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Development of a Methodology for Spatial Composite Indicators: a case study on Landscape.

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Introduction

This thesis proposes a methodology for the construction of spatial composite indicators (SCI). The study starts from the premise that Composite Indicators (CIs) are regarded as very reliable tools to support decision processes. They are usually developed to describe complex phenomena of the reality in various domains, and more specifically, to rank spatial units (usually countries) in which a given indicator is calculated (chapter 1). Despite their wide use and their development, no attention has generally been paid to the spatial dimension of their input data and of their final score. Data are treated as normal statistical sampling, therefore their spatial structure and their spatial importance are considered to be equal across the spatial domain, without considerations about possible spatial variations. Nowadays, this appears to be a serious limit, considering the development of Spatial Data Infrastructures (SDI), which makes a large amount of spatial data available, and the development of spatial statistical techniques implemented in GIS, with combined together offer unprecedented opportunity for the spatialization of CIs.

On the basis of these considerations, the aim of this work is to adapt since the first steps the existing methodology by the Organization for Economic Co-operation (OCSE) and the Joint Research Centre of the European Commission (JRC) for the construction of CIs, in order to expand the application domains to the description of complex spatial phenomena (section 2.1). Considering that the construction of CIs encompass a large number of steps involving statistics, their replacement with spatial statistics techniques appears an interesting research question to explore the possibility to make spatial the existing methodology (section 2.3). As described in the remainder of the thesis, one of the main issues in the construction of composite indicators is the analysis of the data structure and the assignment of weights to the variables involved in the definition of the overall CI (section 1.2). In the original methodology, which works on non-spatial data, it is assumed that there is no spatial variation on the structure of the data, and consequently in the spatial variations of weights. In the spatial case these assumptions may be not acceptable due to the possible presence of spatial heterogeneity. If spatial heterogeneity is not taken into account, a wrong conceptualization of the phenomena may arise, because the phenomenon will be biased by the global relationship among data, rather than by the local ones (section 2.2). Spatial heterogeneity may have important consequences on the local importance of data on the overall CI; hence the introduction of spatial statistical techniques appears to be particularly relevant. Recent developments in spatial multivariate analysis, in particular the Geographically Weighted Principal Component Analysis (GWPCA) (section 2.4), allow to survey the presence and the effect of the spatial heterogeneity on the data, so that it is possible to gather richer information on the importance of data on the overall CI (chapter 5).

The case study of the landscape in Sardinia has been chosen to test the methodology. The attention towards landscape preservation has been particular relevant in Sardinia after the adoption in 2006, of the Regional Landscape Plan (RLP) (section 4.1Furthermore, the Regional Government of Sardinia (RAS) has collected a large number of spatial data themes and has made them available by means of the regional SDI. Therefore, it appears very actual to investigate the possibility to build a spatial composite indicator starting from these data, in order to verify their fitness for the purpose, being the data issue another crucial point in the construction of CIs. In addition, the use of spatial data make it relevant to investigate the possibility to find spatial units alternatives to administrative units, as the original CIs methodology mostly uses. To achieve this objective the area of study has been partitioned in local large spatial units explained in section 4.2

By constructing a CI of landscape, this study aims at demonstrating in general the possibility to create spatial composite indicators. The landscape SCI here developed in fact enables the identification of clusters of valuable landscape areas which can be used in landscape planning (section 5.7).

In the first chapter the state of the art on CI is presented; it presents the main techniques used in the construction of CI, the field of application and selected case studies. Chapter two explains in more detail the reasons that drove this work towards the definition of a spatial composite indicators highlighting the advantages of the use of spatial statistical techniques, in particular of the GWPCA and spatial autocorrelation analysis. Chapter three describes the state of the art on the concept of landscape, with respect to the landscape measurement, in order to build a robust theoretical framework of landscape SCI. Chapter four and five respectively present the data used and results obtained. Finally, conclusions and opportunities for further research are presented.

1. Composite indicators: state of the art and applications domains.

1.1. Definition of Composite indicator.

In general terms a composite indicator represents a measure that encompasses the result of simultaneous and different measures of a certain aspect of the reality. The Joint Research Center defines composite indicators as "*an aggregate index comprising individual indicators and weights that commonly represent the relative importance of each indicator*" (Nardo et al, 2005). Tarantola and Saltelli (after Hammond, 2008) define an indicator as a measure of some characteristics of the reality that are not immediately detectable. A mathematical aggregation of several indicators, according to some criteria, represents a composite indicator. In other words, a composite indicator is the result of the combination of individual indicators that represent different dimensions of a concept whose aim is the description of the analysis (Saisana and Tarantola, 2002). Saltelli (2007) indicates *sensu lato* a composite indicator as a manipulation of different indicators to produce an aggregate ordinal or cardinal measure of a country's performance.

In the last decades CIs have been increasingly used to support decision processes. Between 2005 and 2010, composite indicators developed rapidly, as proved by the fact that a search in Google Scholar yields 992 matches in October 2005 and 5340 on December 2010. A recent compilation of existing CIs lists over 127 indicators (Paruolo et al, 2012). Recent advanced research and practice prove that CIs are very useful in supporting policies for their ability to integrate a large amount of information into a singular measure which may effectively be understood by a large audience (Freudenberg, 2003). While a set of separate indicators may be difficult to interpret, a single value resulting from their aggregation may supply immediate information. The increasing interest toward the use of composite indicators may be attributed to different main reasons, including (Saltelli, 2007):

- the capacity of CI to summarize complex and multidimensional issues;
- the capacity to provide a big picture about a certain phenomenon and to facilitate the construction of a rank for spatial units, usually countries or other administrative units, on complex issues;
- their capability to attract public interest;
- the effectiveness in reducing the size of a list of indicators.

The research on CIs flourished especially in the socio-economic field, in order to assess the level of performance ranking of regions or countries in economic and social development, and to support evidence-based policy making. They have been largely used by many international institutions to supply information for specifics purposes in economical international programs, including the provision of measures to support policy debates. At the beginning of the use of CI, countries were the most used spatial units in which CI were calculated, in order to evaluate national policies. The increase of the use of CI, has led to a wider set of spatial units, so that nowadays other units (for instance regions, urban and sub-urban zones, farms) are used.

In general terms a CI is a model, in mathematical sense, of a particular aspect of the reality, aggregating different variables in order to investigate the presence of latent dimensions of the reality (Paruolo et al, 2012). As a model, a CI is inspired from the natural system that it is meant to describe, and it is influenced by the perception of the reality. Natural systems are formed by causalities that define the structure of the system itself. Therefore, there are no rules to encode them into a formal system. The process of formalization of the real system represents the definition of the *theoretical framework*. This process generates an image that reflects some of the real characteristics of the natural system, but also the choice made by the scientist about how to observe the reality (Nardo et al, 2005). For these reasons, particular attention must be paid in the use of CIs. In fact the formal model may be built to fit well with the objectives and intentions of the user to describe the real system; hence it can be seen as an appropriate tool to express the set of objectives that motivated the use of the CIs (Nardo et al, 2005). A clear definition of the theoretical framework allows to select the most useful variable to build the final composite, and also to understand their importance into the model (Nardo et al, 2005).

Whichever the theoretical framework is, and despite the fact that it may be subjective or imprecise, it always describes a multidimensional phenomenon of the reality to be measured, and in which the single aspects and their interrelations must be specified. The measurement of single aspects in turn depends on the scale of analysis. Different and contradictory implications may arise in case the scale at which a given phenomenon is described changes. An example of this situation is reported by Nardo et Al (2005) with reference to sustainability, which involves social, environmental and economic dimensions; however, the problem of which scale to measure the dimensions still remains. The change of scale of analysis may produce contradictory implications, because some important aspects at the local scale may completely disappear at a larger scale (national, global). According to the aims of the thesis study, the scale problem may be more relevant when the object of the composite is a spatial phenomenon, as shown in the next chapters, as the study of landscape is presented. The choice of the scale of representation of landscape cannot be linked only to the administrative boundaries, but it is necessary to use an appropriate scale, and appropriate spatial units of analysis.

To sum up, the quality of the theoretical framework depends on the feasibility check of the effects of the proposed framework in relation to the different dimensions being described. It also depends on the structure of the problem, addressing several legitimate and contrasting perspectives by different stakeholders and on the ability to handle the uncertainty related to the representation of the real system by the model (Gianpietro et al, 2004). In relation to this last point, it is worth to remind, following Box (1979) that "*all models are wrong, some are useful".*

Since the composite indicators are models strictly related to the perception of stakeholders, a large debate has been generated in the scientific community about the use of CIs. The arguments of the debate mainly concern the doubts of the quality of information provided by mean an aggregate index, and also the way in which the set of indicators are weighted and aggregated. Despite the large debate highlighting the controversial opinion on the use of CIs, a large number of practitioners consider composite indicators as their common yardstick based on their understanding of the issue. Even though the statistical (scientific) part of composite indicator is important, the construction of composite indicators is not just a collection of numbers, but it is a highly articulated social activity.

This is the crucial point in the acceptance of composite indicators: the negotiation is considered superior to science (Nardo et al, 2005). This is due to the fact that, in some cases, pure analytical statistical methods are replaced by expert or public opinion in order to establish both theoretical framework and aggregate variables. Firstly, the problem of the quality of composite indicators depends on the methodological process rather than on the quality of data. A careful construction methodology ensures that composite indicator will provide reliable results (Nardo et al, 2005). Therefore, the users have to be sure about what they exactly want to represent by mean of indicator; otherwise the quality of the indicator may be low. The objective to reach a good quality process is related to a clear description of the aim of the indicator. In order to provide guidance on the construction of a good indicator, and to establish the level of uncertainty the NUSAP (Numeral, Units, Spread, Assessment, Pedigree) method has been planned. It consists in the decomposition of the CI building process in different phases. According to the methods used, a value is assigned at each phase, and later the global value is obtained as sum of the scores of the previous phase.

Saltelli (2007) drove the attention on another point of discordance in the use of CI that comes from two different scientific positions: the aggregators and the non-aggregators. The core of this debate concerns the different opinions about what is better in policy decision: the individual quantitative variable or an aggregation of indicators. In particular, for policy actions and quantitative analyses, individual variables are considered more relevant. Conversely, the construction of composite indicators is driven by the need for advocacy, whose rationale can be mainly identified in the generation of narratives supporting the subject of the advocacy (Saltelli, 2005). Non- aggregators support the hypothesis that an appropriate set of indicators is sufficient to support enough information, without goes the further step of producing a CI (Sharpe, 2004). A fundamental part of the arguments against CIs by non-aggregator is also the weights used to combine the variables or rather, the arbitrary nature of the weighting process. Aggregators support the use of CI because, as summary statistic CI can capture better the reality (complexity) and is meaningful, and that stressing the bottom line is extremely useful on garnering media interest and hence the attention in policy makers (Sharpe, 2004).

Among the objection about the use of CIs the most commons are (Saisana et al, 2002, Nardo et al, 2005):

- CIs may send misleading and non-robust policy messages if they are poorly constructed or misinterpreted; consequently politicians may to draw simplistic policy conclusions;
- the construction of CIs involves some steps in which a judgment has to be made i.e. the choice of sub-indicators, the choice of the model and weighting process;
- the CIs increases the quality of data needed because data are required for all the sub-indicators and for statistically significant analysis.

For some topics of the CIs, the main institutions, like OECD and JRC, provide a list of indices to be aggregated according to the aim of the composite. This fact may overcome of some discordances concerning the use of CIs discussed above. Sharpe (2004) provides a collection of sub-indices at the national level that may be aggregated for a composite indicator construction purpose. OECD supplies a reference system of indicators to develop CIs in economic field, the so called OECD Leading indicator (Nilsson, 1987).

From the above discussion it appears clear that the construction of a CI is not straightforward but it involves several assumptions which have to be carefully assessed. However OCED and JRC, which can be considered the two main agencies in the development of composite indicators, proposed a methodology for a good construction of CI (Saltelli, 2007), which consists of a series of steps. Each step presents several possible alternatives. These points will be described in the next section, according to the guidelines by OECD/JRC.

1.2. The OECD/JRC methodology for constructing Composite Indicators.

The construction of composite indicators is an art rather than a science (Tijssen, 2003).

There is not a standard methodology to build a CI. Nevertheless OCSE and JRC, two institutions that make large use and create composite indicators for several purposes, supply guidelines that take into account the different techniques that may be used for the development of CIs. JRC and OCSE do not suggest a unique method for the construction of composite indicators, rather they want to contribute to a better understanding of the complexity of composite indicators and to an improvement in the techniques currently used to build them (OCES/JRC, 2008). If the methodology is clear, it is then clear what the indicator wants to describe and how it works. This is very important in order to ensure the transparency of the CI building process, the understanding of what the indicator is representing and how and what data is used (Nardo et al, 2005). Transparency must be ensured in the construction of composite indicator, because it reduces the effect of the technical and political uncertainty. Transparency is particular relevant for the weighting procedure that remains the most important source of uncertainty (Tarantola and Saltelli, 2008). A summary of the original methodology is next provided, because it represents the starting point for this study that is the construction of a Spatial Composite Indicator (SCI).

Usually the OCSE/JRC framework for the construction of composite indicators involves an ideal sequence of steps:

1. theoretical framework;
2. data selection;
3. imputation of missing data;
4. multivariate analysis;
5. normalization;
6. weighting and aggregation;
7. uncertainty and sensitivity analysis;
8. back to the data;
9. link to other indicators;
10. visualization of the results;

Each step is fundamental but consistency throughout the process is necessary to develop a good indicator. Indeed, each step can be carried out using several techniques, and the choice of a particular technique rather than another has important implications for all the steps. Therefore a composite indicator builder must ensure the better methodological choice.

Even if the methodology is articulated in several steps, as later explained, in the construction of CIs three main problems must be tackled: finding significant indicators to be combined together, pre-processing the indicators, and finally selecting a method to combine the indicators (Cherchye, 2004). The following section provides an overview of the different steps and which of different methods proposed to develop them, according to the original methodology.

1.2.1. *Theoretical framework.*

The main target in the construction of the theoretical framework is to achieve a quality profile for composite indicators. It means that it must be clear what and how the CI intends to describe. This is not an easy task, because it depends on several aspects concerning the quality of data used, the quality of procedure and the choice of a method rather that another to process the data. Quality is a broader concept that does not concern only the statistical point of view about the accuracy of data, but rather it means “fitness for use” in terms of user need (OECD/JRC, 2008).

The development of the theoretical framework is the crucial and the starting point for the composite indicators construction. The capability of an indicator to describe a certain complex phenomenon strongly depends on its framework. The framework should clearly define the phenomenon to be measured, its sub-components, the selection of individual indicators and weights. Transparency is the most important characteristic to make the CI credible. Defining a concept means that the various sub-groups may be identified by a clear link with the theoretical framework, in order to ensure their relevance in the description of the complex phenomenon.

This nested structure of decomposition in sub-groups helps the users to understand which are the driving forces behind the unique value of the CI. Sub-groups need not be independent from each others, but existing linkages should be described theoretically, rather than statistically. Determining sub-group requires experts’ and stakeholders’ involvement in order to consider the multiple points of view and increase the robustness of the conceptual framework and set of indicators. Despite this fact, as already mentioned in section 1.1, some complex concepts are difficult to define and measure precisely, or may be subject to controversy among stakeholders.

1.2.2. *Basic data selection.*

The selection of variables to use into CIs is a very important point for various reasons. The first reason is that data must be appropriate to describe those aspects of the phenomenon that a given composite wants to draw. Data have to satisfy also quality requirement, because strengths and weaknesses of composite indicators largely derive from the quality of the variables. Contrary to the case of theoretical frameworks, the selection may be quite subjective because there may be not just a single set of indicators. There may be different data to be used to describe a certain aspect; the choice about which kind of data is more relevant or appropriate may depend on the user’s point of view.

Because the fact that usually the aim of CI is to compare the performance of spatial units, data are desirable to be quantitative and internationally comparable. In fact, as previously mentioned, the original purpose of CIs was to compare country performances; hence it was desirable to have cross-country comparable data. Nevertheless when data with those characteristics are unavailable or when cross-country is limited, proxy measures can be used with particular caution. On the basis of this consideration, current practices in the construction of composite indicators suggest that data collection should be improved by identifying new data sources and enhancing the international comparability of statistics. This objective appears to be particularly relevant for this work, because, as later shown, data coming from the SDI of Sardinia are compliant with the European Directive 2007/2/EC INSPIRE which set the rules for the standardization and the accessibility of geographic information.

Quality is a multi-faceted concept whose main characteristic depends on the user's perspective, need and priorities. Considering the fact that composite indicators are mainly used to establish the performance ranking of spatial units, and in some case to forecast economical or social trends, data not only have to be accurate, but also must satisfy other characteristics to be retained of good quality. They have to be recently updated, and to be easily accessible, and they should not contradict other data. Several organizations worked to set different guidelines to the achievement of data quality, including the Eurostat, and the International Monetary Fund. According to OCSE/JRC there are six main dimensions to consider for data in the construction of CI. They are relevance, accuracy, timeless, accessibility, interoperability, coherence.

Relevance refers to the consistency of the dataset into the overall definition of the indicator or sub-dimension. It has to be evaluated on of the overall purpose of the indicator, taking into account several issues, for instance the actual availability of data or the use of proxy data.

Accuracy represents the degree to which data are correctly estimated. Accuracy is strictly related to the concept of error interpreted as the difference between the real aspect and the data used to model it. There are two main kinds of accuracy methods: sample survey based estimated and derived estimated. In the first case the main source of error concerns various aspects including coverage, sampling, and processing. In the derived estimated the source of error comes from the surveys and censuses that provide data. In CI, data accuracy has a very important role because the issue of credibility is crucial.

Credibility refers to the confidence that users place in those products based simply in their image of the data producer. This introduces another important aspect that is the trust in the objectivity of data, strictly related to the concept of transparency. It means that data are perceived to be produced professionally in accordance with statistical standards and policies, and excluding manipulation.

Timeless is the time period between the availability of the data and the phenomenon that they described. A shortest timeless reduce the need to estimates missing data, and consequently the soundness of the data and of the overall indicator.

Accessibility concerns how data are supplied by the original sources. In addition, accessibility also regards considerations about the various data formats, their dissemination and the availability of metadata. Accessibility plays a fundamental role in CI, because it can affect the cost of the production and updating of the indicator over time. Poor accessibility influences the credibility of the indicator, because it makes it difficult for third parties to replicate it. Nowadays several electronic sources are available, but attention must be paid to the fact that the most accessible sources may be not the better ones. The choice has to be made by taking into account the quality dimension. Further discussion on the use of SDI will be supplied in the next chapters.

The interpretability of data reflects the ease with which the user can understand and properly use and analyze the data. Metadata play an important role: they supply information about the definition and the procedures with which data were collected. This information is fundamental when the aim of a composite is to supply products to assess the comparability over time and across spatial units, because it supplies information about what certain data describe, and consequently it makes it possible to understand if data supplied by other data sources may or may not comparable.

Coherence concerns the logical connection between data and methods that is the adequacy of the data to be combined in different ways for various uses. Coherence may be over time or across spatial units, but in both cases it implies that data are based on the same concept, methodology and definition. Differences can be accepted if a sound explanation is supplied.

Ensuring data quality, with respect to the point above described is a good starting point to the construction of a robust composite indicator.

1.2.3. *Imputation of missing data.*

The problem of the missing data is often presented in case studies of CIs and it can be an obstacle for the construction of a robust indicator. There are different ways in which missing data may be distinguished: Missing Completely At Random (MCAR), Missing At Random (MAR), and Not Missing At Random (NMAR). In MCAR missing data do not depend on the variable of interest or on any other observed variable in the dataset. MAR values do not depend of the variable itself, but there are conditioned by the values of the other variables, and finally in NMAR missing values depend on the values themselves.

There are three main ways to treat missing data: case deletion, single imputation or multiple imputations. The first case does not consider the imputation of missing data part of the analysis, and therefore missing data are simply omitted. This approach completely ignores the difference between complete and non-complete sampling, hence it can bring to biased estimations of the original data. Conversely, in the other two approaches the imputation is part of the analysis; therefore they use statistical techniques to obtain missing data. In single imputation a predictive distribution of missing data is created by the use of observed data. Two models are mainly used: implicit or explicit model. In the one the focus is on an algorithm with implicit underlying assumption that should be assessed. This model has been criticized because once imputation is implemented data set is considered complete as no imputation were done. In the implicit model the missing data may be replaced by values obtained from units of proxy variables (e. g. age, income etc). In other cases values are replaced with units not selected into the sample, or missing values are replaced by a constant from an external source. Contrary to implicit models, explicit models predict the distribution of missing data by means of a formal statistical model where the assumption is made explicitly. These models encompass the unconditional imputation that uses the main descriptive statistics parameters (mean, median, mode) to substitute missing values. Regression imputation is also used. In this case missing values are replaced by means of the value predicted from a regression that uses missing values as the dependent variable, while sub-indicators that show strong relation with the missing values are used as regressors. Finally, the Expectation Maximization imputation assesses missing values by using an iterative process: in this case, the sequence of parameters obtained by the model converges to the maximum likelihood.

In multiple imputation methods, the imputation of missing data is done by means of a random process that reflects the uncertainty. Imputation is done N times and each time the standard error is estimated. The algorithms used in this model are, for instance, Monte Carlo or Markov Chain.

The idea of imputation is quite seductive, but all possible effects on data need to be taken into account, due to the level of uncertainty that is unavoidable. This is an important issue also in the case of spatial data as it will be discussed in detail in section 2.3.

1.2.4. *Multivariate analysis.*

Multivariate analysis is usually used to analyze the structure of the data. Despite the fact that in the last decades several CIs have been developed, it often happens that individual indicators are chosen arbitrarily without paying attention to their mutual relation. This fact may lead to confusion or mislead decision makers. Therefore the structure of data has to be analyzed before the construction of the overall composite. This represents a preliminary step that is very important because it provides important information for the subsequent methodological choices, in particular for the weighting step. In the OCED/JRC methodology, the multivariate analysis is done in two dimensions in the data set: for the individual indicators and for units of analysis.

Grouping information on individual indicators is helpful in case of nested structure of singular indicators, to understand if it is well defined. This concept is related to the development of the theoretical framework, where the phenomenon is described and the data set is chosen.

Multivariate analysis is an analytical approach that allows to understand if the set of individual indicators is sufficient to describe the phenomenon (Anderson, missing year). Multivariate analysis may be complementary to the experts' opinions. There are different statistical methods for the multivariate analysis: the most common are Principal Component Analysis (PCA), the Factor Analysis (FA) and the Cronbach coefficient alpha. PCA and FA are similar because they reveal how the various variables change in relation to each other and how they are associate (OECD/JRC, 2008). In addition, they allow to reduce the dimensions of the data set (in terms of number of variables) through the transformation of the original set in a new one of uncorrelated variables using the covariance or the correlation matrix. The difference between PCA and FA is that FA uses a particular statistical model (for further details see Spearman, 1904). Cronbach coefficient alpha is an alternative way to the describe the level of correlation between variables; it estimates the internal consistency of items in a model of survey.

Grouping information of the units of analysis is mainly done by mean of the cluster analysis. In CI construction cluster analysis is used to group units on the basis of their information similarity. It is useful for different reason: it is a statistical method of aggregation, it is a diagnostic tool to support the methodology choices during the construction of a composite, it is a method to disseminate the information on a composite indicator without losing that on the dimension of individual indicators, and finally it is a methods to select group of units for the imputation of missing data. In some cases cluster analysis can be used after PCA.

1.2.5. *Normalization of data.*

As complex phenomena descriptors, CIs have to join together information with different measurement units. Therefore, to make the different indices comparable it is necessary to covert them in the same scale. This is done through the normalization procedure. Unfortunately the problem of indicators comparison is not only a measurement unit dependent, but often also the scale of measurement may be variant to normalization. This aspect may have strong consequences in the weighting procedure, because indicators may change the patterns showed in the results. The scale problem appears to be relevant in linear aggregation when the weights are scale depended. The scale depends always on the measurement scale used for measuring the variable score and on the range that the measurements of variable scores may present (Munda et al, 2005). Since weights are connected with the trade off they also depend on the scale values.

The normalization process can be done in several ways.

Ranking is the simplest method and has the advantage it is not affected by the presence of outliers, but it implies loss of information and the impossibility to make any conclusion about differences in performance.

Standardization or z-score, converts the set of indicators in a new one whose mean is equal to zero and the standard deviation is equal to one.

The min-max algorithm uses the same range for all the indicators which is [0, 1]. This range is obtained by subtracting the minimum value by the given indicator's value and dividing by the range of the indicator (Max – Min).

In the distance to a reference, a target point is fixed. This target may be a value to be reached in a given period of time or it may be external, for instance a benchmarking value for a given spatial unit. In this approach the leader spatial unit (country with the highest score) may be considered the benchmark. Alternatively it is possible to take the average value of spatial units as reference point.

Categorical scale is a normalization procedure that assigns a numerical value to the indicator, on the basis of its original value, (i.e. one, two etc, or a qualitative like 'achieved', 'not achieved' etc). In many cases, the categorical scale is assigned on the basis of the percentile distribution, associating a score to each percentile class. This method excludes a large part of information about the variance of indicators. A solution may be to adjust the percentile scale for individual indicators, in order to obtain a new categorical variable with a distribution similar to the normal one.

A further normalization method is the so called '*indicators above or below the mean'*. This method consists in setting a threshold value *p*. Transformed indicators are zero if they fall in a "neutral region" defined by the threshold; the other indicators take the value 1 or -1 depending on their position with respect to *p*.

Method for Cyclical Indicators (Nilsson, 1987) is a technique used for economic activities when the indicators are in form of time series. This approach is used in the composite leading indicator (OECD, 2012) when it is necessary to minimize the influence of series with market cyclical amplitude to dominate the composite indicator.

A special case of balance of opinion is used to normalize indicators. In this case managers of firms are asked to express their opinion in the firm's performance.

The percentage of annual differences over consecutive years is a method that can be applied only for observations available for a number of years. This normalization procedure represents the growth's percentage with respect to the previous years.

1.2.6. *Weighting and aggregation*

A central step in the construction of CI is the weighting procedure and aggregation. This step represents the biggest problem for composite indicators, because different weighting methods can lead to different result of the final indicator score (Grump and Schubert, 2010). The quality of composite indicators heavily depends on the construction scheme, where aggregation is the main and controversial step (Zhou et al, 2010). CIs always require weights to rank the indicators used for the construction of the composite (Blanc et al, 2008). In general terms, the variable's weight should reflect its importance on the overall composite indicators. Weighting and aggregation procedure consists in combining variables in a meaningful way. The weight assignment is not easy because variables differ in dimension, measures and scales, hence it implies the decision about which model will be used and which procedure has to be applied to aggregate the information. Generally, the purpose of the weight reflects not only the importance of the variables, but also statistical relevance, cyclical conformity, and speed of available date. Usually, when weights reflect the statistical relevance of data, their value is high for statistical reliable data with broad coverage and low percentage of missing data. In this case it may be possible that only measures easy to collect and readily available are considered, therefore neglecting information that are more difficult to be identified and measured. Existing weighting techniques can be divided in two groups: the weighting schemes based on statistical models and participatory methods. Whatever the chosen method is, it needs to be explicit and transparent because weights have a great impact on the resulting ranking of the overall indicator. Despite this, it is likely that no consensus will be reached in the weight assignment. Moreover the weights are essentially value judgments and have to make explicit the objectives underling the construction of the indicator.

The equal weight method assigns the same weight to the variables used in the construction of the indicators. Despite its being a simple method, this method needs some consideration about the level of correlation between variables. In fact, highly correlated variables measure the same dimension, therefore, to assign equal weights for two correlated variables can bring into the composite an over-estimated importance of the dimension that these variables describe. Therefore, before to use this technique a statistical correlation analysis is advised in order to choose only the variables that exhibit a low level of correlation, and to adjust weights correspondingly. Because it is likely that there will almost always be a certain level of correlation between variable, it is often necessary to establish a threshold of correlation beyond which correlation is considered a synonym of double counting. The effect of the equal weighting also depends on how indicator components are divided in categories: equally weighting categories regrouping a different number of sub-indicators could disguise different weights applied to each single sub-indicator. This aspect is not trivial because of the dynamic of one input variable with the other input variable. A solution to deal with this problem is proposed by Stathakis and Perakis (2007) by means of the use of a genetic algorithm able to decide which is the optimal combination of input variables.

The equal weights method is often used to avoid others weighting techniques. This may be done according to the structure of data or when ranges are standardized for example by the use of min-max procedure, because it makes the range of variability of variables uniform. Conversely the use of other normalization techniques requires the application of different weighting techniques to avoid biases in the assessment of the importance of the variables (Blanc et al, 2008).

Statistical models offer a large number of alternative weighting methods, but they all have pros and cons. PCA and FA are statistical methods used in the weight assignment with are collinear to combine variables in a new indicator, capturing the largest possible part of information . In fact the main purpose of these methods is to reveal the set of indicators having the highest association. Information used in this method must have the same measurement units. PCA and FA are used to take into account for the highest possible variation of the indicators set, using the smaller possible number of components or factors respectively. Particular attention has to be paid to the level of correlation between sub-indicators. In the chapter 2 we treat the question of PCA in deeper detail and we suggest the use of a spatial version of this method to achieve spatial weights for spatial variables involved in the SCI construction.

The Data Envelopment Analysis (DEA) (Charnes and Cooper, 1985) is a method that uses techniques of linear programming operation. The aim of this method is to consider an efficiency frontier as benchmark to measure the performance of a set of spatial units. The efficiency frontier is comprised of the value of indicators of the performing spatial units. The weights come from the comparison, and represent the distance between the best performing spatial unit and the other ones.

The main issue in this methodology concerns the construction of a benchmark and the measurement of the distance between spatial units in a multi-dimensional framework.

The construction of the frontier is done assuming that:

- the highest value of one sub indicator corresponds to the best performing units (positive weights);
- non discrimination of units that are best in any single dimension;
- a linear combination of the best performers is feasible.

The distance of each unit with respect to the benchmark is determined by the location of the units and its position with reference to the frontier.

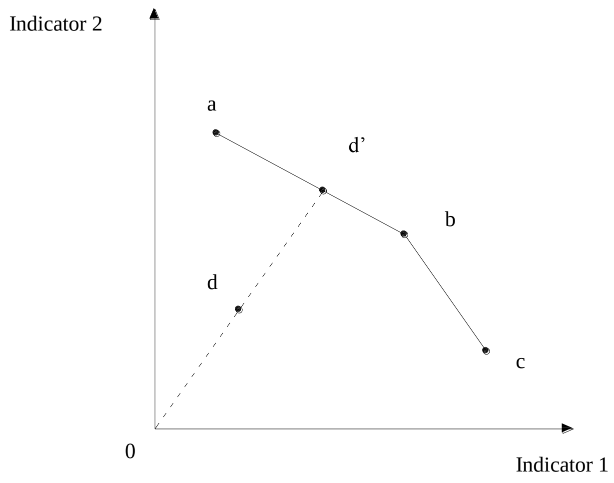

Figure 1: example of performance frontier. Source: Nardo et al (2005)

In figure 1 the axes represent the scores of indicators 1 and 2 for countries a, b, c, and d. Countries a, b, and c support the frontier because they are the best performers, while country d is the worst performer. The indicator of performance is the ratio 0d/0d’ (Nardo et al, 2005).

Therefore the weight for each unit depends on the distance between its position and the frontier. In turns, the frontier corresponds to the set of ideal points with a similar mix of indicators. It may be also determined by decision-makers, who would locate the target in the efficiency frontier with the most preferred combination of individual indicators.

Benefit Of the Doubt (BOD) approach is an application of Data Envelopment Analysis (DEA). It derives from one of the most important concepts of the DEA: the weighting scheme for the unit’s performance can be retrieved from the data that are associate to the units themselves (Cherchye et al, 2007). This approach has the advantage that it established a set of flexible weights, or better a set of weights is assessed for each spatial unit. The flexible nature of the weights can be adapted to the choice of measurement units in order to avoid some problems that can arise from the normalization procedure. In practice this method is able to overcome the fact that it is rather unlikely that agreement about an unique set of weights is reached, and in particular it enforce the idea that uniqueness is not necessary in many situations (Foster and Sen, 1997 in Cherchye et al, 2007). This consideration deals with the idea to spatialize the original methodology for CI: the presence of spatial heterogeneity may lead to the need of different set of weights depending on the locations of the units, as discussed later in section 2 and 5.

Regression approach is a method based on the linkage between a (large) set of indicators and a single output measure that represent the objective to be attained. Usually this method is a linear combination of the set of indicators as show in the following equation:

$$Y_n = b + a_1 I_{1n} + a_{2n} I_{2n} + \cdots + a_n I_{mn} \tag{1.1}$$

where Y_n is the dependent variable that represents the measure of the phenomenon to be described by mean of the indicators I_{mn}. b, a_n are respectively the estimate constant and the regression coefficient. Usually the regression coefficient may be used as weights.

The assumptions for this method are the linear behavior and the independence of the variables. The correlation between the variables may lead to a non adequate estimation of the parameters of the equation that represent the weights of the indicators. Regression is also used to verify o adjust weights, or to interpret sub-indicators as policy actions, because the regression model should be suitable to quantify the relative effect of each policy action on the target. In the Unobserved Component Models (UCO) it is assumed that individual indicators depend on an unobserved variable plus an error term. This method is similar to the regression one, but in this case the dependent variable is unknown. Estimating the unknown components sheds some light on the relationship between the composite and its components.

The participatory methods to the weights assignment are based on the involvement of experts or stakeholders who express their opinions on the importance of sub-indicators, on the basis of the methods used. In the construction of CIs the most used participatory methods are: the Budged Allocation (BAL), the public opinion, and the Analytical Hierarchical Process (AHP).

The BAL method (Moldan and Billharz, 1997) involves experts' opinions. Each expert has a given budget of N points, to be distributed among the sub-indicators. The highest score is assigned to indicators that are considered more relevant. The BAL is developed through four main phases:

- selection of experts for the evaluation;
- allocation of budget to the sub-indicators;
- calculation of the weights
- iteration of the budged allocation until convergence is reached.

Particular attention should be paid on the selection of experts; it is preferable that the group of experts has a wide spectrum of knowledge and experience in order to ensure a correct weighting system.

In public opinion method weights are assigned on the basis of a budget, but in this case t is the general public, and not experts, that are asked to assign the sub-indicators scores. Another difference between public and budget allocation is the fact that in public opinion, the issues are already on a public agenda, and they have the same attention in the media. Hence people are asked to express their opinion in term of "much" or "little concern" about problems measured by some indicators.

The Analytical Hierarchy Process (AHP) is a technique used in multi-attribute decision making (Saaty, 1987). AHP decomposes the final goal in different options that are systematically compared in pairs, evaluating both qualitative and quantitative aspects, in order to create a hierarchy rank. A synthetic explanation of AHP is given by Foreman (1983): *"AHP is a compensatory methodology because alternatives that are efficient with respect to one or more objectives can compensate by their performance with respect to other objectives. AHP allows for the application of data, experience, insight, and intuition in a logical and thorough way within a hierarchy as a whole. In particular, AHP as weighting methods enables decision-maker to derive weights as opposed to arbitrarily assign them".* It is important to notice that in AHP weights represent the trade-off across indicators. They are a measure of the possibility to exchange a variable with another; hence they are not a measure of importance of the variables themselves. Misunderstanding could appear if the weights from AHP are interpreted as importance of sub-indicators.

The weighting part needs some final consideration. The choice of which method to use for the assignment of weights influences the final result of the indicator or the position ranking of a spatial unit. This variability appears to be inevitable, but the variability of weights and their consequences on the final score of the indicator may be taken into account by means of the sensitivity analysis, which is a fundamental part of the methodology for the construction of composite indicators.

Despite the large number of weighting techniques, they are not always applied. Burton (2000) in a study about the advantages of compact cities avoided the use of weights for the variables, in order to avoid the problem of their interpretation. As measure of the importance of the variables she considers the consistency of the indicators.

The Aggregation is a procedure whose aim is to calculate the ranking for units, and groups them on the basis of the performances level of the different sub-indicators. There are several methods for the aggregation of the information, but the most used are the additive ones. Linear aggregation methods are very useful when sub indicators have the same measurement units, or when the effect of the different scale has been neutralized. The simplest of these methods consists in the calculation of the rank position, units by units, based on the sum of the position of individual sub-indicators.

$$CI_c = \sum_{q=1}^{Q} w_q \, I_{qc} \qquad (1.2)$$

where CI_c is the composite indicators for the country c, I_{qc} is the indicator q for the country c and w_q is the weights associate to the indicator q. Q is the total number of indicators.

An alternative method is based on the number of sub-indicators that are above or below a certain benchmark. The benchmark may be established arbitrarily.

The most common aggregation method is the weighted sum of normalized sub-indicators, but it requires that the conditions under which weighted summation can be properly done are known. The quality of the overall composite for this method depends upon on the sub-indicators used in the aggregation and on their measurement unit. In the use of additive aggregation the independency between the sub-indicators is required, in order to ensure that the trade-off of a certain sub-indicator is not influenced by the other variables. The popularity of this method is due to the transparency and ease of implementation, but it is criticized because it assumes the independence among sub-indicators which is often an unrealistic condition in practice (Zhou, 2010).

In additive or multiplicative methods weights have the meaning of substitution rates and do not indicate the importance of the sub-indicator. This means that in the weighted summation case, the substitution rates equal the weights of the variables up to a multiplicative coefficient (Munda and Nardo, 2003). This implies a compensatory logic to overcome to create disadvantages on some variables and large advantages on others ones. When a number of variables are used on a set of spatial units, some may be favorable for a particular unit. Hence, a non compensatory multi-criteria approach is used taking into account the absence of preferential independence. The non-compensatory methods divide the mathematical aggregation in two phases: the pair wise comparison of units according to the whole set of indicators and the ranking spatial unit in a complete pre-order. The pair wise comparison is different to the one used in the AHP, because in the aggregation case the focus is on whether a certain indicator is higher for a spatial unit than for another one; if this condition is satisfied then the indicator for the unit under consideration is the weight of the individual indicators which enter into the computation of the overall importance of units, in a manner consistent with the definition of weights importance.

The concept of 'minimum information loss' is the essential part of aggregation methods. In fact as previously mentioned, one of the controversial points in the use of composite is the fact that many scholars (the non-aggregators) maintain that the aggregation procedure may be the cause of loss of information, and so it may lead to misinterpretation (Nardo et al, 2005). Different aggregation methods have been recently proposed with the aim to lose as little information as possible. According to Zhou et al (2010) the problem in the method model is the transmission of information from the set of sub-indicators to the final composite.

1.2.7. *Sensitivity analysis.*

The sensitivity analysis is a fundamental step in the construction of CI, because it is strictly related to the aggregation/weighting methods. A CI can be built in several ways, but it is impossible to have a perfect mathematical aggregation. This implies the need to test how results change in relation to the different chosen weighting procedure (Tarantola and Saltelli, 2008), in order to avoid non-robust policy message.

To be useful, a CI must be robust. It means that the level of uncertainty must be assessed. The focus of this step is to investigate whether small changes in the variables and weights produces changes in the results.

Uncertainty is a consequence of each of the previously described steps, as data quality, weighting scheme, and aggregation. A combination of uncertainty and sensitivity analysis helps to understand the robustness of the composite indicator and to increase its transparency.

The uncertainty analysis focuses on how the uncertainty in the inputs are propagate through the structure of the model for the indicator and its consequences on the final result, while sensitivity analysis studies how each source of uncertainty affects the output variance. Despite the importance of this step, the assessment of the robustness is not enough to ensure the sensibility of the composite indicators, because it firstly strongly depends on the goodness of the theoretical framework. Uncertainty analysis is a based simulation methods, where simulation are carried out on various equations that constitute the model. The most common method for uncertainty analysis is the Monte Carlo simulation, based on a multiple evaluation of the model with k randomly selected input factors.

Sensitivity analysis focuses on the variance of the output of interest, so the first task is to identify the output variables that are relevant to the issue addressed by the model. As previously mentioned the model is considered to be the composite indicator itself. Sensitivity analysis using variance-based methods techniques are model-free techniques and display additional convenient properties, such as:

- they allow an exploratory analysis of the whole range of variation of the input factors;
- they are quantitative, and can distinguish main effects from interaction effects;
- they are easy to interpret and to explain;
- they allow for sensitivity analysis whereby uncertain input factors are treated in groups instead of individually;
- they can be justified in terms of rigorous setting for sensitivity analysis.

Details on the sensitivity analysis are widely discussed in Nardo et Al (2005) and OECD/JRC (2008).

1.2.8. *Back to the data/details and link with other variables.*

CI is a summary indicator used in policy decision process. Nevertheless, in the decision process, CI is not the final goal, but it is the starting point for future considerations. Indeed, composite can be decomposed in order to identify the contribution of each sub-indicator and to extend the analysis of units' performance. This step appears to be very useful in the understanding of the factors that need to policy decision to improve units' performance, or to achieve a pre-defined goal.

In this perspective, the possibility of the composite to be linked to other variables is relevant. This feature of composite comes from the fact that usually it measures concepts that are linked to well-know and well measurable phenomena, and these phenomena may be used to test the explanatory capacity of the composite. The link could be obtained by means of correlation analysis that measures the mutual variation of the data. Correlation analysis has to not be confused with causality analysis that still remains unclear in the correlation analysis. Also the weighting scheme may play a role in the level of correlation between composite indicators and another variable of interest. In this case Monte Carlo simulation is suggested to investigate how differences in the weights influence the correlation.

1.2.9. *Presentation of results*

The capacity of CI to provide information strongly depends on the way in which indicators are presented. There are several methods to present results; the choice depends on the situation or the type of data to be shown.

Presentation in form of table shows data in form of numerical values, and in increasing or decreasing way, according to the performance ranking assessed by mean of the indicator. The same goal may be achieved by means of the use of bar-charts in which the length of the bar is proportional to the spatial unit's score. Line charts or trend diagrams are more useful in the presentation of the variations of the indicator or of its variables across time. In the spatial case, the most common presentation form is a map. Maps are able to show how the final indicator score and variable values vary across a given spatial domain. Further details are provided in chapter 2, 4 and 5.

1.3. Composite Indicators: best practices and selected case studies

The use of CIs is facing a growing development in particular for indicators that concern the description of complex social and economic phenomena, and other policy areas. To provide an idea about the range of the field and the kind of indicators developed Freudenberg (2003) reports the following table 1:

Area	Name of Composite Indicator	Developer
Economy	Composite of Leading Indicator	OECD
	OECD International Regulation Database	OECD
	Economic Freedom of the World Index	Economic Freedom Network
	Economic Sentiment Indicator	EC
	Internal Market Index	EC
	Business Climate Indicator	EC
Environmental	Environmental Sustainability Index	World Economic Forum
	Wellbeing Index	Prescott-Allen
	Sustainable Development Index	UN
	Synthetic Environmental Indices	Isla M.
	Eco-Indicator 99	Pre Consultants
	Concern about Environmental Friendliness	Puolamaa
	Environmental Policy Performance Index	Adriaanse
Globalization	Global Competitiveness Report	World Economic Forum
	Transnationality Index	UNCTAD
	Globalization Index	A.T. Kearny
	Globalization Index	World Markets Research Centre
Society	Human Development Index	UN
	Corruption Perceptions Index	Transparency International
	Overall Health Attainment	WHO
	National Health Care Systems Performance	King's Fund
	Relative intensity of Regional Problems	EC
	Employment Index	Storrie and Bjurek
Technology Innovation	Summary Innovation Index	EC
	Networked Readness Index	CID
	Investment in Knowlwdge-based Economy	EC
	National Innovation Capacity Index	Porter and Stern
	Technology Achievement Index	UN
	General Indicator of Science and Technology	NISTEP
	Information and Communications Technologies Index	Fagerberg
	Success of Software Process Improvement	Emam

table 1: examples of composite indicators. Source: JRC (2002), in Freudemberg (2003).

The table does not report all the existing CIs (for a complete list of existing composite indicators, see the web site of Joint Research Centre: https://composite-indicators.jrc.ec.europa.eu/?q=publications). There is a wide range of composite indicators and more are continually being developed. table 1 shows that composite indicators are developed in various domains, including several aspects of human development. It is also evident that there are many institutions that produce composite indicators. All indicators reported in the table shared the fact that they are assessed at the national scale. This fact may be explained with the consideration that the main data sources are the national census agencies that collect data at the national level. More recently the data are supplied at the finer scale too, so the use of CI is starting to encompass administrative units. It is the case of the Regional Competitiveness Index (Annoni and Kozovska, 2010) that use the regional scale.

The OECD leading indicators represent the oldest set of indicators used for the construction of composite indicators. They were developed in the 1970s with the aim to supply information about signals of turning points in economics activities, and their methodology has been the same since the 1981 (Nilsson and Gyomai, 2007). OECD leading indicators are a selection of indicators representing the economics characteristics of the OECD Nations to be composed in a unique indicator. It is important to notice that they are used to forecasts future economic trends for countries, taking into account cyclical behavior of the reference time series. The set of indicators is not the same for the involved countries in order to allow for a correct account of the difference in economic structure. The only common point in leading indicators is that they have to be selected on the basis of their economics relevance (Nilsson, 1987). The usefulness of leading indicators is proven by the fact that they are still widely used in public analysis about the economic situation (see OECD website). Leading indicators are uploaded continuously by the OCED, in order to achieve information about the economic trend of a given country, and so to survey if this trend differs from the past series, and therefore understand the reason of this difference, and so to decide policy actions.

Leading indicators do not represent the only example of continuously uploaded indictors. For instance the Technological Achievement Index TAI, originally proposed in 2002 by Desai et al has been re-assessed in 2010 by the use of data collected in 2009. The aim of TAI is to assess the technological performance of a country in creating and using technology. Contrary to Leading indicators, TAI identifies in a clear way the dimension of technologically advanced achievements and which are the sub indicators to populate them. The TAI index originally used the budget allocation method to weight its eight sub indicators. It was done by interviewing 21 experts. The weighting method was replaced with that later modified by Cherchye et al (2006), by using the Data Envelopment Analysis (DEA) as a tool for constructing CIs, because the budget allocation was deemed unable to produce an acceptable set of weights. This case study is a clear example about the discordance that often emerges in the use of some methods rather that another one, that is one of the main cons for the acceptance of CIs as tools for support decision. Furthermore this aspect confirms the fact that the weight assignment is the crucial phase in construction of composite indicators.

The problem of the weight assignment is faced also in the index of social inclusion performance in EU by Cherchye et al (2004). In this case, the problem of the weight assignment is related to the fact that at the national level, each country implements different polities on social inclusion. This leads to two important considerations. The first is related to the multidimensional nature of social inclusion and to the fact that the different European countries perform different strategies in relation to their priorities. This brings to the second consideration that is that the set of weights used to aggregated indicators should be sensitive to the national policy priorities. To achieve this objective, the authors propose an aggregation methods based firstly on the benchmark performances of the singular countries. The proposed methodology appears to be a linear program in which the function that describe the indicators is maximized by means of a set of weights whose combination ensures that the specific performance of a country are taken into account, even in comparison with the others ones.

Recent examples of composite indicators show that the CIs are applied at different scale (sub-national and local scale.)

The first example reported is the case of the evaluation of agricultural sustainability proposed by Gòmez-Limòn and Sanchez-Fernandez (2010), by means of a CI of Agricultural Sustainability (CIAS), where the basic spatial units of analysis are the farms. The use of farm as basic unit of analysis is an atypical solution, if compared with the majority of composite indicators, which use the countries as spatial units. The theoretical framework proposed is the application of the so called SAFE (*Sustainability Assessment of Farming and the Environment Framework*), that is a method for agricultural sustainability framework development, suggested by Van Cauwenberg et al (2007) (in Gòmez-Limòn and Sanchez-Fernandez, 2010). SAFE is a hierarchical framework based on the goods and services provided by agricultural ecosystems that assigns the highest position to the principles that are correlated with the three dimension of sustainability: environmental, social and economics. The framework has been applied to a list of sustainable indicators for agricultural, suggested in literature review, further restricted on the basis of a selection done by experts. The result of the theoretical framework is reported in table 2:

Dimension of sustainability	**Principles**	**Indicators**
Economic	Economic Function	Income of agricultural producers
		Contribution of agriculture to GDP
		Insured area
Social	Social Function	Agricultural employment
		Stability of work-force
		Risk of abandonment of agricultural activity
		Economic dependence on agricultural activity
Environmental	Function of range of biotic resource	Specialization
		Mean area per plot
	Function of soil quality	Soli cover
		Nitrogen balance
		Phosphorus balance
		Pesticide risk
	Function of amount water extraction	Use of irrigation water
	Function of energy balance	Energy balance
	Function of range of habitats	Agro-environmental subsidy area

table 2: indictors used in the composite indicator for agricultural sustainability.

In order to feed numerical values for the selected indicators at the farms level, data have been collected by drown survey of farmers. The indicators are combined together by using PCA and Analytical Hierarchical Process (AHP), in order to apply two different kinds of weighting techniques: the PCA belonging to the “positive” one, and the AHP belonging to the “normative” one. The positive is called also endogenous techniques, because it takes into account only the statistical characteristics of data, while the normative or exogenous techniques assign different weights on the basis of expert opinion or external decision makers. A further analysis concerned the regression analysis between the final score of CIAS and its variable in order to analyze the relationship between the final indicator and the other relevant variables (for more details about the results see Gòmez-Limòn and Sanchez-Fernandez, 2010).

Another example of sub-country level composite indicators is the Regional Competitiveness Index (RCI), developed by Annoni and Kozovska (2010) from the Joint Research Centre (JRC). The index associates the concept of competitiveness at regional level (NUTS2) for European Regions. The choice of assessing a composite index at the regional level comes from the fact that regional competitiveness has received increasing attention for the key role of regions in organizing and governance of the economic growth, and that the regional level is the middle point between firms and national level. The concept of competitiveness is multidimensional, because it involves several different aspects. Starting from existing indicators of competitiveness elaborated by several international organizations, like the World Economy Forum, the authors suggest a framework of eleven indicators to describe the various dimensions of the regional competitiveness. Pillars are organized into three main groups: basic, efficiency and innovation (table 3). In turn, each pillar is populated by means of a set of indicators chosen on the basis of expert opinion and data availability. Eurostat has been the main data source, with some further additional official sources, in case no appropriate data were directly available from Eurostat.

Composite Indicator	Pillars	Indicators
	Basic Pillars	Istitutions
		Macroeconomic Stability
		Infrastructure
		Health
		Quality of Primary and Secondary Education
Regional Competitive Index	Efficiency Pillars	Higher Education/Trainning and Lifelong Learning
		Labor Market Efficiency
		Market Size
	Innovation Pillars	Technological Readiness
		Business Sophistication
		Innovation

table 3: theoretical framework of the RCI.

The statistical methods applied in this case study are conducted both in univariate and multivariate way. The univariate one is applied on the data used to calculate each singular indicator, in order to detect the possible presence of problems like missing data, different measure scale, asymmetry, and consequently to identify methods to address these problems. The multivariate analysis is applied at the pillar levels on the set of indicators that describe them with the aim to assess the contribution of each indicator in the definition of the pillar or in describing latent dimension. In addition, the multivariate analysis has been used to detect the presence of anomalous indicators and consequently to exclude them. It is the case of the 'Government debt' in the Macroeconomic Stability pillar (for further details see Annoni and Kozovska, 2010). Compared to the other case studies, the RCI presents a further weighting method. Once the three groups of pillars have been calculated, the overall indicator is obtained as a weighted sum of the three groups. The weights are estimated on the basis of the Gross Domestic Product (GDP) of countries. According with the World Economic Forum approach modified by Annoni and Kozovska to fit to the case of European regions, the GDP allows to identify different level of development in European Regions: medium, intermediate and high stage of development. On the basis of this classification, different weights have been assigned to each group of pillars, in order to obtain the final score of the indicator (table 4).

	Weights assigned to the region stage		
Pillar	Medium Stage	Intermediate stage	High Stage
Basic	0.4	0.3	0.2
Efficiency	0.5	0.5	0.5
Innovation	0.1	0.2	0.3

table 4: weighting scheme on the basis of the regional stage.

Other two examples of composite indicators applied to sub-national basic area units are the Busan Index of Multi-deprivation (Nam et al, 2014) and Indice di Deprivazione Multipla in Sardegna [Multi-deprivation Sardinian Index] (IDMS) (Regione Sardegna, 2009).

The first one is based on the previous UK's Index of Multiple-deprivation, modified to take into account the peculiarity of the city of Busan, Korea. The indicator framework divides the deprivation in seven dimensions, which in turns encompass different indicators that describe them. Indicators are chosen on the basis of five criteria: consistency with existing studies, external validity, availability of data, relevance on the variable of interest, generalizability. Indicators are assessed on the most recent data at the *tong or dong* level *(dong and tong are administrative sub urban areas)* depending on the availability data level. Indicators are aggregate using three procedures: weighting according to *tong* leaders, weighting according to *dong* leaders, according to professionals and finally according with the IMD weighting values. In order to be more useful as decision support tools, *tong* and *dong* were ranked in a classification system that shows the deprivation index. The classification concerns the *dong* level, and it is based on the size of the composite deprivation index, which yields rankings for the degree of deprivation in each variable of interest. In this way it has been possible to identify the area units in need of immediate attention by policy authorities.

Domain	Weighted according to tong leaders	Weighted according to professionals	IMD weighted values
Income deprivation	11.7%	19.3%	22.5%
Employment deprivation	11.40%	20.30%	22.50%
Health deprivation and disability	18.00%	19.80%	13.50%
Educational deprivation	17.70%	12.60%	13.50%
Housing conditional deprivation	25.00%	10.70%	9.30%
Social security deprivation	14%	9.70%	9.30%
Living environmental deprivation	2.20%	7.60%	9.30%

table 5: comparison among different weighting scheme for the BIMD.

The IDMS is similar to the previous case study. It concerns the quantification of deprivation for municipalities in Sardinia, in order to define in which areas (Group of Sardinia municipalities) actions to reduce the social disadvantage are needed, and to discover its causes. In this study, IDMS use seven dimensions, like in the BIMD, with the difference that in case of Sardinia the dimension 'Housing conditional deprivation' is replaced by 'Access to facilities'. For the final score of the IDMS two methodologies were applied. The first one use only the equal unitary weights to aggregate the dimensions, while in the second also another weighting system that give highest weights to the dimension considered more relevant has been used. Security deprivation was not take into account in the final score of IDMS, because the difficulty to achieve a good quality dataset.

Domain	Weights
Income	30.0%
Employment	12.5%
Health	12.5%
Educational	20.0%
Access to facilities	20.0%
Living environmental	5.0%

table 6: weights for the DRES domains

A further example of CI assessed in a smaller spatial units than country is provided by Stathakis and Tsilimigkas (2014) in a study about the compactness of European medium-sized cities. The spatial units of analysis are the urban zones of the selected cities, in which compactness was assessed. Compactness has been considered as a complex phenomenon, involving four main dimensions: density, dynamics, composition and configuration. In turns each dimension is described using a set of sub-indicator (table 7)

Compacteness	Density	densgr1
		densblt1
		dendres1
	Dynamics	construction
	Composition	porosity
		supfacts2
		denlow
	Configuration	Simpson
		coreness
		adjacency

table 7: Framework for the compactness description. (Source: Stathakis and Tsilimigkas (2014)).

1.4. *Pros and cons of the use of composite indicators and potential for extension of the methodology.*

Despite the fact that the use of CIs is still subject to a large and ceaseless debate, they are accepted as a tool to communicate in a synthetic way the performance level of units (mainly countries) in complex domains. Recently, composite indicators have been widely advocated and increasingly accepted as a useful tool for performance comparison, publication communication, public communication and decision support in a wide spectrum of field, mainly economic, environmental and technology development (OECD/JRC, 2008). The temptation of practitioners to summarize complex and elusive processes in a single value is the main pros of composite indicators (Saisana, 2005). This aspect is also the main cause of the opposition, to the use of the composites by some scholars.

Pros and cons of the composite indicators can be summarized, as reported in the following table 8

Pros	Cons
• Can summarize complex or multi-dimensional issues in view of supporting decision-makers. • Easier to interpret than trying to find a trend in many separate indicators. • Facilitate the task to ranking countries on complex issues in a benchmarking exercise. • Can assess progress of countries over time on complex issues. • Reduce the size of a set of indicators or include more information within the existing size limit. • Place issues of country performance and progress at the centre of the policy arena. • Facilitate communication with general public and promote accountability.	• May send misleading policy messages if they are poorly constructed or misinterpreted. • May invite simplistic policy conclusion. • May be misused to support a desired policy, if the construction process is not transparent and lacks sound statistical or conceptual principles. • The selection of indicators and weights could be the target political change. • May disguise serious failing in some dimension and increase the difficulty of identifying proper remedial action. • May lead to inappropriate policies if dimension of performance that are difficult to measure are ignored.

table 8: pros and cons of the use of composite indicators. Source: Nardo et al, 2005.

Composite indicators, as a singular measure, are easier to interpret than large set of indicators. But the ease is object of controversial because it has been argued that summarizing large amount of information into a singular measures may bring to information loss and therefore to a misinterpretation of the understanding of the phenomenon.

A crucial point of the use of CIs is that the dimensions of the complex phenomena to be used for its construction are subject to expert or political choice, increasing to possibility to have biased information based on the desires of the stakeholders. In the previous sections the importance of the transparency about the construction of the theoretical framework has been largely discussed; this issue needs great attention to avoid the creation of biased indicators, based on policy desires or policy manipulation. In addition the construction of a robust theoretical framework allows to reduce the risk to obtain simplistic conclusions and ensures that each dimension of the phenomena is taken into account. Still the problem remains about the allocation of the correct importance to each dimension. This point is still object of a large debate and of ongoing research, as demonstrated by the number of case studies about the comparison of different weighting procedure.

Nevertheless, the debate about the use of composite indicators and the research to improve their performance, confirms the increasing interest on this tool.

The analysis of the case studies has revealed that composite indicators are still used and improved, using different methodologies for their construction and using different scale of analysis: from the typical national scale, to the regional and sub-regional scale. On the basis of this new emphasis on research about composite indicators, in the following section a modification of the methodology above described is proposed, to introduce spatial data and spatial analysis since the earlier steps in order to build a framework for a Spatial Composite Indicator.

2. Methodology: towards spatial composite indicators

2.1. Why a spatial composite indicator? New opportunities: advances in SDI, and in spatial statics.

The previous chapter showed the building process for CIs. Also, the fact that CIs are mainly constructed starting from census, usually connected to countries - the most commonly used spatial unit for CIS. Sometimes, other administrative units are used, like regions, while municipalities or sub-municipality units are quite unusual. The use of countries as spatial units is primarily due to the fact that CIs are used to measure and to compare the country's performances in socio-economic, or environmental field. The second reason is strictly related to the fields of interest: usually data that describe economics and social aspects are collected at the administrative level, mostly national, and regional. Therefore the simplest way to spatially represent data and indicators is to refer them to the administrative levels. Generally, further investigation on spatial dimension of data is neglected: the relationship between indicators and their spatial distribution is still a rather unexplored field. Little or no attention is paid to the spatial dimension of the variables (Anselin and Griffith, 1988) in the existing CI construction methodology. The term spatial dimension refers to the way in which data, sub indicators, and finally CIs, are spread in a given area, and whether their spatial distribution exhibits any spatial dependence. With regards to the research issue, making robust policy decisions on the basis of CIs requires a clear understanding of the importance of the various sub-indicators on the overall CIs, and also understanding whether their importance is equal in every location (spatial unit) or if there is spatial variation. As matter of fact, the value of a given CI may be the same for two different locations, but it is possibile that the value of CI may be more dependent on a certain sub-indicator in a given location, and another sub-factor in different location. This kind of knowledge is very important in policy decision making to tackle problems in an efficient way, distinguishing the causes of problems at local level. Furthermore, it is necessary to analyse whether the spatial distribution of the CI and its sub indicators is random or shows any patterns. (Anselin, 1993; Griffith 2009; Annoni et Kozovska, 2010). In the latter case, patterns may reveal the presence of spatial dependence, which should be investigated for various reasons. Firstly, from a spatial point of view, the spatial dependence among locations has important consequences on models used to forecast or to estimate missing data in a given location, for example regression models. From a political perspective, understanding the spatial distribution of data and indicators may be helpful to better understand where the most critical value of the composite indicators is, and what kind of spatial dependences may exist between variables and CI.

Recently, several studies recognized the importance of surveying the spatial dimension of indicators and of the variables that make them up (Anselin, 1999 and Goodchild et al, 2000). The analysis of spatial dimension became an important component of the social science thanks to the rapid changes in perceived space, due to the improvement in technology, communication, transportation and, last but not least, to the changes in political landscapes. These changes have been strongly affecting the spatial organization in social, economic, political and cultural domains, where the focus of social science is. Therefore social scientists recognized the importance of the use of sophisticated technologies and new methodologies for spatial analysis (Goodchild et al, 2000). Concurrently, the development in the provision and quality of digital data create new opportunities for spatial and temporal measurement of the socio-economic aspects, also at finer scale, than in the past, also on an intra-urban scale (Longley and Tobon, 2004).

Regarding data sources, nowadays, Spatial Data Infrastructure (SDI) provides a large amount of spatial data. According to article 3 of the European Directive 2007/2/EC INSPIRE SDI can be defined as an *infrastructure for spatial information means metadata, spatial dataset and spatial data services and technologies; agreements on sharing, access and use; and coordination and monitoring mechanisms, processes and procedures, established, operated or made available in accordance with the directive,* while spatial data are defined as *data with direct or indirect reference to a specific spatial location.* Creation of SDI was due to the necessity of having a common framework in order to ensure data collection, data change and data interoperability across European countries, with the aim of having a high level of environmental protection that takes into account the differences of the various regions of the community. The inclusion of spatial information is useful for the formulation and implementation of policies in the environmental field. This fact is enforced by the Six Environment Action Programme that requires in depth information to ensure quality environmental policy, developed in an integrate way, able to take into account regional and local differences. From this perspective, the development of SDI should assist politicians in their activities which may have an important impact on the environment. With the implementation of SDI, member states have to collect, store, and maintain available spatial data at an appropriate level, in order to ensure the most quality spatial information. The purpose of the INSPIRE Directive is to supply implementing rules and technical arrangements to ensure the interoperability and harmonization of spatial data and spatial data set services.

The recent and growing availability of spatial data makes their possible introduction in the methodology for CIs construction a current and urgent issue, in order to explore the possibility of expanding the use of composites to the description of different spatial phenomena, and to give more attention to the spatial dimension of social and economical aspects.

It is worth noting that spatial data and digital data are similar, but different. Digital data are mainly data, like census data, available in digital format, and provided by the census offices both public and private. The concept of spatial data is slightly different; spatial data have a specific location (INSPIRE, 2007). Therefore, the difference is the fact that spatial data do not need to be geo-referred, because they already have their own location. This is due to the fact that they measure phenomena within a designated area (e. g. the pollutant diffusion) or within some spatial characteristics, like the location of cities, location of forests or other characteristics like elevation and so on. Spatial data also have their own shape (point, line or polygon, and raster) and consequently their own boundaries. Hence it raises the possibility of changing the usual spatial units like administrative limits, to better describe how and where spatial phenomena happen, and how their value changes in relation to different locations.

Concurrently, the recent and rapid development of the Geographic Information Systems (GIS) and the growing computing power allows handling of large amounts of data. The capability of visualization and rapid data retrieval, and manipulation in GIS, encouraged the development of new technologies for the exploration and the analysis of data, focusing on its spatial aspects (Longley et al, 1999). Various tools implemented in GIS allow the performing of in depth spatial analysis to better describe the spatial nature of data, including tools for the Exploratory Spatial Data Analysis

(ESDA) and spatial statistics. According to Anselin et Al (2007), the proliferation of social indicator databases requires spatial analytical methods; ESDA is suggested as a tool to leverage the information contained in social indicator databases. The application of the spatial analysis on social indicators can contribute to the discovery of interesting patterns in the distribution of socio-economic characteristics and, consequently, provide information for policy and programs development. In this sense, the term "interesting pattern" means a group of spatial units that show atypical values of a given phenomenon (Anselin, 1996).

The use of spatial analysis can be helpful for enhancing the set tool of social scientists in three main areas (Anselin 1999, Goodchild et al. 2000):

- data integration, because spatial analysis provides a basis for integration and data collection at different spatial scales and time dimensions. This is the central function of the application of GIS.
- Exploratory Spatial Data Analysis (ESDA), that is a sub set of Exploratory Data Analysis with the focus on the particular characteristics of spatial data, in particular on spatial autocorrelation and spatial heterogeneity (Anselin, 1994).
- confirmatory spatial data analysis that refers to spatial data modeling technique to be implemented to explicitly embed the mechanism underlying the spatial patterns.

On the basis of these considerations, the need to build a methodology for the construction of spatial composite indicator (SCI) to take into account the spatial effects on data from the first steps, appears to be an interesting and current research issue. It is important to keep in mind that explanation of indicator can vary among the different regions.

2.2. The special nature of spatial data.

Space plays a central role as an organizing concept in regional science, therefore it is expected that the analysis of spatial dimension receive considerable attention (Anselin and Getis, 1992). The analysis of spatial dimension of data is becoming a crucial point both for spatial and socio-economic data, and in the quantitative scientific tradition in geography. In general terms, spatial analysis can be considered a quantitative analysis on a given phenomena in space (Anselin, 1990). In spatial analysis, the importance of the location where data is collected is very important because, according to the first law of geography by Tobler (1979), "*everything is related with everything else, but near things are more related than distant things*". Spatial data are different from other kinds of data. While non-spatial data contains only the attribute dimension, spatial data has attribute as well as geographic information; in some cases, spatial data have the time dimension (Demsar et al, 2012). Hence spatial data links a given measure to the location in which the measure was collected. From a geographical perspective, location has the three-dimensionality of the physical world (Demsar et al, 2012). For the characteristics of spatial data, the traditional techniques for data exploration are not sufficient to analyze the spatial dimension correctly. Exploratory Data Techniques (EDA), a collection of non-spatial methods, encompasses a large range of methods which focus attention on the interaction between the individual data points by displays and graphs. EDA techniques are used to combine GIS and spatial analysis, but they are not able to take into account the two main characteristics of spatial data: spatial dependence and spatial heterogeneity

(Anselin, 1990). Spatial dependence and spatial heterogeneity invalidate the standard statistics assumptions of the independence of data and of the random distribution of data across space (Cliff and Ord, 1970). In addition, spatial data are affected by the effect of spatial scale (Anselin and Getis, 1992). For these reasons, spatial data need specific tools to be explored correctly. The recent advances in spatial statistics allow the correct investigation of the spatial dimension and its consequences, in order to discover the presence of spatial association and different spatial regimes.

2.2.1. *Exploratory spatial data analysis (ESDA): main characteristics.*

The use of spatial statistics techniques remained limited for a long time, because of the lack of an easy and effective way to explicitly incorporate the spatial aspect of the data. Development of GIS has largely eliminated this problem allowing the implementation of different kinds of spatial analysis (Anselin and Getis, 1992, Anselin, 1993, Goodchild and Al, 1993 Anselin et al, 2006). According to Anselin (1990) there are two main approaches to tackle spatial data: the data driven approach and the data-model approach. The data-driven assumes that data speak with themselves, and it attempts to receive information about spatial pattern, spatial structure and spatial interaction without constrains of a pre-conceived theoretical notion; in most respects this approach falls under the "Exploratory Data Analysis (EDA)" methods. In the data-driven approach, spatial patterns, spatial structure or spatial dependence are derived only from the data. Application of data-driven approach is not considered to be straightforward in the description of the spatial dimension of spatial data because of EDA methods assume the spatial independence of data. Therefore, EDA cannot be implemented uncritically for spatial data (Anselin, 1990), because of the fact that spatial dependence and spatial heterogeneity nullify the basic EDA assumption of spatial independence among data points.

Conversely, the model-driven approach originates from a different theoretical framework. It consists in a non-spatial or spatial model, but in each case the important characteristic is that the calibration of the model is carried out by spatial data. In fact, the properties of spatial dependence and spatial heterogeneity require the application of particular statistical techniques, whatever the nature or the model is. Generally the model-driven methods are linear models, as in the case of regression models. The main conceptual problem is how to formalize the role of space. This aspect can be seen in three main methodological problems: the choice of spatial weight matrix, the modifiable area unit problem and the boundary value problem (Anselin, 1990).

The use of space in both the data-driven approach and the model-driven one, leads to a number of concepts that are worthy of particular attention: the most important is the spatial error (Anselin, 1990). The comprehension of the spatial error is very important for the description and explanation of spatial analysis. First, it is necessary to distinguish between errors due to the measurement or specification errors, or a combination of both. Measurement is a very relevant element in modern cartography, and occurs when the location of a variable is observed with imperfect accuracy. The main important consequence of this aspect is that it (the geometries and the graphics representation) gives an imperfect impression. The accuracy with which the location of observed data is measured has important consequences in the evaluation of distances between relative position, and influences operations like aggregation and interpolation (Anselin, 1990).

A second important type of spatial error in the measurement concerns the imperfect way in which data, specifically socio-economic data, are collected or grouped in spatial units (e.g. administrative units). This aspect appears to be relevant in case of composite indicators that largely use this kind of data to describe socio-economic phenomena. Despite the fact that in CI, spatial analysis occurs rarely (Trogu and Campagna, 2012), the interdependence of locations and value in spatial data leads to distinctive characteristics of the errors (Anselin, 1990).

Specification error is particularly relevant in the model-driven approach (Anselin 1990). The error may come from a wrong model, for instance a recursive model instead a simultaneous one, an inappropriate functional form of the model or a wrong set of variables. The functional form refers to the use of linear or nonlinear models used to represent relations between the variables. Specification error generates error on spatial patterns, and it occurs when location-specific phenomena, spatial drift, regional effects or spatial interaction are ignored and a false homogeneity assumption is forced (Anselin, 1990). This kind of error also occurs when the scale of observation and the process scale of the data are different.

For these reasons EDA needs to be integrated with other tools which are able to deal with the peculiarity of spatial data. Exploratory Spatial Data Analysis (ESDA) can be seen as an extension of the traditional EDA methods for detecting spatial properties of datasets, where for each attribute there is a location datum (Haining et al, 1998). ESDA can be broadly defined as the collection of techniques to describe and visualize spatial distribution, identify atypical distributions, discover patterns of spatial association, and suggest different spatial regimes or other forms of spatial instability and spatial non-stationary (Anselin, 1993).

ESDA takes explicitly into account the special nature of spatial data. ESDA techniques have been developed quite recently, and nowadays these tools are implemented in more GIS suites. The visualization tools are an important part of ESDA methods. They encompass different graphs and maps for the visualization of data across space. Cartograms, quantile and percentile maps are examples of these tools. They supply a spatial distribution of data and suggest the presence of spatial dependence to be further surveyed. The outliers map for visualization of extreme values are particularly relevant in visualization of tools (Anselin et al, 2007). Outliers maps are the geographic representation of the standard box plot in which the extreme values are represented by the extreme segment of the box plot. In addition to this, the use of visualization tools in GIS allows having different views of data in different forms at the same time: maps and graphs. With this method it is also possible to link different representations. This means that every observation highlighted in one of these views is also highlighted in the others ones. Linking is a fundamental technique in high dimensional data visualization and underlies the exploratory approaches (Anselin 1993, Anselin et al 2007).

In some cases, functions as variogram are used to understand the spatial distance in which spatial dependence is relevant. The variogram is a function that describes the spatial dependence of a set of geo referenced values. Usually, the variogram is used in spatial models like kriging for prediction of values over the given area, to supply more description of spatial dependency and to add information to the measure of autocorrelation. The variogram is defined as the variance of the difference of the value of the variable of interest at separate points in the spatial domain (Annoni and Kozovska, 2011).

ESD methods also encompass the spatial regression method. Regression methods for spatial data model the relationship between a chosen dependent variable and a set of regressors or independent variables. This relation is modeled by the research of the coefficient associated to each regressor. In addition, it supplies a measure of the error that occurs as the effect of unobserved variables and error observations. These methods are used in spatial applications to explore data or for predictive purposes (Smith et al, 2007). Simple regression method may be applied in case of ascertained spatial homogeneity. Conversely, if the distribution of data throughout a given area reveals spatial dependence or spatial heterogeneity it is better to apply regression spatial methods capable of considering the local variation of relationship between data, and of identifying different spatial regimes. Geographically Weighted Regression (Fotheringham et al, 2002) is a spatial method indicating where non-stationary is taking place on the map (Bivand, 2013). By the use of GWR the dependent variable for a given location may be predicted starting from the independent variables available for the same location (Charlton and Fotheringham, 2009). In Practice the coefficient for the regressors are assessed performing local regression models in order to achieve a model that fits well with the presence of spatial heterogeneity.

2.2.2. *Spatial autocorrelation*

The central concept in ESDA is the notion of spatial autocorrelation or spatial association, global and local. Spatial autocorrelation is a phenomenon in which locational similarity (observations in spatial proximity) is matched by values of similarity (attribute correlation) (Anselin, 1993). In other words, spatial autocorrelation is the correlation among values of a single variable strictly attributable to their relatively close location positions on a two-dimensional surface, introducing a deviation from the independent observation assumption of classical statistic (Griffith, 2009). Spatial autocorrelation is a measure of how spatial units are clustered in global terms, and it is assessed by a test of the so called null hypothesis at random location. When spatial autocorrelation occurs it is possible to reject null hypothesis (Anselin, 1993). Hence it can be seen as a measure of the presence of spatial dependence between values of a variable in neighboring or proximal locations, in accordance with Tobler's first law of geography. The concept of spatial autocorrelation is therefore central in regional studies and urban econometrics, because it provides test models to avoid misinterpretations due to wrong spatial assumptions. The presence of spatial autocorrelation may be revealed when the spatial distribution values of a variable across space shows systematic patterns. In this sense, spatial autocorrelation, in the study of human phenomena, conceptualizes the basis for human spatial interaction (Getis, 2007).

Spatial autocorrelation has many interpretations. It is captured by a model specification because its presence is necessary for a good description, and usually interferes with the estimation of parameters of the given spatial model (Getis, 2007). In this sense, spatial autocorrelation can be seen as a nuisance parameter. Correlation that arises from the geographic context within which attribute values occur, and can be expressed in terms of product-moment correlation coefficient in which the neighboring values of a certain variable replaces those of the related variable. Spatial autocorrelation can be interpreted in terms of trends, gradient or mosaic across a map: the map patterns (Griffith, 2009).

As a diagnostic tool spatial autocorrelation plays a fundamental role, particularly in model-based inference whose foundation is a set of valid assumptions rather than a scientific sampling design (Getis, 2007).

Spatial autocorrelation also means redundant information because it represents duplicated information contained in spatial data, linked to missing values estimation as well as to the notion of effective simple size and degrees of freedom. Inference about a geographic variable means a non-zero spatial autocorrelation. (Griffith, 2009). This characteristic is important for the calibration of predictive spatial models or to obtain missing data in a certain location. The value of a given location can be predicted with a certain level of accuracy from the values of nearby locations (Getis, 2007).

Furthermore spatial autocorrelation can be interpreted as an outcome of area unit demarcation, strictly relating with the Modifiable Area Unit Problem (MAUP) (Getis 2007).

Spatial autocorrelation can be measured globally or locally.

At the global level, the most common estimator for spatial autocorrelation is Moran's *I*. It is a correlation measure that incorporates the spatial dimension by the introduction of a weights matrix.

$$I = \frac{n \sum_i \sum_j w_{ij}(x_i - \mu)(x_j - \mu)}{\sum_i \sum_j w_{ij} \sum_i (x_i - \mu)^2} \tag{2.1}$$

In equation (2.1), μ represents the mean of the variable x in n observations, x_i and x_j are the observations in location i and j, and w_{ij} represents the so-called 'spatial weight'. Moran's I varies in a range between -1 and 1. If I is close to -1 or 1, there is strong spatial autocorrelation among data, strong negative and strong positive respectively. It is a sign of the presence of non-stationary among spatial data that consequently show different spatial regimes. Negative spatial autocorrelation indicates opposite trend of a certain variable between the spatial units. In social science the presence of negative spatial autocorrelation is usually interpreted in terms of geographic competition (Griffith, 2009). Values around zero indicate the non-presence of spatial autocorrelation and consequently no spatial dependence exists among spatial units.

The main advantage of the use of Moran's I is that it possible to represent it in a scatter plot of spatial variables, the Moran scatter plot, as a slope of the regression line (Figure 2).

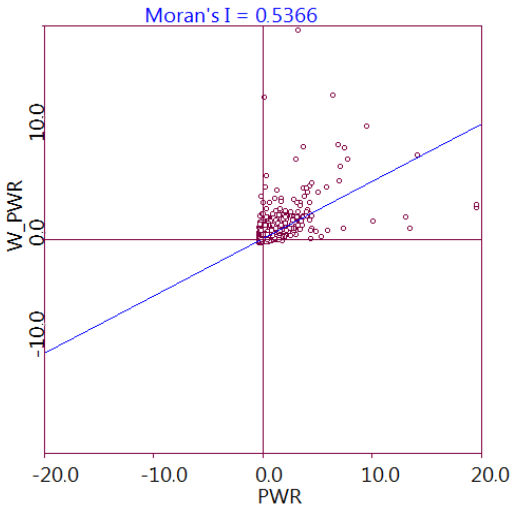

Figure 2: an example of Moran's scatter plot. Source: Caschili et Al (2014).

The scatter plot also allows easy categorization of the nature of spatial autocorrelation. As it is possible to see in the Figure 2, the scatter plot has four quadrants corresponding to four different types of cluster. In particular, the lower-left and the upper-right are the part of the graph that describes the positive spatial autocorrelation. These two quadrants represent potential spatial cluster; in other words, the falling point in these quadrants are values of the variables surrounded by similar neighbors. Conversely, in the other two parts of the graph, the upper-left and the lower-right quadrants, the spatial autocorrelation assumes negative values (Anselin, 1995).

Even if global spatial autocorrelation provides a measure of the cluster level in the study area, it does not supply any information about where clusters or outliers are located (Anselin et al, 2007, Anselin, 1995). The importance of the recognition of local spatial patterns led to a new class of local indicators, named Local Indicators of Spatial Association (LISA) (Anselin, 1995). They allow the decomposition of Moran's *I*, highlighting the contribution of each observation. LISA can be interpreted as indicators of local pockets of non-stationary, or hot spots, and they can also be used to assess the influence of individual locations on the magnitude of the global autocorrelation and consequently to indentify outliers, like the Moran scatter plot (Anselin, 1995). LISA are identify by two main characteristics: for each observation, LISA supply the extent of a significant spatial cluster, and summarizing the value of LISA at each location over the spatial domain provides the value of the global indicator of spatial autocorrelation (Anselin, 1995).

Local clusters are classified in four types corresponding to the four quadrants of the Moran scatter plot. Clusters can indicate location of spatial autocorrelation (high-high or low-low) or conversely local spatial outliers (low-high or high-low) (Anselin, 2007). The assessment of significance level of local spatial association is based on a conditional permutation procedure (Anselin 1995).

Autocorrelation (global and local) can be assessed in both univariate and multivariate ways. In the case of multivariate, the value of a variable at a specific location is related to a different variable at neighboring locations (Anselin, 2003).

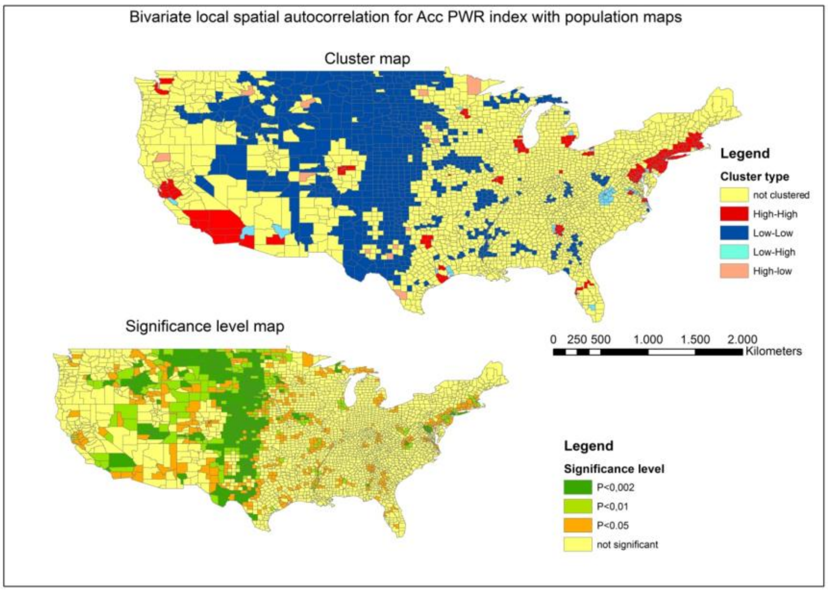

Figure 3: an example of bivariate LISA. Source: Caschili et Al (2014).

The spatial weights are a central concept in the application of spatial autocorrelation; the final score of the coefficient of spatial autocorrelation depends on their value. In general terms, spatial weights can be seen as a measure of proximity between the spatial units that make up the study area. In fact, in the matrix W, each of the non-zero values of w_{ij} represents neighboring spatial units j to the location i (Anselin, 2007). The importance of the weights depends on the fact that the structure of w_{ij} expresses a prior notion for which the location is important in driving the spatial correlation (Anselin, 2007). Despite the great importance of the weights in autocorrelation implementation, it is impossible to choose the best weight matrix. There are different perspectives for the assessment of spatial contiguity. The simplest method consists in the calculation of the number of neighbors of a given spatial unit. Contiguity plays a fundamental role in the definition of how many spatial units can be considered as neighbor. Contiguity can be calculated in two main ways: rook contiguity and queen contiguity. In the first case only spatial units that share borders are considered, while the second case considers both spatial units that share borders and vertices (Anselin et al, 2006). Because contiguity is a concept strictly related to the distance decay, that is to say that the mutual influence between spatial units is less than the increase of the distance, spatial weights can be assessed at different contiguity levels. The research of the best contiguity level is done by a sensitivity analysis on the final result. In addition to the numbers of neighbors, spatial weights can be evaluated as the distance between spatial units. In this case the distance is measured between the centroids of spatial units (Anselin et al, 2007).

2.2.3. *The importance to survey spatial dimension: some case study*

The importance of surveying the spatial dimension of indicators is proved by several studies on the spatial distribution of social indicators across a given spatial domain. These studies concern empirical cases in which the spatial analytical perspective is taken into account to evaluate the importance of methodology in assessing the degree or distribution of some social characteristics (Talen and Anselin, 1998). Often, they are strictly related to social hardship or disadvantage, with the aim of supplying deeper spatial information about spatial behavior of social indicators, as well as their mutual spatial relationship (Talen and Anselin, 1998, Longley and Tobon, 2003, Anselin et al, 2007, Rouske, 2009 etc). From a planning point of view, this information appears to be relevant in the decision-making process, because it allows understanding of whether there is spillover effect or local association. The spatial dimension about how phenomena manifest themselves across space is important in policy design, because there is no sense in improving social or economic performance in a given area without contemporaneously and explicitly considering similarities across neighboring areas (Webber and Rossouw, 2010).

Generally, these kinds of analysis are not made to construct a composite indicator itself, but rather to discover the spatial relationship between a socio-economic phenomenon and the variable recognized as its determinant, and if and how they form a cluster in the spatial domain. This is done in order to identify where and how the variable is more relevant in relation to the overall phenomena.

Talen and Anselin (1998), for instance, studied the spatial equity for accessibility in public facilities in the city of Tulsa (Oklahoma, USA). The focus of this study was to research spatial patterns between several measures of accessibility to the playgrounds of the city and some socio-economic variables, like income, race, age etc. The analysis was conducted by LISA indicators for the spatial distribution of playgrounds in the city districts, and also between them and several measures of accessibility. The choice of different measures of accessibility was make to meaningfully relate public service facilities and population groups, and, consequently, to survey the spatial distribution. The main result obtained in this study was that it is possible to spatially characterize social equity by means of spatial analysis.

Another example of ESDA application in the study of spatial distribution of social disadvantages is provided by Thongdara et Al (2012). They used these methods to discover why poverty in Thailand is more relevant in one area rather than another. The overall objective of the study was to investigate factors influencing rural poverty and to identify appropriate analytical tools for improving the efficiency of poverty alleviation programs and make better use of limited national investments. Spatial autocorrelation was the tool used for this kind of analysis, because of its capability in exploring the spatial dependence and spatial patterns of the phenomenon, and in bringing a better understanding of the behavior of spatial phenomenon and spatial patterns. Given the spatial dependency of poverty, geographical targeting of the poor would help develop and implement poverty alleviation programs more affectively.

In this particular case study, poverty is intended as rural poverty, based on the consuming approach. Form this point of view, the Net Farm Income (NFI) was considered a contributor to rural poverty, that measure how much farmers make from their farming. NFI is an indicator for assessing agricultural sustainability and tracks financial viability (for more details see, OECD 2001).

Various kinds of data were collected for the implementation of this study, both by questionnaire survey and geographical layers (table 9).

Data	Base source
Political Boundary	Topographic Map
Contour elevation	
River and road network	
Land use	Land use map
Soil and laboratory analysis	Soil map
Demographic (households and population)	Census Data
Rainfall data	Census data
Administrative boundary	Administrative map
Poverty line	Census Data
Household characteristics and agricultural production	Census Data
Farm location	GPS

table 9: data and data source used in the study of the spatial relationship for the NFI. Source: Thongdara et al, 2012.

First, NFI was studied in terms of regression analysis (no spatial regression) in order to understand what the variables that significantly influenced the indicators were. Conversely, the spatial analysis concerned the use of GIS only to investigate the status of farm land, with respect to reported damages, size of farms holdings and land suitability. These kinds of analyses are not quantitative; they are only used to visualize patterns of the characteristics mentioned above, and to map the spatial distribution of NFI. Spatial autocorrelation, both global and local, has been applied to confirm quantitatively the cluster tendency of the spatial distribution of household NFI. No further spatial relationship has been inspected, for example in terms of multivariate spatial autocorrelation to further investigate the level of spatial dependence between NFI and the independent variables used in the regression analysis.

Geographically Weighted Regression was used in the study of the spatial dependence and heterogeneity in patterns of hardship for the city of Bristol (Longley and Tobon, 2003). In this study, a comparison was provided between the spatial patterns of spatial dependence and spatial heterogeneity between the census district of Bristol. In this case study, the concept of hardship was intended as household income, and the relationships between income and other census conventional variables were detected (table 1010).

Variabel	Description
OLDPSN	percentage of households per ED where residents are aged 65-74
2534NK	percentage of households per ED where residents are aged 25-34
WKWIFE	percentage of households per ED where there are married females working
BIGACC	percentage of total households per ED with seven or more rooms.
HHTCA	percentage of households per ED owing two cars
UNSKLD	percentage of households per ED with unskilled workers
QUALML	percentage of qualified male residents per total households in the ED

table 10: census variables used in the study of social deprivation. Source: Tobon and Longley, 2003.

LISAs are used to measure the degree of spatial dependence between the value of the variable at a certain location and its neighbors. LISAs are able to accommodate non-stationary across a given area and to identify the spatial clusters. The application of LISAs revealed well defined spatial patterns, leading to the decision of applying the Geographically Weighted Regression in order to accommodate geographical variability in the regression specification. If OLS estimates the regression parameters considering each individual area independently of its neighbors, it can only be seen as yielding an average parameter value for the study area as a whole, and this representing a global characterization of the prevailing relationship (Longley and Tobon, 2003) between income and regressors. Conversely GWR provides an indication of varied spatial patterns for the same variables. With the application of the spatial techniques of Longley and Tobon, it is possible to demonstrate the need to extend our interest toward the analysis of the spatial dimension of the census data, in order to obtain newer more complete data, relevant to urban geography.

A case study of spatial analysis strictly related with composite indicators is the case of the spatial analysis on the spatial structure for the Regional Competitive Index (Annoni and Kozovska, 2011). As in the previous case, the aim is to supply further spatial information about the spatial dependence among the EU region (NUTS2 level) with respect to the indicator score and its sub-domain. In addition to this, further investigations have been carried out to discover how proximity matters in the distribution of RCI score, special cluster level between the regions – that is, the tendency of regions with similar values to be close together , and finally if spatial dependence exists and how far it has spread.

With the application of spatial analysis it is possible to make an important point: it is not possible to bind competitiveness by administrative borders, because it is the result of several factors which interact with each other as well as with the surroundings regions. It refers to the trade between regions, the mobility of technological diffusion, which are recognized as factors to be interpreted as sources of spatial dependence. With this assumption, the actual presence of spatial dependence has been inspected by the implementation of some ESDA techniques. Primarily, ESDA was implemented for the RCI score and the three sub-indices related with three groups of pillars: RCI basic, RCI efficiency, RCI innovation.

The ESDA analyses proposed in this study do not differ substantially from the analyses presented in the previous case studies. They concern the visualization of RCI score and the three sub-indices by cloropleth maps (percentile and standard deviation map), and the assessment of the spatial autocorrelation, both global and local, in order to identify the regional clusters with similar performance, or the presence of spillover regions. The most important difference, with respect to the case studies presented above, is the use of the variogram. In this particular case study the variogram has been used to assess the distance in which the effect of spatial dependence is relevant. It is worth keeping in mind that spatial dependence is a phenomenon subjected to the distance decay effect; therefore it decreases as distance increases. Distance can be measured in several ways, depending on the aim of the study. For the RCI case study, three kinds of distances have been taken into account: Euclidean distance, distance along the road network and travel time distance. The result of variogram with the type of distances has been compared; the outcome confirms the presence of spatial dependence, shown by the use of spatial autocorrelation, but also provides information about the distance between regions in which the dependence is more relevant.

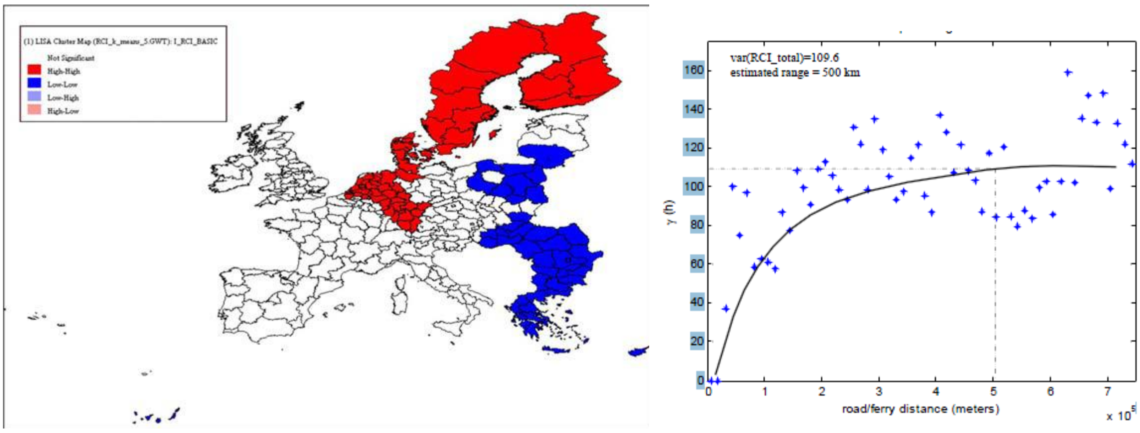

Figure 4: LISA cluster map output (left) and semi-variogram output (right), resulting from the spatial analysis on RCI and its indicators. Source: Annoni and Kozovska, 2011.

The case analysis study confirmed how the analysis of the spatial structure of data is relevant in social science. The exploration of spatial data supplies a better understanding about how a phenomenon manifests itself in a given area, and helps discover the spatial causes of its behavior. In policy perspective this information may be useful for taking appropriate local action, rather than attempting the development of a 'global' solution. According to Longley (2003) non-spatial analysis are able to take into account only the more relevant relationship between data and phenomena, while the presence of spatial dependence may bring to spatial differentiation of these relationships, and consequently to different spatial regimes.

The analysis of case studies confirms what was anticipated in the first chapter; spatial analysis is barely applied to the study of composite indicators. As in the case of RCI, when exploration of data is done in spatial terms, it is applied to the final score of the indicator.

According to OCSE/JRC methodology, the analysis of data is a necessary step in the construction of composite together with the weighting procedure to obtain the importance and relevance of the data on the overall phenomena. Despite the fact that recent advances in spatial data analysis proved that the structure of data and their importance may be different depending on the location. To deal with this spatial consequence, a variation of the original methodology is proposed in this work.

A recent attempt in the construction of a spatial composite indicator is the study about the social vulnerability to malaria in East Africa by Kienberg and Hagenlocher (2014). This is an interesting case study about the spatialization of the vulnerability, and is based on an extension of the concept of *geons* (Lang et al, 2008). The concept of *geons* refers to homogeneous spatial objects in terms of varying spatial phenomena under the influence of policy intervention, and is generated by scale specific spatial regionalization of a complex and multidimensional geographical reality incorporating expert knowledge (Kienberger, 2014). Geons was delineated using a multi-resolution segmentation algorithm by regionalization of the weighted indicators used to describe the relevance of vulnerability. The weights for the indicators were chosen by mean of expert opinion. This case study represent a good attempt at building a spatial indicator of vulnerability. Despite the fact that this case study represents a good example for the construction of spatial composite indicators, the weights that come from the expert opinion do not appear to be spatial, in the sense that they do not vary throughout a given area.

Conversely, in this thesis the main objective is to consider the spatial effect on the weights. Therefore the next section proposes the introduction of the spatial multivariate analysis to discover the spatial structure of variables involved in the description of the phenomenon and consequently to determine their local spatial importance.

2.3. Methodology: the integration of spatial statistics to account for the spatial dimension.

In the previous chapters, the special nature of spatial data and its consequences were discussed. In the aforementioned case studies, spatial statistics are applied only to understand the spatial structure of a certain phenomenon and their mutual spatial relations. This study aims to introduce these methods in the overall CI construction process, in order to spatialize the OCSE/JRC methodology from the first step. The aim is to provide more detailed spatial information during the CI procedure to better take into account the consequences of the possible spatial dependence and spatial heterogeneity. This attempt appears to be necessary if composite indicators are intended as tools to support policy decision-making. In fact, according to Goodchild et Al (2000), efficiency in policy decision-making comes from a better spatial understanding of the phenomenon and its characteristic. In light of this, there is a proposed variation of the original methodology. table 11 provides a comparison between the two methodologies. The spatial methodology will be tested, chapter 4 – a case study on landscape evaluation in Sardinia, using spatial data provided by the regional SDI.

OECD/JRC Methodology	Spatial methodology
Definition of the theoretical framework	
Definition of sub-indicators and data collection	
Imputation of missing data	
Data analysis	Data modeling and data analysis
Multivariate analysis	Data normalization
Data normalization	Spatial multivariate analysis
Weighting and aggregation	
Sensitivity analysis	
Back to the real data	
Results presentation	

table 11: methodology comparison. On the left the OCES/JRC methodology, on the right the new proposal to obtain a spatial composite indicator.

The development of the theoretical framework still remains the starting point for the definition of the model, and its representation scale.

The core of the variation of the methodology is the introduction of the spatial multivariate analysis, in particular the Geographically Weighted Principal Component Analysis (GWPCA). This recent spatial statistics technique is able to distinguish regions in the geographic space in which different PCA have to be performed, so as to consider the spatial heterogeneity (Demsar et al, 2012). Further details about how this geographical model works will be provided in paragraph 2.4.

In spatial methodology, GWPCA is used both to explore the structure of data, and to obtain an objective method for selecting weights for the variables used to build the spatial composite indicators of landscape.

OCES/JRC indicate the use of PCA as a one of the methods for obtaining information about the data structure, in particular for understanding the relationship between variables, and for discovering the possibility of reducing the dimensions of variables, transforming the original set of variables into another one whose main characteristic is the independence between the new variables in order to avoid redundant information. The new set of variables account for the majority of information about the original data. Furthermore, variable loading resulting from the application of GWPCA has been used to assess the spatial (local) importance of the variables (see following paragraph and chapter 4), in order to obtain an objective weighting system, not biased by the stakeholders background or perspectives.

A further difference between the two methodologies concerns the order in which normalization of data is carried out. In the OCED/JRC methodology, normalization is carried out before the aggregation procedure in order to avoid comparison among different measurement units. In case of spatial methodology, normalization has to be carried out before the application of the GWPCA, because the effect of the use of non normalized data is still subject to further research (Gollini et al, 2013).

The use of spatial data may imply the use of spatial data modeling in order to identify the minimal spatial units of analysis. This aspect is strictly related to the choice of spatial scale, which is an essential aspect when spatial phenomena are studied (Longley, 2003) (Further details in chapter 4).

The imputation of missing data is also different in case of spatial data. As mentioned in chapter 1 (section 1.2.3.) the imputation of missing data is achieved by the application of various statistical techniques. In case of spatial data the imputation of missing data depends on the format of the spatial data (point, line, polygon, or raster). Several spatial statistical techniques are appropriate for this task. The most common are interpolation and spatial regression methods.

Interpolation methods encompass some statistical procedures which are able to estimate the value trend between points of a given characteristic, measured in turns in specific points. Generally the output of these procedures is surfaces in vector or raster formats, representing the values of the characteristic under consideration. Examples of these methods are the inverse distance weighting or spatial kriging, mainly used in Digital Elevation Models (DEM) or to estimate the chemical concentration of certain elements or pollutants. The output of these methods is a raster surface. Other interpolation methods, like Triangulated Irregular Network (TIN) result in a digital data structure, vector based surface. In some cases spatial regression methods are used to predict the missing variable.

2.4. Local multivariate analysis: Geographical Weighted Principal Component Analysis (GWPCA).

The Principal Component Analysis (PCA) is a statistical technique widely used in social and physical sciences (Harris, 2011). The aim of PCA is to explain the main part of the variance of the data through few linear combinations of the original data (OCSE/JRC, 2005). It consists in a multivariate linear procedure for reducing the dimensionality of a multivariate set of data, but, at the same time, it tries to take into account most of the variance explained by the original data (Anderson G. B, missing year). Data dimension means the number of variables measured. PCA is often used as a preprocessing method to discover the relation between variables and eliminate redundant information. In this context, it can be considered an exploratory data technique.

Therefore, given a set of x1,…, xq variables, the principal component is a series of Z1,…,Zq, in which each Z variable is a linear combination of the Q ones

$$
\begin{aligned}
Z_1 &= a_{11} x_1 + a_{12}x_2 + \ldots + a_{1Q}x_Q \\
Z_2 &= a_{21} x_1 + a_{22}x_2 + \ldots + a_{2Q}x_Q \\
&\ldots \\
Z_Q &= a_{Q1} x_1 + a_{Q2}x_2 + \ldots + a_{QQ}x_Q
\end{aligned}
\qquad (2.4.1)
$$

PCA transforms the original set of variables into a new one (principal component) whose main characteristics are un-correlation with each other, because they are made orthogonal by the PCA procedure and are ordered on the basis of the amount of variation explained by the original variables. The un-correlation between components means that they are describing different statistical dimensions, hence redundant information is avoided.

Because the new Z variables are ordered according to the increasing variation explained, it is now possible to reduce the number of dimension by the choice of N (N<Q) of Z variables to describe the original set of data, losing a small part of information in comparison with the original data. In order to preserve a significant amount of variance in the original data, N is chosen so that the total amount of variance is equal or more than 75%, and the eigenvalues associate to Z variables must be higher than or equal to 1 (Harris et al, 2013).

In algebraic terms, PCA involves finding the eigenvalues associated to the principal components of the covariance matrix. Covariance matrix is decomposed as follows:

$$LVL^T = R \qquad (2.4.2)$$

Where R is the correlation or the covariance matrix and denotes the variance of the corresponding principal component, V is a diagonal matrix in which the diagonal elements are the eigenvalues, and L is the matrix of the eigenvectors. L represents the variable loading of each variable in each component, while the component score is obtained by multiplying the matrix X by L (Charlton et al, 2010). Values of the L matrix are the coefficients a_{ij} applied to the x_j variables in the equation (2.4.1). The coefficients are chosen in order to satisfy the previous condition about Z components: un-correlation between them, and Z components account for the maximum portion of the variance of the original variables (Nardo et al, 2005).

The methodology assumes that covariance is constant across a given spatial domain. In other words, if applied to the case of spatial data, PCA is not able to consider the presence of possible variation of the covariance across space. Despite this fact, in some case PCA is used in non-spatial way on spatial data (Demsar et al, 2012, Gollini et al, 2013). In the case of spatial data, any standard statistic provides a summary and does not allow for geographical variation in the values of observation or the relation between them (Lloyd, 2010).

Variation of the covariance must be taken into account in order to define in a correct way the spatial structure of data, and therefore their local influence on principal components. To achieve this goal some modification has been introduced in the global PCA model described above. In particular the spatial modification differentiates the variable collection on the basis of their location, described by mean of their coordinates (Charlton et al, 2010). The introduction of variation on the methodology is the fact that spatial data have a location associated to their attributes that may generate spatial heterogeneity and spatial autocorrelation (Demsar et al, 2012) as described in the section 2.2.

Geographically Weighted PCA is a local spatial form of the PCA. It is used when the global PCA is not considered able to describe in a correct way the structure of data across the space for the presence of spatial variation (non-stationary condition). In general terms GWPCA assumes that there are different regions into a given spatial domain in which there is need to apply different and distinct PCA. In this way it is possible to consider the continuous variation of the results across space. GWPCA allows assessment of representivity of standard PCA by providing locally-derived set of principal components at all data locations (Lloyd, 2010). Furthermore the patterns in the behavior of local eigenvalues supply information about the intrinsic local complexity and data, in order to provide local dimension reduction. Because local PCA describes local relationship between variables; it could be used to derive local indicators that depend on the local environmental circumstances. (Demsar et al, 2012).

Following the previous notation, let x_i be a vector of observation at the location i, and let as assume that it has a normal distribution with mean vector μ and variance matrix $\sum$:

$$x_i \sim N(\mu, \sum) \tag{2.4.3}$$

In order to take into account the geographic effect, the coordinates u and v of the location i are introduced in the previous equation. This way also μ and $\sum$ became function of the location:

$$x_i \mid (u, v) \sim N(\mu(u, v), \sum(u, v)) \tag{2.4.4}$$

Since μ and $\sum$ are respectively vector and matrix, the fact that they are now function of the position (u, v) imply that each element of the mean vector and of the variance matrix is in turns function of the position. Thus $\mu(u, v)$ and $\sum(u, v)$ are the geographically weighted mean and the geographically weighted variance-covariance.

Geographically weighted principal components are obtained using the decomposition of the variance-covariance matrix, but in this case the variance-covariance matrix is geographically weighted. Therefore the result of the decomposition provides the geographically weighted eigenvalues and the geographically weighted eigenvectors. Multiplying the i^{th} row of the data matrix by the i^{th} the component score is obtained. The geographically weighted decomposition for the covariance matrix assumes the form:

$\sum(u, v) = X^T W(u, v)X$ (2.4.5)

where X is the data matrix with m variables (column) and n row (number of location for each observation), $W(u, v)$ is a diagonal matrix of geographic weights. The diagonal matrix of weights can be generated by the use of one of different kernel functions.

The geographically weighted principal components at each location (u_i, v_i) can be written as:

$L(u_i, v_i) V(u_i, v_i) L(u_i, v_i)^T = \sum(u_i, v_i)$ (2.4.6)

where $L(u_i, v_i)$ is the matrix if the geographically weighted eigenvectors and $V(u_i, v_i)$ is the diagonal matrix of the geographically weighted eigenvalues. This way for GWPCA with m variables, there are m components, m eigenvalues, m sets of component scores, and m sets of component loadings at each observed location. (Gollini et al, 2013, Harris et al, 2011).

2.5. Local calibration and significance test

In order to be applied GWPCA needs a previous calibration, which represents the main challenge to their use (Harris et al, 2011). Calibration is obtained through a procedure that tries to minimize the distance between original data and components.

If the data matrix X contains m variables, then each vector of observation is a vector in m-dimensions. Let q be the number of component extracted, that represent the new sub-space with principal components as new coordinates. Therefore the q-dimensional sub-space is the sub-space that maximizes the variance of the data points projected on the new q-axis. $q<m$ and it is chosen in order that the new space contains a reasonable portion of the original variance of the original data. The remained $q-1$ sub-space represents the deviation between m-space and q-space. In algebra terms if M_q is the matrix with the first q columns and $M_{(-q)}$ is the matrix with the first columns removed, it is possible to describe the first q components as XL_q and the remained components as $XL_{(-q)}$ the best rank q approximation to X is XL_qL_qT and the residual matrix $S = X - XL_qL_qT$ that can be written also as $S = XL_{(-q)}L_{(-q)}T$ (Joliffe, 2011). The application of PCA minimize the expression

$\sum_{ij} ([X]_{ij} - [S]_{ij})^2$ (2.4.7)

With respect to S, where S is a q rank matrix. The variance level of the matrix S measure the so called ‘goodness of fit’ (GOF) of the projected sub-planes (the new space dimension) whose equation is

$GOF_i = \sum_{j=q+1}^{j=m} s_{ij}^2$ (2.4.8)

That represents the GOF for the i^{th} observation. s_{ij} is the j^{th} component score for observation i.

The total GOF is

$$GOF \quad = \sum_{i=1}^{i=m} GOD_i \qquad (2.4.9)$$

Harris et Al (2011) suggested the procedure for the GWPCA is similar to the case of non-spatial PCA; the main difference is that in the spatial case the correspondent loading are defined locally. Therefore in the spatial case the following expression is minimized:

$$\sum_{ij} w_i ([X]_{ij} - [S]_{ij})^2 \qquad (2.4.10)$$

where w_i is the weight associate to the *i* location. *GOF* and *S* are defined in similar way than in normal PCA.

The importance of the *GOF* in the spatial case is due to the fact that this statistics provide the optimal bandwidth to calibrate the model, by mean of a leave-one-out methodology or the holdback sample (Harris et al, 2011).

An important difference between the PCA and the GWPCA calibration is that in the spatial case the number of principal component extracted has to be chosen at priori, in order to ensure an optimal bandwidth calibration. This fact may generate some difficulties because no pattern of data explains how many components to retain.

As said above, eigenvalues are assessed for each location, but to justify the use of GWPCA, instead of normal PCA it is need to survey if eigenvalues vary significantly across the space and if they are randomly distributed. The significance test is performed by the use of a Monte Carlo test for a specified number of permutations. In practice, significance test associate location to the variables of the dataset in a random way, and after each randomization a new GWPCA is applied. A new standard deviation for the obtained local eigenvalues is assessed. The value of standard deviation is included in a ranked distribution together with the standard deviation values of the original eigenvalues. The position of the original standard deviation in this distribution determines the presence or not of significant spatial variation of the chosen eigenvalues. A Monte Carlo simulation results is the *p-value*. If the *p-value* is equal or lower than 0.05, then it is possible to conclude that eigenvalues are non-stationary (Lu et al, 2014, Harris et al, 2011).

2.6. Review of case studies of application of GWPCA

Since nowadays, GWPCA has been rarely used for spatial analysis. The fact that it is a quite recent spatial technique and software to perform it is currently improving may be the cause of its infrequent use.

This trend is confirmed by the literature review that presents only two recent cases study that used the GWPCA. Both cases concern the research of the population structure and underline the differences between the normal PCA and GWPCA. The first one is the case of the population characteristics of Northern Ireland by Lloyd (2010), while the second one is the analysis of the population structure in the Great Dublin by Harris (2011). The main topics of these cases study is to underline how in case of georeffered data, the application of the normal PCA supplies only a global summary, that is it captures general trends but may mask marked local variation (Lloyd, 2010).

Conversely, GWPCA allows assessment of representativity standard PCA by providing locally-derived sets of principal component analysis for each location.

In the case of the analysis of the Northern Ireland population, the study considers some census data derived from 2001 Northern Ireland Census grid (1 km cell size).

Data	Abbreviation
Person < 15 years old/ person 16-19 years old	ilr (LE15/1619)
Person < 15 years old x person 16-19 years old/person 30-64 years old	ilr (LE15,1619/3064)
Person < 15 years old x person 16-19 years old x person 30-64 years old/ person> 65 years old	ilr (LE15,1619,3064/GE65)
Owner occupier households/all rented households	ilr(HHOO/HHRent)
Households with no car/household with one or more cars	ilr(HHNoCar/HHCar)
Employed economically active person/unemployed economically active person	ilr(EAInEmp/EAUnEmp)
Person with no qualification/person with qualification at level 1 or 2	ilr(QualNon/Qual12)
Person with no qualification x person with qualification at level 1 or 2/person with qualification at level 3, 4 or 5	ilr(QualNon,Qual12/Qual345)
Person in approximated social grades AB/person in approximate social grade C1	ilr(SGAB/SGC1)
Person in approximated social grades AB x person in approximate social grade C1/person in approximated social grade C2	ilr(SGAB,C1/SGC2)
Person in approximated social grades AB x person in approximate social grade C1 x person in approximated social grade C2/person in approximated social grade D	ilr(SGAB,C1,C2/SGD)
Person in approximated social grades AB x person in approximate social grade C1 x person in approximated social grade C x person in approximated social grade D/person in approximated social grade E	ilr(SGAB,C1,C2,D/E)
Catholics by community background/non catholic by community background	ilr(CathCB/NonCathCB)
Person with a limiting long-term illness/person with no limiting long-term illness	ilr(LLTI/NLLTI)

table 12: variables used in the characterization of the population structure in Northern Ireland. Source: Lloyd, 2010.

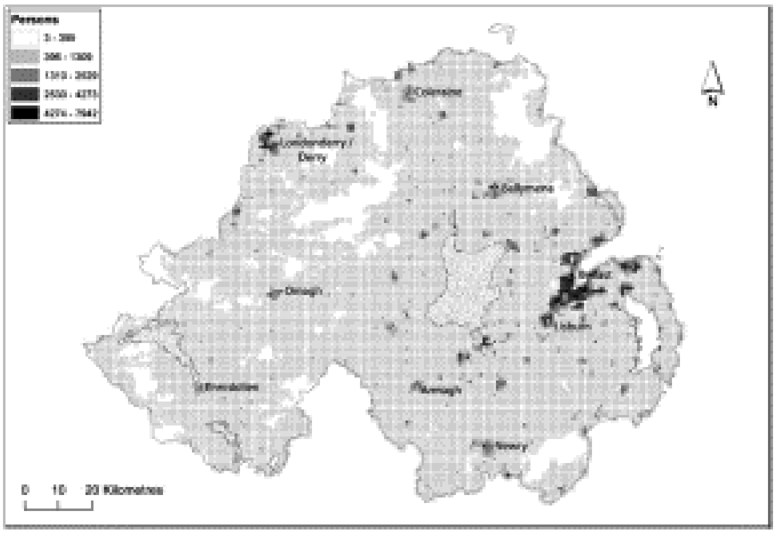

Figure 5: census grid (size 1 km). Cells are the basic spatial units of analysis. Source: Lloyd, 2010.

The cells represent the basic area units to the analyzed. According to Lloyd (2010) the use of a grid square data offers an unusual perspective of population, characteristics not determined by irregular shaped zones which cover the study area completely. The analysis of GWPCA was done using a bandwidth of 12.5 km, 25 km and 50 km. As it was expected, the comparison between PCA and GWPCA revealed the presence of relevant geographical variation in the definition of population's structure that global PCA did not showed. These variations and consequently the population's structure can be mapped.

Similarly, Harris et Al (2011) analyzed the social structure of the Greater Dublin comparing PCA and GWPCA. In this specific case study the basic area units are the electoral districts, in which data about the social structure were collected.

Data	Abbreviation
one year migrants	DiffAdd
local authority renters	LARent
social class one	SC1
unemployed	Unempl
without any formal educational	LowEduc
age group 18-24	Age18_24
age group 25-44	Age25_44
age group 45-64	Age45_64

table 13: variables used in the characterization of the population structure in Greater Dublin. Source: Harris et al, 2011..

Conversely than the Lloyd case study, the bandwidth was selected not by user specification, but through the research of the optimal bandwidth. In this case a Kernel bandwidth can be found automatically using a cross-validation approach which has a similar nature that the regression approaches. In practice, it returns the bandwidth that reduces the error terms of the model (Gollini et al, 2013). Another difference with the Lloyd case study is that the bandwidth is not assessed in term of metric distance, but in terms of the minimum number of basic spatial units used to calibrate the model (similar to the concept of contiguity in section 2.2). As in the previous case, the application of GWPCA allowed to discover the spatial patterns in the social structure of the population expressed in spatial terms.

These two case studies confirm the assumptions presented in the previous sections: when the analyses are performed using spatial data, it is necessary to use techniques able to deal with their special nature, in order to achieve deeper information about their spatial behavior. As it was demonstrated by the case studies, global techniques are not able to distinguish the local structure of data, but they are able to highlight only the global general trend, and consequently they may leads to wrong conclusions.

3. Case study: Landscape.

3.1. Introduction

Landscape has been chosen as case study to test the methodology proposed to the achievement of spatial composite indicator because it is a spatial and complex phenomenon. Spatial because it happens in the space and complex because it is the result of the interaction of a large number of different aspects. These reasons make the landscape interesting to be represented by a composite indicator, in order to obtain a measure able to embed all the several aspects that compose it, and therefore to express a comprehensive representation. A complete way to measure landscape takes into account all its composing aspects, as many scholars argued recently. According to the OCES/JRC methodology, the first and fundamental step towards the creation of a composite indicator is to define a robust theoretical framework; therefore a brief state of the art about the landscape is presented, stressing the attention on the landscape measurement.

3.2. The evolving concept of landscape.

Landscape is one of the most important concepts in planning activity since Olmsted in the middle of the 1800 century in the creation of natural spaces into American cities. During the years, the concept of landscape evolved to a more rich and complex meaning. It became clear that the landscape is not only a beautiful place to see or a place with a high natural level, but it is a complex mix that involves several aspects. It is the result of an ongoing interaction between natural processes and human activities; hence it is also a dynamic process (Antrop, 2000). This brings the concept of landscape toward an ecological/ecosystem point of view, in which landscape is considered as the result of the interaction between its flora, fauna, and cultural components (Fry et al, 2009). This definition appears to drive strictly the concept of landscape toward the natural sciences. Many scholars argued that there is another important component that should be taken into account, which is the perceptive component of the landscape. In fact, in many studies, the landscape value is assigned on the basis of the liking level of appreciation of the people. The perceived point of view is broader than aesthetical aspects, as it concerns also how the people interpreted the landscape, in addition to its beauty, and to attribute value to it.

AS result of interaction of various components, landscape is not easy to be defined. According to Antrop (2000), landscape is a holistic, perceived and dynamic concept. Holistic because it encompasses several and different aspects from each other, but each important in the overall definition of landscape. In general terms, landscape is an abstract concept that has no borders in which being defined, but it is a continuous concept across the space. Even if it is possible to recognize different types of landscapes in a typological sense. The complexity of the landscape is demonstrated by the various approaches used to define it; each approach focus on a particular landscape aspect, so that landscape have been studied from different points of view: ecological, historical/cultural and perceived., The different approaches has been rarely integrate together.

Recently the European Landscape Convention gives a broad definition of landscape, taking into account either physical, cultural, and perceptive aspects: *"Landscape means an area, as perceived by people, whose character is the result of the actions and interaction of natural and/or human* *factors" (EU, 2000).* European Landscape Convention focus on the importance of landscape as a place and as a resource in which local communities has formed their own culture, creating and modifying the different places that create the overall European landscape . The terms resource refers to the environmental and cultural resources. Starting to these premises, the convention stresses the importance for the Member States to develop policies to protect the landscape, in a sustainable manner.

As dynamic process, landscape change continuously. Landscape change is an inevitable process, both for natural causes, and for human modification. Natural change is a process mainly due the natural events, or natural disaster. Usually natural events are out of control of the planning activity. In some cases it is possible to predict them, as for example, in case of some climate phenomenon, or limit the damages using appropriate methods of mitigation. The changes due to human activities are responsible to the fast modifications of landscape that in some cases may brings to an undesirable consequences, while in others case they produce very appreciable landscape (as in case of cultural landscape). Mankind modify the landscape to satisfy their need of food, housing and energy, and furthermore the need of services (transportation and infrastructures) (Antrop 2000, Botequilha-Leitao, 2006). These modifications appear to be more relevant and fastest since the end of the Second World War (Antrop, 2000). Depending on the landscape study approach, the focus is to understand the effect of the disturbance in environmental/ecological, in cultural or in visual aspect. The aim is always to deal with the landscape change and so to propose alternatives plans for the future and to create a basic understanding about the alteration of landscape and its consequences (Botequilha Leitao et al, 2006). According to Steiner (2000) the best tools to measure the landscape change are indicators.

3.3. Measuring landscapes.

Landscape complexity makes no easy its description through indicators. Despite the fact that indicators represent an efficient tool to measure these interactions (Steiner, 2000) the main difficult in their use is to understand what exactly indicators should measure, that depends on the landscape approach adopted. Usually, in landscape studies, the objective is to obtain indices able to supply information about the state of environment, and the consequences of landscape changes on the landscape structure, in order to understand if changes are desirable or not (Fry et al, 2009). The dynamic characteristic of landscape, in time and space represents another difficult on the use of indicators for landscape measurement, because it makes necessary to specify both the spatial and the temporal scale (Gustafson, 1998, Harings et al, 1998).

The spatial scale refers either to the choice of the extension of the study area, and the choice of the reference spatial units. Spatial scale strongly influences the relevance of the landscape factors and also their behavior across the space. Hargis at Al. (1998) and Wu (2004, 2000) demonstrated how the landscape fragmentation and its patterns vary on basis of the scale of analysis. Another reason that makes the spatial scale very important in landscape analysis is that landscape does not exist in isolation but it is nested with largest landscape and so on, but, at the same time it has a context or a regional setting regardless of the scale in which landscape is defined (McGarigal at Al, 1994). Gustafson (1998) puts the emphasis on the fact that, because landscape change involves factors and processes, it is critical to measure them at the same spatial scale. Also he highlights how spatial scale influences the level of heterogeneity. On the other hand, the time scale takes into account the evolution of landscape changes and spatial pattern directions (Gustafson, 1998).

Landscape indicators can be divided two main groups (Botequilha-Leitao, 2002, and Fry et al 2009): the first one concerns the indicators about the physical and ecological characteristics of the landscape; the second one regards visual, social and cultural aspects of the landscape.

The first group provides measures about the so called objective components of landscape that are landscape form, landscape structure, and the landscape physical/ecological function. Landscape function means how the landscape and its changes affect species and communities (Turner, 1989). A prerequisite to understand the landscape function is to understand its structure.

Landscape structure concerns two important aspects: composition and configuration (Botequilha-Leitao, 2002). Composition refers to *non spatial explicit* characteristics of the landscape, or rather non explicit spatial characteristics. Composition metrics measure landscape characteristics such as proportion, richness, evenness, dominance and diversity. On the other hand, configuration is related to spatial *explicit* characteristics of the land cover type in given area, namely those associate with the patch geometry or with the spatial distribution of patches. Usually configuration metrics are characteristics including shape index, type of edge, relative location of patches contagion, fractal dimension and interspersion metrics (Botequilha-Leitao, 2002). When composition and configuration indices are combined together indices of fragmentation or heterogeneity are obtained (Hargis at Al, 1998, Jaeger, 2000, Botequilha-Leitao, 2002, Llausàs, 2010). An operative problem affects this kind of indices: because they measure landscape characteristics in different ways, there is the risk to use redundant information when they are used together to landscape evaluation. For this reason, it is necessary to understand which landscape metrics are independent each other. The independency of the metrics depends on the kind of landscape under investigation, but as suggested by Li and Reynolds (1993), the fundamental components have to be found using factors analysis, multivariate analysis or principal component analysis.

The second main group of landscape indicator focuses mainly on the perceptive aspects of the landscape. They are indices designed to quantify the aesthetical and evocative level of the landscape. These indices are based on the subjective perception of the people; therefore they need further techniques to encourage the participation of the local communities or the involvement of experts in landscape science (Daniel, 2001). The main problem in the quantify landscape perception is to assess a value of landscape that come from the "pleasure view" or from the cultural and aesthetic importance of a given landscape (Daniel 2000, Terkenli, 2001). Landscape value are not only an objective thing, deriving from the intrinsic beauty of the things, but it concerns also a subjective component that come from the history of a given landscape and the fact that it represents an important part of the culture for the local communities (Daniel, 2000, Landscape European Convention, 2000).

The European landscape convention brings the social dimension of the landscape to the forefront of the landscape definition, and highlight the need to develop indicators that are sensitive to take into account both physical and human perceptions (Lluas and Nogué, 2012). The attempt to combine the two dimensions together reveals that the common point between the physical and perceived component is the level of fragmentation of the landscape. Fragmentation is intended as disturbance that affects both the ecological and perceived aspects (Fry at Al, 2009).

In both cases, physical and perceived indicators, the data issue has been one of the reasons that limit their use, in particular for wide areas, because the difficult to collect data for landscape purpose. In fact, landscape indicators need a large amount of data to be calculated in an efficient way; this is particular relevant for those that concerns landscape structure (Gustafson, 1998). At the same time, when data are available, they covered only a small portion of land, the portion object to the landscape survey. This may be due to the fact that in case of landscape there is need to specific data, about landscape characteristics, including habitats, species, and morphology. Nowadays this problem could be in part overcome tanks to the development of the already mentioned SDI that provides several territorial data, however still remains the problem about how to collect a large amount of data concerning the perceived aspect of landscape. In addition to the data problem, Gustafson (1998) indentify the lack of dedicate software for the calculation of landscape indicators as another limit in the use landscape indicator. This problem has been overcome by the introduction of landscape tool in GIS platform, or in other cases, by the development of dedicate landscape software, as Fragstat, Zonation or Marxan. GIS tools and landscape software perform the calculation of the so called landscape metrics, deriving from the Landscape Ecology approach that will be described in the next section.

3.3.1. *Quantify physical aspects of the landscape: the landscape ecological approach and landscape metrics.*

Landscape metrics are the most used set of indicators to measure landscape. This group encompasses a large number of indicators till subjected to revision and implementation. Landscape metrics come from the Landscape Ecology approach that focuses the attention on the physical aspects of the landscape with the aim to evaluate the state of the landscape in an ecological point of view. According to Faring (2005) Landscape ecology can be defined as a branch of the ecology focused on the landscape spatial structure, with particular regards on the abundance and distribution of organisms in a territory. Turner (1989) defined Landscape Ecology as the study of the effects of the spatial arrangement of habitats on the ecosystem processes. For Botequilha at Al (2000) Landscape Ecology is a discipline that comes from the union of biogeography and ecology, but it is different from the ecological sciences because it focuses on the description of the spatial structure and of the mosaic of the different ecosystems into a heterogeneous landscape. In addition, Landscape Ecology introduces different perspectives in landscape study. These perspectives are essential for planner, and they can be recap in three point:

1. the spatial dimension of ecological processes that can be vertical or horizontal. The vertical dimension represents the topological relationship, while the horizontal one is the chorological relationship among ecosystems. Understanding these connections allows planners to compare the effects of the different spatial configurations of the land use and consequently, to verify the effects of the landscape change introduced by human activities. In this way it is possible to prevent and to manage the ecological consequences of the landscape change.

2. Landscape Ecology stresses on the so called human ecology that considers the human activities as part of the ecosystem. This point of view is fundamental also for the definition of cultural landscape (as it will be explained later in paragraph 3.3.2).
3. landscape is intended as the main spatial unit of analysis. In nature, forms and functions of the landscape define the spatial units of analysis, because they are mutual related, and its relationship produces the landscape evolution. In this way, landscape is divided according to its physical characteristics, and its spatial arrangement of ecosystem.

Landscape changes affect the landscape function and the landscape structure that are described by landscape metrics used to compare different landscape configuration, in order to find the best alternative in designating landscape boundary. This introduces the already mentioned problem of the landscape borders, and how to define them. In ecological terms, landscape is an open system in which energy, materials, and organism move into and out of it. For example, the morphology, as watershed can be considered boundary because it limits the animal's movement. Conversely in case of a study about bird population watershed have little impact. Therefore, the landscape border depends on the particular phenomenon under investigation that, in turn, influences the scale of analysis. This bring to the consideration that the application of landscape metrics and consequently the interpretation of their ecological significance requires a deep awareness of the landscape context in terms of species, geomorphology, and disturbance (Mc Garigal at Al, 1994). The ecological nature of the landscape metrics is evident. What is most important for the Landscape Ecology approach is to assess, on the basis of the landscape metrics, the level of disturbance of landscape change on the landscape structure, and functions. Landscape structure, on the landscape ecology point of view, is intended made up of three main parts: patches, corridors and mosaic. Patch is the littlest homogeneous part of landscape that differs from its surroundings. It provides functions as habitats or sources and sinks for species and nutrients, it is possible identify several kinds of patches: agricultural, villages, forests etc.

Corridors are linear elements that have particular land cover type different from the rest of the context. They are important because they supply different function on landscape, as pathways for species, animals or nutrient, or conversely they may be a barrier for the flow of animals and energy.

Finally the matrix is the dominant land cover type in terms of area, degree of connectivity and exerted over the dynamics of the landscape (Botequilha, 2000).

Landscape change may compromise the landscape structure, bringing to the so called landscape fragmentation that is the interruption of the connectivity between habitats, including isolation of ecosystem, and loss of biodiversity. Landscape metrics supply tools to measure and to predict these consequences.

It is worth to underline the difference between landscape metrics and spatial statistics in order avoid confusion. While landscape metrics describe the geometry and the spatial properties of patches, spatial statics is an efficient tool to study the spatial structure of a given variable (Gustafson, 1998, Botequilha-Leitao, 2002). Spatial statistics is a very useful tool to survey the change of the landscape in time and space, or in other words to analyze the landscape patterns. Landscape patterns are very important in the study of the landscape because they come from the interaction between landscape structure and ecological and human processes. The analysis of landscape patterns allows understanding the change in landscape, what the main cause of this change is, and how the change influences on the ecological/human process in turns (Turner, 1990). Landscape metrics are tool to characterize the geometric and spatial properties of the landscape structure elements (e.g. patches) (Botequilha-Leitao and Ahern, 2002).

By the use of landscape metrics, landscape analysis can be conducted at three levels, depending on the desired emphasis. In this way it is possible to recognize:

- patch level. Patch is dynamic, because it changes in space scale and time scale on the basis of the landscape or land use change. The variation in spatial scale occurs from an organism centered perspective, and varies as a function of each animal’s perspective (Mc Garigal, 1994). The landscape metrics calculate at this level quantify the patch’s characteristics in terms of shape, size distance from other similar patches, and number (the number of equal patches). They may be represented as a polygon vector data, or as cell of a raster grid.
- class level. A class is a set of patches of the same type (Botequilha, 2000). The indicators calculated at this level are almost the same than the patch level, seeing as class level metrics derived from the patch ones. Because they measure the configuration of a particular patch type, in many cases class metrics are used as indicators of fragmentations or aggregation. Similarly to the patches, classes can be represented as polygon vector data, or as an ensemble of cell with the same value in a raster grid.
- landscape level is the landscape set of all patches in a given landscape. Landscape level metrics describe the overall composition of the landscape mosaic. For this reason they are interpreted as landscape heterogeneity indices. In terms of data representation, landscape level is the total collection of patches and class polygon, while in raster format it is grid containing all the class values.

Depending on what aspect of the landscape structure they measure, landscape metrics can be classified in:

Landscape metrics are classified in different groups according to the aspect of landscape they describe (table 14.)

Group	Landscape Level		
	Patch	**Class**	**Landscape**
Area and edge metrics	Patch Area	Total Class Area	Total Area
	Patch Perimeter	Percentage of Landscape	Largest Patch Index
	Radious of Gyration	Largest Patch Index	Total Edge
		Total Edge	Edge Density
		Edge Density	Patch Area Distribution
		Patch Area Distribution	Radius of Gyration Distribution
		Radius of Gyration Distribution	
Shape metrics	Perimeter Area Ratio	Perimeter Area Fractal Dimension	Perimeter Area Fractal Dimension
	Shape Index	Perimeter Area Ratio Dimension	Perimeter Area Ratio Distribution
	Fractal Dimension Index	Shape Index Distribution	Shape Index Distribution
	Relate Circumscribing Circle	Fractal Index Distribution	Fractal Index Distribution
	Contiguity Index	Linearity Index Distribution	Linearity Index Distribution
		Related Circumscribing Square Distribution	Related Circumscribing Square Distribution
		Contiguity Index Distribution	Contiguity Index Distribution
Core area metrics	Core Area	Total Core Area	Total Core Area
	Number of Core Area	Cora Area Percentage of Landscape	Number of Disjunct Core Area
	Core Area Index	Number of Disjunct Core Area	Disjunct Core Area Density
		Disjunct Core Area Density	Core Area Distribution
		Core Area Distribution	Disjunct Core Area Distribution
		Disjunct Core Area Distribution	Cora Area Index Distribution
		Cora Area Index Distribution	
Contrast metrics	Edge Contrast Index	Contrast-Weighted Edge Density	Contrast-Weighted Edge Density
		Total Edge Contrast Index	Total Edge Contrast Index
		Edge Contrast Index	Edge Contrast Index
Aggregation Metrics	Euclidean Nearest Neighbor Distance	Interseption and Juxtaposition	Contagion
		Percentage of Like Adjacencies	Interseption and Juxtaposition
	Proximity Index	Aggregation Index	Percentage of Like Adjacencies
	Similarity Index	Clumpiness Index	Aggregation Index
		Landscape Shape Index	Landscape Shape Index
		Normalized Landscape Shape Index	Patch Cohesion Index
		Patch Cohesion Index	Number of Patches
		Number of Patches	Patch Density
		Patch Density	Landscape Division Index
		Landscape Division Index	Splitting Index
		Splitting Index	Effective Mesh Size
		Effective Mesh Size	Euclidean Nearest Neighbor Distance Distribution
		Euclidean Nearest Neighbor Distance Distribution	Proximity Index Distribution
		Proximity Index Distribution	Similarity Index Distribution
		Similarity Index Distribution	Connectance
		Connectance	
Diversity metrics			Patch Richness
			Patch Richness Density

		Relative Patch Richness Shannon's Diversity Index Simpson's Diverty Index Modified Simpson's Diversity Index Shannon's Evenness Index Simpson's Evenness Index Modified Simpson's Evenness Index

table 14: classification of the main landscape metrics. Source, McGarigal et Al, 1994.

In according to Botequilha-Leitao (2000) and McGarigal et Al (1994) each group has a different ecological meaning. Furthermore into each group some indicators could have the same meaning. In other case metrics should be used together in order to provide a more complete information about the ecological aspect of the landscape.

Area and edge metrics

This group of metrics refers to the size of patches. In an ecological contest, the importance of these metrics is due to the fact that certain species needs a minimum area as habitat, and also that small patches are more probable to be subject to contagions by neighbor patches; in some case contagions may bring to a habitat loss. On the other hand, the edge effect is important to establish relationship between species. Especially in a landscape perspective, edge effect is strictly related to the concept of spatial heterogeneity.

Shape metrics

Shape metrics are important in ecological processes in which the shape of patches may influence for example migration of species or animal foraging strategies. It is clear that influence depend on the particular species under consideration. Moreover, shape metrics provide only a quantification of the geometry of patches, but they do not take into account morphological aspects, that are very important for the animal movement.

Core area metrics

In general terms, the core area represents the inner area within a patch with a specificity edge distance (buffer). Core area may be seen as the area without edge effect and therefore it is important to determine the character and function of patches. For this reason, core area is a much better predictor of habitat quality compared with patch area metrics. It is worth to notice that core area is affected by the patch shape. In fact, a patch may be large enough to support particular specie, but at the same time it cannot have sufficient core area to support the species protection.

Contrast Metrics

Contrast refers to the quantification of the difference between adjacent patches. The difference level influences the ecological processes. Contrast effect strongly depends about the species under consideration and the scale of the ecological phenomenon under investigation.

Aggregation metrics

Aggregation metrics refer about the tendency of patches to be spatially aggregated, so that to depict the landscape texture. Aggregation metrics enclose a set of related concepts that are: dispersion, interspersion, sub division and isolation.

Texture of the landscape is very important aspect of landscape pattern and also in many ecological processes. Dispersion and interspersion are aspect of landscape texture. Dispersion quantifies how patches are spread in the space, while interspersion refers to the intermixing of patch type, without considering the dispersion. Usually dispersion and interspersion are used together.

Interspersion affects the quality of habitat for many species that need different patch. Moreover efforts in wild life management are driven on maximizes the habitat interspersion because juxtaposition of different habitats is considered able to increase the biodiversity.

Dispersion plays a crucial role in habitat loss. Disaggregated or isolated patches allow a less movement of species, reducing the dispersal success and patch colonization rates bringing to a decline of the persistence of individual population and enhance the probability to regional extinction across the landscape. Moreover the increase of dispersion of patch types may affect the propagation of disturbance.

Subdivision is a property strictly related to patch themselves, in fact it measures the degree to which patch are broken into separate patches.

Isolation metrics measure the isolation level to which patches are isolated from each other in the space. Conversely to the subdivision metrics, isolation metrics take into account the distance between patches. In an ecological point of view isolation is a critical factor in the dynamics of spatial structure population. Isolation is particularly relevant in biogeography to identify ecological islands, and to discover and preserve endangered species.

Landscape division index, splitting index and effective mesh size provide an alternative and more explicit measure of subdivision. When they are calculated at the class level, they provide a measure of fragmentation for a particular patch type. At landscape level, these metrics measures the graininess of the landscape. Landscape division index is based on the degree of coherence that is defined as the probability that two animals placed somewhere might find each other. The degree of landscape division is simply the complement of the degree of coherence that is the probability that two randomly chosen places in the landscape are not situated in the same undissected patch. Landscape division index range from zero to one, when zero represents a landscape with a single patch.

Splitting index is the number of patches one gets when dividing the landscape into patches of equal size in such a way that this new configuration leads to the same degree of landscape division obtained for the observed cumulative area distribution. Splitting index represents the effective mesh number of a patch mosaic with a constant size dividing the landscape into S patches, where S is the splitting index. Splitting index increase as increased landscape subdivision into small patches. The maximum value is achieved when every cell is a separate patch.

Effective mesh size denotes the size of patches when the landscape is divided in S areas with the same degree of landscape division. Similarly to the landscape division index, effective maximum value of effective mesh size is reached when the landscape consist of a single patch.

The main advantage in the use Landscape division index, Splitting index and Effective mesh size is related to the fact that they are insensitive to the omission or addition of a very small patch. This is due to the fact that they are from the cumulative patch distribution.

According to MacGarigal (1994), Landscape division index and Effective mesh size are redundant and they are perfectly but conversely correlated. The difference between these metrics is that landscape division index is interpreted as probability, while effective mesh size represents an area.

Diversity metrics

Diversity index are the most used in a variety of ecological applications, in particular to measure landscape structure or landscape composition (Turner 1990). They are influenced by two main components: richness and evenness. Richness is a measure of the number of patches that are into the landscape. Richness is strongly relate to the scale of analysis so that larger areas are generally rich that the smaller ones. Evenness measure another aspect of landscape diversity that is the distribution of area among patch type.

Recently landscape metrics have been criticized for the increase of the complexity of calculation and for their ease of interpretability with respect to landscape change. For instance, it has been argued that they can produce different interpretation about the habitat fragmentation if the fragmentation process is cause by extensive disturbance (as in case of urban sprawl) or linear disturbance (as in case of highways disturbance) (Llausàs and Nogué, 2012). In addition, the fragmentation level of a given landscape is not a unique value, but it depends on the particular process under investigation. Fragmentation process varies significantly in relation of the species, because different species have different functional areas (Faring, 2005). Landscape metrics may be not interpreted individually, but in a combining way to the others, in order to achieve more information. Despite the large number of landscape proposed, the better sub-set must be chosen on the basis of the particular phenomenon under investigation. The choice of the best set of landscape metrics is useful to avoid redundancy of information; in fact many landscape metrics measure the same landscape aspect, therefore there is no need to assess all of them. Furthermore it has been noted that different metrics can have similar values when analyzing a given pattern, while the same metrics can report very different values if the patterns is modified. This fact makes landscape metrics inconsistence from the point of view of the quantification of landscape change.

3.3.2. *Perceived component of the landscape*

Quantify the perceived aspect of the landscape appear to be a not easy task. The main difficult is the fact that perception is inevitable subjective and different people see and appreciate the landscape in different ways. This fact is the main accountable of the short range of indicators measuring landscape perception. In fact it makes the data collection about the people a hard work for different reason. The first one is that to achieve people opinion questionnaires must be submit. The second one is the difficult to have a representative sample. When this approaches were used they covered only a small areas.

The European Landscape Convent gave more emphasis on the fact that the perceptive aspect of the landscape is made up to the social and cultural aspects of the landscape. In the Convention it is declared that '*Noting that the landscape has an important public interest role in the cultural, ecological, environmental and social fields, and constitutes a resource favourable to economic activity and whose protection, management and planning can contribute to job creation;'* and furthermore '*Aware that the landscape contributes to the formation of local cultures and that it is a basic component of the European natural and cultural heritage, contributing to human well-being and consolidation of the European identity* (EU, 2000). Therefore it is essential '*to recognize landscape in law as essential component of people's surroundings, an expression of the diversity of their shared cultural and natural heritage, and foundation of their identity'* (EU, 2000).

The introduction of the concept of cultural landscape is able to make the local communities aware of the fact that cultural places cannot be considered isolated but there are part of a broader systems with the ecological aspect, creating links in space and time (Rossler, 2006).

On the basis of these considerations there is the need to identify in a strictly way what the cultural landscape is. Farina (2000) defines the cultural landscape as a portion of land in which the human activities created, in thousands of years a particular system of patterns and processes. A more recent definition proposed by the UNESCO (Rossler, 2006) cultural landscapes can be grouped in three main categories:

1. landscapes created intentionally by human, such as parks or gardens;
2. organically evolved landscapes, which can be either relict landscapes or continuing landscapes. There are those landscapes originally modified for economical, social or religious reasons. During the years these landscapes has developed its present form by association to its natural elements. It is the case of traditional agricultural landscape, or the Regional Mine Park in Sardinia.
3. associative cultural landscape that enclose palaces with powerful religious, artistic or cultural association of the natural elements rather than material cultural evidence.

In the cultural landscape, where human impact is relevant, (as the first two cases described above), the landscape change is mainly caused by economical and social reasons, and they mainly concern modification in agricultural and forestry practices, abandoned agricultural land, disaster or human disturbance due to urban center growth. These changes are responsible to fast modifications of the landscape and threaten cultural landscape, causing, in many case their loss (Van Eetvelde and Antrop, 2004). The main causes of the cultural landscape change can be summarized in four fundamental points:

1. the increasing of the agricultural production, responsible of the transformation of some natural areas, it can cause changes in the traditional techniques of growth (Weinstoerffer and Girardin, 2000).
2. urban sprawl and the resulting increase of services and infrastructures for the new settlements. Sprawl causes strong impacts on the environmental and consequently on the on

the landscape. It causes modification on the land use and it is deeply connected to the fragmentation of the landscape.

3. touristic activities that hasten the landscape modification. It is particularly relevant in coastal areas. Furthermore, touristic settlements create disturbance to the traditional activities, and they increase the anthropic stress on the areas in which they are located.
4. the last point is the land abandonment. It is relevant in those areas that are a high level of rurality and remoteness, and in which there is a strong economic and social deprivation.

From the definition of the cultural landscape it is evident that landscape is considered an artefact, a place built by human and in which local communities recognized its identity; hence, the landscape has a social aspect, as well as natural. On the basis of this point of view, landscape is intended as a place that people interpret in order to increase the own awareness about the past activities, that are represented by the actions on the land and by historical heritage (Scazzosi, 2006, Botequilha, 2000). Thanks to these characteristics the cultural landscape is worthy to measures able to quantify it, and to quantify its interaction with the other landscape components.

3.4. Current approaches to the development of a framework of landscape indicators.

The problem of how to measure the different aspect of landscape together has been particularly relevant from the agricultural point of view, according to fact that agricultural practice is one of the main causes of the cultural and natural landscape change (paragraph 3.3.2). In addition, it must be considered that agriculture policy is one of the huge policy fields in European Community that supports different programs for the agricultural development. Recently these programs focus on a sustainable development of the agricultural practices, with particular attention to the landscape protection, where landscape is indented in its complexity (environmental, cultural and perceived aspects). When agricultural and landscape are both taking into account, the problem is how to quantify the agricultural and the landscape aspects together in order to provide a system of indicators able to supply information about the state of the landscape and to monitor and assess the consequences in environmental change and effectiveness of measures taken to promote sustainable agriculture.

Taking in mind the pro and cons of the use of indicators (see section 1.4) and the aim to quantify the effect of agricultural policy on the landscape, various international agencies have developed various frameworks to approach to the landscape indicators. These indicators are calculates at the national level, in order to make possible a comparison between countries, as in the field of composite indicators (Piorr, 2003). In the OECD approach the construction of a relevant landscape indicator have to satisfy different tasks, included:

- the existing link between biodiversity, natural habitats and landscape;
- indicators should be selected for which data are available;
- flexibility. Landscape indicators need flexibility to be adapted to the very different condition between European Countries, in particular agri-environmental condition;
- the establishment of a threshold values to facilitate the country comparison.

Following table 15 summarizes the proposal of the EU for the construction a system of landscape indicators, based on the OECD approach.

Issue	Characteristics	Meaning	Data type	Indicators
Land characteristics	Natural and biophysical	Landscape classification system	Soil type, morphology, clime,	
		Landscape structure	Land cover	Landscape metrics
	Environmental appearance	Visual and aesthetic value		To be developed on long-term basis: perception, frequency of visitors
	Land type features	Land cover/land use change	Land cover/land use flow matrices	Expansion/withdrawal Intensification/extensification Concentration/marginalisation
Cultural feature		Cultural identity, regional specific character, cultural assets, etc	Inventory of cultural landscape features: architectural, historic, hedgerow, stone walls	Number and status point features, length of linear features, surface of aerial features, share of regional specific land use patterns
Management functions		Landscape protection areas, nature conservation areas	Area estimates	Area under commitment related to total agriculture area

table 15: landscape indicators on EU level. Source: Piorr, 2003.

A more recent classification schema for landscape indicators is supplied by the PAISs (Proposal on Agri-environmetal Indicators) (EU, 2001). This project is further effort of the EU to suggest a set of indicators within the domain in landscape, rural development and agriculture, applicable at EU level.

Landscape dimension	Thematic indicator group	Indicator item
Landscape features	Landscape composition	Stock and change of broad land cover categories
		Stock and flow land cover/land use matrices
	Landscape configuration: structure	Fragmentation
		Diversity
		Edges
		Shape
	Natural landscape features	Stock and changes of biotopes and habitats
		Hemerobie
		Habitat/biotope fragmentation
		Habitat/biotope diversity
		Habitat/biotope quality
	Historical-cultural landscape features (state and change) statistics/inventories	Point features
		Linear features
		Area features
	Present-cultural landscape features (state and change)	Point features
		Linear features
		Area features
Human perception	Visual and aesthetic	-
Landscape management, conservation and protection schemes	Cultural landscape protection/conservation	-
	Nature conservation/protection	-

table 16: classification scheme for landscape indicators. Source Piorr, 2003).

It is relevant the absence of examples of indicators for visual and aesthetic values and for Cultural landscape that confirms what it has been said about the quantification of these landscape aspects.

In summary of this chapter it is possible to say that to measure landscape in an efficient way it is necessary to take into account all its aspects (environmental, cultural). Despite the large number of indicators no effective attempt has been made to date to combine them in order to achieve a unique landscape measure that encompasses all the aspects considered. This enforces the idea form which this thesis starts: the creation of a Spatial Composite Indicator of landscape.

Despite the fact that at international (European) level, it has been tried to supply a general framework to the achievement for landscape indicators, at the national level the creation of landscape indicators still depends on the local situation. In fact, according to the definition of cultural landscape, landscape takes into account the local identity that is not possible to reproduce in other contexts (EU, 2000). We refer here to the Italian experience, as described by Malcevschi and Poli (2008) where the proposal of landscape indicators strongly depends on the regional characteristics and on the aims of the indicators. This generated a large amount of indicators mainly used for the evaluation of the consequences of policy decision on the landscape, therefore it is not surprising that most part of the indicators has been used or created in Strategic Environmental Assessment, in order to deal with local characteristics.

Cultural and perceived indicators represent only the smallest group in landscape measures, while the largest is the group of indicators is related to the land use and to the ecological aspects of the landscape. This last group encompasses landscape measures deriving from the landscape ecology approach *(section 3.3.1.)*.

Because landscape indicators are mainly used the evaluation of plans and programs, they are usually assessed at different administrative levels, mostly at the municipality level. This fact creates a sort of landscape bound. According to what it has been said by Antrop (2000), assessing landscape using administrative units, appears to be a limit in landscape study, because landscape is a phenomenon that develops itself across the space continuously. In the next section we suggest a spatial partition to overcome the limit of spatial units so to furnish a continuous landscape assessment grid.

4. A SCI for Landscape in Sardinia.

4.1. Introduction: reasons of the choice of the landscape in Sardinia

As we have seen in the previous chapter, the European Landscape convention gave a new emphasis towards the landscape protection, management and planning, and it establishes specific measures that each member state should adopt. According to the fact that landscape is a complex spatial phenomenon and that indicators are recognized to most efficient tools to support planning decision, in this case study the quantification of the landscape in Sardinia by a spatial composite indicator is proposed. Landscape is taken in great account in the planning law framework of Sardinia; it importance rose since the 2006 with the adoption of the Regional Landscape Plan (RLP). It is a plan written according to the adoption in Italy, of the Landscape European convention by the legislative decree of 22th January 2004, n°42, the so called 'Codice Urbani'. The decree establishes the notion of landscape goods, that are defined as '*all the areas and buildings recognized as the expression of cultural, historical, natural and aesthetic values of the territory'* (Dlgs 42, art.2), and in addition it is said that '*Landscape is intended the portion of land whose characteristics are the representation of the identity* (Dlgs 42, art 134). The protection of landscape have to be ensured by the adoption of the so called' *landscape plans'* elaborated by Regional governments and ministry. The aim of the landscape plans is to identify all the areas and heritage that have relevant landscape importance and to establish the actions to protect them.

According to what established by the '*Codice Urbani'* Government of Sardinia adopted its own Regional Landscape Plans (RLP) (2006). Currently it is the highest planning tool, in hierarchical scale, in Sardinia. RLP furnishes guideline and constrains, for the sub-level planning tool, in order to ensure a correct landscape protection and management, in a sustainable point of view. What is important for the aim of this study is that, during the phase of identification of the landscape goods and landscape heritage, the Regional Government collect a large amount of spatial data, current available in the Sardinia's SDI. Data were collected, uploaded and supply in according to the directive 2007/2/EC INSPIRE (2007). These data are used in this study as a main data source for the assessment of some landscape indicators, as will be explained in the next sections.

In fact, beside the test of the methodology described in chapter 2, a secondary aim of the presented work is to understand in which way SDI is useful for a complete description of the landscape. Unfortunately, despite the large amount of spatial layer, a small selection of them proved to be useful to quantify landscape aspects in particular aspect concerning specific surveys on specific species. This brought to the fact that the spatial composite indicator of landscape presented in the following parts is intended to be only a simple example to test the methodology to spatialize the OECD/JRC methodology for the creation of SCI of landscape.

4.2. Data presentation and data modeling

The study area is a limited part of the overall Sardinia landscape, and it is located on the west coast. The reason of the choice of a limited area is that the study of the overall landscape in Sardinia requires high computational power (Figure 6: study area location.).

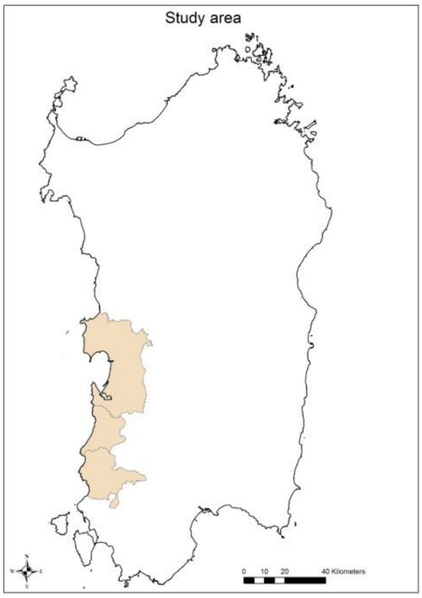

Figure 6: study area location.

On the basis of the existing literature, we consider the landscape framework composed by three main macro-dimensions: environmental, cultural and settlement (Figure 7). In turns, each macro dimension is described through a set of landscape sub-indicators chosen considering both the literature review, and the spatial data available to achieve landscape indicators.

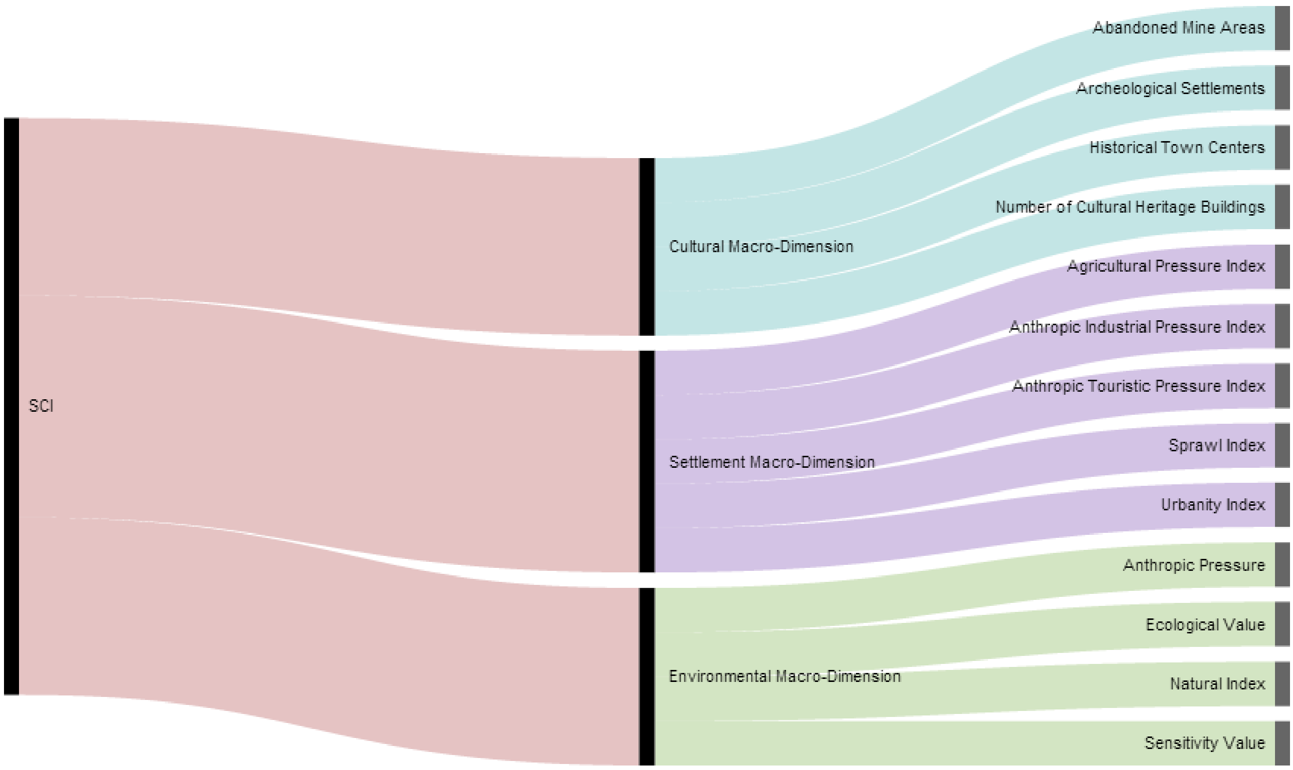

Figure 7: framework of the landscape spatial composite indicator of landscape.

It has been said in more parts of the thesis that data is one of the main issues in the construction of a robust CI. Despite the large amount of spatial layer in the regional SDI, only few of them have proved to be suitable for their use in landscape indicators calculation. This fact has reduced the number of sub-indicators, chosen on the basis of the possibility to populate them by mean of spatial data from SDI. Data from SDI supply general information about the position of certain landscape characteristics, in particular for the position of human infrastructures, land soil use, different kind of forest etc. Description of landscape characteristics in a deeper way, require collecting more specific data and information not available from spatial theme in Regional SDI. In section 3.3 it has been said that landscape measures are, as landscape metrics require specific information about including specie characteristics, and habitats not supplied by Regional SDI. This fact reduced the number of indicator used to test the SCI methodology.

Once data has been collected, indicators need spatial units in which being calculated, in order to make possible a further investigation about their spatial structure by GWPCA. As spatial phenomena landscape as no border (Antrop, 2000), and therefore using administrative units for its spatial description appears to be an inappropriate solution. To overcome this drawback, in this study we propose to model the study area by a regular vector grid. Each cell represents a basic spatial unit of analysis in which sub indicators are calculated. The size of grid cell is fixed in 1 kilometer. Although the model grid introduces an approximation for the representation of the landscape, in our opinion it fit well to the landscape description that administrative boundary, because it allows to model better the landscape spatial continuity.

4.2.1. *Environmental macro-dimension*

According to the state of art about landscape, in particular to the landscape ecology approach, the description of the environmental macro-dimension takes into account those aspects strictly related to the ecological function of the landscape. Four indicators have been selected:

- Natural index (*NI*)
- Ecological Value (*EV*)
- Ecological Sensitivity (*ES*)
- Anthropic Pressure (*AP*)

EV, *ES* and *AP* are indicators assessed by the Istituto Superiore per la Protezione e la Ricerca Ambientale (ISPRA) in a study about Sardinia ecological aspects called ‘Carta Natura della Sardegna’(2009). In this work ISPRA identified different biotypes, and for each biotype it collected several information, that has been combined together by TOPIS procedure in order to achieve the three indicators mentioned above. Data used to the assessment of *EV*, *ES* and *AP* are shown in table 17. These kinds of data are not all available in the regional SDI, or better, they exist, but they are considered confidential, therefore they are not published in the spatial data infrastructure. Exception on the supply of data has done for public studies.

The choice of these indicators appears to be coherent with the state of the art about landscape because some of these data belong to the group of landscape metrics, as the degree of fragmentation or the ratio between perimeter and area, while other data are available in the Sardinia’s SDI, like Site of Community Importance (SCI) or Special Protection Areas (SPA).

The values of indicators are linked to each cell of the spatial grid used to divide the study area by simple geoprocessing procedure. The value associated in each cell corresponds to the value concerning the entire biotope that fall in the cell, completely or in part. This has done to preserve the biotype entirely.

Indicator	Data
Ecological Value	Inclusion in a SCI
	Inclusion in a SPA
	Ramsar Area
	Habitat of interest by EU
	Potential presence of vertebrate
	Potential presence of rare flora
	Width of biotope compared with the habitat
	Rare habitats
	Perimeter/area ratio
Ecological Sensitivity	Primary habitat
	Presence of rare vertebrate
	Presence of rare flora
	Isolation level
	Width of biotope compared with the habitat
	Width of biotope compared with the total area
Anthropic pressure	Degree of fragmentation for infrastructures
	Biotype constrain
	Diffusion of anthropic disturbance

table 17: data used by ISPRA to the evaluation of Ecological Value, Ecological Sensitivity and Anthropic Pressure.

The *NI* is calculated starting from the environment component dataset, which is provided by the Sardinia SDI. It is a vector layer, whose features are distinguished by the natural level. The value of the natural level is achieved by experts on the basis of the external amount of energy provided by the human activities to the environmental component. Natural level ranges from 1 to 4, where 1 means the most natural level and 4 the lowest. Cell by cell the Natural Level has been assessed in according to the equation (4.1):

$$NI_j = \sum_{i=1}^{n} A_{ik} * N_i \tag{4.1}$$

$A_{ijk} = Area\ of\ features\ i\ with\ natural\ level\ k\ fallowing\ in\ cell\ j$

$N_{ik} = natural\ level\ of\ fetaure\ i\ with\ natural\ level\ k$

table 18 summarizes the set of indicators and data used to the evaluation of the environmental macro-dimension. Figure 8 and Figure 9 show the spatial distribution of the score of the above indicators.

Macro-dimension	Indicator	data
Environmental	Natural Index (NI)	Environmental component
	Ecological Value (EV)	ISPRA data
	Ecological Sensitivity (ES)	ISPRA data
	Anthropic Pressure (AP)	ISPRA data

table 18: data used for the calculation of environmental sub-indicators.

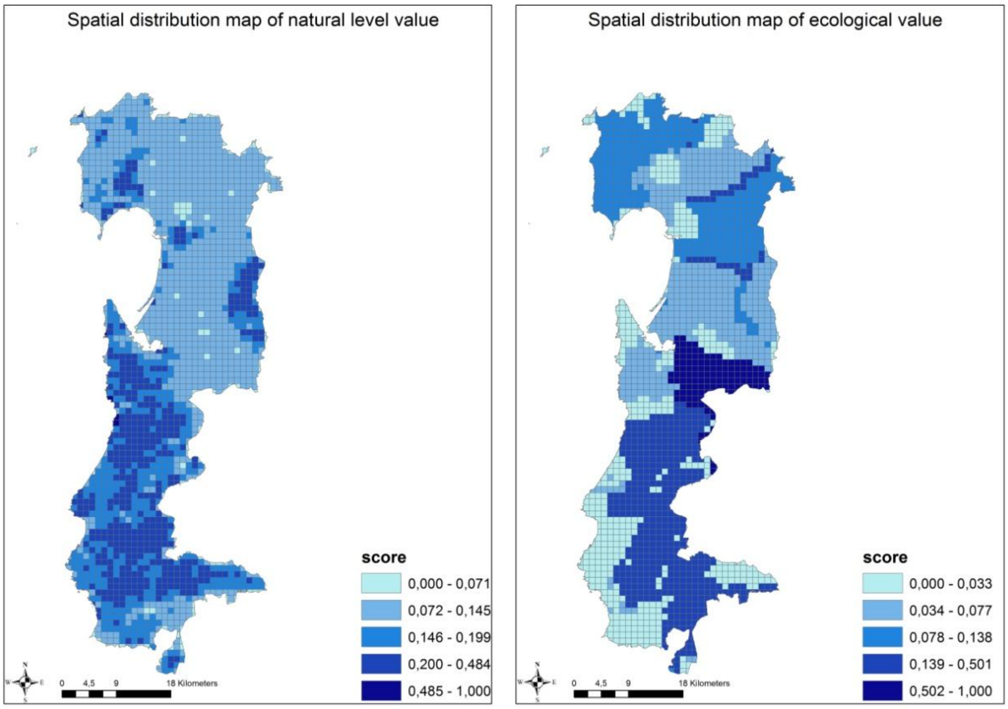

Figure 8: spatial distribution of Natural Index (left), and Ecological Value (right).

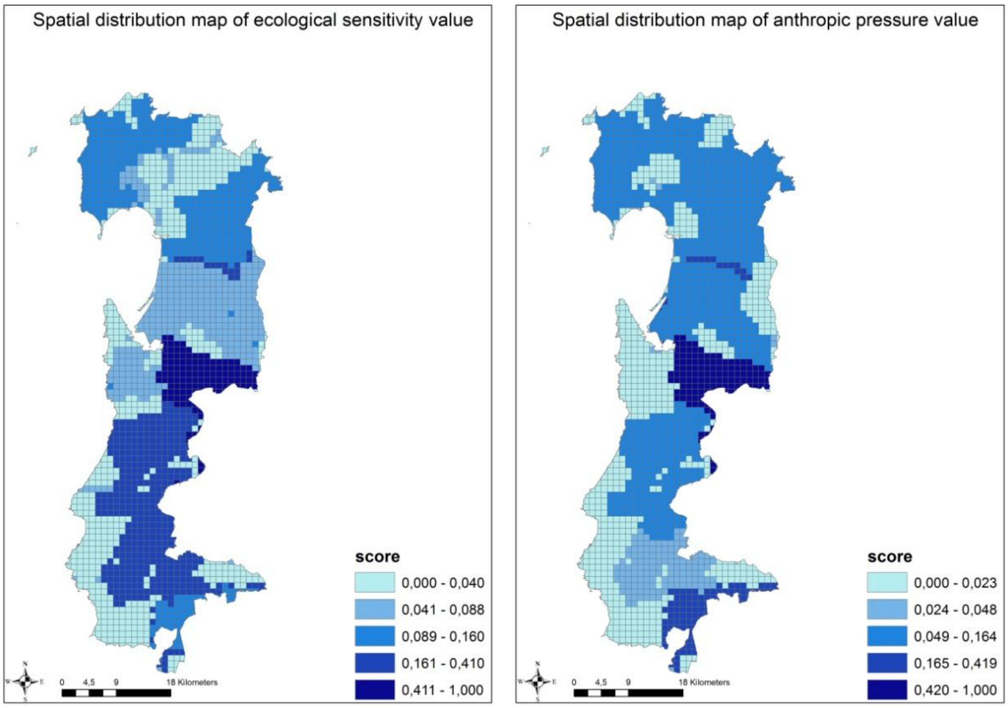

Figure 9: spatial distribution of Ecological Sensitivity (left) and Anthropic Pressure (right).

4.2.2. *Cultural macro-dimension*

Cultural macro-dimension quantifies those aspects of the landscape that, according to the definition given in section 3.3.2, create a particular linkage between the population and the territory. On the basis of this definition and the availability of data it has been possible to populate four sub-indicators to describe this macro-dimension:

- Number of Cultural Heritage Buildings (*NCHB*)
- Archeological Settlements (*AS*)
- Historical Town Centers (*HTC*)
- Abandoned Mine Areas (*AMA*)

Macro-dimension	Indicator	data
Cultural	Number of cultural heritage building (NCHB)	Cultural heritage points
	Archeological settlements (AS)	High cultural level areas
	Historical town centers (HTS)	Settlement component Cultural heritage points
	Abandoned mine areas (ABA)	Settlement component

table 19: data used for the calculation of cultural sub-indicators.

The *NCHB* represents the number of historical edifices falling within a cell of the model grid. It has been assessed starting to the layer ‘Cultural heritage’ that is a collection of points representing the buildings of historical and cultural interest. The thematic attribute of the dataset did not allow to distinguish buildings by date or typology, because in some cases attributes were incomplete.

$$NCHB_j = number\ of\ cultural\ heritage\ buildings\ fallowing\ in\ cell\ j \tag{4.2}$$

The *HTC* represents the area of the ancient parts of a town. These areas are very important in the definition of the cultural landscape, because they represent the original matrices of the urban centers and still have the original characteristics of the building, which represent the statement of the original building techniques. Data used for the calculation of this indicator are the vector layer representing the historical centers and the layer of the heritage building. *HTC* has been evaluated in terms of surface area of historical centers. In addition to this, the *NCHB* belonging to a certain centre, has been used as weight, so that a centre with high number of historical building is more appreciable than others. Equation (4.3) describes the model for the index:

$$HTC_i = A_i * NCHB_i \tag{4.3}$$

A_i = area of the historical centre in cell i

$NCHB_i$ = number of cultural heritage buildings in cell i

AS area represents an area occupied by archeological ruins. This index associate the overall area of the site to each cell in which the archeological site falls, in order to avoid fragmentation of the important areas, in a protection perspective. Equation (4.4) describes the model for the *AS*:

$$AS_j = area\ of\ archeological\ settlement \tag{4.4}$$

The same model has been used to the *AMA*, as described in equation (4.5):

$$AMA_j = area\ of\ abandoned\ mine \tag{4.5}$$

The importance of the areas of abandoned mine is a particular case of landscape modified by human for economical purpose. Nowadays these areas are a statement of the past culture of those particular areas in which mine activity becomes a strong part of the culture of the population living in those areas. This importance is proved by the efforts of the regional government towards the creation of the so called ‘Parco Geominerario’, with the aim to promote the territory with a strong mine connotation.

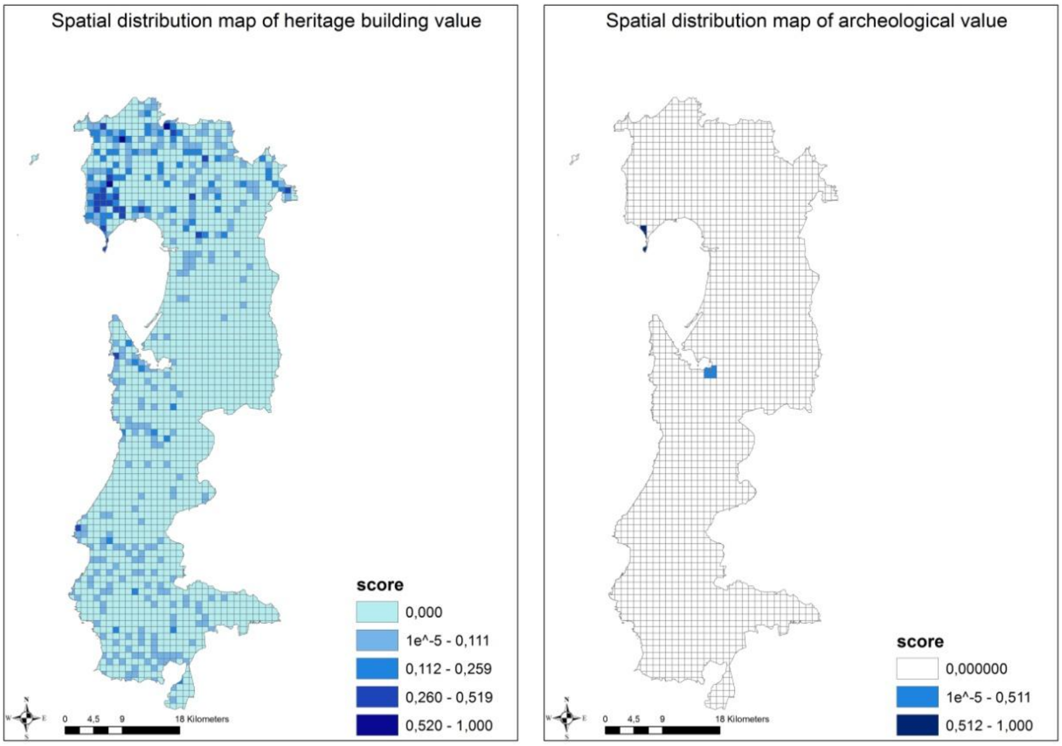

Figure 10: spatial distribution of Cultural Heritage Buildings (left), and Archeological Settlement (right).

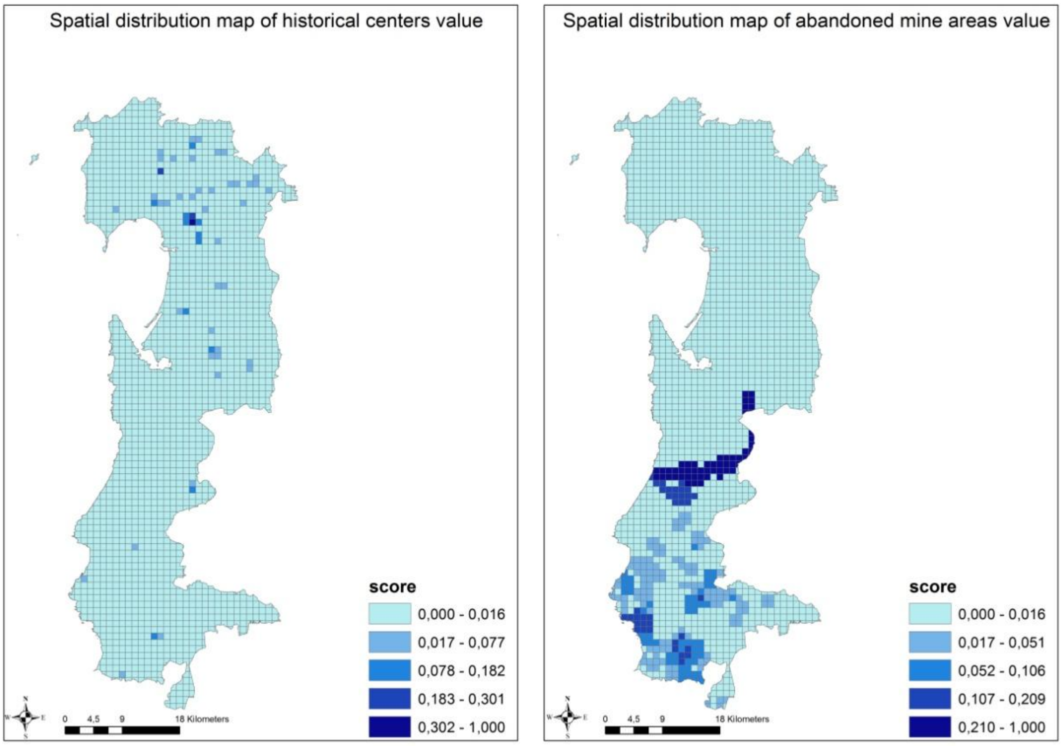

Figure 11: spatial distribution of Historical Centers (left) and Abandoned Mine Areas (right).

4.2.3. *Settlement macro-dimension*

The settlement macro-dimension encompasses human activities that create disturbance in landscape, on the basis of what has been said in the previous chapter (section3.3.2). Spatial data from regional SDI allowed to populate five sub-indicators:

- Sprawl Index (*SI*) (Gibelli, 2007 in Malcevschi 2008) (SI)
- Urban Index (*UI*)
- Anthropic Touristic Pressure (*ATP*)
- Anthropic Industrial Pressure (*AIP*)
- Agricultural Pressure (*AP*)

Macro-dimension	Indicator	data
Settlement	Sprawl index (SI)	Spread buildings
		Road network
	Urban Index (UI)	Settlement component
	Anthropic touristic pressure (ATP)	Settlement component
	Anthropic industrial pressure (AIP)	Settlement component
	Agricultural pressure (AP)	Land use map

table 20: data used for the calculation of settlement sub-indicators.

Sprawl is considered one of the most important human phenomenon able to create significant disturbance on the landscape, as landscape fragmentation, that is very dangerous for the ecological aspect. The urban sprawl is an aspect still subject to studies in order to understand how it develop itself across the space and what are their causes and consequences (Jaeger et All, 2010, Jat et al, 2008, Song and Knaap, 2007). The *SI* proposed in this study is calculated by mean of two dataset: the spread building and road network, both available in Sardinia's SDI. According to Gibelli (2007), for each dataset a buffer has been created, and it are 50 m for buildings and 30 m for roads. The final *SI* is the ratio between buffers area and fishnet cell area. Equation (4.6) describes the model for the SI:

$$SI_j = \frac{a_{bj} + a_{rj}}{A} \qquad (4.6)$$

a_{jj}= area of buildings falling in cell j

a_{rj}= area of roads falling in cell j

A= total area (cell)

UI measures the area of a cell occupied by a built area. Urban areas are in completion with natural areas, and they represent ecological disturbances. Data used to calculate this indicator derive from the settlement dataset. Equation (4.7) describes the model for the urban index:

$$UI_j = \frac{a_{uj}}{A} \tag{4.7}$$

a_{uj}= area of urban centre falling in cell j

A= total area (cell)

The further three sub-indices are indices of anthropic pressure. According to Van Eetvelde and Antrop (2004), the human pressure is the main responsible to the loss of identity of landscape, the cultural landscape in particular. On the basis of these considerations and of the data available, three indicators of human pressure have been calculated. Data used for these indicators have been extracted from the settlement dataset in case of touristic and industrial settlement, while agricultural data has been extracted from the land use map. Agricultural data extracted concerns only those features classified as intensive agricultural.
They represent the *AIP* is calculated as ratio between areas occupied by industrial settlements in each cell, and the area of the cell. Equation (4.8) describes the model for the AIP:

$$AIP_j = \frac{a_{Ij}}{A} \tag{4.8}$$

a_{Ij}= area of industrial settlement falling in cell j

A= total area (cell)

Similarly *ATP* represents the ratio between the area of touristic settlements falling in each cell and the overall cell area, as shown in equation (4.9):

$$ATP_j = \frac{a_{Tj}}{A} \tag{4.9}$$

a_{Tj}= area of touristic settlement falling in cell j

A= total area (cell)

The *AP* is calculated cell by cell as the ratio between agricultural area and overall cell area. Equation (4.10) describes the model for the agricultural pressure index:

$$AP_j = \frac{a_{Aj}}{A} \tag{4.10}$$

a_{Tj}= area of touristic settlement falling in cell j

A= total area (cell)

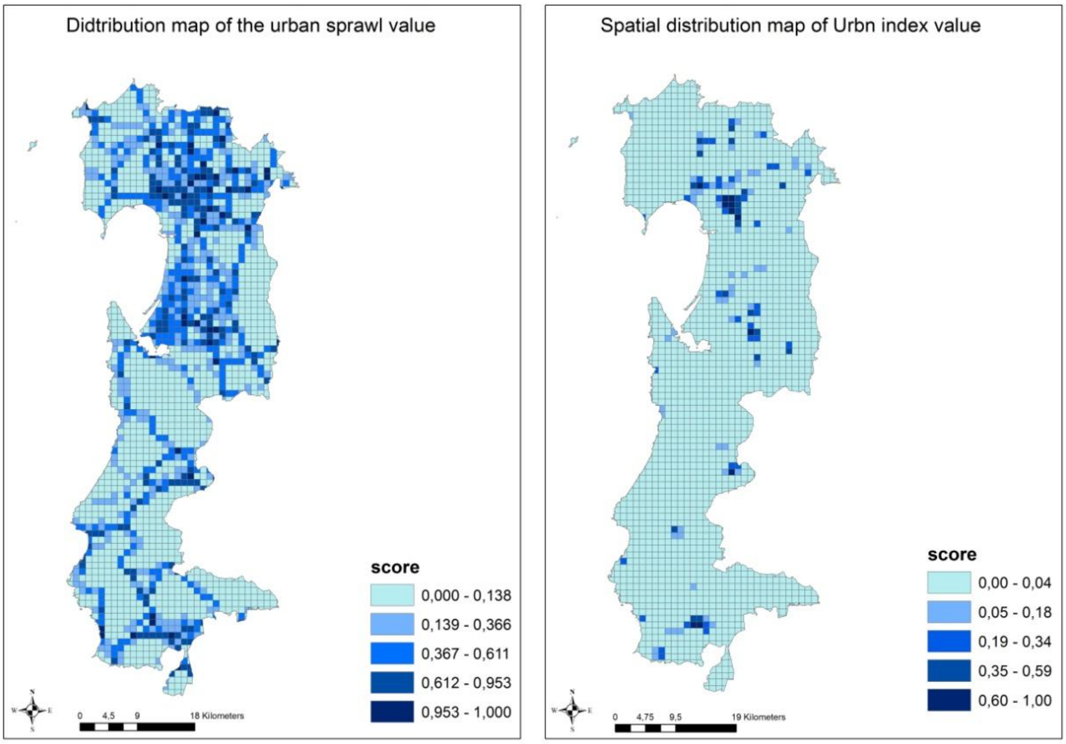

Figure 12: spatial distribution of urban sprawl index (left), and urban index (right).

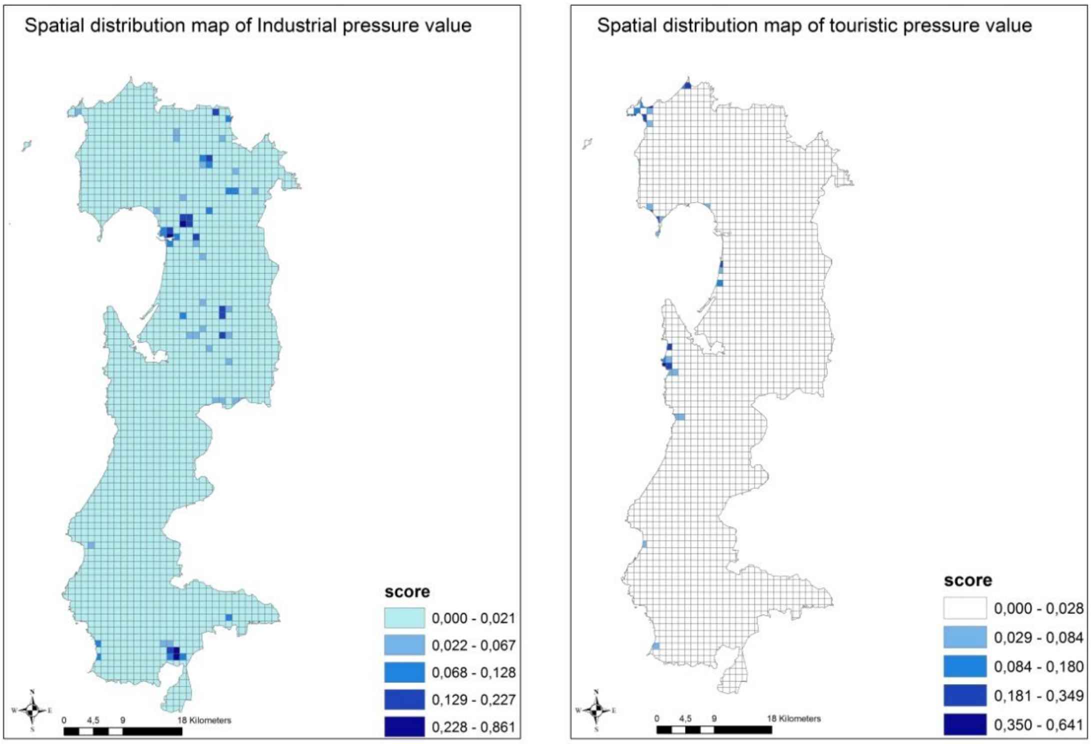

Figure 13: spatial distribution of industrial pressure (left) and touristic pressure (right).

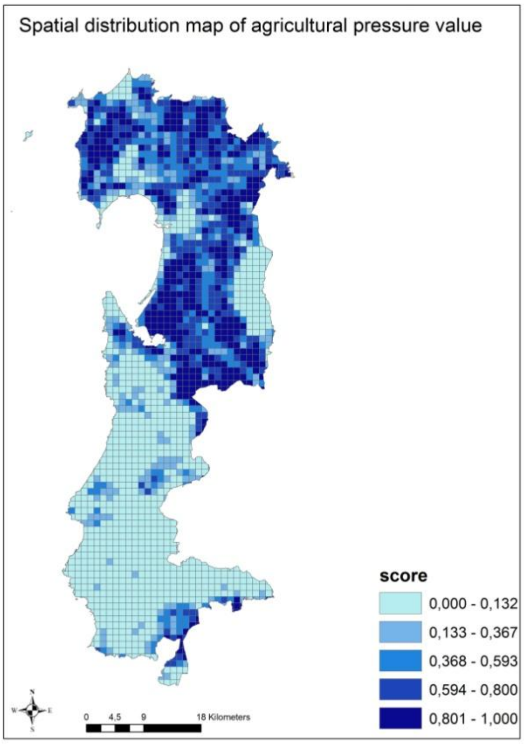

Figure 14: spatial distribution of agricultural pressure

4.3. Analysis of the spatial distribution of the dataset.

As it is possible to see in the figures, the spatial distribution of the sub indicators appears to be quite heterogeneous. Some indicators are present in some spatial units and completely missing in other ones. This behavior is particular evident for cultural and settlement macro-dimension, where the sub-indicators describe aspect located in a well defined space. This behavior may imply the presence of spatial heterogeneity and different spatial regimes. Hence since the aim is to achieve the spatial importance of each indicator there is need to investigate the spatial structure of each macro dimension in deeper details, in order to take into account the local behavior of the variables. Therefore a Geographically Weighted Principal Component Analysis has been applied for each set of macro-dimension's variables as it will be explained in chapter 5.

The reasons of this choice are:

- there is need of spatial techniques able to distinguish local relationship of the data. As mentioned in chapter 2, the application of aspatial multivariate analysis highlight only the main relationship between data, that is the relation at the global level. In case of spatial data relation among data may be locally different, and it must be taken into account to understand the spatial structure of the data. GWPCA appears to be the most appropriate tool.
- multivariate analysis is a fundamental step in the construction of composite indicators (see section 1.2), but spatial data require a spatial version of this techniques.
- the variable loading obtained as a result of GWPCA, may as the variable weights (Gollini et al, 2013) to use in the aggregation function. According to the OCSE/JRC methodology PCA can be used for this purpose, hence, in case of spatial data, we propose its spatial version.

In the next chapter results of the application of GWPCA, and the overall result of the spatial composite indicator of landscape will be presented.

5. Application of the method and results

5.1. Introduction

Once data are collected and indicators are calculated and mapped, the further and central step in the creation of SCI of landscape is to establish the set of weights to assign to each variable. As discussed in chapter 1, weights may represent the relevance of each variable into the composite, and multivariate analysis is a method used for this. In this specific case study, the interest is to achieve the spatial importance of the variables involved in the indicator of landscape. It means that, despite the use of the same variables across the spatial domain, they may have different local importance because of the probable presence of spatial heterogeneity. GWPCA has been recognized as a spatial multivariate technique able to perform various principal component analyses, on the basis of the width of the variation of data across the space. Variable loadings returned by the GWPCA reflect the local importance of the variables, and they have been used to calculate spatial weights for the variables.

GWPCA has been applied to each macro-dimension. In particular we are interested in the capability of GWPCA to extract the local importance of a certain variable by means of the local variable loading, obtained as the product of the matrix X of the variables and the matrix L of the eigenvectors (see section 2.4.). In addition, we are interested in finding out the local variance explained by individual component in order to understand if it is possible to reduce the dimension of the phenomenon.

Both PCA and GWPCA have been performed to highlight the differences between the two methods, and to enforce the use of GWPCA instead of the normal PCA, in case of spatial data. At the end a significance analysis is presented in order to validate the use of GWPCA and understand if it is possible to reject the null hypothesis concerning the random spatial distribution of the eigenvalues, and consequently of the weights. As multivariate analysis GWPCA returns a group of variables (components) that are independent each other, in order to avoid problems of double counting in the aggregation stage (Gomes-Limon and Sanches-Fernandez, 2010).

GWPCA has been performed in R platform using the GWmodels Package (Gollini et al, 2013, Lu et al, 2014). For the implementation of the analysis we used a bi-square kernel function (Gollini et al, 2013).

Before the application of the GWPCA, the original set of indicators has been normalized by using the Max-Min method. This is in accordance with Gollini et al (2013) that warn about the still unknown consequence about a normalization done after the application of GWPCA. The Min-Max method has been chosen because it rescales all the sub-indicators in a scale that ranges from 0 to 1.

The application of the GWPCA requires the calibration of the model, in R platform this is done automatically by using a cross-validation approach, using the method discussed in section 2.5. Cross-validation score is calculated for all possible bandwidth selections, and the optimal one is the bandwidth that shows the smallest cross validation score (Gollini et al, 2013).

5.2. Environmental macro-dimension

The global PCA highlights the fact that the first component accounts for more than 93% of the total variance of the data, as reported in the following table (table 21).

	% of total variance
Comp.1	93.135
Comp.2	4.921
Comp.3	1.771
Comp.4	0.172

table 21: global PCA, percentage of total variance explained by components extracted.

Table of loadings (table 22) reveals that the first component represents the three indicators from the Carta Natura study, as it is possible to see by looking at their scores on the first component. Looking at the of correlation values (table 23) it is possible to notice that the three variables with the higher loading in component one are strictly and positively correlated. This may be due to the fact that these indicators measure ecological aspects about the biotypes in Sardinia, as previously described in section 4.2.1.

	Comp.1	Comp.2	Comp.3	Comp.4
Natural Index (NI)	0.011	0.826	-0.563	-0.028
Ecological Value (EV)	-0.571	0.196	0.312	-0.734
Ecological Sensitivity (ES)	-0.542	0.303	0.401	0.673
Anthropic Pressure (AP)	-0.616	-0.433	-0.652	0.086

table 22: global PCA, component loading for each component.

	Natural Index (NI)	Ecological Value (EV)	Ecological Sensitivity (ES)	Anthropic Pressure (AP)
Natural Index (NI)	1	-0.009	0.026	-0.144
Ecological Value (EV)	-0.009	1	0.993	0.947
Ecological Sensitivity (ES)	0.026	0.993	1	0.929
Anthropic Pressure (AP)	-0.144	0.947	0.929	1

table 23: global correlation matrix for environmental macro-dimension variables.

Natural Index has a high score for component two. It is possible that the global PCA describes two main important characteristics of the environmental macro-dimension: the ecological component (component 1) in which ecological variables play the most important role, and one natural component (component 2), in which the natural index is more important.

Global PCA does not reveal any information about the spatial heterogeneity; therefore, GWPCA has been applied.

The first piece of information collected from this local analysis is the value of the bandwidth. The model has been calibrated using 2023 out of 2043 locations. According with Lu et al (2014) this fact means that there are no important differences between the global and local model, and so spatial heterogeneity may be not significant for the environmental macro-dimension.

Notwithstanding we performed a GWPCA in order to achieve the loading for each variable in each of 2043 location of the spatial model.

Similarly to the global model, the first component explains the most variance of the data, but in this case the variance is assessed for each spatial location as reported in the following table 24 and in the following Figure 15(left).

id location	% of total variance	% of total variance	% of total variance	% of total variance
1	92.050	5.619	2.091	0.240
2	92.069	5.607	2.084	0.239
3	92.097	5.589	2.076	0.238
4	92.116	5.577	2.069	0.238
5	92.074	5.602	2.085	0.239

table 24: GWPCA, percentage of total variance explained by the components extracted. Table shows data for 5 out 2043 locations.

Summary statistics for the overall spatial domain shows that the total percentage of variance explained by the first component ranges from 92% to 96%with an average value of 94 % (table 25). This confirms the trend of the global model.

	comp.1	comp.2	comp.3	comp.4
max	96.369	5.686	2.154	0.244
min	91.916	2.653	0.883	0.081
mean	94.62	3.922	1.321	0.137

table 25: GWPCA summary statistics of the percentage of total variance explained.

In order to obtain the weights for the variables belonging to the environmental macro-dimension, variable loadings for the first component obtained by the GWPCA are used (section 2.1). The choice to consider only the first component is mainly due to the fact that it represents the most variation of the data, almost the total of variation. The scores of the variables in the first component are shown in the following table 26 for the first five locations.

id location	Natural Index (NI)	Ecological Value (EV)	Ecological Sensitivity (ES)	Anthropic Pressure (AP)
1	0.028	-0.567	-0.539	-0.622
2	0.028	-0.567	-0.539	-0.622
3	0.028	-0.567	-0.539	-0.622
4	0.028	-0.567	-0.539	-0.622
5	0.028	-0.567	-0.539	-0.622

table 26: GWPCA, variable loadings for each component.

It is possible to notice that score values are quite similar to values in the global model.
In order to obtain the weights to use in the aggregation model, the variable scores have been considered in absolute value and rescaled in order that for each location its sum is equal to 1 (Munda and Nardo, 2005). In the table 277 weights are shown for the first five spatial locations.

id location	Natural Index (NI)	Ecological Value (EV)	Ecological Sensitivity (ES)	Anthropic Pressure (AP)
1	0.016	0.323	0.307	0.354
2	0.016	0.323	0.307	0.354
3	0.016	0.323	0.307	0.354
4	0.016	0.323	0.307	0.354
5	0.016	0.323	0.307	0.354

table 27: variables weights for the environmental macro-dimension. Table shows the 5 out 2043 locations.

Contrary to the case of the application of PCA, where weights are not different among the different spatial units, the use of the GWPCA allowed to obtain weights for each variable in each location. This should represent the main advantage of the use of this spatial techniques. Once weights are obtained, the overall value of the environmental macro-dimension has been obtained as the weighted sum (linear combination) of the variables, location by location (equation 4.11).

$$EMD_j = \omega_{ij} * NI_j - \omega_{ij} * EV_j + \omega_{ij} * ES_j - \omega_{ij} * AP_j \qquad (4.11)$$

where ω_{ij} is the weight of the variable i in the location j.

Anthropic Pressure (*AP*) is a negative term, because according to ISPRA (2009) it represents a threat or disturbance for the biotopes.
Figure 15 shows the spatial distribution of the environment macro-dimension across the space.

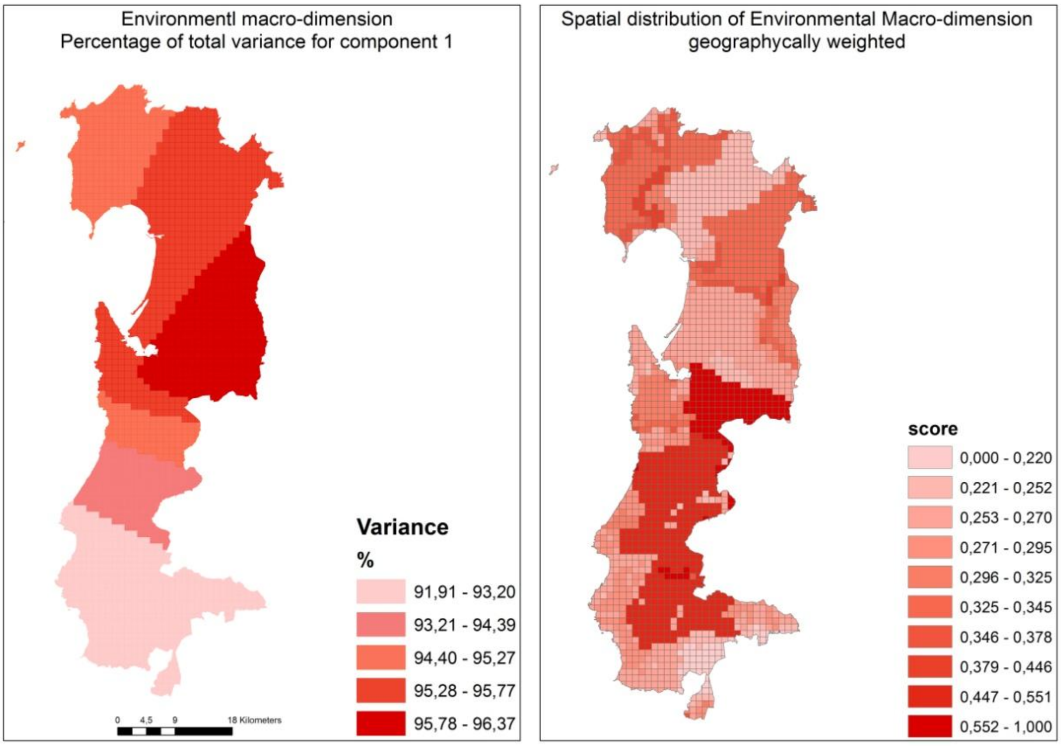

Figure 15: spatial distribution of the percentage of total variance for the first component (left), and spatial distribution of the environmental macro-dimension score (right).

The spatial distribution of the score of the environmental macro-dimension appears to be higher in the spatial locations having a greater value of the ecological and sensitivity value, despite the fact that in some of these locations the anthropic pressure is high (Figure 13, Figure 14). The percentage of variance appears to be more relevant in the middle part of the spatial domain, corresponding to the location in which the indicators about ecological and sensitivity values and anthropic pressure are higher. For what concerns the Natural index, it is worth to notice Figure 8 (left), that its variation across the spatial domain is smoother if compared with the other environmental macro-dimension variables. This may be the reason why its score is lower in the first principal component extracted. Therefore the spatial structure of this macro dimension follows the spatial patterns of the ISPRA indicators (Figure 8 right, Figure 9).

5.3. Cultural macro-dimension

The results of global PCA show that the first component of the cultural macro-dimension dataset describes the 72% of the total variance of data (table 28).

	% of total variance
Comp.1	72.21
Comp.2	15.3
Comp.3	9.988
Comp.4	2.502

table 28: global PCA, percentage of total variance explained by the components extracted.

Contrary to what happens in the environmental macro-dimension, in this case the score of the variables vary substantially into within a given component.
If we look at the first component, only the abandoned mine area index has a high value, while the scores of the other variables appear to be negligible. This fact may be related to the fact that, in global terms, Abandoned mine areas is the variable with the greatest variation. In the second and in the third component only Archeological Settlement and Number of Heritage Buildings have a significant score, while in the fourth component, only the Historical Centers index has a high score. If we consider only the global model, we may take a chance to neglect the others variables, which may play an important role locally. Therefore GWPCA is applied.

	Comp.1	Comp.2	Comp.3	Comp.4
Historical Centers (HTC)	0.003	0.03	-0.026	0.999
Abandoned mine areas (AMA)	-0.999	0.031	-0.006	0.002
Archeological settlement (AS)	0.007	0.393	0.919	0.012
Number of heritage buildings (NCHB)	0.031	0.919	-0.392	-0.037

table 29: global PCA, variable loadings for each components.

Furthermore, correlation matrix (table 30: global correlation matrix of variable of cultural macro-dimension.shows those variables are not correlated in global terms.

	Historical Centers (HTC)	Abandoned mine areas (AMA)	Archeological settlement (AS)	Number of heritage buildings (NCHB)
Historical Centers (HTC)	1	-0.017	-0.005	0.071
Abandoned mine areas (AMA)	-0.017	1	-0.014	-0.055
Archeological settlement (AS)	-0.005	-0.014	1	0.154
Number of heritage buildings (NCHB)	0.071	-0.055	0.154	1

table 30: global correlation matrix of variable of cultural macro-dimension.

The application of GWPCA confirms the presence of spatial heterogeneity. Bandwidth is 115 out of 2043. This means that there is rapid spatial variation in the results (Lu et al, 2014).
Similarly to the case of environmental macro-dimension, to decide if it is possible to select only one component to describe data, the total percentage of variance has been assessed. Result shows that the first component explains the most part of the variance in each location (table 31). Summarizing results for the overall spatial domain, the first components ranges from 40% to 100% with an average value of 85% (table 32).

id location	% of total variance	% of total variance	% of total variance	% of total variance
1	64.733	35.098	0.169	0
2	62.268	37.588	0.144	0
3	59.646	40.227	0.127	0
4	57.138	42.787	0.074	0
5	64.849	34.969	0.182	0

table 31: GWPCA, percentage of total variance explained by the components extracted. Table shows the 5 out 2043 locations.

	comp.1	comp.2	comp.3	comp.4
max	100	48.916	25.15	1.85
min	40.336	0	0	0
mean	85.064	14.445	0.487	0.004

table 32: GWPCA, summarize statistics of the percentage of total variance explained by the components extracted

Similarly to the case of environmental macro-dimension variable weights are assessed using the variable loadings for the first component, in each location. Loadings have been rescaled so that in each location their sum is equal to 1. Results are shown in table 33.

id location	Historical centers (HTC)	Abandoned mine areas (AMA)	Archeological settlement (AS)	Heritage buildings (NCHB)
1	0.0022	0.9321	0	0.0657
2	0.0014	0.9299	0	0.0687
3	0.0008	0.926	0	0.0731
4	0.0003	0.9106	0	0.0891
5	0.002	0.9318	0	0.0661

table 33: variable weights for the cultural macro-dimension.

The value of the cultural macro-dimension is obtained as weighted sum of the variables, as described in the equation (5.12) and its spatial distribution is reported in Figure 16.

$$CMD_j = \omega_{ij} * NCHB_j + \omega_{ij}\, ABA_j\ \omega_{ij} * AS_j + \omega_{ij} * HTS_j \tag{5.12}$$

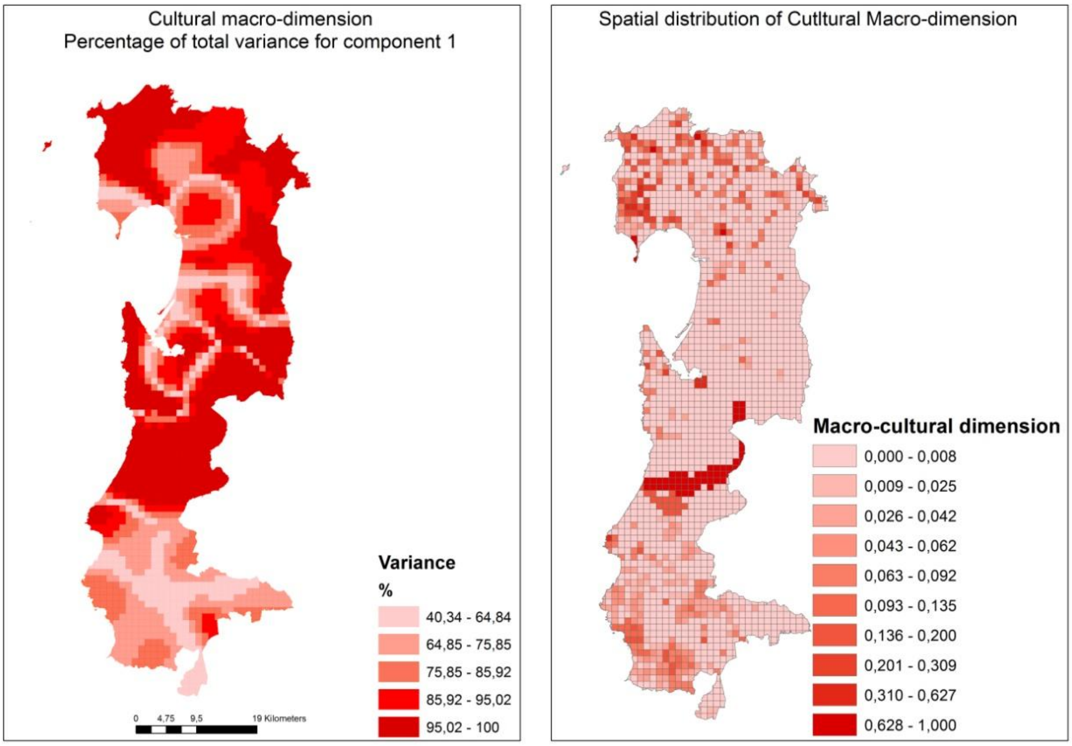

Figure 16: spatial distribution of the percentage of total variance explained for the first components (left), and spatial distribution of the cultural macro-dimension (right).

Contrary to the previous case the interpretation of the cultural macro-dimension appear to be more complicate. The first reason is that spatial heterogeneity is very significant; hence there is large spatial variation among data. It is simple to notice from Figure 10 and Figure 11 that the variables used in this macro-dimension are spread in a non-continuous way across the spatial domain; they are located in a precise position of the space, and create clear patterns. GWPCA model fits well with this spatial heterogeneity to measure the importance of each variable in each location, and so to define the spatial structure of this macro-dimension. As shown in Figure 16 (right), the highest values of the cultural component of landscape can be found in locations with high presence of cultural data, and the percentage of total variance explained is significant in locations where more than one data is present.

5.4. Settlement macro-dimension

Results of global PCA show that the first component describes around the 86% of the total variance of the data (table 34).

	% of total variance
Comp.1	85.997
Comp.2	7.899
Comp.3	3.567
Comp.4	1.63
Comp.5	0.908

table 34: global PCA, percentage of total variance explained by the components extracted.

For what concerns the variable loading into the component, it is possible to notice in table 35 that Agricultural pressure has a significant value in the first component. Likely, this is due to the fact that agricultural pressure index is the variable with the largest spatial distribution in the spatial domain, as it is possible to see in Figure 14. Similarly to the case of the cultural macro-dimension this fact brings to the consideration about the possible presence of high spatial heterogeneity, hence a GWPCA is performed.

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5
Urban Sprawl (US)	-0.100	0.009	0.422	0.006	0.037
Urban Index (UI)	0.013	0.426	-0.905	-0.003	-0.004
Agricoltural pressure (AP)	-0.995	-0.085	-0.055	0.009	-0.003
Industrial pressure (AIP)	-0.001	0.032	0.002	-0.013	-0.999
Touristic pressure (ATP)	0.009	-0.003	-0.005	1	-0.013

table 35: global PCA, variable loadings in each component.

	Urban sprawl (US)	Urban Index (UI)	Agricultural pressure (AP)	Industrial pressure (AIP)	Touristic pressure (ATP)
Urban sprawl (US)	1	0.264	0.303	0.086	-0.027
Urban Index (UI)	0.264	1	-0.065	0.024	0.004
Agricultural pressure (AP)	0.303	-0.065	1	0.003	-0.066
Industrial pressure (AIP)	0.086	0.024	0.003	1	-0.009
Touristic pressure (ATP)	-0.027	0.004	-0.066	-0.009	1

table 36: global correlation matrix for settlement macro-dimension variables.

GWPCA confirms the presence of spatial heterogeneity; in fact the model is calibrated by means of a bandwidth of 166 out of 2043 spatial units, indicating spatial rapid variation of the results.
At the local level the first component explain the main part of the variance in every location; the percentage of the variance explained range from 46% to 99, 5% (table 38).

id location	% of total variance	% of total variance	% of total variance	% of total variance
1	64.733	35.098	0.169	0.000
2	62.268	37.588	0.144	0
3	59.646	40.227	0.127	0
4	57.138	42.787	0.074	0
5	64.849	34.969	0.182	0

table 37: percentage of total variance explained by the components extracted.

	comp.1	comp.2	comp.3	comp.4	comp.5
max	99.537	36.712	19.885	6.733	2.005
min	46.414	0.459	0	0	0
mean	78.733	14.946	5.322	0.941	0.058

table 38: GWPCA, summarize statics of the percentage of total variance explained by the components.

Considering that the first component describes the most variation of data, we used the local variable loading from the first component to obtain weights for the variables. The value of the settlement macro-dimension is calculated in each location using the equation (5.13) and its spatial distribution is shown in Figure 17.

$$SMD_j = SI_j + \omega_{ij} * UI_j + \omega_{ij} * ATP_j + \omega_{ij} * AIP_j + \omega_{ij} * AP_j \qquad (5.13)$$

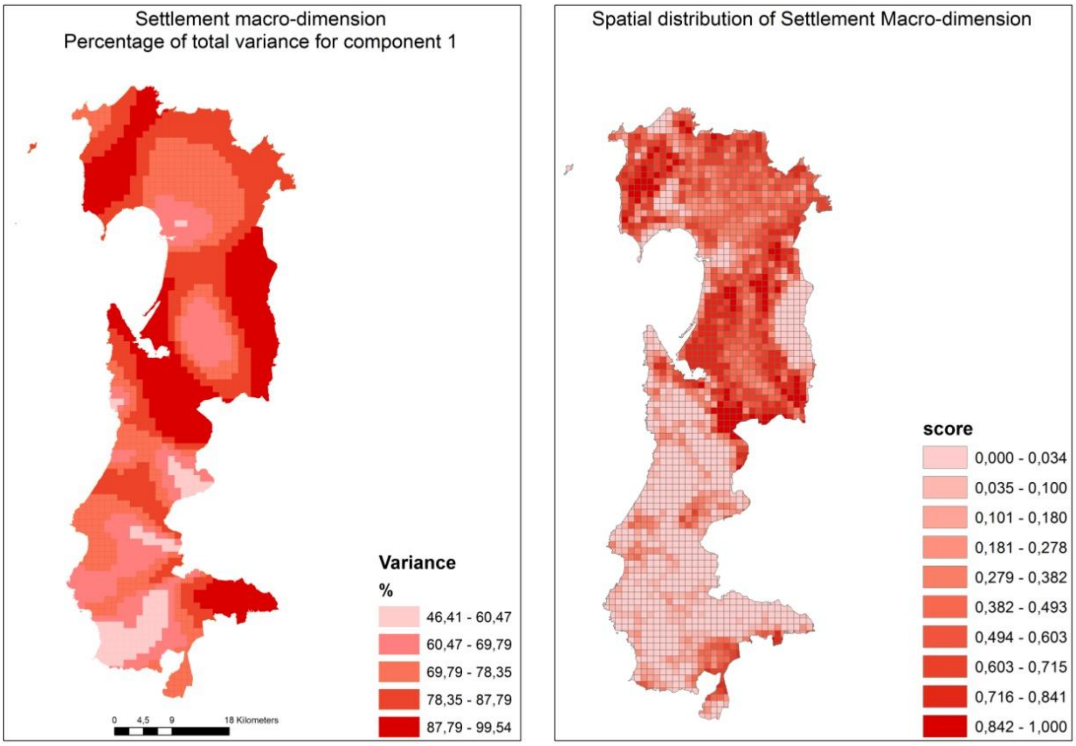

Figure 17: spatial distribution of the percentage of total variance for the first component (left) and spatial distribution of the settlement macro- dimension (right).

The score of the settlement macro dimension is highest in those location where upper part of the spatial domain. This is not surprising because in this area the presence of urban centers is very relevant. Furthermore in these locations the agricultural practice is very strong because locations fall in the Campidano plans (the strong red in figure 17 left), the most important intensive agricultural area of Sardinia. The percentage of total variance (Figure 1 left) is higher in those locations with high scores of agricultural pressure and urban sprawl. This may be due to the fact that these two variables are the most spread in the space, and therefore they have a large spatial variation across the spatial domain. Nevertheless areas with the highest percentage of variance explained by the first component are those where there is only agricultural pressure. This may be due to the fact that, like the global PCA, the first local component considers mainly the agricultural pressure, similarly to global case. Areas with the lowest percentage of variance explained are those that correspond to the main urban centers. As described for the cultural macro-dimension, to achieve a more accurate description, a second component should be taken into account.

5.5. Significance analysis

Significance analysis has been conducted in order to further investigate the relevance of spatial heterogeneity, in particular the spatial relevance of the distribution of the eigenvalues, that drove the value of weights across the spatial domain.

A significance test has been performed for the first principal component of each set of data: environmental, cultural and settlement macro-dimension. Results are reported in Figure 18, Figure 19 and Figure 20.

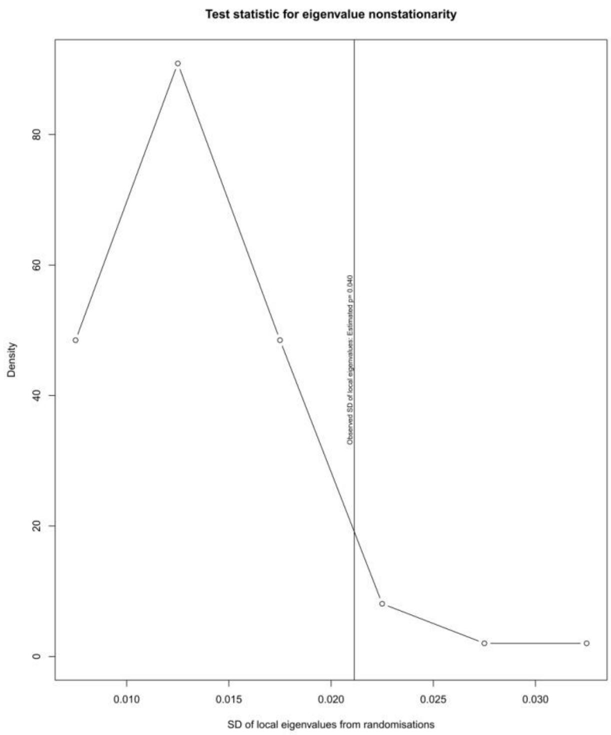

Figure 18: significance test for the first component of the environmental macro-dimension; p-value = 0.04.

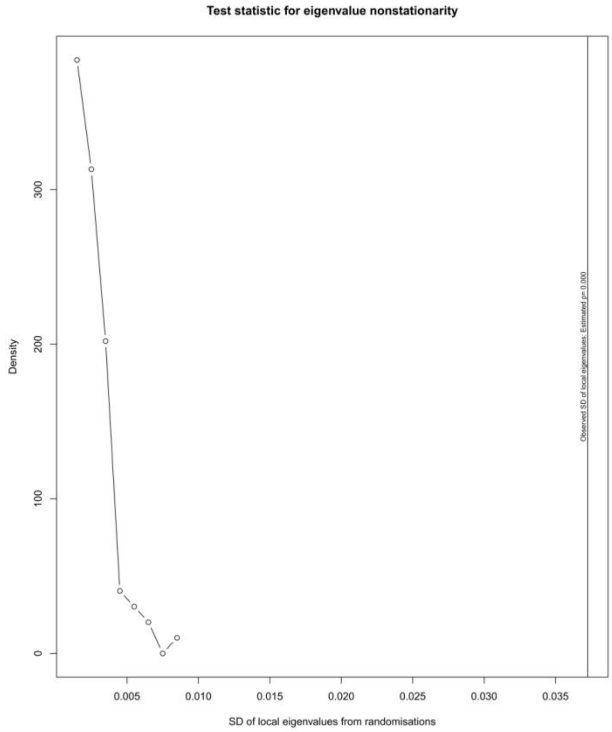

Figure 19: significance test for the first component of the cultural macro-dimension; p-value < 0.001.

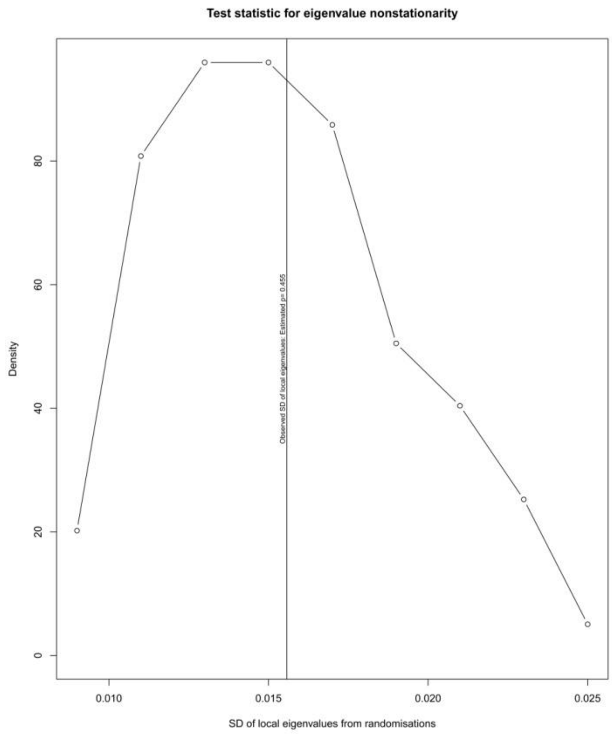

Figure 20: significance test for the first component of the settlement macro-dimension; p-value = 0.0455.

In all of the three cases it is possible to note that the significance test enforces the hypothesis of the presence of spatial heterogeneity, because in every macro-dimension the p-value is lower than 0.05. Therefore it is possible to reject the null hypothesis of random distribution of the eigenvalues. This result provides further support for the chosen GWPCA specification (Lu et al, 2014).
p-value obtained for the cultural macro-dimension is very small. This may be due to the fact that, looking at the Figure 10 and Figure 11, variables that compose the cultural macro-dimension are not widely spread across the spatial domain, but they have defined patterns. For what concerns the other two macro-dimensions, p-value has a larger value, although it is lower than 0.05. In fact environmental and settlement variables are more spread on the study area.

5.6. Spatial composite indicator of landscape

The overall landscape value is assessed as linear combination of the three macro-dimensions: environmental, cultural and settlement.
Because the aim of the model is to give a measure of landscape quality, environmental and cultural macro-dimension have been considered positively, while the settlement one negatively, as shown in equation 5.14

$$SCIL_j = EMD_j + CMD_j - SMD_j \tag{5.14}$$

where:

$SCIL_j$ is the landscape value at location j;

EMD_j, CMD_j, SMD_j are the environmental, the cultural and the settlement macro-dimensions respectively.
The macro-dimensions have not been weighted in this case because they are considered equally important on the basis of the literature review on landscape. As previously explained in chapter 3 landscape is composed by these three macro-dimension, and all of these play the same fundamental role in landscape description.
According to the landscape literature review, environmental and cultural macro dimensions contain those aspects that increase the landscape quality (ISPRA 2005, Botequilha 2006, Farina, 2000). Instead, the macro-dimension settlement contains factors that cause disturbance both to the environmental and to the cultural aspect; this is the reason why it has been considered as a negative element in the equation (Van Eetvelde and Antrop, 2004).
The spatial trend of the global spatial composite index of landscape is reported in Figure 21.

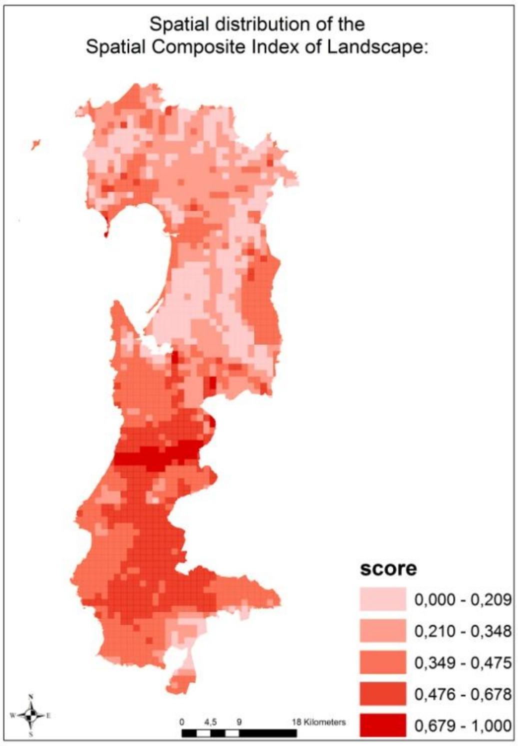

Figure 21: spatial distribution of the Spatial Composite Indicators of landscape score.

Comparing the map in Figure 21 with those that show the spatial macro-dimensions distribution, it is possible to notice that locations in which the landscape value is high are those in which there are no human activities. These areas are mainly located in correspondence of zones with high natural value and lower anthropic pressure (Figure 8 and Figure 9) and furthermore these areas show a relevant presence of abandoned mine areas (Figure 11 right) which is a very important cultural factor. Conversely disturbance in the settlement component is almost missing.
Areas with the lowest landscape value are those in blue in which the settlement component is particularly strong (Figure 12, Figure 13, Figure 14). These areas have a high level of infrastructures and they are exploited for intensive agricultural practice. Despite this fact, Figure 21 shows the presence of a few scattered locations having a significant landscape value. These locations represent historical centers of tows or areas in which the natural/cultural aspects are more relevant that the settlement disturbance.
From a planner's point of view, the local value of the indicators, together with the value of the variables, may help in policy making. In fact, it is possible to identify areas in which although the overall landscape value, significant values of environmental or cultural elements are present. This indicates the need for policy to restrict human disturbance. Conversely, areas with high landscape score need decisions that preserve the elements that make the landscape so appreciable.

5.7. Spatial autocorrelation analysis

Spatial autocorrelation analysis has been performed for the overall landscape indicator, in a univariate way, and for the indicators and their macro-dimensions, in a bivariate way, to highlight the presence of spatial dependence between the spatial units and to gain more information about the spatial structure of the indicators. The purpose is to understand if the value of the SCIL at a certain location is influenced by its value in the closest spatial units. Spatial autocorrelation is presented both in global and local form. The global one is able to reveal the presence of spatial autocorrelation by the Moran's *I*, while the local one reveals spatial units in which the level of spatial autocorrelation is more significant. In this way it is possible to understand the cluster pattern into the spatial domain and the cluster type that is the type of spatial relation between spatial units. Spatial autocorrelation is used as a tool to discover clusters of areas having similar landscape value, to identify and delimitate the portion of land with high or low landscape value. The distinction between the two types of areas appears to be very useful in a planner's point of view. The areas with high landscape scores may represent those areas to be protected, because the high level of landscape. According to the framework of the landscape composite indicators, the areas with low landscape value are those in which human disturbance is more relevant, hence they need action in order to limit damage stemming from human activities, in a landscape protection's point of view as declared by the European Landscape convention.

Spatial autocorrelation analysis has been performed by using of GeoDa platform, using the queen contiguity as spatial weights function; in this case local neighbors are those spatial units that share either borders or vertices.

5.7.1. *Univariate spatial autocorrelation.*

Univariate spatial autocorrelation analysis has been performed in order to understand the mutual spatial influence among spatial units and the value of the overall spatial composite indicator of landscape. As first task for the assessment of the spatial autocorrelation different weight matrices have been compared in order to test for their influence on the autocorrelation score. Different levels of contiguity have been tested using both queen and rook contiguity. The rook and the queen contiguity are both based on the Euclidean distance between centroids of the spatial units. The results are shown in the Figure 22.

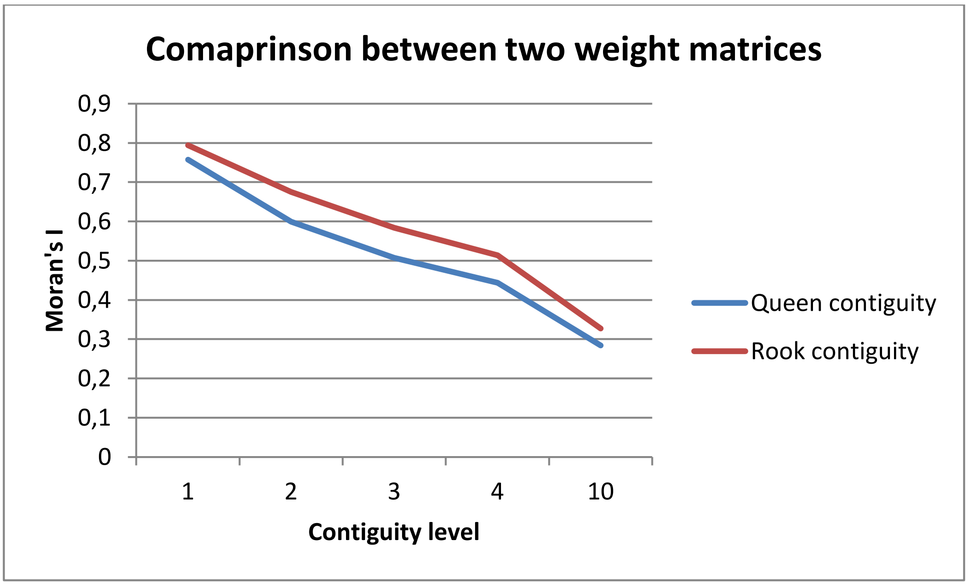

Figure 22: comparison of the influence of the matrices of weights on the Moran's I trend.

As it is clear from the definition of spatial autocorrelation, the spatial effect decreases with the increase of the distance between spatial units. In fact higher values of the Moran's *I* correspond to lower levels of contiguity (table 39). It appears that the SCIL is positively spatially autocorrelated (table 39, and Figure 23), and for all statistics the *p value* is equal to 0.001 (the number of permutations for each significance test is equal to 999). *p-value = 0.001* means that it is possible to reject the null hypothesis about the random spatial distribution of the SCIL values. It means that there is spatial dependence among spatial units, for what concerns the value of the SCIL. It means that the value of the indicators in a given spatial units is influenced by those in the surrounding neighbors.

	Type of spatial weights matrix	Contiguity level	Moran	mean	SD	p-values
SCIL	queen	1	0.7574	0.001	0.0121	0.001
		2	0.599	0.0005	0.0088	0.001
		3	0.5074	0.0006	0.0076	0.001
		4	0.4439	0.0006	0.0066	0.001
		10	0.2838	0.0004	0.0048	0.001
	rook	1	0.7943	0.0006	0.0161	0.001
		2	0.675	0.0004	0.0115	0.001
		3	0.5842	0.0008	0.0099	0.001
		4	0.5134	0.0006	0.0087	0.001
		10	0.327	0.0002	0.0063	0.001

table 39: Moran's I statistics for SCIL: comparison between different spatial weights matrices and contiguity levels.

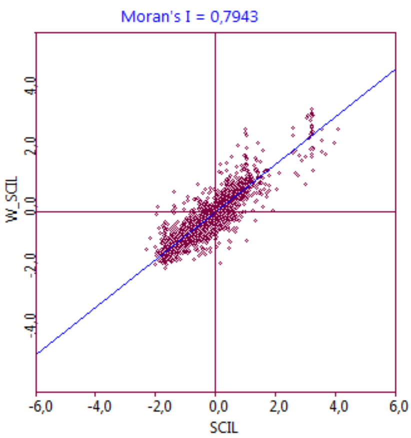

Figure 23: Moran's scatterplot for global spatial autocorrelation using rook contiguity.

Because the Moran's *I* is higher for the rook contiguity at the first order, we used this weight matrix.

The Moran coefficient provides the global measure of spatial autocorrelation, without specifying where it is relevant. Therefore, LISA statistics has applied in order to identify in which spatial units' spatial autocorrelation is significant. The results are shown in a cluster map and significance map (Figure 24).

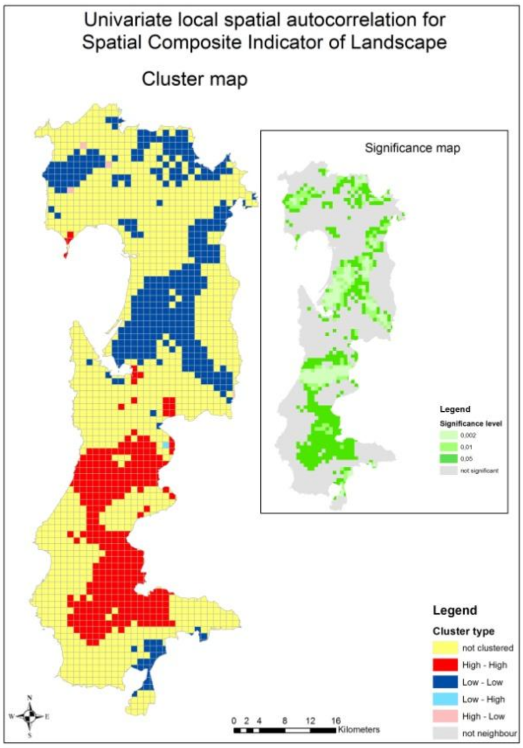

Figure 24: univariate LISA map for SCIL.

It is possible to see that there are two main clusters (Figure 24). The first one (in red) represents those spatial units with a high score of SCIL surrounded by spatial units with high SCIL score, while spatial units in blue are the ones with a low SCIL score surrounded by similar values. It is clear that there is a high level of spatial dependence among spatial units for what concerns the SCIL value, and this spatial dependence is relevant. This means that there is the tendency for spatial units with similar score to be close together.

Clusters in blue are mainly located in those areas in which human disturbance is stronger than in other areas. In particular, the biggest blue cluster occurs in the main agricultural area of the study area. This area is part of the so-called Campidano plan, the most important plan of Sardinia, with high development of intensive agriculture. In addition, it is the part of the study areas where urban centers and infrastructures are mostly located. Looking at the significance map, it is possible to see that the presence of spatial autocorrelation is very significant in the main part of blue clusters, because there is a high presence of spatial units with *p-value <= 0,002.*

Contrary to the blue clusters, the red clusters are delimitated areas with high landscape level, located mainly in the lower part of the study area. The maps of the original variables reveal that in these areas the environmental of the cultural components is very strong. The relevance of the cultural dimension is due to the presence of the main mining sites in Sardinia. This fact is shown in the significance map, in which it is possible to see that the spatial units in which the spatial autocorrelation is more relevant are those spatial units falling in the mine areas (see also Figure 11: spatial distribution of Historical Centers (left) and Abandoned Mine Areas (right).

5.7.2. *Bivariate spatial autocorrelation*

Spatial autocorrelation has been performed also in a bivariate way, in order to obtain more information about the level of spatial dependence among the value of the composite indictor of landscape and its macro-dimensions. As shown later, the results of the bivariate spatial autocorrelation confirm the interpretation of the univariate one. As it is possible to see in Figure 27, Figure 30, and Figure 33, the clusters division is confirmed, even though there are some small differences.

Similarly to the case of the univariate analysis various weights matrices and contiguity levels have been compared, we chose the weights that return the highest values for the Moran's *I*.

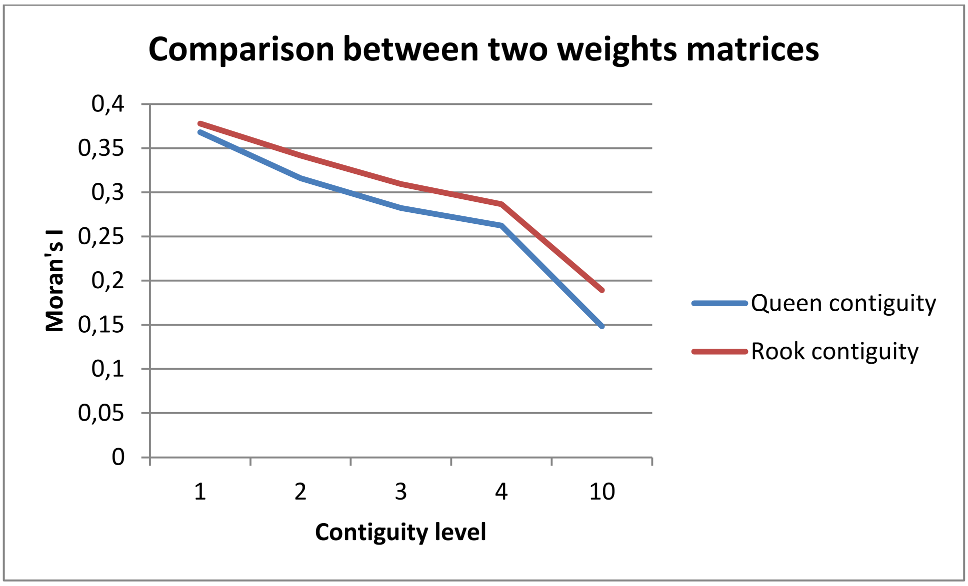

Figure 25: comparison between two weights matrices for the bivariate analysis among SCIL and the environmental macro-dimension.

	Type of spatial weights matrix	Contiguity level	Moran	mean	SD	p-values
SCIL	queen	1	0.368	-0.0002	0.0124	0.001
		2	0.3159	-0.0003	0.0092	0.001
		3	0.2822	-0.0007	0.0075	0.001
		4	0.2622	-0.0005	0.0067	0.001
		10	0.1484	-0.0006	0.0046	0.001
	rook	1	0.378	-0.0014	0.017	0.001
		2	0.3415	-0.0006	0.0117	0.001
		3	0.3095	-0.0002	0.0103	0.001
		4	0.2866	-0.0003	0.009	0.001
		10	0.1892	-0.0004	0.0061	0.001

table 40: Moran's I statistics for SCIL: comparison between different spatial weights matrices and contiguity levels.

The global bivariate autocorrelation analysis indicates that the level of autocorrelation between SCIL and its environmental macro-dimension is not very strong: *I=0.378*. Contrary to the global case, the scatterplot (Figure 26) shows that points representing spatial locations are separated in three groups. Points farthest from the straight line are the locations of the highest level of significance for spatial autocorrelation (see Figure 27).

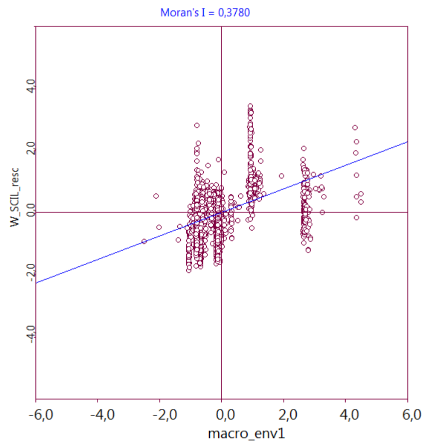

Figure 26: Moran's scatterplot for global bivariate spatial autocorrelation using rook contiguity

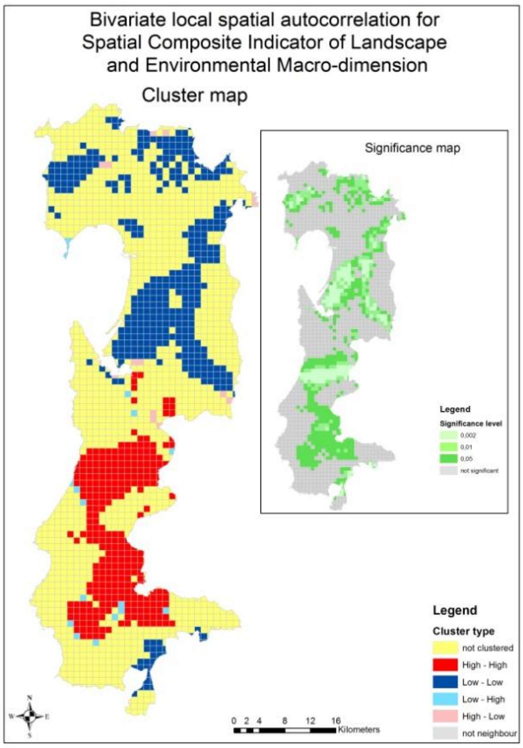

Figure 27: bivariate LISA map between SCIL and environmental macro-dimension.

Bivariate LISA with the cultural macro-dimension exhibits a similar behavior to that of the case of bivariate case with the environmental macro-dimension. The interpretation of the scatterplot is similar to the previous case: also in this case points farthest from the line are spatial units where spatial autocorrelation is more relevant (Figure 30). The cluster type showed in Figure 30 is particular. Due to the original distribution of original data, it is possible to see that cluster in red represent areas with very high score of both SCIL and cultural-macro-dimension, while cluster in light blue are areas with high score of SCIL surrounded by spatial units with low cultural score. It is worth to remind that cultural indicators are not spread across the spatial domain, but they are located in precise spatial units. Clusters highlight this aspect and their relationship between the score of SCIL. According to Anselin (1995) the cluster in red represents a hot spot, that is an area in which the score of the cultural component is particular relevant compared to the others.

	Type of spatial weights matrix	Contiguity level	Moran	mean	SD	p-values
SCIL/cultural macro-dimension	queen	1	0.3248	-0.0005	0.012	0.001
		2	0.2243	-0.0003	0.0089	0.001
		3	0.1712	-0.0003	0.0074	0.001
		4	0.1387	-0.0007	0.0066	0.001
		10	0.0674	-0.0004	0.0049	0.001
	rook	1	0.353	-0.0007	0.0161	0.001
		2	0.274	0.0006	0.0123	0.001
		3	0.2199	-0.0003	0.0099	0.001
		4	0.1769	-0.0005	0.0092	0.001
		10	0.0826	-0.0004	0.0061	0.001

table 41: Moran's I statistics for SCIL: comparison between different spatial weights matrices and contiguity levels.

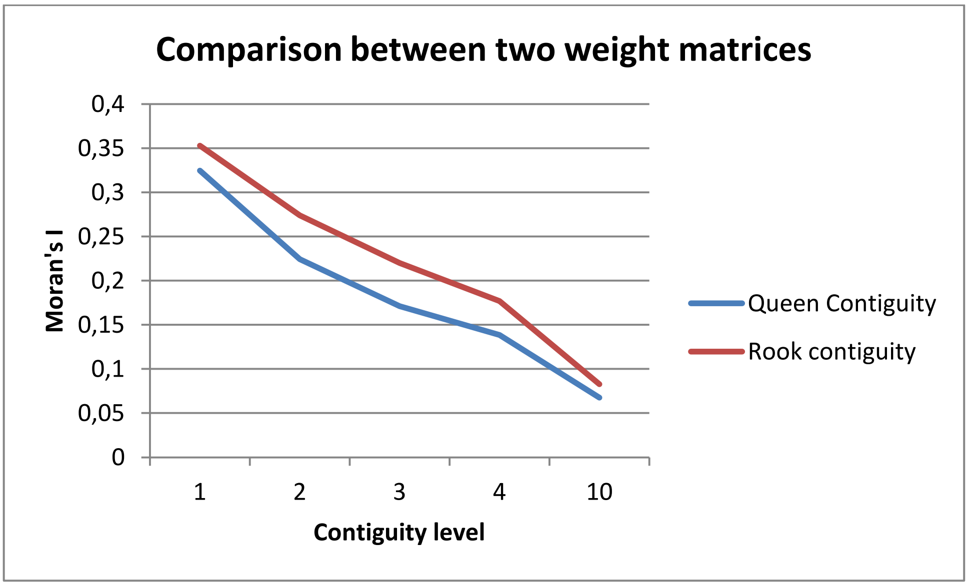

Figure 28: comparison between two weight matrices for the bivariate analysis among SCIL and cultural macro-dimension.

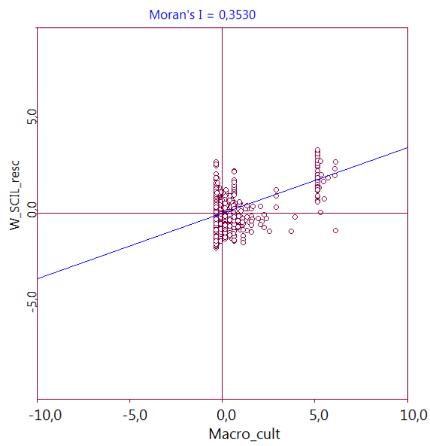

Figure 29: Moran's scatterplot for global bivariate spatial autocorrelation using rook contiguity.

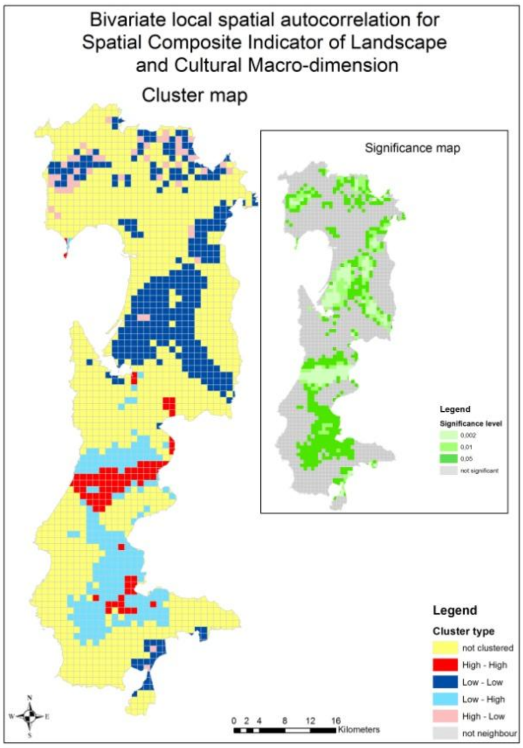

Figure 30: bivariate LISA map between SCIL and cultural macro-dimension.

The biavariate analysis between SCIL and settlement macro-dimension reveals a strong negative spatial autocorrelation (*I=0.6472*), using the rook contiguity. It is obvious if the model of the SCIL is taken into account (equation 5.14), where settlement macro-dimension is a negative terms.

	Type of spatial weights matrix	Contiguity level	Moran	mean	SD	p-values
SCIL/settlement macro-dimension	queen	1	-0.6196	-0.0006	0.0128	0.001
		2	-0.495	-0.0007	0.0088	0.001
		3	-0.4219	-0.0007	0.0076	0.001
		4	-0.3672	-0.0008	0.0068	0.001
		10	-0.2549	-0.0003	0.0049	0.001
	rook	1	-0.6472	-0.0007	0.0167	0.001
		2	-0.5537	-0.0008	0.0118	0.001
		3	-0.4814	-0.0004	0.01	0.001
		4	-0.4245	-0.0005	0.0089	0.001
		10	-0.2826	0	0.0063	0.001

table 42: Moran's I statistics for SCIL: comparison between different spatial weights matrices and contiguity levels.

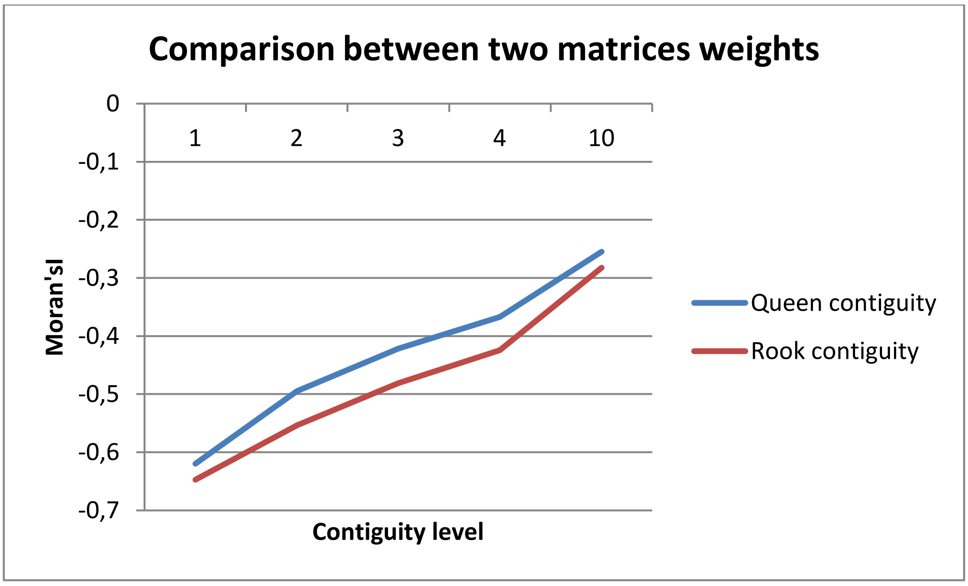

Figure 31: comparison between two weight matrices for the bivariate analysis among SCIL and settlement macro-dimension.

The scatterl plot shows a cloud distribution of the points, but, in this case the distribution of points is contrary to previous two cases (Figure 32), indicating the negative spatial autocorrelation. The distribution of the points on the scatterplot may be due to the continuos spatial distribution of the macro-settlement score. The cluster map (Figure 33) shows that the mainly cluster tipe high-low or low-high. The negative spatial autocorrelation and the custer type reveal that there is compotion among areas. This fact may be interpreted with the fact that the human activities that descibe the settlement macro-dimension create landscape disturbance, while the overal indicator of landscape measure landscape quality. Specifically clusters pink colored are spatial units with high settlement macro-dimension score surrounded by spatial units with low SCIL score. The light blue cluster have the opposite behaviour.

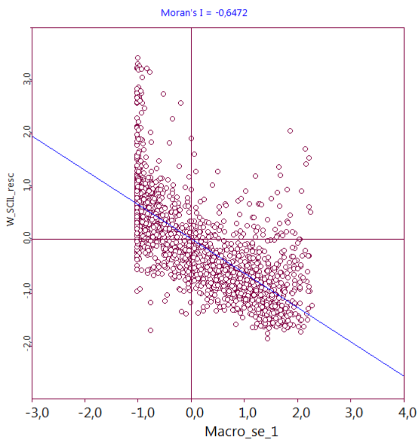

Figure 32: Moran's scatterplot for global bivariate spatial autocorrelation using rook contiguity.

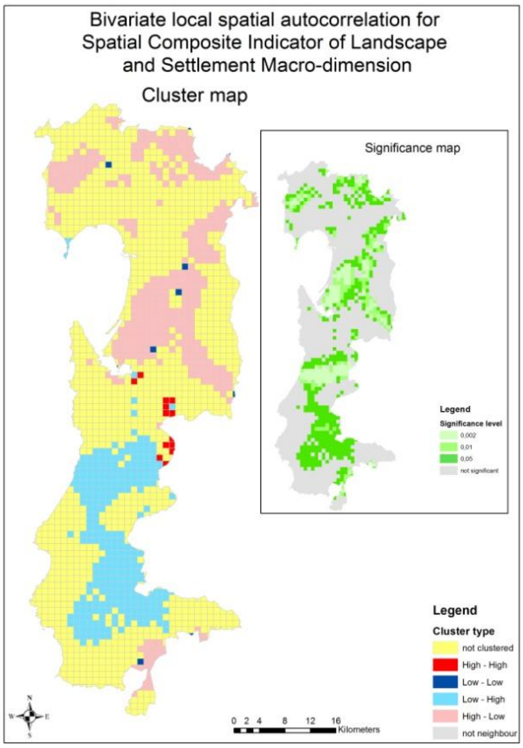

Figure 33: bivariate LISA map between SCIL and settlement macro-dimension.

5.8. Results and limitation of this method in this particular case study.

The methodology proposed shows some advantages in particular for what concerns the investigation of the spatial dimension into the set of variables used to describe the macro-dimension. It has been possible to investigate at the same time the spatial structure of the data highlighting the presence of spatial variability in the dataset and to obtain the local spatial importance of each variable in the description of macro-dimension, contrary to the non-spatial methods in which the importance of the variables is kept constant all over the spatial domain, which may lead to misinterpretation of the phenomena.

Despite the fact that the main goal of obtaining the spatial weights has been achieved, some limitations still remain. The first limitation of the method applied to this specific case study is that the input data were not optimal. This is due to the fact that a large amount of data is needed to describe landscape. Data supplied by the Sardinian SDI have made it possible to populate only a few indicators of landscape. This leads to another limit in this case study, that is, the possibility to perform a good sensitivity analysis. Generally, sensitivity analysis is performed by replacing some variables or by considering one variable at time, in order to explore the behavior of the overall indicator (Nardo et al, 2005). In some cases sensitivity analysis is carried out by discarding one of the indicators at time, while keeping all the others (Kienberger and Hagenlocher, 2014). In other cases sensibility is performed by application methods on spatial models in which the model is decomposed in sub groups of variables to analyze the variability of data, usually the variance of the input (Lilburne et al, 2005). The scarcity of variables makes this kind of analysis (the one in which one indicator is discarded) unfeasible, while in the second kind of methods need a spatial model. According to Harris et al (2014) GWPCA is not a model, like regression, but it is a spatial technique able to consider the important spatial effects. In addition to this when sensitivity analysis is performed on weights of the model, weights are not spatial. It means these are weights that do not vary across the space, as in the case study presented in this work, where weights are locals. Therefore the question about how perform sensitivity analysis in a case where the weights are local still remains opened. In part, this lack is partially overcome by the significance analysis encompassed in the GWPCA methods, as described in section 2.5.

Another limit is worth to discuss. The method here presented uses only the first component extracted because it explains the most part of the variance of data. Unfortunately, this is not true for all the spatial units; therefore, the method needs to be improved so as to discriminate the spatial units on the basis of the winning component. This may be useful to understand also the latent dimension in spatial units on the overall set of data, and to provide deeper information on the behavior of the phenomenon (landscape in this case).

Conclusions

Recent research and practice advances have proven that CIs can be used as reliable tools to evaluate the overall performance of spatial units of analysis, such as countries or regions, on the basis of a single index, used to represent a complex multidimensional concept: this generated growing interest in academic circles, media and among policy-makers. A CI is a multidimensional measure which synthesizes the synergy of a multi-dimensional set of sub-indicators in quantifying certain complex characteristics of given spatial units of interest. Administrative boundaries at the national or regional scale are usually chosen as spatial reference units. In seldom cases, literature reports on case studies carried out at a larger scale (i.e. county or municipal level units). A major advantage in using CIs is that they are proven to be reliable to describe the overall synergic effect of sub-indicators and factors by means of a single synthetic value. Since the early 2000s, research and design of CIs have boosted especially in the socio-economic domain, where they are often used to describe characteristics as economic development, productivity, or social well-being of nations or regions, in order to calculate performance rankings to support evidence-based policy making. Traditionally, CIs are calculated by combining data which are eventually georeferenced and mapped to large spatial unit (sections 1.1, and 1.3).

Uses and reliability of CIs are still object to controversial debate, but at the same time CIs are gaining considerable attention by scientists and policy-makers as a useful means in policy analysis and communication (section 1.1 and 1.4).

According to a methodology which can be considered mature and well-established, the design and calculation of CIs involves a series of steps necessary to select data and combine them in efficient, reliable and robust way. Following a draft design of a CI, most of the subsequent steps involve the application of statistical techniques such as factors analysis, principal components analysis, clustering, multi-criteria analysis or policy expert opinions, which are used to understand which sub-factors play a significant role in the definition of the CI (section 1.2).

Nevertheless, in existing CI design methodologies often little or no attention is paid on the spatial dimension of the variables. The term spatial dimension refers to the way in which each sub-factor and the overall composite indicator are spread in the space, and/or whether factors express any geographic or spatial measure (section 2.2). With regard to the former issue, making robust policy decisions on the basis of composite indicators analysis requires to clearly understand what are the factors that play a fundamental role in the definition of indicators. This kind of knowledge is very important if policy-makers want to deal with problems effectively (section 1.1, and 1.2).

Attention to the spatial dimension of information has grown in the last decades only after the development of GIS enabled to work with the geographical components of data and to apply techniques to explore them. Only recently development on GIS and Exploratory Spatial Data Analysis (ESDA) techniques have enabled to process large amounts of geographic data made available by Spatial Data Infrastructures, offering reliable data and tools previously un available. In fact, in the last decades the data availability has increased because of the development of web services and of standards in data production and exchange, therefore offering favorable conditions to support the construction of composite indicators at much larger scales (i.e. smaller spatial units). ESDA can be defined as the statistical study of phenomena that manifest themselves in space.

Location of spatial data is the focus of this kind of analysis, because it leads to two major spatial effects: spatial dependence and spatial heterogeneity. Spatial dependence refers to the relationship between locations and variables and it contrasts with the usual statistical assumption of independence of observations. Spatial heterogeneity highlights the spatial differences in values of a given variable depending on the location. These characteristics of spatial data have to be taken into account because, if present, they invalidate the basic statistics assumption of data independency, which in turns may generate wrong understanding of a certain spatial phenomenon (section 2.2).

Supporting the introduction of these spatial statistics methods allowed the exploitation of spatial data for the construction of what would later became spatial composite indicators (SCIs), and what may find extensive ground for application in spatial policy-making and decision-making. The concept of SCI refers either to the understanding of spatial dependence of composite indicators and their factors, or to the use of spatial factors, or both. Moreover, it opened interesting research questions on the opportunity to extend the type of spatial reference units, from traditional statistical boundary units, to smaller large scale geographical units (section 2.1). Such an approach is presently seen as particularly urgent, as developments in Spatial Data Infrastructures give access to huge collection of large scale spatial data.

This work is articulated in 5 parts. Firstly the literature review on CIs was presented, focusing on their use and on the methodology proposed by OCES/JRC. The second part focused on the spatial extension of the original methodology. Recent advances in spatial statistics and the large amount of spatial data available in SDI make it relevant to study the possibility to introduce the spatial dimension since the first step of the methodology for CI construction. The third part presented current approaches in the formalization and the measurement of the concept of landscape which is the case study here chosen to test the spatial methodology. Landscape is described with regard to its relevance to planning activities. Moreover different landscape measures were described. Part four showed the landscape model expressed by a SCI, the data collected, and the data modeling. In the fifth part the results and the discussion are proposed, with particular emphasis to the use of the spatial multivariate analysis.

The introduction of spatial statistics techniques in the original methodology is the novel contribution of this study which allows to take into account the special nature of spatial data (section 2.2) because they are able to reveal the presence of spatial heterogeneity on a given set of data used in CI construction. The Geographically Weighted Principal Component Analysis has been identified as a useful and powerful tool that can replace the Principal Component Analysis (PCA) (section 2.4). As shown in paragraph 1.2.4 and paragraph 1.2.6, PCA is widely used to assess the weights for the variables used in the CI construction, therefore its replacement with its recent geographic version allows for the introduction of the spatial dimension on the design of CI. GWPCA has been used to detect the spatial weights to associate to the variable involved in the construction of CI. Hence the importance of the variables is now local rather than global. It means that the use of GWPCA allows to take into account the local relevance of a variable, in terms of relationship between the other variables involved, while the normal PCA highlights only the stronger global relationship that may be wrong in some parts of the spatial domain because of the possible presence of the spatial heterogeneity. The introduction of the GWPCA has required the application of the data normalization before the application of the spatial multivariate analysis, in order to avoid undesirable effect of the results.

The spatially modified methodology was tested on the case study of landscape in Sardinia. Landscape has been chosen because the literature review revealed that it is a complex and spatial phenomena, and it is a very important concept in the planning field (see section 3.2). The complexity of landscape comes from the fact that it is a holistic concept involving a large number of aspects. The literature review has put in evidence that landscape is composed of three main aspects: the environmental dimension, the cultural dimension, and the settlement dimension (see section 3 and sections 4.2). The main part of these aspects has been measured by using of selected metrics (section 3.3 and section 3.4), but up to now no single indicator collecting the effect of the different metrics has been created; some scholars have underlined the need for this kind of indicator. Landscape is also a spatial phenomenon because it develops itself across the space in a continuous way, without administrative limits constraints.

The Sardinian landscape was chosen as case study because of the growing attention of the Regional Government towards landscape protection, and of the large availability of data from Regional SDI (section 4.1The use of the vector spatial grid to model the landscape data, has demonstrated that it is possible to treat spatial phenomena using of spatial units different to the administrative units usually used for the CIs assessment. This made it possible to explore the possibility to obtain the more appropriate spatial units for the specific phenomenon. In the case of landscape the spatial grid allowed to study the landscape at a finer scale, so that it has been possible to capture landscape indices across the study area better than it would have been possible if administrative spatial units had been used. Section 4.2 has shown how the indicators used in the construction of landscape SCI are spread across the spatial domain; their distributions suggested the possible presence of strong spatial heterogeneity, and enforced the need of the application of the spatial methodology for the construction of the overall landscape SCI.

The results reported in chapter 5 confirm a strong presence of spatial heterogeneity for all the dimensions used in the definition of the landscape SCI, in particular the cultural and the settlement macro-dimensions. This fact is demonstrated firstly by the number of spatial units used to calibrate the GWPCA; it is very low, compared to the total number of spatial units, for the cultural and settlement macro-dimension. Moreover the significance analysis for all the components confirms that the spatial distribution of the indicators of each macro-dimension across the spatial domain is not random but affected by spatial heterogeneity (p-value < 0.05). Therefore the null hypothesis about the spatial randomness is rejected (see section 5.5 and results in sections 5.2, 5.3, and 5.4). The presence of spatial heterogeneity suggested the use of the variable loading coming from the application of the GWPCA as local weights to assign to the indicators in the calculation of the score of each landscape dimension (section 5.2, 5.3 and 5.4). To reduce the dimensions of each macro dimension, only the first component extracted has been taken into account, because it explains the main part of the variance of the data in the main part of the spatial units. The three landscape dimensions have been aggregated by means of a simple sum function, in order to obtain the final score of the landscape SCI (section 5.6). The score of the landscape SCI is high for valuable landscape spatial units, while it is low in spatial units with strong presence of landscape disturbances.

The application of the local spatial autocorrelation on the landscape SCI, and in bivariate way, on landscape SCI and its components revealed which are the groups of spatial units having either high or low landscape quality, in order to provide a new definition of valuable landscape areas. This point is crucial in planning, in particular to support decision processes to protect areas with high landscape quality and to make decisions on how to improve the landscape quality in the other areas, by mean the identification of the factors that generate the most disturbances (section 5.7).

Some critical points rose during the development of this work. The first concerns the quality of the data provided by the Regional SDI. Spatial dataset provided, despite their large number do not supply enough information to describe in a good manner some aspects of the landscape, in particular the environmental macro-dimension. The environmental macro-dimension strongly depends on the particular characteristic of an ecosystem or of a habitat. These kinds of information are not currently available in SDI data; this is the reason why the use of the environmental indicator provided by ISPRA (Istituto Superiore per la Protezione e la Ricerca Ambientale) has been necessary.

The second critical point was the use of the vector grid as spatial unit of analysis. Despite the fact that it has recognized very useful to the description of the spatial continuity of the landscape, it should be taken into account that landscape characteristics vary independently from the grid (as discussed in chapter 3). Therefore the best spatial units should be detected referring to the Modifiable Area Unit Problem (MAUP), in order to discover the best size for the grid. Further research on this field should definitely address MAUP integration in the methodology as well as the detection of the optimal spatial units of analysis. This may require the application of various grids with different cell sizes, in order to perform different attempts, and to evaluate the results on landscape measures and landscape SCI.

Finally, this work used only the first component extracted by the GWPCA. As shown in chapter 5 (section 5.2, 5.3 and 5.4) the first component does not explain the whole part of the variance in each spatial unit. In some cases the variance explained by the second component would be needed. Therefore further effort to identify these spatial units in order to improve the local set weights is needed. The software used for the GWPCA does not allow to identify automatically the winning component in the spatial units, making the finding of the winning component very difficult because of the high number of spatial units. Despite this, on the basis of the percentage of the variable explained by the first component, it may be possible to consider the use of the variable loadings of this component as an acceptable compromise.

The study demonstrated that the integration of spatial multivariate analysis and the use of spatial data in the original methodology for CIs can be considered an innovative step towards the construction of Spatial Composite Indicators. This work focused in particular on the identification of spatial weights by means of the GWPCA. This point represents the main important novelty in the use of this spatial multivariate technique. In other case of attempts to build spatial indicators, weights were estimated in a non-spatial way i.e. expert opinion. In these cases weights do not vary across the space but they are fixed. The practical benefit of the methodology presented in this work is represented by the integration of the spatial analysis in the methodology of the construction of composite indicators. The advantage that comes from this novel methodology is the fact that it is possible to consider the spatial influence on data and on datasets and therefore to appreciate their local importance, to better represent the behavior of the phenomena. A further advantage is the fact that this method can be applied also in other case studies or using other kinds of data, for example socio-economic data associated with spatial units, in order to understand spatial relationships still neglected in the construction of composite indicators. From a planner's perspective, it has been possible to introduce a new analytic criteria to assess landscape quality, and on the basis of this criterion, to achieve a new delimitation for homogeneous landscape areas. The structure of the indicator allows to distinguish the areas that need protection policies from those in which actions should aim at increasing landscape quality.

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