI_5
C1	Břeclav	6	3	4	8
C1	Brno-venkov	9	13	9	14
C1	Hodonín	21	29	19	24
C1	Znojmo	31	27	29	25
C1	Uherské Hradiště	18	20	14	17
C1	Olomouc	11	8	11	10
C1	Zlín	10	7	8	6
C1	Vyškov	24	24	20	20
C1	Nový Jičín	12	10	6	5
C1	Kroměříž	33	43	32	39
C1	Opava	25	18	23	16
C1	Přerov	32	38	30	34
C1	Prostějov	52	54	49	49
C2	Ústí nad Labem	5	12	5	11
C2	Karviná	15	21	13	18
C2	Sokolov	42	46	42	51
C2	Teplice	36	53	39	55
C2	Chomutov	35	56	41	60
C2	Most	44	68	43	67
C3	Litoměřice	19	25	16	22
C3	Beroun	23	19	27	21
C3	Mělník	26	22	28	19
C3	Kladno	22	30	26	32
C3	Náchod	41	31	35	28
C3	Blansko	46	55	44	56
C3	Kolín	45	47	48	48
C3	Jindřichův Hradec	55	51	55	50
C3	Ústí nad Orlicí	37	37	36	38
C3	Chrudim	64	64	59	63
C3	Třebíč	62	65	58	64
C3	Žďár nad Sázavou	53	48	50	44
C3	Rychnov nad Kněžnou	48	39	47	40
C3	Nymburk	39	34	37	36
C3	Jičín	54	52	51	47
C3	Plzeň-město	7	6	12	9
C3	Jihlava	50	40	53	42
C3	Rokycany	58	63	62	66
C3	Havlíčkův Brod	66	58	65	58
C3	Rakovník	75	74	74	74
C3	Svitavy	61	61	57	57

(Table continued the next page)

(Continued)

Cluster	LAU 1 Region	CI_9	CI_10	CI_1	CI_5
C3	Benešov	56	44	56	46
C3	Klatovy	71	59	71	59
C3	Domažlice	60	60	61	61
C3	Trutnov	51	41	52	41
C3	Semily	59	49	60	45
C3	Louny	70	75	67	72
C3	Plzeň-sever	63	62	68	69
C3	Kutná Hora	73	70	73	71
C3	Tábor	57	50	63	52
C3	Pelhřimov	74	66	75	68
C3	Příbram	67	57	70	65
C3	Strakonice	77	77	77	77
C3	Písek	76	73	76	75
C4	Česká Lípa	17	23	18	30
C4	Vsetín	30	36	31	33
C4	Frýdek-Místek	27	33	25	31
C4	Český Krumlov	49	42	54	43
C4	Prachatice	68	71	69	73
C4	Liberec	16	4	17	4
C4	Děčín	38	35	34	35
C4	Cheb	20	14	24	13
C4	Tachov	40	45	46	54
C4	Šumperk	69	67	66	62
C4	Jeseník	43	32	38	26
C4	Jablonec nad Nisou	47	28	45	27
C4	Bruntál	65	72	64	70
C4	Karlovy Vary	34	26	40	37
C5	Praha-západ	3	3	3	3
C5	Hradec Králové	8	11	7	12
C5	Praha-východ	4	5	10	7
C5	Pardubice	13	15	15	15
C5	České Budějovice	28	16	33	23
C5	Mladá Boleslav	14	17	21	29
C5	Plzeň-jih	72	76	72	76
C6	Brno-město	2	2	2	2
C6	Ostrava-město	29	69	22	53
C7	Hlavní město Praha	1	1	1	1

Source: Own computation.

REGIONAL STATISTICS, 2013, VOL. 3: 117–140

Appendix 2

Final results of analysis of 77 Czech LAU 1 regions (excluding Prague)

Cluster	LAU 1 Region	CI_9	CI_10	CI_1	CI_5	CI_2	CI_6
C1	Zlín	5	6	3	3	5	4
C1	Olomouc	7	7	9	5	6	6
C1	Brno-venkov	8	11	6	11	11	15
C1	Břeclav	10	13	4	15	9	16
C1	Nový Jičín	12	12	12	7	8	7
C1	Uherské Hradiště	18	19	15	16	18	19
C1	Hodonín	23	27	20	25	22	36
C1	Opava	25	18	22	20	17	17
C1	Vyškov	28	28	25	26	28	31
C1	Přerov	31	37	29	27	34	33
C1	Znojmo	32	29	32	45	31	44
C1	Kroměříž	34	41	31	30	39	39
C1	Prostějov	51	56	48	48	53	54
C2	Ústí nad Labem	9	14	5	4	13	9
C2	Karviná	15	17	13	9	16	13
C2	Chomutov	33	53	38	35	56	48
C2	Teplice	35	49	35	32	47	41
C2	Sokolov	40	48	41	40	51	43
C2	Most	42	61	43	41	64	58
C3	Plzeň-město	3	3	8	6	4	5
C3	Litoměřice	20	26	17	19	24	26
C3	Kladno	22	24	23	23	29	25
C3	Beroun	26	22	27	31	25	32
C3	Mělník	27	25	28	29	23	29
C3	Ústí nad Orlicí	36	32	34	36	37	35
C3	Náchod	39	30	37	38	30	28
C3	Nymburk	41	39	39	39	38	38
C3	Kolín	43	50	46	50	48	55
C3	Blansko	44	55	42	44	55	52
C3	Jihlava	46	36	50	47	41	40
C3	Rychnov nad Kněžnou	48	42	47	52	42	47
C3	Trutnov	49	38	51	46	40	37
C3	Žďár nad Sázavou	50	45	49	49	43	49
C3	Jičín	53	54	52	53	50	53
C3	Jindřichův Hradec	54	52	54	59	54	57
C3	Benešov	55	46	56	57	46	46
C3	Tábor	56	47	55	51	45	42
C3	Semily	57	51	60	58	52	51
C3	Svitavy	58	60	57	55	57	59
C3	Rokycany	59	67	63	66	66	71

(Table continued the next page)

(Continued)

Cluster	LAU 1 Region	CI_9	CI_10	CI_1	CI_5	CI_2	CI_6
C3	Třebíč	60	65	58	65	61	68
C3	Domažlice	61	62	61	61	63	64
C3	Chrudim	62	64	59	67	62	70
C3	Havlíčkův Brod	63	58	62	62	58	61
C3	Příbram	64	57	67	63	60	56
C3	Plzeň-sever	65	63	69	69	69	67
C3	Klatovy	67	59	70	68	59	60
C3	Louny	70	73	66	64	72	66
C3	Pelhřimov	72	66	73	72	67	65
C3	Kutná Hora	73	70	72	71	70	72
C3	Rakovník	74	74	74	75	74	74
C3	Písek	75	72	75	73	73	69
C3	Strakonice	76	76	76	76	76	75
C4	Liberec	16	4	16	12	3	3
C4	Česká Lípa	17	23	19	17	26	21
C4	Frýdek-Místek	21	21	18	18	19	18
C4	Cheb	24	15	24	22	14	11
C4	Karlovy Vary	29	20	33	34	27	20
C4	Vsetín	30	35	30	28	35	34
C4	Děčín	37	34	36	33	36	27
C4	Tachov	38	44	44	42	49	45
C4	Jeseník	45	40	40	37	33	23
C4	Jablonec nad Nisou	47	31	45	43	32	22
C4	Český Krumlov	52	43	53	56	44	50
C4	Bruntál	66	71	64	54	68	62
C4	Šumperk	68	68	65	60	65	63
C4	Prachatice	69	69	68	70	71	73
C5	Praha-západ	2	2	2	2	2	2
C5	Praha-východ	4	5	10	14	7	8
C5	Hradec Králové	6	8	7	8	10	10
C5	Pardubice	11	10	14	10	12	12
C5	Mladá Boleslav	14	16	21	21	21	24
C5	České Budějovice	19	9	26	24	15	14
C5	Plzeň-jih	71	75	71	74	75	76
C6	Brno-město	1	1	1	1	1	1
C6	Ostrava-město	13	33	11	13	20	30

Source: Own computation.