Soc Indic Res (2017) 131:973–997
DOI 10.1007/s11205-016-1288-3

Using *ClustOfVar* to Construct Quality of Life Indicators for Vulnerability Assessment Municipality Trajectories in Southwest France from 1999 to 2009

Vanessa Kuentz-Simonet[1] · **Amaury Labenne**[1] · **Tina Rambonilaza**[1]

Accepted: 26 February 2016 / Published online: 12 March 2016

Abstract Climate change is increasingly accepted as a major worldwide issue, bringing with it a host of long-term consequences for both human beings and ecosystems. To more effectively limit the damage caused by natural hazards and global change, it is essential that we gain a greater understanding of the complex question of social vulnerability—a subject that has been widely discussed in the literature. This paper examines the use of a conceptual "human wellbeing" framework to analyse vulnerability. It also proposes an innovative statistical method (*ClustOfVar*) to capture the multidimensional nature of that vulnerability. Using our approach, it is possible to construct composite indicators of residents' living conditions at municipality level. To test our methodology, we carried out a comprehensive evaluation of the development of residents' quality of life for two specific years (1999 and 2009) in areas close to the Garonne and Gironde rivers in southwest France. The results reveal different municipality trajectories in terms of quality of life profiles. This study helps to understand the multivariate characteristics of communities with higher social vulnerability.

Keywords Vulnerability · Global change · Quality of life · *ClustOfVar* · Composite indicators

1 Introduction

Adapting to climate change will be one of the greatest challenges faced by the world in the coming years. Societies are increasingly vulnerable to the impacts and consequences of climate change, combined with the functional problems of modern society (O'Brien et al.

✉ Vanessa Kuentz-Simonet
vanessa.kuentz-simonet@irstea.fr

[1] UR ETBX, IRSTEA, Centre de Bordeaux 50 avenue de Verdun Gazinet, 33612 Cestas Cedex, France

2004; Pielke et al. 2007). Socio-economic processes (including socio-economic conditions, the quality of institutions, and governance) may amplify the local consequences of extreme events, meaning that groups who are already at risk from natural and biophysical hazards may also become more vulnerable to climate change on a social level (Kelly and Adger 2000). Vulnerability has thus become a global phenomenon, fuelled by a mix of economic, social and environmental problems (Brooks 2003). In view of these, some regions will need to be better prepared than others, simply because they are more vulnerable. This is particularly the case in rural regions, where primary sectors such as agriculture, forestry, and tourism serve as good indicators of vulnerability to climate change, but must always be considered in association with the vulnerability created by urban expansion. The spatial distribution of urban growth (demographic structures, economic activities, and availability and accessibility of services and amenities) determines the extent to which resources, opportunities and institutional processes can reduce social vulnerability, notably by developing people's ability to anticipate and respond to climate disturbances (Eakin et al. 2010). The aim of this study is to provide an analytical framework and statistical methodology to identify measurable components of "quality of life" that can be used in evaluating the ability of peripheral and rural communities to cope with and adapt to global change (including climatic hazards).

The socio-economic and ecological impacts of urban growth indeed have the potential to influence the quality of life of social groups and specific communities (Ward and Brown 2009), making them more vulnerable (unable to anticipate and to respond) to climate disturbances in the future. By developing a valuable method to identify measurable components of quality of life, we can advance our understanding of the vulnerability and adaptive capacity of peripheral and rural communities, as well as identifying areas where the need for public policy interventions would appear the most acute. The first relevant aspect for the construction of a vulnerability index is to find the underlying variables with which the composite index can be computed. Many indicators and index studies in climate change literature are data-driven (Nelson et al. 2010; Vincent 2007). However, focusing solely on empirically-derived indicators may classify vulnerability systems in such a way that they are of little use for policy-making purposes. This study creates a theoretical foundation for the nature and causes of vulnerability, thus making it possible to identify proxy variables that can be used to generate indicators of vulnerability or adaptive capacity to climate change. Our proposed indicators are based on the life domains' approach (Noll 2002, 2011), a shared approach for the construction of the European System of Social Indicators. Based on the existing literature on vulnerability and adaptation to climate change, the capacity of local communities or households to manage climate risks and adverse impacts of global change is founded on:

1. Housing characteristics (Cutter et al. 2003) and the quantity of affordable and available housing for low-income households (Aurand 2013)
2. Employment conditions (Dolan et al. 2008) and job opportunities (Heltberg et al. 2009)
3. Financial conditions
4. Better access to educational facilities (Striessnig et al. 2013)
5. Better access to health facilities (Few 2007)
6. Better accessibility and quality of services
7. The social environment including family, friends, and neighbours (Helgeson 2003; Pelling and High 2005; Dhillon et al. 2003)

8. Natural environmental conditions measured by land-use and land-cover change (Antrop 2004; Millennium 2005).

Another relevant aspect for the construction of an index for quality of life is to find an aggregation method that combines sub-indicators to produce a one-dimensional composite index. Due at least in part to its computational simplicity, Principal Component Analysis (PCA) is the common methodology by which to determine variables accounting for the largest proportion of quality of life (Vincent 2007). PCA provides a data-driven dimension reduction and linear weighting procedure to obtain the new indicators represented by principal components. However, the effectiveness of the PCA approach can be questioned if only a small part of the variation in the complete set of variables is accounted for by the first principal component. There is a chance that the procedure will ignore some non-redundant but valuable information. Distance-based approaches such as DP_2 distance and DEA are currently gaining attention in constructing quality of life indicators (Carboni and Russu 2014; Zarzoza Espina and Somarriba Arechavala 2013; Sanchez Dominguez 2013; Martin 2012; Somarriba and Pena 2009). These methods belong to the family of “distance” measures and thus fulfill a series of nice mathematical properties (Zarzoza Espina and Somarriba Arechavala 2013). The outcome is a cardinal measure, capable of determining how much better or worse the state of the synthetic indicator in a given unit is with respect to another or with a reference situation, thus making it possible to effect comparisons in space or time.

In this paper, the aim is neither to construct a one-dimensional quality of life index given a defined set of variables nor to re-conceptualise life domains. Our goal is to single out indicators within one domain that are homogeneous (statistically speaking) with indicators of other domains, thus revealing the multivariate characteristics of quality of life. To achieve this, we propose the use of variable clustering (SAS/STAT 2011; Vigneau and Qannari 2003; Vigneau and Chen 2015; Dhillon et al. 2003 for example) by extending the application of *ClustOfVar* (Chavent et al. 2012) to the construction of quality of life indicators for vulnerability assessment. By rearranging the variables into homogeneous clusters in which variables are strongly related to each other, *ClustOfVar* is well suited to measuring quality of life, because it makes it possible to highlight the multiple dimensions of the concept (corresponding to the clusters). It also simultaneously computes synthetic variables (SVs) in each cluster, which play the role of the composite indicators of quality of life. The writing of these SVs originates both from theoretical statistical properties and from the internal structure of data (Bartholomew et al. 2002). When computed as such, quality of life indicators (measured by SVs) constitute a way of measuring an underlying socio-economic process which is not directly observable, and which can be interpreted as a factor contributing to vulnerability. Note that in *ClustOfVar*, numeric and categorical variables such as threshold-based measure data or dichotomous coded situational variables can be integrated. However, regardless of the type of initial data, these synthetic variables are always numeric and can be read as a kind of gradient. These SVs are quite easy to interpret and label since they only refer to the variables in the corresponding cluster. Finally the *ClustOfVar* approach meets the requirements of the OECD handbook on selecting appropriate weighting and aggregation procedures for the construction of composite indicators (Nardo et al. 2008) in sense that it respects both the theoretical framework and the data properties.

For our case study, a combination of more than forty variables representative of the eight life domains were derived from censuses and official databases for application to a number of areas close to the Garonne and Gironde rivers in southwest France.

The remainder of the paper is organised as follows. Section 2 covers our data. Section 3 details the statistical methodology. Section 4 contains the presentation and discussion of the results. Section 5 provides some conclusions.

2 Data Description and Variables Employed

This empirical study focuses on the quality of life of people living within the socio-ecological system of the Garonne–Gironde Zone (GGZ) in southwest France. The two rivers span most of southwest France, coming together at the Atlantic coast to form one of the largest and most heavily protected estuaries in Europe. The perimeter of our study area encompasses approximately 3300 municipalities, with a combined population of 4.4 million people, all of which are located <50 km from either the rivers or the estuary. This represents a total surface area of 50,000 km^2—some 10 % of the total surface area of mainland France. Contrary to other large river-estuary systems in Europe (Rhine, Seine), the GGZ is largely rural in character. Most of the municipalities continue to have low population densities, and their landscapes are mainly driven by the development of forestry and agricultural land-uses. Densely populated areas are found in two locations: the Toulouse metropolitan area in the upstream sector, and Bordeaux and its surrounding suburbs further downstream. The "full control" approach—building dikes and canal systems—to protect against floods, and the extension of irrigated agriculture, both of which have been prevalent in recent decades, have led to the development of economic and residential activities without much consideration being given to changes in hydrological regimes. Some municipalities with direct access to the river are becoming attractive as places of residence, offering a range of environmental amenities thanks to their proximity to wetlands and marsh landscapes. However, climate projections for southwest France, including GGZ, underline the likelihood of increasingly frequent and intense flooding events (floods, coastal flooding and mudflows) and drought (low flows and shrinkage and swelling of clay) in the coming decades (Etcheber et al. 2013; Bonneton et al. 2013). Analysing the evolution of living conditions within municipalities is a key step in understanding the processes that have controlled the quality of life of their residents: the evolution of agriculture, urban sprawl, and ageing populations. The next step is to discuss whether or not these changes can be considered as factors of vulnerability.

When identifying indicators relating to quality of life, it is important to use data reflecting the underlying processes that determine variations in that quality (Rojas 2014). There must be as much comparable information available as possible (Villamagna and Giesecke 2014). In view of this, we obtained our data sets from two different tables, populated during two different periods (1999 and 2009). Socio-economic data were extracted from the SIDDT portal of Irstea, which contains census databases published by INSEE, the French Institute of Statistics and Economic Studies. For land-use patterns, we opted for Corine Land Cover (CLC) raster data (with precision of 25 ha) provided by the European Environment Agency (the 2000 database is used for 1999 and the 2006 database for 2009). The combination of these various data sets provided a system of 55 variables and 3287 municipalities for 1999. For 2009, the corresponding variables are 46 and the number of municipalities slightly increases to 3289 (due to changes in the layout of certain municipalities). The indicators reflecting living conditions according to the 8 selected life domains are shown in "Appendix 1" for illustrative purposes.

3 *ClustOfVar*-Based Methodology

To the best of our knowledge, this is the first time that a variable clustering approach has been used to develop composite indicators of objective components for quality of life. As the inventors of the *ClustOfVar* method,[1] we think that this approach will help to provide insights into the multidimensional concept of quality of life. *ClustOfVar* combines two steps simultaneously, one is is agglomerative and aims at maximising an homogeneity criterion by successively aggregating the variables into clusters (with a hierarchical ascendant clustering algorithm). The other is representative and consists in defining the synthetic variable of each cluster (reached by a principal component approach for mixed data). In the following, we put the emphasis on the two key points of the application of *ClustOfVar* to construct quality of life composite indicators: the aggregation of variables and the weighting scheme of the initial variables.

3.1 Aggregation of Variables: *ClustOfVar* Criterion for Hierarchical Ascendant Clustering

The aim is to find a partition of a set of numeric/categorical variables such that the variables within a cluster are strongly related to each other. We note $\{\mathbf{x}_1, \ldots, \mathbf{x}_{p_1}\}$ a set of p_1 numeric variables and $\{\mathbf{y}_1, \ldots, \mathbf{y}_{p_2}\}$ a set of p_2 categorical variables. Let $P_K = (C_1, \ldots, C_K)$ be a partition of the $p = p_1 + p_2$ variables into K clusters. The objective is then to determine a partition P_K that maximises the homogeneity criterion $\mathcal{H}$ defined below. It is the sum of the homogeneity of its clusters:

$$\mathcal{H}(P_K) = \sum_{k=1}^{K} H(C_k), \tag{1}$$

where $H(C_k)$ measures the homogeneity of the cluster C_k, that is the link between the variables in the cluster and its synthetic numeric variable denoted $\mathbf{f}_k$ (which will be defined in Sect. 3.2):

$$H(C_k) = \sum_{\mathbf{x}_j \in C_k} r^2_{\mathbf{x}_j, \mathbf{f}_k} + \sum_{\mathbf{y}_j \in C_k} \eta^2_{\mathbf{y}_j | \mathbf{f}_k}, \tag{2}$$

where r^2 denotes the squared Pearson correlation and $\eta^2 \in [0, 1]$ denotes the correlation ratio measuring the part of the variance of $\mathbf{f}_k$ explained by the categories of $\mathbf{y}_j$.

The first term measures the link between the numeric variables in C_k and $\mathbf{f}_k$ independently of the sign of the relationship and the second measures the link between the categorical variables in C_k and $\mathbf{f}_k$. The homogeneity of a cluster is at its highest when all the numeric variables are correlated (or anti-correlated) to $\mathbf{f}_k$ and when all the correlation ratios of the categorical variables are equal to 1. It means that all the variables in C_k are strongly linked.

To maximise the homogeneity criterion $\mathcal{H}$ defined in (1), we use the hierarchical ascendant clustering function available in the R package, known as *ClustOfVar*. Details of the algorithm are given in "Appendix 2".

[1] The actual name of the method is hierarchical ascendant clustering of variables with the function hclustvar of the R package *ClustOfVar*, but it is more commonly referred to by the name of the package.

3.2 Weighting of Variables: Implementation of the Composite Indicators

The synthetic variable $\mathbf{f}_k \in \mathcal{R}^n$ of a cluster C_k is defined as the numeric variable that is the "most linked" to all the variables in the cluster. It maximises the homogeneity of C_k and is then the solution of the following optimisation problem:

$$\mathbf{f}_k = \arg\max_{\mathbf{a}\in\mathcal{R}^n}\left(\sum_{\mathbf{x}_j\in C_k} r^2_{\mathbf{x}_j,\mathbf{a}} + \sum_{\mathbf{y}_j\in C_k}\eta^2_{\mathbf{y}_j|\mathbf{a}}\right). \tag{3}$$

It can be shown that the synthetic variable $\mathbf{f}_k$ is defined as the first principal component of PCAMIX, a principal component method for a mixture of categorical and numeric variables (Kiers 1991). In *ClustOfVar* we use a Singular Value Decomposition (SVD) approach to PCAMIX (Chavent et al. 2012).

Specifically, the calculation of $\mathbf{f}_k$ is reached according to the following steps:

1. Recoding of $\mathbf{X}_k$ and $\mathbf{Y}_k$, the matrices made up of the columns of $\mathbf{X}$ and $\mathbf{Y}$ corresponding to the variables in C_k:

   (a) $\tilde{\mathbf{X}}_k$ is the standardized version of the numeric matrix $\mathbf{X}_k$,

   (b) $\tilde{\mathbf{Y}}_k = \mathbf{JGD}^{-1/2}$ is the standardized version of the indicator matrix $\mathbf{G}$ of the categorical matrix $\mathbf{Y}_k$, where $\mathbf{D}$ is the diagonal matrix of frequencies of the categories. $\mathbf{J} = \mathbf{I} - \mathbf{1}'\mathbf{1}/n$ is the centering operator where $\mathbf{I}$ denotes the identity matrix and $\mathbf{1}$ the vector with unit entries.

2. Concatenation of the two recoded matrices: $\mathbf{Z}_k = \frac{1}{\sqrt{n}}(\tilde{\mathbf{X}}_k|\tilde{\mathbf{Y}}_k)$.
3. SVD of $\mathbf{Z}_k$: $\mathbf{Z}_k = \mathbf{U}_k\Lambda_k\mathbf{V}'_k$, where $\mathbf{U}'_k\mathbf{U}_k = \mathbf{V}'_k\mathbf{V}_k = I_r$, Λ_k is the diagonal matrix of eigenvalues (in weakly descending order) and r is the rank of $\mathbf{Z}_k$.
4. Calculation of the synthetic variable $\mathbf{f}_k$ of cluster C_k:

$$\mathbf{f}_k = \sqrt{n}\lambda^1_{C_k}\mathbf{u}^1_k, \tag{4}$$

   where $\mathbf{u}^1_k$ is the first left eigenvector of $\mathbf{Z}_k$ (first column of $\mathbf{U}_k$) and $\lambda^1_{C_k}$ is the first eigenvalue in Λ_k. Note that $\lambda^1_{C_k} = \mathrm{Var}(\mathbf{f}_k)$.

From the SVD, the synthetic variable $\mathbf{f}_k$ of a cluster C_k can also be computed as:

$$\mathbf{f}_k = \mathbf{Z}_k\mathbf{v}^1_k, \tag{5}$$

where $\mathbf{v}^1_k$ is the first right eigenvector of $\mathbf{Z}_k$ (first column of $\mathbf{V}_k$). Thus, the principal components are non correlated linear combinations of the columns of $\mathbf{Z}_k$ (the coefficients of the combination are given by $\mathbf{v}^1_k$) with maximum link to the original variables belonging to cluster C_k. The final weighting scheme of $\mathbf{f}_k$ (the composite indicators of quality of life) as linear combination of the initial variables is given in "Appendix 2".

4 Results

4.1 Construction of the Quality of Life Indicators for Year 1999

The R package called *ClustOfVar*, available on the CRAN, was used for hierarchical ascendant clustering of variables. The tree produced by this clustering (see "Appendix 3") illustrates the successive aggregations of all variables and helps visualise the links between them. Note that the aggregation criterion is used as the relevant node height in the tree. Thus, in addition to observing the tree, the progressively increasing level of aggregation (corresponding to loss of homogeneity) provides a suitable tool to select the number of clusters when partitioning variables. However, the choice of the number of synthetic variables is not only based on statistical arguments. In our case study, the emphasis is on understanding the clusters of variables and analysing them in connection with the issue at stake. To detect the main variables in the building up of the clusters, the R package provides the squared loadings, which are equal to squared correlations (resp. correlation ratios) between the initial numeric (resp. categorical) variables of the cluster and the composite indicator. The squared loading belongs to [0,1] and measures the link for both numeric and categorical variables on the same scale. For numeric variables, the table also gives the correlation to reflect the direction of the link (positive or negative). The table is given in "Appendix 3". We then choose to retain five distinct clusters of variables for the 1999 data set. Each of these clusters group together similar variables in order to summarise the information in one composite indicator per cluster. This can be viewed as the sub-indicator through which living conditions vary (as measured at the municipality level). Table 1 shows the reading of the five composite indicators.

Table 1 Reading of the five composite indicators for 1999

Composite indicator	Negative values	Positive values
Landuse and Natural Environment Conditions	High prop. of land with forest or other vegetation	High prop. of agricultural land
	Low prop. of working-age people in employment	High prop. of working-age people in employment
Job Opportunities across Economic Sectors	Employment within the department	Employment in the municipality of residence
	Low prop. of farmers	High prop. of farmers
	Dwellings built between 1975 and 1989	
Urban Socio-Economic Environment	Low prop. of developed surface area	High prop. of developed surface area
	Low population density	High population density
	Low average income	High average income
		Employment in urban center
		Childhood services
		Dwellings built between 1949 and 1974
Structure of Households and Lifestyles	Low prop. of retirees	High prop. of retirees
	High prop. of couple with children	High prop. of couple with no children
	Low prop. of people in active employment	High prop. of people in active employment
Availability and Accessibility of Services	Few services	Many services to individuals
	Dwellings occupied by owners	Rental housing

We call the first cluster of variables “Landuse and Natural Environment Conditions”. It is made up of the proportion of agricultural land uses (as measured at municipality level), which is strongly correlated with the average number of rooms in dwellings and the employment rate of people of working age. This demonstrates that until 1999, people in employment lived predominantly in municipalities where the main activity was agriculture.

Cluster 2 describes the employment conditions of residents of the municipality, which are correlated with the state of repair of their accommodation, and the standard of living of residents (the head of family has an intermediate occupation). The synthetic variable is negatively correlated with the proportion of residents employed outside their municipality, and with a high proportion of modern buildings (built between the seventies and the nineties). On the other hand, the variable is negatively correlated with the proportion of farmers within the employed population and the proportion of employment provided by the municipality. We call this cluster “Job Opportunities across Economic Sectors”.

Cluster 3 reflects the process of urbanisation. Unsurprisingly, this group combines the proportion of artificial surfaces in the total area of the municipality, with the density of the population on this scale. We can note also that these two variables are linked to the availability of nurseries and preschools within the municipality. This cluster is also characterized by the proportion of residents who work in the urban area of their municipality and the average pre-tax income for the municipality. We call this cluster “Urban Socio-Economic Environment”.

Cluster 4 shows a positive correlation between the proportion of retired people in the municipality and the proportion of households without children. The synthetic variable of this cluster is more strongly correlated with higher proportions of people without a specific profession. These statistical relationships indicate that the population of retirees is made up of couples without children, while high proportions of couples with children co-evolve with high proportions of housewives. We call this cluster “Structures of Households and Lifestyles”.

Cluster 5 groups together all variables for the presence of services and facilities in the municipality, without distinguishing between public services, amenities and shopping services. We call this cluster “Availability and Accessibility of Services”.

4.2 Municipality Quality of Life Profiles in 1999

The five composite indicators previously defined are used to establish municipality quality of life profiles. More precisely, we use a hierarchical ascendant clustering algorithm (HAC, with Ward criterion) on municipality scores measured using the five indicators. To choose a convenient number of municipality classes, we analyse the top of cluster tree and the histogram showing the HAC level indices: a five-classes typology seems relevant to highlight the quality of life profiles in 1999.

Table 2 gives the mean value of each composite indicator in the five classes of municipalities from the typology.

The parallel with the label of SV (Table 1) makes interpreting results quite easy. Specifically, for each SV, we compare the mean for each cluster of municipalities to that of the total sample (null mean because in the variable clustering approach used, the synthetic variables are centered). Table 2 shows in bold the negative (positive) means that are significantly lower (superior) to 0 (p value $< 10^{-3}$). Note that this test has no real statistical value (as the composite indicators were used to create groups of municipalities), but it is useful to indicate which indicators are discriminant.

Table 2 Mean of the composite indicators for the five groups of municipalities in 1999

Composite indicator	Municipality class				
	1 $n = 476$	2 $n = 1188$	3 $n = 1010$	4 $n = 458$	5 $n = 155$
Landuse and Natural Environment Conditions	**−2.53**	**0.84**	**0.56**	−0.56	−0.66
Job Opportunities Across Economic Sectors	0.4	**1.45**	**−1.86**	0.49	**−1.68**
Urban Socio-Economic Environment	−0.67	**−0.79**	−0.15	0.63	**7.22**
Structure of Households and Lifestyles	**0.77**	**0.44**	**−0.83**	0.14	−0.71
Availability and Accessibility of Services	**−1.41**	**−1.75**	**−0.92**	**5.36**	**7.91**

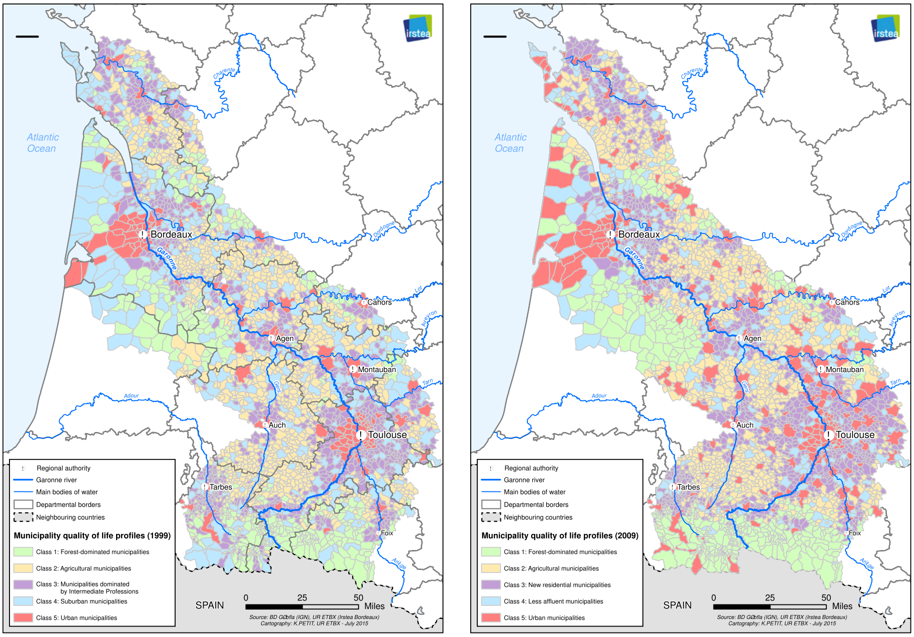
In bold: values significantly below or above the mean of the composite indicator in the total sample (by construction equal to 0); p value $< 10^{-3}$

The first class includes 476 municipalities where the lifestyle closely resembles that of the retired population. Indeed, the composite indicator of the quality of life "Structure of Households and Lifestyles" for this class is affected by a positive mean value, which implies a higher proportion of retired people. It is also observed that for these municipalities, the jobs are located in the municipality because of the positive value on the indicator "Access to Employment". According to the negative value of indicator "Availability and Accessibility of Services", these municipalities provide few services. They are more suitable for forestry activities, because the proportion of forest areas in the total area of the municipality is higher, and the unemployment rate is higher (negative value of indicator "Natural Environment Conditions and Employment Rate"). They are far away from urban centers and the river as shown in Fig. 1a. It is called "Class 1: Forest-dominated municipalities".

The second class includes 1188 municipalities for which the value of the composite indicator for quality of life of residents is guided first by a high proportion of agricultural land use within the municipality. These agricultural uses are associated with a higher proportion of residents in employment. These municipalities are places of residence for retired people and households without children. The standard of living of their residents is the same as that of farmers. Their residents have little access to local facilities and services. This class is named "Class 2: Agricultural municipalities".

The third class merges 1010 municipalities where residents' quality of life is objectively driven by conditions of employment. The residents work outside their municipality and belong to the socio-professional category of middle managers. Agricultural activity remains widespread within the municipality. The family environment and lifestyles of residents correspond to those of a couple with children. Municipalities offer few local services and facilities. It is called "Class 3: Municipalities dominated by Intermediate Professions", which already points out the arrival of new residents on agricultural lands.

The fourth class corresponds to 458 municipalities where residents' living conditions are first improved by the availability and access to services offered in the area. These municipalities are characterized by a large proportion of urban land, a variable strongly correlated with high population density. The average pre-tax income of residents is higher. The proportion of older buildings in the municipality is higher in comparison with the rest of the region. These municipalities are located at the periphery of the two urban areas of



(a) **(b)**

Fig. 1 Municipality quality of life profiles for (**a**) 1999 and (**b**) 2009

the river-estuarine system: Toulouse and Bordeaux (see map of Fig. 1). It is called "Class 4: Suburban municipalities".

The final class of municipalities differs from the previous one. It brings together 155 urban and suburban municipalities where residents' quality of life is first marked by a growing number of buildings and a higher population density. Average pre-tax income of residents is higher. The buildings are older. Residents' living conditions are positively affected by the availability of services. Residents are employed outside their municipality of residence. Finally, the social environment of residents is characterized by a high proportion of households consisting of a couple with children. These municipalities correspond to the two urban areas of Toulouse and Bordeaux. It is named "Class 5: Urban municipalities".

4.3 Quality of Life Indicators and Municipality Profiles in 2009

Quality of Life Indicators Once processed, the data for 2009 were organised into variables describing the living conditions at municipality level in five clusters (see "Appendix 4" for the results). Table 3 reveals several changes in the reconfiguration of the dimensions of quality of life.

Concerning the first cluster "Landuse and Natural Environment Conditions", a high proportion of agricultural land at the municipality level is now highly correlated with a high proportion of main home residence in the municipality, forming a first group of variables. Agricultural uses are no longer associated with a high proportion of residents in employment. Given the statistical principle that guides *ClustOfVar* method, this change

Table 3 Quality of life indicators for 1999 and 2009

1999	2009
Landuse and Natural Env. Conditions	Landuse and Natural Env. Conditions
Job Opportunities Across Economic Sectors	Job Opportunities across Economic Sectors
Urban Socio-Economic Environment	Urban Conditions
Structure of Households and Lifestyles	Lifestyles and Standards of Living
Availability and Accessibility of Services	Employment Conditions

means that municipalities whose economic vocation was agriculture in 1999 had by 2009 become more focused on housing development. This can be explained by the attractiveness of farmland both aesthetically—as a landscape—and as a factor for primary production.

Second, we note the growing importance of employment as a structuring component of quality of life. In 2009, the corresponding synthetic variable is very positively correlated with the proportion of residents with access to employment in their municipality and to the proportion of farmers. Inversely, the synthetic variable is negatively correlated with both the proportion of residents employed within their department and the proportion of residents belonging to the working class. Thus the keeping of indicator "Job Opportunities Across Economic Sectors" between 1999 and 2009 highlights that agriculture remains the major sector providing employment at the municipality scale because the area of study is rural. Also, a new dimension emerges related to "Employment Conditions", combining the employment rate of residents and the proportion of people aged 25–54 years in the municipality who found a job. Finally, the family component in 1999 "Structure of Households and Lifestyles" has an additional connotation relating to professional conditions in 2009 "Lifestyles and Standards of Living". In the corresponding cluster, the synthetic variable is negatively correlated with the proportion of retirees. On the contrary it is highly positively correlated with the proportion of households consisting of a couple with children, the average pre-tax income, and the proportion of both highly qualified and intermediate professions.

Another significant phenomenon is the development of services that has accompanied densification. Before 1999, services and degree of urbanisation were two independent components, but from 1999 to 2009, the development of services has gone hand in hand with the densification of municipalities. The related cluster includes several variables that characterise the social and urban economic environment: the proportion of built-up areas, the presence of a wide range of services, the population density, and very heterogeneous levels of access to accommodation. This last cluster is called "Urban Conditions".

Municipality Profiles We next identify classes of municipalities using HAC with regard to their scores for each of the five composite indicators for the quality of life of their population. A number of five classes (as for 1999) is statistically relevant and will enable to analyse the trajectory of municipalities from 1999 to 2009. The mean of the composite indicators for the five groups is given in "Appendix 4".

The first class includes 460 municipalities where residents' quality of life is guided by three synthetic variables. For these municipalities, residents can benefit in 2009 primarily to a higher proportion of forest area. It is also observed that in these municipalities, the employment rate of the resident population and the proportion of primary residences in dwellings are lower. The proportion of retired people is higher. The proportion of highly qualified jobs and the average income are lower. This class is called “Forest-dominated municipalities”.

A second class deals with 1097 municipalities where residents’ living quality of life is objectively affected by the presence of farmland. These municipalities are places of residence for farmers and retirees. People are employed in their municipality of residence. They offer very few services on site. It is named “Class 2: Agricultural municipalities”.

The third class corresponds to 1162 municipalities where the living conditions for their inhabitants are drawn first by maintaining agricultural land uses. The proportion of primary residences is higher, with many households containing a couple with children. There is also a larger proportion of individuals from the class of executives or middle management with a high average income, working outside their municipality of residence (within the department). The inhabitants have very little access to local services. This class of municipality is called “Class 3: New Residential municipalities”.

A fourth class covers the municipalities (318) for which the living conditions of the population essentially represent a suburban environment with many services. The quality of life is impacted by the residential character of municipalities (a high proportion of rental main homes in the municipality). It is called “Class 4: Suburban municipalities”.

A final class of 252 municipalities offers their people a quality of life characterized by a wider access to services and characteristics of an urban environment (more than the fourth class). This class also differs from the previous one since the population density and the rental housing are higher. Finally, the proportion of residents with access to employment in the municipality is higher there. This class is named “Class 5: Urban municipalities”.

4.4 Municipality Trajectories and Their Vulnerability

The statistical analysis we conducted was primarily aimed at building composite quality of life indicators for municipalities for 1999 and 2009. We can now explore the trajectory of each municipality and the vulnerability to climate change of community living there. This is done by using a table with two entries, which crosses the municipality quality of life profile for 1999 and the corresponding profile for 2009 (Table 4). The table includes the five municipalities’ profiles for 1999 and the same number of profiles for 2009. From the nineteen municipality trajectories (1999–2009) identified using cross-tabulation analysis and by comparing the mapping in Fig. 1, the most significant results are: an agricultural

Table 4 Cross tabulation of municipality typologies from 1999 to 2009

	Class in 2009				
	1. Forest-dominated	*2. Agricultural*	*3. New residential*	*4. Suburban*	*5. Urban*
Class in 1999					
1. Forest-dominated	344	105	27	0	0
2. Agricultural	28	845	315	0	0
3. Intermediate professions	56	108	801	44	1
4. Suburban	32	37	18	252	119
5. Urban	0	0	1	22	132

intensification for forest dominated areas, an agricultural regression and residential development for agricultural dominated municipalities following the sprawl of both Bordeaux and Toulouse, but also of small towns, and the densification of inner suburban municipalities of both Bordeaux and Toulouse. These results suggest that agricultural activities and farming still predominate within large parts of the territory. However, newcomers' lifestyles has gained importance in rural municipalities. Consequently, it is important to see to what extent the redefinition of living conditions of rural communities is changing their vulnerability to (or their capacity to cope with) climate change.

Our results show that municipalities which were part of Classes 1 in 1999 remained largely in Classes 1 in 2009. These municipalities (344/476) are located in mountainous or forest areas far away from urban centres, and remain unaffected by urbanisation. Because of the low availability of services in these municipalities, their population (composed mainly of retired individuals) would be more vulnerable to risks associated with climate change. More specifically, access to health care is a key tool in protecting the elderly against health complaints associated with weather and/or climatic hazards (Few 2007). However, older people's vulnerability is not only defined by the fact that they live in unfavourable economic conditions, but also by their ability to mobilise resources and support during an event. In old age, vulnerability is more often than not a result of insufficient care, and neglect by family and other members of the community (Wolf et al. 2010). Social interaction is assumed to be an increasing function of population density (Brueckner and Largey 2008). The decrease of population in these municipalities has made the aged population more vulnerable.

A third of the municipalities were agricultural dominated municipalities (Class 2) in 2009. These municipalities are mainly located along the river bank. Other forest dominated municipalities (Class 1 in 1999) (105/476 = 22 %) were transformed into agricultural dominated municipalities (Class 2) in 2009. In total, about 7 % of the population of the GGZ lived in these areas. Agricultural dominated municipalities were first and foremost areas of production and provided employment for their residents. The main threats posed by climate change to these municipalities relate to the longevity of agricultural activities and farm employment. Indeed, the experience of unemployment is one of the factors that have the strongest negative impact on people's subjective well-being (Dolan et al. 2008). Job availability and earnings are indicative of the capacity of a socio-economic system to build resilient communities (Heltberg et al. 2009). Consequently, in the absence of adaptation and in light of uncertainty around future rainfall projections, irrigated agriculture in the GGZ will have fallen, and will have ended with declines in agricultural employment, and the populations will decline. Rural abandonment by the active population will contribute to elderly people's vulnerability to climate hazards that could induce less family and neighbourhood support in case of disaster.

Continuous residential development between 1999 and 2009 increased the size of rural municipalities on the outskirts of both Bordeaux and Toulouse. Furthermore, agricultural municipalities (placed in Class 2 in 1999), that were attractive because of their proximity to medium-sized cities offering employment to individuals in intermediate professions (Fig. 2a), moved to Class 3 in 2009. A lot of family with children choose to live in these areas for better housing conditions. Indeed, the trends of urban sprawl (preference for single-family dwellings) have negatively affected the quantity of affordable and available housing for middle-income households (Aurand 2013). These municipalities are not adequately equipped with services and facilities. However, with respect to adaptive capacity of the communities to climate change, the availability of local services would appear less important than social cohesion and community care. Indeed, the social environment plays a

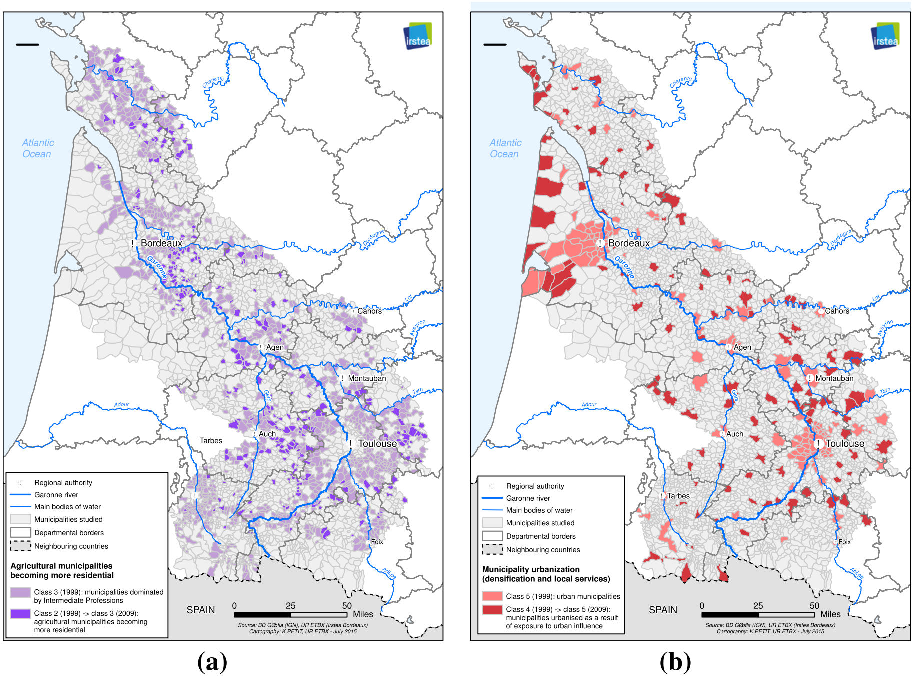


Fig. 2 Municipality trajectories (**a**) Agricultural municipalities becoming more residential (**b**) Municipality urbanization

critical role in socio-economic vulnerability, since social and economic diversity challenges community cohesion. The social environment determines the nature of social capital and the resources and support to which individuals have access in case of disaster (Helgeson 2003). Social networks and norms (Pelling and High 2005), as well as inter-individual relationships (Cutter et al. 2003), are key resources that may improve a community's resilience when faced with risks and natural hazards. The migration of young families with children to these areas could be seen, for instance, as a significant opportunity to build social capital and ensure the resilience of rural communities.

At the other extreme, we find suburban (Class 4) and urban municipalities (Class 5), accounting for three quarters (76 %) of the GZG population. One third of municipalities that were in Class 4 in 1999 had reached Class 5 by 2009. This is particularly true of municipalities located between the city of Bordeaux and the Atlantic coast, and those situated between Toulouse and the medium-sized city of Montauban. This transition is attributed in part to greater availability of jobs and increased investment in local services (Fig. 2b). These municipalities demonstrated the existence of an urban environment combining the advantages of good availability of services and facilities and better accessibility to jobs. However, for the majority, good accessibility to services and facilities may play a compensatory role and offset the effects of bad conditions of housing (a large proportion of dwellings were built between 1949 and 1974). The vulnerability of these urban communities to climate change could be associated to poor housing conditions which are known factors of increased risks of health problems related to climate variation (heat and cold stresses) (Cutter et al. 2003).

By highlighting these major trends, it can be argued that the urban growth phenomenon can amplify the socio-economic vulnerability of certain rural municipalities in the medium term. The densification of municipalities under the influence of two major urban centers (Toulouse-Bordeaux) and their peripheries has led to services, infrastructure and jobs being concentrated in these same municipalities. Conversely, rural municipalities located far away from centers of employment, and which offer very limited services to their population, remain isolated. If there is no influx of new residents, their populations will become increasingly older and increasingly vulnerable to crises and risks associated with climate change. For these two reasons, the development of medium-sized cities that have to invest in infrastructure for public services and facilities plays a vital role here, to make rural communities less vulnerable to global change. However, regional planners need to be cautious about the potential of polycentric urban development. The continuous development of rural municipalities located on the outskirts of these medium-sized cities will represents a threat to the ecosystem services associated with the maintaining of forest and agricultural land uses.

5 Concluding Remarks and Discussion

This paper uses a "quality of life" conceptual framework to assess the vulnerability (or the capacity to adapt) to climate change of 3.300 municipalities close to the Garonne and Gironde rivers in southwest France. Eight of the life domains covered by the European System of Social Indicators are assumed to represent the capacity of local communities to manage climate risks and the adverse impacts of global change. Given the complex, multifaceted nature of the concept of "quality of life", defining an appropriate weighting and aggregation method to combine multiple aspects into composite indicators represents a significant challenge.

Our proposed use of *ClustOfVar* to re-build the structural elements of living conditions within municipalities demonstrates that for the year 1999, the quality of life of people in this region can be measured by five dimensions: (1) Natural Environmental Conditions, (2) Job Opportunities for permanent residents; (3) Standard of living and lifestyles of households; (4) Urban Socio-Economic Environment; (5) Availability and Accessibility of Services. Traditional cluster analysis of observation units (in this case municipalities), combined with class mapping, confirms that there are significant differences in the quality of life components between municipalities in this region of France. Application of the same methodology in 2009 identified the five dimensions of the quality of life indicators for this year, resulting in a reconfiguration of "municipality quality of life" profiles. Comparison of municipality profiles obtained from the two periods provided indications of the changes in living conditions of communities over the decade, and highlighted on their vulnerability profiles. The results show that urban sprawl has exacerbated the vulnerability of older people in marginalised rural areas. At the extreme, rural municipalities located on the outskirts of medium-sized cities has gained new residents, but at the expense of agricultural land. This represents a threat to the ecosystem services associated with this type of land use. However, agriculture-based employment continue to be the main factor of the quality of life for population of rural municipalities in this region, making them particularly sensitive to climatic changes.

Drawing upon the statistical literature, *ClustOfVar* belongs to multivariate analysis methods such as PCA, which is the most popular one, probably to its computational simplicity and user-friendly mathematical properties. In a sense, *ClustOfVar* is close to PCA because it uses a principal component approach (PCAMIX) to build the composite indicator in each cluster of variables. However the methodology is different since the aim of PCA is to reconstruct the variation of the data set by studying its overall structure. The components are mainly outlined by the directions of high variance of the data, assigning marginal weights to loosely correlated subsets of variables. One consequence is that the interpretation of the indicator with respect to these variables may be difficult. The advantage of *ClustOfVar* over PCA is that it offers more flexibility when building composite indicators, since it does not impose orthogonality constraints between them. Indeed *ClustOfVar* generates several groups of variables, according to the similarities in the way units are measured by the variables. The simultaneous construction of SVs does not follow the reconstruction of inertia in the whole data set, but instead follows the structuring of variables into clusters by extracting the synthetic variable in each one with PCAMIX. The application of *ClustOfVar* to re-build the structural elements of living conditions shows that natural environment conditions build an independent component of quality of life and that socio-economic variables are structured around four dimensions : job opportunities, lifestyles, urban conditions and services. It cannot be excluded that, with PCA (or rather PCAMIX in view of the nature of our data), socio-economic variables would have built a first principal component with high percentage of inertia, because of large number and strong relationship between them. Searching for a second principal component, orthogonal to the first one, would have probably given a component with low inertia and difficult interpretation. Thus we can suppose that the importance of environmental variables (few in number) in the construction of the indicators, would have been masked. Note however that there is some uncertainty on the dimension of services, because categorical variables have almost exclusively built this cluster of variables. Obviously this reveals the agglomeration of services in municipalities, but a possible tendency of the method to gather separately categorical variables from other variables cannot be excluded. As this is the first time *ClustOfVar* has been applied to construct composite indicators for quality of life, it would be interesting to investigate this point by applying the same methodology on other data sets or analysing the behaviour of the method with simulation studies.

Another advantage of *ClustOfVar* is when this first step of constructing composite indicators is followed by a clustering of units, as carried out in this paper. In this respect, our sequential approach is quite similar to "tandem analysis" (Arabie and Hubert 1994) consisting of applying PCA, followed by clustering of units. We argue that the advantage of *ClustOfVar* over PCA is that it makes it possible to take into account more information in the clustering of units, contrary to PCA that may mask some, due to the imposed orthogonality of principal components. Other alternatives in multivariate analysis are based on a simultaneous clustering of both observations and variables such as "factorial k-means" (Vichi and Kiers 2001) or "disjoint clustering and principal component analysis" (Vichi and Saporta 2009). An extension of our approach for composite indicators would be to propose a method that simultaneously maximises the homogeneity criterion for variable clustering and the inertia criterion related to unit clustering. Using this method, we could simultaneously search for homogeneous groups of variables while seeking to identify typical profiles of municipalities. Statistical theoretical developments are needed to define a new homogeneity criterion. In particular, special attention will need to be given to the writing and reading of the synthetic variables which are essential in the application of *ClustOfVar* (instead of factor analysis) for quality of life indicators measurement, helping to understand the structure of "quality of life".

Acknowledgments This project was carried out as a part of "ADAPTEAU" (ANR-11-CEPL-008), a project supported by the French National Research Agency (ANR), as part of "The Global Environmental Changes and Societies (GEC&S) programme". The authors are very grateful to Kevin Petit, GIS specialist at Irstea Bordeaux (UR ETBX) for his valuable help in the fields of data processing and cartography.

Appendix 1: The Definition of Variables for Year 1999

Life domain	Variable	Description	Mean
Housing conditions	SingleFamilyRes	≥90 % of single-family primary residences$^{\diamond}$	0.64
	Owner	Prop. of dwellings occupied by owner	74.5
	SocialHousing	≥5 % of social housing primary residences$^{\diamond}$	0.11
	NbRoomsDwell	Number of rooms per dwelling	4.4
	Dwellings15_48	Prop. of dwellings built between 1915 and 1948	7.8
	Dwellings49_74	Prop. of dwellings built between 1949 and 1974	13.8
	Dwellings75_89	Prop. of dwellings built between 1975 and 1989	21.2
	DwellingsAfter90	Prop. of dwellings built after 1990	10.8
Labour market and working conditions	WorkDepartment	Prop. of working-age people employed within the department	56.9
	WorkMunicip	Prop. of working-age people employed in their municipality of residence	32.4
	EmployZone	Prop. of working-age people employed in the employment zone	48.8
	EmployUrbanCenter	Prop. of working-age people employed in the urban center	5.1
	WorkingAgeEmploy	Prop. of working-age people in employment	88.1
	15_24Employ	Level of employment of people aged 15–24	22.9
	25_54Employ	Level of employment of people aged 25–54	78.1
	55_64Employ	Level of employment of people aged 55–64	33.6
Standard of living—economic inequality	Income	Average net taxable income of households	8489894.9
	Farmers	Prop. of farmers	7.1
	TradeSelfEmploy	Prop. of tradesmen, other self-employed people, business owners	4.3
	HighlyQualified	Prop. of managers and other highly-qualified jobs	3.6
	IntermediateProf	Prop. of workers and other employees	9.4
	MiddleLevelWorkers	Prop. of middle-level workers	27.5
	NoDiploma	Prop. of people having no diploma	21.5

Life domain	Variable	Description	Mean
Social interaction and lifestyles	PopDensity	Population density	80.0
	CpleNoChild	Prop. of households composed chiefly of couples with no children	31.9
	CpleWithChild	Prop. of households composed chiefly of couples with children	36.0
	SingleParent	Prop. of single-parent households	6.8
	SingleWoman	Prop. of households made up of a single woman	11.9
	SingleMan	Prop. of households made up of a single man	11.0
	Retirees	Prop. of retirees	28.3
	NotActive	Prop. of people not in active employment	20.0
Natural environmental conditions	DvpedSurfaceArea	Prop. of developed surface area	3.7
	AgriLand	Prop. of agricultural land	70.5
	ForestVegetation	Prop. of land with forest of other vegetation	24.7
	WaterBodies	Prop. of water bodies	1.0
	DistceRiverEstuary	Distance from river/estuary in kilometers	23.9
Accessibility and quality of services	Banks	Presence of banks◇	0.12
	Butchers	Presence of butchers and delicatessens◇	0.22
	Bakeries	Presence of bakeries◇	0.33
	PostOffices	Presence of post offices◇	0.30
	Supermarkets	Presence of supermarkets◇	0.09
	Veterinary	Presence of veterinary surgeries◇	0.08
	Restaurants	Presence of restaurants◇	0.41
	Petrol	Presence of petrol station◇	0.23
	Tobacco	Presence of tobacco shops◇	0.42
	BarCoffee	Presence of bars and coffees◇	0.49
Educational facilities	Schools	Presence of schools◇	0.08
	ColNurseries	Presence of collective nurseries◇	0.05
	FamNurseries	Presence of familial nurseries◇	0.09
	PrimarySchools	Presence of primary schools◇	0.38
	PreSchools	Presence of pre-schools◇	0.47
	AfterSchoolCenters	Presence of after-school centers◇	0.46
	DayCares	Presence of daycare centers◇	0.10
Health conditions	GPs	Presence of GPs and specialist doctors◇	0.25
	Pharmacies	Availability of pharmacies◇	0.20

The symbol ◇ indicates that the variable is categorical. The variables of the two last life domains may have two or more categories. But for simplicity reasons, we only give the mean value for the presence of the service, which could be one or more on the municipality

Appendix 2: Statistical Details on *ClustOfVar*

Ascendant Hierarchical Clustering

Let $\mathbf{X}$ and $\mathbf{Y}$ be the corresponding numeric and categorical data matrices of dimensions $n \times p_1$ and $n \times p_2$, where n is the number of observation units. For the sake of simplicity, we denote $\mathbf{x}_j \in \mathcal{R}^n$ the j-th column of $\mathbf{X}$ and $\mathbf{y}_j \in \mathcal{M}_j^n$ the j-th column of $\mathbf{Y}$ with $\mathcal{M}_j$ the set of categories of $\mathbf{y}_j$.

It builds a set of p nested partitions of variables in the following way:

1. Step $l = 0$: initialisation. Start with the partition into singletons (p clusters).
2. Step $l = 1, \ldots, p-2$: aggregate two clusters of the partition into $p - l + 1$ clusters to get a new partition into $p - l$ clusters. For this, choose clusters A and B with the smallest dissimilarity defined as:
$$d(A,B) = H(A) + H(B) - H(A \cup B) = \lambda_A^1 + \lambda_B^1 - \lambda_{A\cup B}^1. \tag{6}$$
We can prove that $\lambda_{A\cup B}^1 \leq \lambda_A^1 + \lambda_B^1$, which implies that the merging of two clusters A and B at each step results in a decrease of criterion $\mathcal{H}$. This dissimilarity measures the loss of homogeneity observed when the two clusters are merged. The strategy therefore consists in merging the two clusters that result in the smallest decrease in $\mathcal{H}$. Using this aggregation measure the new partition into $p - l$ clusters maximises $\mathcal{H}$ among all the partitions into $p - l$ clusters obtained by amalgamation of two clusters of the partition into $p - l + 1$ clusters.
3. Step $l = p - 1$: stop. A single cluster consisting of all variables is obtained.

The height of a cluster $C = A \cup B$ in the tree is defined as $h(C) = d(A,B)$. This approach provides a tree which enables the user to see the successive aggregations between the variables, and gives a graphical illustration to aid in selecting the number of clusters to be used.

The Final Weigthing Scheme of the Quality of Life Indicators

The weighting scheme of $\mathbf{f}_k$ as linear combination of the initial variables (belonging to cluster) is:

$$\mathbf{f}_k = \beta_0 + \sum_{k=1}^{p_1+m} \beta_k \mathbf{x}_k \tag{7}$$

where the vectors $\mathbf{x}_1, \ldots, \mathbf{x}_{p_1+m}$ are the columns of $\mathbf{X} = (\mathbf{X}_k|\mathbf{G})$. The values of β_0 and $\beta_k, k = 1, \ldots, p_1 + m$ are given in Appendix.

$$\begin{aligned}
\beta_0 &= -\sum_{l=1}^{p_1} v_{li} \frac{\bar{\mathbf{x}}_l}{\sigma_l} - \sum_{l=p_1+1}^{p_1+m} v_{li} \frac{n}{n_l} \bar{\mathbf{x}}_l \\
\beta_k &= v_{ki} \frac{1}{\sigma_k}, \text{ for } k = 1, \ldots, p_1 \\
\beta_k &= v_{ki} \frac{n}{n_k}, \text{ for } k = p_1 + 1, \ldots, p_1 + m
\end{aligned}$$

with $\bar{\mathbf{x}}_k$ and σ_k respectively denote the empirical mean and standard deviation of the column $\mathbf{x}_k$.

Appendix 3: Complement Results for 1999

See Fig. 3; Table 5.

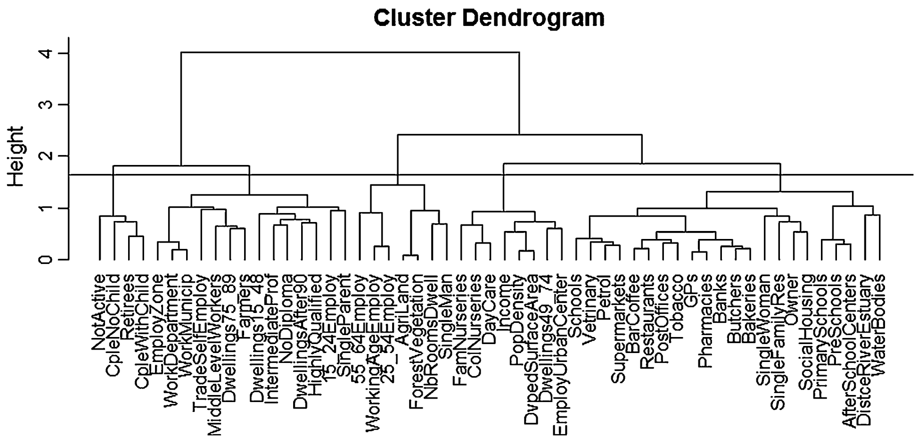


Fig. 3 Dendrogram of the hierarchy of the variables of the 1999 data set built with *ClustOfVar* (the *line* indicates a cutting into five clusters)

Table 5 Link between the initial variables and the synthetic variables for each cluster in 1999

Variables	Squared loading	Correlation (for num. var.)
Cluster 1: Landuse and Natural Environment Conditions		
AgriLand	0.62	0.79
ForestVegetation	0.57	−0.75
NbRoomsDwell	0.46	0.68
WorkingAgeEmploy	0.39	0.62
25_54Employ	0.35	0.59
SingleMan	0.16	−0.40
55_64Employ	0.11	0.34
Cluster 2: Job Opportunities Across Economic Sectors		
WorkMunicip	0.69	0.83
WorkDepartment	0.68	−0.82
EmployZone	0.60	−0.78
Dwellings75_89	0.43	−0.66
Farmers	0.36	0.60
DwellingsAfter90	0.33	−0.57
IntermediateProf	0.30	−0.55
NoDiploma	0.21	0.45
HighlyQualified	0.18	−0.42
MiddleLevelWorkers	0.12	−0.35

Table 5 continued

Variables	Squared loading	Correlation (for num. var.)
Dwellings15_48	0.07	0.26
15_24Employ	0.03	0.17
TradeSelfEmploy	0.01	−0.08
SingleParent	0.00	0.02
Cluster 3: Urban Socio-Economic Environment		
DvpedSurfaceArea	0.78	0.88
Popdensity	0.64	0.80
ColNurseries	0.55	–
PreSchools	0.51	–
EmployUrbanCenter	0.44	0.66
Income	0.41	0.65
Dwellings49_74	0.38	0.62
FamNurseries	0.35	–
Cluster 4: Structure of Households and Lifestyles		
Retirees	0.66	0.81
CpleWithChild	0.65	−0.81
CpleNoChild	0.38	0.61
NotActive	0.29	−0.54
Cluster 5: Availability and Accessibility of Services		
Bakeries	0.78	–
Pharmacies	0.76	–
Butchers	0.74	–
Tobacco	0.70	–
GPs	0.69	–
Petrol	0.69	–
BarCoffee	0.67	–
Banks	0.67	–
Restaurants	0.63	–
PostOffices	0.59	–
Veterinary	0.51	–
Schools	0.50	–
Supermarkets	0.49	–
PrimarySchools	0.45	–
Preschools	0.41	–
SocialHousing	0.36	–
AfterSchoolCenters	0.35	–
Owner	0.28	−0.53
SingleFamilyRes	0.21	–
SingleWoman	0.07	0.27
WaterBodies	0.05	0.23
DistceRiverEstuary	0.02	−0.13

Appendix 4: Some Results for Year 2009

See Tables 6, 7 and 8.

Table 6 Link between the initial variables and the synthetic variables for each cluster in 2009

Variables	Squared loadings	Correlations (for num. var.)
Cluster 1: Landuse and Natural Environment Conditions		
ForestVegetation	0.90	−0.95
AgriLand	0.85	0.92
PrimaryResid	0.57	0.76
TradeSelfEmploy	0.03	−0.17
Cluster 2: Employment Conditions		
25_54Employ	0.83	0.91
WorkingAgeEmploy	0.75	0.87
NotActive	0.16	−0.39
15_24Employ	0.04	0.20
Cluster 3: Job Opportunities Across Economic Sectors		
WorkMunicip	0.71	0.84
WorkDepartment	0.68	−0.83
Farmers	0.39	0.62
MiddleLevelWorkers	0.26	−0.51
Cluster 4: Lifestyles and Standards of Living		
Retirees	0.57	−0.76
CpleWithChild	0.54	0.74
Income	0.44	0.70
HighlyQualified	0.41	0.64
IntermediateProf	0.37	0.61
NoDiploma	0.20	−0.45
55_64Employ	0.17	0.41
CpleNoChild	0.15	−0.39
SingleWoman	0.13	−0.36
SingleMan	0.03	−0.18
SingleParent	0.00	0.03
Cluster 5: Urban Conditions		
Pharmacies	0.86	–
GPs	0.81	–
Dentists	0.80	–
Bakeries	0.75	–
Banks	0.72	–
Butchers	0.69	–
PrimarySchools	0.68	–
Restaurants	0.66	–
Nurseries	0.66	–

Table 6 continued

Variables	Squared loadings	Correlations (for num. var.)
Supermarkets	0.63	–
Schools	0.61	–
Veterinary	0.60	–
PostOffices	0.57	–
DvpedSurfaceArea	0.47	0.69
PreSchools	0.43	–
SingleFamilyRes	0.42	–
Owner	0.41	−0.64
SocialHousing	0.38	–
PopDensity	0.32	0.56
Minimarkets	0.29	–
Greengrocers	0.24	–
WaterBodies	0.04	0.19
DistceRiverEStuary	0.02	−0.15

Table 7 Reading of the five composite indicators for 2009

Composite indicator	Negative values	Positive values
Landuse and Natural Environment Conditions	High prop. of land with forest or other vegetation	High prop. of agricultural land
	Low prop. of primary residence in dwellings	High prop. of primary residence in dwellings
Employment Conditions	Low prop. of working-age people in employment	High prop. of working-age people in employment
Job Opportunities Across Economic Sectors	Employment within the department	Employment in the municipality of residence
	Low prop. of farmers	High prop. of farmers
	High prop. of middle level workers	Low prop. of middle level workers
Lifestyles and Standards of Living	High prop. of retirees	Low prop. of retirees
	Low prop. of couple with children	High prop. of couple with children
	Low average income	High average income
	Low prop. of highly-qualified jobs	High prop. of highly-qualified jobs
	Low prop. of workers and other employees	High prop. of workers and other employees
Urban Conditions	Few services	Many services
	Low prop. of developed surface area	High prop. of developed surface area
	Low population density	High population density
	High prop. of dwellings occupied by owner	

Table 8 Mean of the composite indicators for the five groups of municipalities in 2009

Composite indicator	Municipality class				
	1 n = 460	2 n = 1095	3 n = 1162	4 n = 318	5 n = 252
Landuse and Natural Environment Conditions	**−2.96**	**0.44**	**0.69**	0.28	−0.06
Employment Conditions	**−0.67**	−0.01	**0.52**	−0.30	−0.74
Job Opportunities Across Economic Sectors	0.01	**0.90**	**−0.90**	−0.23	0.50
Lifestyles and Standards of Living	**−0.76**	**−1.08**	**1.37**	−0.08	−0.12
Urban Conditions	−1.2	**−1.57**	**−1.31**	**3.95**	**10.08**

In bold: values significantly below or above the mean of the composite indicator in the total sample (by construction equal to 0); p value $< 10^{-3}$

References

Antrop, M. (2004). Landscape change and the urbanization process in Europe. *Landscape and Urban Planning*, *67*, 9–26.

Arabie, P., & Hubert, L. (1994). Cluster analysis in marketing research. In R. P. Bagozzi (Ed.), *Advanced methods of marketing research* (pp. 160–189). Cambridge, MA: Blackwell.

Aurand, A. (2013). Does sprawl induce affordable housing? *Growth and Change*, *44*, 631–649.

Bartholomew, D., Steele, F., Moustaki, I., & Galbraith, J. (2002). *The analysis and interpretation of multivariate data for social scientists*. Raton, London, New York, Washington DC: Chapman Hall/CRC.

Bonneton, P., Abadie, S., Castelle, B., Favennec, J., Mallet, C., & Sottolichio, A. (2013). Chapitre 6.1: Modification du littoral. In H. Le Treut (Ed.), *Les impacts du changement climatique en Aquitaine. Un état des lieux scientifique*. Bordeaux: Presses Universitaires de Bordeaux.

Brooks, N. (2003). Vulnerability, risk and adaptation: A conceptual framework. *Tyndall Centre for Climate Change Research*, Technical report 38.

Brueckner, J. K., & Largey, A. G. (2008). Social interaction and urban sprawl. *Journal of Urban Economics*, *64*, 18–34.

Carboni, O. A., & Russu, P. (2014). Assessing regional wellbeing in italy: An application of malmquist-dea and self-organizing map neural clustering. *Social Indicators Research*, *122*, 677–700.

Chavent, M., Kuentz-Simonet, V., Liquet, B., & Saracco, J. (2012). Clustofvar: An R package for the clustering of variables. *Journal of Statistical Software*, *50*(13), 1–16.

Chavent, M., Kuentz-Simonet, V., & Saracco, J. (2012). Orthogonal rotation in pcamix. *Advances in Data Analysis and Classification*, *6*(2), 131–146.

Cutter, S. L., Boruff, B. J., & Shirley, W. L. (2003). Social vulnerability to environmental hazards. *Social Science Quarterly*, *84*, 242–261.

Dhillon, I., Marcotte, E., & Roshan, U. (2003). Diametrical clustering for identifying anticorrelated gene clusters. *Bioinformatics*, *19*, 1612–1619.

Dolan, P., Peasgood, T., & White, M. (2008). Do we really know what makes us happy? A review of the economic literature on the factors associated with subjective well-being. *Journal of Economic Psychology*, *29*, 94–122.

Eakin, H., Lerner, A. M., & Murtinho, F. (2010). Adaptive capacity in evolving peri-urban spaces: Responses to flood risk in the Upper Lerma River Valley, Mexico. *Global Environmental Change*, *20*, 14–22.

Etcheber, H., Coupry, B., Coynel, A., Sauquet, E., Baron, J., Bernard, C., et al. (2013). Chapitre 8.3: disponibilit des eaux de surface. In H. Le Treut (Ed.), *Les impacts du changement climatique en Aquitaine. Un tat des lieux scientifique* (LGPA ed.). Pessac: Presses Universitaires de Bordeaux.

Few, R. (2007). Health and climatic hazards: Framing social research on vulnerability, response and adaptation. *Global Environmental Change*, *17*, 281–295.

Helgeson, V. S. (2003). Social support and quality of life. *Quality of Life Research: An International Journal of Quality of Life Aspects of Treatment, Care and Rehabilitation*, *12*(1), 25–31.

Heltberg, R., Siegel, P. B., & Jorgensen, S. L. (2009). Addressing human vulnerability to climate change: Toward a no-regrets approach. *Global Environmental Change*, *19*, 89–99.
Kelly, P., & Adger, W. (2000). Theory and practice in assessing vulnerability to climate change and facilitating adaptation. *Climatic Change*, *47*, 325–352.
Kiers, H. (1991). Simple structure in component analysis techniques for mixtures of qualitative and quantitative variables. *Psychometrika*, *56*(2), 197–212.
Millennium Ecosystem Assessment. (2005). *Ecosystems and Human Well-being: Synthesis*. Technical report, Washington, DC.
Nardo, M., Saisana, M., Saltelli, A., Tarantola, S., Hoffman, A., & Giovannini, E. (2008). *Handbook on constructing composite indicators: Methodology and user guide*. OECD, European Commission, Joint Research Centre.
Nelson, R., Kokic, P., Crimp, S., Meinke, H., & Howden, S. M. (2010). The vulnerability of Australian rural communities to climate variability and change: Part II conceptualising and measuring vulnerability. *Environmental Science & Policy*, *13*, 8–17.
Noll, H. H. (2002). Towards a European system of social indicators: Theoretical framework and system architecture. *Social Indicators Research*, *58*, 47–87.
Noll, H. H. (2011). The Stiglitz-Sen-Fitoussi-report: Old wine in new skins? Views from a social indicators perspective. *Social Indicators Research*, *102*, 111–116.
O'Brien, K., Eriksen, S. E. H., Schjolden, A., & Nygaard, L. P. (2004). *What's in a word? Conflicting interpretations of vulnerability in climate change research*. Technical report, CICERO.
Pelling, M., & High, C. (2005). Understanding adaptation: What can social capital offer assessments of adaptive capacity? *Global Environmental Change*, *15*, 308–319.
Pielke, R., Prins, G., Rayner, S., & Sarewitz, D. (2007). Climate change 2007: Lifting the taboo on adaptation. *Nature*, *445*, 597–598.
Rodriguez Martin, J. A. (2012). An index of child health in the least developed countries (ldcs) of africa. *Social Indicators Research*, *105*, 309–322.
Rojas, M. (2014). *Encyclopedia of quality of life and well-being research*. New York: Springer.
Sanchez Dominguez, A. (2013). *A multidimensional regional development index as an alternative allocation mechanism of eu structural funds remittances*. Congress of the Spanish Association of Regional Science, Smart Regions for a Smarter Growth Strategy.
SAS/STAT 9.2 User's Guide. (2011). *The VARCLUS Procedure*. SAS Institute Inc. Cary , NC, USA.
Somarriba, N., & Pena, B. (2009). Synthetic indicators of quality of life in europe. *Social Indicators Research*, *94*, 115–133.
Striessnig, E., Lutz, W., & Patt, A. G. (2013). Effects of educational attainment on climate risk vulnerability. *Ecology and Society*, *18*.
Vichi, M., & Kiers, H. A. L. (2001). Factorial k-means analysis for two-way data. *Computational Statistics & Data Analysis*, *37*(1), 49–64.
Vichi, M., & Saporta, G. (2009). Clustering and disjoint principal component analysis. *Computational Statistics & Data Analysis*, *53*(8), 3194–3208.
Vigneau, E., & Chen, M. (2015). *Clustvarlv: Clustering of variables around latent variables*. R package version 1.3.2. http://CRAN.R-project.org/package=ClustVarLV.
Vigneau, E., & Qannari, E. (2003). Clustering of variables around latent components. *Communications in statistics Simulation and Computation*, *32*, 1131–1150.
Villamagna, A., & Giesecke, C. (2014). Adapting human well-being frameworks for ecosystem service assessmentsacross diverse landscapes. *Ecology and Society*, *19*(1).
Vincent, K. (2007). Uncertainty in adaptive capacity and the importance of scale. *Global Environmental Change*, *17*, 12–24.
Ward, N., & Brown, D. (2009). Placing the rural in regional development. *Regional Studies*, *43*, 1237–1244.
Wolf, J., Adger, W. N., Lorenzoni, I., Abrahamson, V., & Raine, R. (2010). Social capital, individual responses to heat waves and climate change adaptation: An empirical study of two UK cities. *Global Environmental Change*, *20*, 44–52.
Zarzoza Espina, P., & Somarriba Arechavala, N. (2013). An assessment of social welfare in spain: Territorial analysis using a synthetic welfare indicator. *Social Indicators Research*, *111*, 1–23.