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Geoinformatic Methodologies and Quantitative Tools for Detecting Hotspots and for Multicriteria Ranking and Prioritization: Application on Biodiversity Monitoring and Conservation

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“Anyone who has never made a mistake has never tried anything new”.

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1 The Problem: State of the Art

1.1 Introduction and Objectives

In the present Ph.D. Thesis in Geoinformation, some multidimensional statistical methodologies useful to order a collection of “objects”, ecological-environmental objects in this case, are discussed and compared. Each one of the environmental objects is described and analyzed by a set of ecological indicators.

In this context the methodologies are used for the individuation of the so called “hotspots” (i.e. ecological critical points/objects/areas or their clusters). The term “hotspot” means something unusual and very improbable from a statistical point of view.

The field of application of these methodologies concerns the evaluation and planning of part of the Italian territory. These methodologies are “collocated” in the context of the Landscape Ecology, a discipline that, even if appeared relatively late on the setting of ecological disciplines, has assumed a relevant and significant importance both in theory and practice.

The general environmental goal of these methodologies is to individuate and propose some statistical tools useful for the conservation of the biodiversity patrimony of a country. This aim includes not only the areas officially protected (Parks, Reserves, etc.), but also all the diffuse naturalistic traits of the landscape which, even if external to the protected areas, play a strategic role in maintaining the same protected areas.

From this point of view it is suggested the necessity to overcome the peculiar “limits” of the ecological basic research, so that the obtained results can be easier understandable and usable also by the administrative and political decision-makers. Indeed the decision makers are more and more often involved in deliberating actions that affect critical areas without having appropriate cognitive support.

Since any form of environmental policy in practice finds expression in funds to spend in local administrative partitions involved in ecologically critical situations, there is the primary necessity to find methodologies to identify environmental critical points in order to guide public stakeholders in allocating funds only where it is truly necessary.

It is also necessary to integrate ecological-naturalistic information in the human context in order to ameliorate the environmental evaluations and to provide guidelines for conservation action and planning (Rookwood, 1995; Wyant *et al*., 1995). Planning for conservation is a process that uses scientific data, but that ultimately depends on the expression of human values (Theobald *et al*., 2000).

The pursuit of environmental continuity for the conservation of biodiversity has given rise to the development of a specific area of the territorial planning, the Ecological Network design.

Particularly, the specific goals of this Thesis are:

- Propose and experiment a quantitative methodology which integrates the information deriving from sets of ecological indicators using different ranking objects techniques to identify ecologically critical habitats. These habitats should be protected.
- Propose a methodology which coupling demographic indicators with ecological ones, can provide general guidelines that helps the decision-makers in their choices for landscape management.
- Propose and test different statistical quantitative methods to identify and rank the most ecologically worthy administrative partitions to receive funding from Central Environmental Decision-makers (i.e. National Ministry of the Environment).
- Discuss the results concerning the application of Systematic Conservation Planning techniques to design an Ecological Network of an Italian area, in the light of multidimensional concepts of the Map of Italian Nature project.

The Thesis is divided in five sections or chapters:

Chapter 1 describes the general purposes of the Thesis, in the light of the state of the art of the scientific literature relative to the problems faced.

Chapter 2 describes the ecological-environmental features of italian areas object of the study and the characteristics of the database provided by the Italian Environmental Ministry. These data belongs to the Italian Project "Map of Italian Nature" (Rossi and Zurlini, 1998; Rossi, 2001; Zurlini *et al*., 1999).

Chapter 3 presents and discusses the utilized methodologies to order the "environmental-administrative units" object of the analysis. Moreover it identifies critical areas (Hotspot Detection).

Chapter 4 illustrates and discusses the scientific results achieved applying the methodologies defined in Chapter 3.

Chapter 5 discusses the results obtained and provides the environmental stakeholders with some useful practical-management suggestions for the biodiversity conservation.

1.2 The International and National background: The “Natura 2000” network, the Map of Italian Nature Project and their effects on the Environmental Planning.

During the past few decades, the inadequacy of the current nature conservation policies to contrast the growing environmental pressures and to protect the ecological processes ensuring the biodiversity maintenance has clearly emerged (Wätzold and Schwerdtner, 2005; Delbaere, 2006; Bergsenga and Vatn, 2009; Martín-López, 2009). In the recent past the scientific literature has mainly dealt with preserve design (Murphy and Wilcox, 1986) but proactive conservation planning is becoming increasingly important due to the growing threats to biodiversity and the limited financial resources (Mohan, 1993; Poiani *et al.*, 1998; Pierce *et al.*, 2005).

Many studies (Pierce *et al*., 2005; Maiorano *et al*., 2006) have underlined that the preservation of populations, communities and ecosystems cannot be limited to the establishment of Parks and Reserves, especially if isolated or small, but it is necessary to take into account the ecological-environmental processes concerning broader scales than those involved in the single Protected Areas (Zaccarelli *et al.*, 2008). In effect the biodiversity patrimony of a country includes not only the areas officially protected (Parks, Reserves, etc.), but also all the diffuse naturalistic traits of the landscape which, even if external to the protected areas, play a strategic role in maintaining the same protected areas.

Particularly, what emerged was the awareness that the persistency of the biodiversity is strongly contrasted by the growing fragmentation of natural and semi-natural environments, and that biodiversity can be preserved only through adequate land-use planning extended to the whole landscape (Wiens, 2009; Mander and Uuemaa, 2010).

From this point of view, the maintenance of a physical-territorial and of an ecological-functional continuity among natural and semi-natural environments has been suggested as an effective strategy in order to mitigate the effects of fragmentation on populations and communities (Rossi P. *et al*., 2008).

The pursuit of environmental continuity has given rise to the development of a specific area of the territorial planning, the E.N. design, in a perspective of general rethinking of the tools for land control, management and protection. The topic of E.N. is now established as focal in environmental politics, starting programmes and initiatives corresponding to a logic of integration (i.e. of network) among individual actions on the environment (Kati *et al*., 2004; Opdam *et al*., 2006). The knowledge concerning the E.N. theme has been partly acquired at a planning level, and not only at a normative one, and included in International

Conventions (European Landscape Convention, 2000), in Council Directives of the EEC, in pan-European strategies and in national guidelines.
The Council Directive 79/409/EEC (Birds Directive, 1979), concerning the designation of Special Protection Areas (SPAs), and the Council Directive 92/43/EEC (Habitats Directive, 1992), aimed to designate Special Areas of Conservation (SACs), have achieved a great importance. These Directives represent the result of a European agreement oriented towards the definition of a great ecological-naturalistic value network defined “Natura 2000”.
Natura 2000 network is the most important project concerning the nature conservation and biodiversity monitoring and involving the whole European Union (UE) territory. The basic aim of this Network is the natural and seminatural habitats and wildlife conservation to preserve the biodiversity through the detection and management of the sites provided for “Habitat Directive” and “Birds Directive”.
Furthermore with Natura 2000, a system of strictly connected areas from a functional point of view (and not only a simple cluster of isolated zones and chosen among the most representative ones). Natura 2000 network assign relevance not only to the highly natural areas but also to the contiguous territories essential to relate areas spatially far but near considering their ecological functionality. Moreover the need is not to manage and protect a set of disjoined areas, but to provide resources and knowledge, to study management models as much shared as possible. This aspect will allow to start a “relations network” on the territory, permitting a “dialogue” among the areas, establishing the conditions for ecological connections.
This new system setting is integrated with the strategy defined by the European Council of promoting a more comprehensive and less parcelled approach in territorial government which has leaded to the adoption of the European Landscape Convention. The definition of Natura 2000 network has implied for the entire UE a cognitive and organizational effort that represents a good example, at world level, of the application of the International Convention on Biological Diversity in relation to the natural resources management.
The Italian protected areas are more than 1.000 (the Official Registry of the Ministry of Environment, under revision, records 772 protected natural areas) covering more that 11% of the national territory (Italian Ministry of Environment, 2006) but the current percentage is expected to rise to 15% by the addition of new areas in the next few years.
Natura 2000 network in Italy is composed by 2283 Special Areas of Conservation (SACs), and by 589 Special Protection Areas (SPAs). The networks of SACs and of SPAs together

cover around the 15% of Italy. As a whole the Natura 2000 network, as consequence of an overlapping of 300 zones, covers around the 19% of the national territory.

Natura 2000 network consists in a scientific-administrative process focused to preserve the residual wild nature and its more valuable elements through the surveillance and the monitoring. This network shows many critical aspects. Among them, the realization of Natura 2000 management plans appears as a process strongly backward and sometimes completely lacking in its final results (rarely in agreement with the Guidelines established by the Italian Ministry of Environment in 2002). It means that currently the available territorial management tools are inadequate and ineffective and consequently there is a serious mortgage on the future process of recognition of SACs and SPAs. A process that should take place “as faster as possible and within a maximum deadline of six years since the designation of SACs by a part of the States members of UE in agreement with the European Commission” (art. 4 par. 4 Directive 92/43/CEE).

The Law 394/91 on the Protected Areas of Italy introduced an element of great novelty within the frame of problems related to the management of the territory. It states in an explicit way that the realization and the management of Protected Areas must be inserted in a background of general territorial planning making use of the Map of Italian Nature. For its intrinsic dynamism, The Map of Italian Nature is a basic aid for the control and the check of the observance and of the effectiveness of the lines of the territorial organization.

The aims of Map of Italian Nature are defined in the Law 394/91 called “Framework Law on Protected Areas”: Map of Italian Nature “individuates the status of the natural environment of Italy, underlying the natural values and the profiles of territorial vulnerability” and born as necessary tool to define “the basic lines of territorial structure referring to the natural and environmental values”.

Essentially, the informative tool of the Map of Italian Nature must be considered as the reference for Regional Administrations in order to proceed in planning and scheduling the conservation and protection of environmental resources policies.

The Map of the Italian Nature Project (Rossi and Zurlini, 1998; Rossi, 2001; Zurlini *et al*., 1999) envisions all Italy, but the starting step of it has analyzed 7 millions of hectares (about 23% of the national territory), mapping habitat types, according to the CORINE Biotopes Project Habitat Classification (CEC, 1991). In 2007 the Map of Italian Nature was completed in Regions of Valle d’Aosta, Veneto, Friuli Venezia Giulia, Molise and Sicily, with expectation of ending Umbria and Latium in 2008 and Apulia, Campania and Sardinia in 2009. In Abruzzo and Basilicata the works are in progress, while in the remaining regions stands at the realization of some few areas. Actually more than 50% of Italy has been covered.

This national project aims:

1. to supply an overall representation and evaluation of the naturalistic patrimony of Italy, including the areas which are not officially protected in agreement with the idea that all the diffuse naturalistic traits play a strategic role in maintaining and preserving the protected areas;
2. to help in the individuation and evaluation of new areas of high ecological value but subjected to natural degradation and to excessive human pressure;
3. to help in the definition of the development lines of a territory in order to balance the necessity of the nature conservation and the exigency of the socio-economic development.

The principal assumption of the Map of Italian Nature is that there is a continuum of environmental situations from zones of concentrated nature (Parks, Reserves, etc.) to others where naturalistic traits and human activities can live together. It is assumed that concentrated and diffuse natures are interdependent parts of a unique system and both should be included in the general planning of a given territory. This approach is supported by the recent developments of the Conservancy which is expanding its focus from preserves to protecting biodiversity at landscape-level (Miller and Hobbs, 2002; Poiani *et al.*, 1998; Waldhardt, 2003). This broader perspective requires being able to couple socio-economic needs with the environmental needs in the same territory. In order to implement a correct and efficient conservation policy, it is necessary to move from a naturalistic perspective to an administrative one, keeping knowledge of environmental situation and human needs in a view of sustainable land use planning of biodiversity conservation (Kim and Pauleit, 2007).

Since any form of environmental policy in practice finds expression in funds to spend in local administrative partitions involved in ecologically critical situations, there is the primary necessity to find quantitative methodologies to identify environmental criticality in order to guide public stakeholders in allocating funds only where it is truly necessary.

For this reason, ecological information integrated in the human context is an essential aspect to make environmental evaluations and provide guidelines for conservation action and planning (Rookwood, 1995;Wyant *et al.*, 1995). In fact planning for conservation is a process that uses scientific data, but that ultimately depends on the expression of human values (Theobald *et al.*, 2000).

1.3 Landscape Ecology as methodological and essential interpretative support for environmental evaluation processes

The ecological-environmental evaluation of study areas here examined is carried out at a landscape scale. In effect the majority of the information necessary for this evaluation and in general for the territorial planning, is characterized by a spatial component.

Landscape Ecology is a discipline that studies the landscape itself as a biological level of life organization. Its management- operative aspects are even more relevant.

The term Landscape Ecology has been coined by Troll (1950) who states that “it can be described as a marriage of geography (land and landscape) and biology (ecology)”.

Landscape Ecology evolved in different directions thanks to the contribution of scientists driven by the “narrowness” of the classical ecology relatively to the territorial applications (Naveh and Lieberman 1984; Zonneveld and Forman, 1990; Forman and Godron, 1986; Zonneveld and Forman, 1990; Naveh 1990;).

In Italy the Landscape Ecology appears since 1986 and stands out as scientific and stand-alone discipline with the institution of a working group in the range of Italian Society of Ecology and, later, with the establishment of the Italian Society of Landscape Ecology in 1988.

Landscape Ecology is particularly suitable to be used in territorial planning and management because it is the only ecological discipline that recognizes a fundamental importance to spatial dimension i.e. to the ecosystem localization, distribution and shape.

The shape of landscape elements influence the functions and *vice versa*.

In this context one of the most popular and accepted definition is given by Forman and Godron (1986). According to these authors the landscape is defined as a mosaic or to be more precise as “[…] a heterogeneous portion of territory composed by a whole of interactive ecosystems which recurs with a recognizable structure in the space”.

The purposes of Landscape Ecology towards conservation problems are:

- To provide principles, theoretical criteria of reference and methodologies for landscape study:
- To provide environmental diagnosis also with the support of appropriate indices and quantitative models;
- To provide synthetic predictive models;
- To address the conservation and territorial management choices;
- To provide controls on the planned transformations.

For what concerns principles and criteria, these suggestions seems really useful and innovative:

- the systemic view of landscape impose the consideration of natural systems in relation to the anthropic ones in order to highlight their mutual influences
- concepts of heterogeneity and co-evolution turn over the traditional criteria of evaluation of landscape patches, imposing a revaluation of elements having a low successional level in relation to the environmental mosaic;
- the theory of sink/source dynamics, inserts the importance of size and geographical distribution of environmental mosaic patches;

It is specific task of Landscape Ecology to verify, on the basis of the objectives to pursue:

- the possibility to make the intervention according to the rules of a correct planning and design;
- the need to make the intervention in order to pursue the prefixed aims of recover and/or mitigation;
- the environmental compatibility level of the intervention;
- the effectiveness of the intervention from a technical and broadly speaking ecological point of view.

The environmental analysis performed using the paradigms of Landscape Ecology consists basically of four methodological approaches: the numerical approach *sensu strictu*, the spatial approach, the multi-scalar and the modellistic one. In the first approach structure and complexity of the environmental mosaic are analyzed using numerical indices which collect information concerning a given area ignoring the spatial component (Kareiva, 1990; Hansen and Di Castri, 1992). All the numerical diversity indices belong to this category (e.g. Shannon eveness index). Otherwise the spatial analysis takes into account the emerging characteristics of habitats because they are discrete entities located in a well-defined position in the landscape (Turner, 1990; Lamberson *et al*., 1992; Rossi P. *et al.*, 2003). Utilized indices are able to quantify the elements distribution in the mosaic (e.g. distance index of each habitat from the nearest of the same type). The multi-scalar approach underline the characteristics that are maintained passing through different space-time scales (Jones *et al*.,1991; Ferrarini *et al*., 2005). Finally in the fourth approach, the spatial modellistic configures as one of the most incisive tool in order to detect and simulate environmental dynamics (Lek *et al*., 1999; Jenerette *et al*., 2001; Sui and Zeng, 2001).

1.3.1 The Ecological Value and the Ecological Sensitivity of a natural habitat

The Ecological Value (E.V.) and the Ecological Sensitivity (E.S.) of the habitats of a given landscape are essential and preliminary dimensions to be considered in planning and conservation policy and are essential for identifying critical sites in a given landscape.

Ecological Value, as well as Ecological Sensitivity, are multidimensional concepts and their quantitative evaluation requires a set of different ecological indicators (Margules and Usher, 1981; Smith and Theberge, 1986).

The selection of sites having the greatest ecological-conservationistic Value takes place through an evaluation procedure based on their comparison.

The sites' comparison is necessarily performed choosing evaluation criteria definable as conceptual tools through which is possible to express a judgement (Boyle *et al*., 1998). The choice of criteria expressing the Ecological Value (biodiversity, rarity, wilderness, size, etc.) is still one of the main themes of discussion in Applied Ecology (Ratcliffe, 1977; Margules and Usher, 1981). Regardless of the adopted criteria, the sites' comparison on the basis of the criteria chosen requires a quantification process.

In the scientific literature E.S. is understood as the synonym of Ecological Fragility (E.F.) or Ecological Vulnerability (Nilsson and Grelsson, 1995) assuming, in general, the connotation of environmental risks (Rossi, 2001). Sensible areas are considered as essential landscape elements to maintain biodiversity and natural resources level both in the site itself and in the nearby regional zones (Ndubisi *et al*., 1995).

For what concerns the concepts of E.S. and E.F. Ratcliffe (1977) suggested that E.F. implies and recall the E.S. that is conceptually characterized as habitat proneness to environmental change involving a combination of intrinsic and extrinsic factors. However Ratcliffe doesn't specify which are the external factors and if, among them, can be considered natural and/or human disturbances. Otherwise Wright (1977) and Xu *et al.* (2004) underline how different ecosystem types have a dissimilar ability in sustaining biodiversity and in maintaining their own structural and functional integrity. These authors also suggested that the external factors are basically connected to the disturbance produced by human activities (i.e. Human Pressure).

1.3.2 The Ecological Attention and the Ecological Fragility of a natural habitat

In this Thesis it is accepted and utilized the concept of Ecological Attention defined by Rossi P., *et al* (2008). Ecological Attention (EA) is defined as the ecological status of a habitat characterized, at the same time, by great ecological value and great ecological sensitivity (Rossi P. *et al*., 2008). The habitats so characterized in identifying the conservation priorities. They should be protected.

Another important status of a habitat is revealed by its Ecological Fragility (EF).

The identification of species, ecosystems and fragile habitats is a crucial goal in a view of biodiversity conservation and sustainable development. In scientific literature doesn't exist an unique approach to the concept of ecological fragility and two main recognizable conceptual approaches stands out:

1. Some authors distinguish between areas that are fragile as consequence of great natural internal changes and areas that modifies mainly as result of external pressures, principally having anthropic origin (Goldsmith, 1983; Fox and Fox, 1986);
2. Other authors include in the concept of fragility external and internal factors, being them natural or anthropic (Ratcliffe, 1971; Smith and Theberge, 1986).

Many scientists tried to quantify the concept of Ecological-Environmental Fragility.

The research on this argument stands out that in most of the cases the Ecological-Environmental Fragility of sites (or environmental units) has been evaluated through the assignment of scores usually in a completely subjective way (Sargent and Brande, 1976; Xu *et al*., 2004).

In Italy, the Map of Italian Nature project (Rossi and Zurlini, 1998; Rossi, 2001) has chosen the perspective of Ratcliffe (1977), that is the EF reflects the degree of Sensitivity of a habitat to environmental changes and, as a consequence, represents a combination of intrinsic and extrinsic factors. The EF is related with possible events that potentially (risk) can determines unfavourable modifications on the habitat itself. In particular EF of a habitat is settled by the combination of its Ecological Sensitivity and the actual level of "unfavourable events" on it. A particular level of EF can be reached by a habitat according to different combinations of levels of ES and external "unfavourable events".

Scientific literature shows a general consensus upon the identification of these unfavourable events with the negative impact of the human activities (Anthropic Pressure) on habitats (Ratcliffe, 1977; Kunin and Lawton, 1996; McCann, 2000). On the basis of this, the conceptual model proposed by Rossi (2001) can be schematized as below (Fig.1-1):

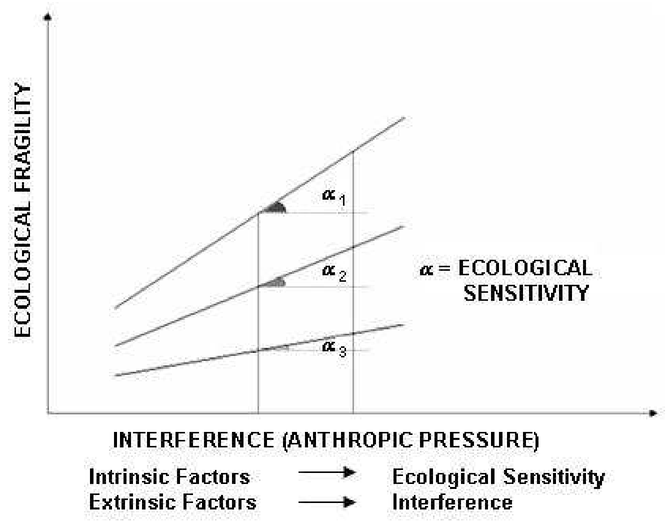


Figure 1-1 Conceptual model of the effect of Ecological Sensitivity on Anthropic Pressure results on Ecological Fragility (Rossi, 2001).

The E.F. is “correlated” to the corresponding score of Human Pressure (H.P.) acting on the habitat.

The Anthropic Pressure (i.e Disturbance) is considered as the whole pressures (Disturbance, Pollution, Transformation; see Rossi and Zurlini, 1995) that currently burden on an environmental unit, being them internal or external.

That conceptual model can be mathematically formulated as follow:

$$E.F. = \alpha * H.P. \qquad (1.1)$$

Where E.F. represents the fragility degree of a habitat using an arbitrary semiquantitave scale; α is the coefficient of specific Fragility (i.e. the Sensitivity of a habitat) and expresses the fragility modification resulting to an Anthropic Pressure variance; H.P. is the Anthropic Pressure acting on a habitat and measured using an appropriate semi-quantitative scale.

For the sake of simplicity and in first approximation, a linear relation has been assumed. Its increasing trend express the current prevalent consensus regarding the negative effect of the Pressure on habitat Fragility.

Because of this reason two different habitats can reach the same level of E.F. according to an appreciable different level of Human Pressure, as a consequence of their different E.S.. Basically the E.S., quantitatively expressed by the coefficient α, plays the role of multiplier between E.F. and Human Pressure. As a consequence, one habitat can be subjected to a modest Human Pressure but, being its E.S. elevated, may have an elevated level of E.F.. On the contrary, a low E.S. can determine, in conditions of high Pressure, a modest level of E.F..

1.4 Relationships between demographic structure of the territory and environmental conservation policies

Consumption of food, water, wood, oil and carbon, soil erosion, climatic changes and biodiversity loss are perhaps the most important environmental factors which are tendentially correlated with the population growth.

Since 1950, the world population increased from 2.5 to 6 thousand million and United Nations (UN) estimates that in 2050 it will reach 9-10 thousand millions. Because of the recent and diffuse decreasing birth rate, the population growth has been relevant but not so much as expected in the 90's. However the population increase of 3.5 thousand millions will determine a further growth in resources consumption causing their progressive reduction.

The ecosystem impact should be monitored because the environmental conservation and its sustainable use affect the human health. In effect the natural resources are non-renewable and so they must be preserved for future generations.

The problem of the world demographic growth hides many regional differences. In effect the attempt of a sustainable development and of an amelioration of the life quality not necessarily requests an higher consumption of resources.

Population needs is an essential aspect to be considered in environmental conservation policies. They must be taken into account non only for scientific reasons but also to achieve a more exhaustive view of the problem to effectuate correct actions. It is also a political exigency and an administrative need. In all democratic countries the environmental planning aims and methods must be shared with the population and based on its active participation in order to obtain the consensus.

In Italy, according to the Law 394/91 on Protected Areas, the objectives of protected areas (biodiversity conservation at any level) must be collocated in the general territorial planning context which includes the human population and socio-economical aspects. Each community and its administrators play the explicit role to plan and coordinate conservation actions and to increase the value of the naturalistic patrimony according to the population exingecies.

In 2003 at Bruxelles, during the "Spring Council" has been pointed out the four main action lines of sustainable development: public health, **natural resources management**, climatic changes, and amelioration of transport systems. For the period 2007-2013 structural funds has been mainly allocated to sustain Research, Development and Innovation. They regard also the environmental technologies in an integrated sustainable development view of the problem.

In Italy (2005) has been approved the National Plan for Growth and Development (PICO). Five categories of intervention are indicated:

- The extension of the degrees of freedom of citizens and companies;
- The promotion of scientific research and technological innovation;
- The consolidation of human resources education;
- The adjustment of material and intangible infrastructures;
- The environmental protection.

The list shows the necessary interdisciplinary approach of Sustainable Development which integrates both environmental, economical, social, institutional aspects.

In hystorically anthropized areas, like Italy, the last decades has shown a substantial stability in population rate. The population rate of natural increase is currently negative and it is only partially balanced by a strong stranger net migration rate. Also the internal mobility has been elevated causing territorial opposite effects. Mountain and isolated regions, characterized by a low economical development, has been subjected to a continuous depopulation. On the contrary, hilly, coastal and flat regions, characterized by an high quality of life, has been subjected to a relevant overpopulation.

In this context of low birth rate, the Italian internal mobility of young people is mainly aimed to job research and determined an elevated ageing in areas subjected to emigration. On the contrary, this tendency has produced in areas just more developed, a demographic structure more favourable for the economical growth. The different demographic structure determines different opportunities and perspectives for the socio-economical future of resident communities. In mountain and isolated regions, already poor and depopulated, a further depopulation can cause, as extreme consequence, the total abandonment of the territory in few decades. In hilly, coastal and flat regions, having already reached high levels of affluence, there will be a further demographic increase, due to the presence of young people, and the capability to attract further immigration.

European Directives aims to planning conservation practices which don’t ignore this demographic evolution. These practices and policies must be clearly focused on present socio-economical exigencies in order to continuously ameliorate the life quality.

In Italy, demographic forecasts underline pronounced regional differences.

In the South part of the country, which is poorer and characterized by a lot of young unoccupied people, the investments for nature conservation must belong to the Central Administration, must be aimed to increase the qualified employment with short term results, in order to obtain population consensus.

In North-Central part of Italy, the unemployment rate is low and the ageing rate very high. In this situation the available resources are mainly local and aimed to the tourism development and to the landscape maintenance.

The territorial characteristics deeply affect the community size and its economic growth, determining the migratory flux and so its demographic structure.

An inaccessible territory, characterized by the risk of landslides, and far from the main road/communication system, without places for industries, houses and infrastructures in general, in the past was densely populated for defence reasons. Currently, being a period of low birth rate, these areas are less populated than the past and characterized by a progressive emigration especially of young people. There are small and mainly aged communities. As consequence these areas has little or null perspectives of continuity.

These problems have been object of discussion by Italian and French demographers since the 80’s (Roussel, 1988; Golini and Mussino, 1987; Golini and Bruno, 1997).

In Communes located in mountain territory, usually population density is below 20 inhabitant/km^2.

The main question regards the presence of a possible critical depopulation threshold. Below this threshold an irreversible process of socio-economical “desertification”, and consequently total middle-term abandonment, occurs. The demographic analysis show that, under a certain value of population density, the administrative abilities to ensure the maintenance of the collective patrimony decrease (due to the too small financial entrances) and in the community feelings of isolation and abandonment spread.

The socio-economical interpretation of mountain demographic decline is focused on lower quality of life than the nearby areas. The incomes are appreciably lower, for young people, the perspectives to find a qualified employment and the infrastructures are lacking. The spatial distance from more developed areas and the territorial characteristics themselves, often becomes an insuperable limiting (i.e. restrictive) factor. People of these communities cannot be resettled in the industrial and productive development of the nearby zone.

For what concerns these areas subjected to a continuous depopulation, the suggested policies should favour the maintenance of the community. Perhaps in these areas, often characterized by an progressive uncontrolled naturalization without any economical value, a different territorial policy should be followed. Sometimes the resources for these support policies are easily available in a local or provincial administrative level. This is the case of areas located near zone of touristic value or near Communes densely populated. In other cases only the administrative regional or central intervention can grant adequate financial resources. Finally, in some cases, it can be necessary to accept the territorial abandonment and an alternative use of the area.

The necessity of wider farms, the diffusion of mechanization in agriculture, the economical productivity changes of many cultivations and in general the EU agricultural policy, have deeply modified the landscape. It has been moved from small cultivated plots to wider areas of monocultures (usually represented in hilly areas by olive groves and vineyards and in mountain by woods). This is another transformation that must be managed and ruled and that offers relevant economical advantages.

On the contrary, a territory which permits productive and living settlements, provided with an efficient communication network, is characterized by a growing population due to immigration and mainly composed by people in working age. The economic growth favours the expansion of the built-up and of industrial areas. The high incomes, together with the favourable demographic situation, determine a numerical increase of the population. This increase, even if requests a considerable territorial consumption for houses and infrastructures can be managed respecting the environment and favouring the investments to protect the diffuse naturalistic traits and to defence and maintain the current structure of the landscape.

The territorial planning must reconcile the continuity of the economic development and the defence of high levels of social development with environmental quality.

Demographic aspects which comprise both the population structure and its future trend are essential factors. They have the advantage to be directly connected to the economic situation of a given area. Understanding the connections between demographic situation and ecological indices allows not only to show the current situation but also to determine the short and middle-term tendencies and so to choose the most suitable intervention lines.

The relations between demographic characteristics and ecological indices of a given territory are neither simple nor constant. They depend to the administrative culture and to the priorities assigned to the territory respect to the socio-economical ones.

1.5 Methodological statistical tools: State of the Art

The general methodological objective of this Thesis is to utilize and compare different statistical methods concerning “data mining”, “hotspot detection” and “prioritization and ranking”, orienting the results in ecological-environmental field of application.

In the wide field of available Multivariate Statistic techniques and methodologies (Rossi O *et al.,* 2009), has been used not only Data Mining ones but mainly Hotspot Detection methodologies, typical for a new discipline denominated Geoinformatic Surveillance, and Object Ranking techniques.

Data mining is the name given to the process of extracting patterns from data. Data mining is becoming an increasingly important tool to transform this data into information. It is commonly used in a wide range of profiling practices, such as marketing, surveillance, fraud detection and scientific discovery.

Data mining commonly involves four classes of tasks:

- **Classification** - Arranges the data into predefined groups. Common algorithms include decision tree learning, nearest neighbour, naive Bayesian classification and neural networks.
- **Clustering** - Is like classification but the groups are not predefined, so the algorithm will try to group similar items together.
- **Regression** - Attempts to find a function which models the data with the least error.
- **Association rule learning** - Searches for relationships between variables.

Each analysis (in this case ecological-environmental), whatever is the object of the study, bring on the table of each researcher/scientist a relevant number of different kind of variables.

If the variables were completely independent, would be convenient and easy to proceed separately with as many univariate statistics analysis as the number of the considered variables. But being the variables characterizing each environment or environmental process highly interdependent, it is much more useful and, to summarize, more realistic to proceed with a multivariate analysis which takes into account, at the same time, the whole of variables for each object (i.e. environmental unit in the chosen field of application).

Multivariate Statistics offer a rich set of methodologies which allows the researcher to explore and obtain, time by time, the necessary information from the original mass of available environmental data.

Geoinformatic (Geographical) Surveillance for the detection of spatial and temporal hotspots is a declared need for the modern society. A hotspot refers to a cluster of events in space and time with elevated responses, an unusual occurrence and an oddity, such as an outbreak, or any departure from a geo-referenced set of prior expected responses. The causes are varied and maybe wilful, natural, or accidental. The need of monitoring, etiology, management, or early warning concerns development of statistical methods for the detection of hotspots and software infrastructure. Identification of critical hotspots (coldspots have depressed rates and are treated similarly), evaluation of the significance of the found cluster and assessment of covariates form the skeleton of a hotspot detection method and the associated software. This family of statistical methods and tools has immediate potential for use in critical societal areas, such as public health and disease surveillance, ecosystem health, water resources and water services, transportation networks, persistent poverty typologies and trajectories, environmental justice, biosurveillance and biosecurity, among others.

Another important aspect of data mining is concerned with the question of **Ranking** a finite collection of objects when a suite of indicator values is available for each member of the collection. The objects can be represented as a cloud of points in indicator space, but the different indicators (coordinate axes) typically convey different comparative messages and there is no unique way to rank the objects while taking all indicators into account.
When a ranking of some objects (chemicals, geographical sites, river sections, etc.) by a multicriteria analysis is of concern, a conventional solution is to assign a composite numerical score to each object by combining the indicator information in some fashion.
Rather than trying to combine indicators, it is possible to take the view that the relative positions in indicator space determine only a partial ordering and that a given pair of objects may not be inherently comparable.

1.5.1 HotSpot Detection methodologies

Actually many different methods of Hotspot detection exist. The majority and frequently utilized of them derives from medical and epidemiological scientific literature. Cluster detection is an important part of spatial epidemiology because it can help identifying environmental factors associated with disease and thus guide investigation of the aetiology of diseases.

There are over hundred disease cluster tests in the peer-reviewed literature.

Several questions must therefore first be answered before choosing a test or a specific method. The main question is: What kind of clustering is hypothesized? Because of their large number, some tests are identical with others and some are special cases or extensions of others. Generally, they can be classified as follows: space tests, when they identify clusters over particular locations; time tests, when they test for temporal clustering within a single time series or in several time series simultaneously; and space-time tests, when they are used to detect clustering in space-time. Space tests can also be referred to as global, local or focused. The large number of these tests makes it difficult to choose among them, as well as to discuss all of them individually in a single paper.

A cluster is generally defined as a discernible aggregation of cases of specific diseases (incidence, mortality) in a small region relative to the distribution of population at risk. Many specific definitions have been proposed (Caldwell and Health, 1976; Knox, 1989; Aldrich *et al*., 1991; Heath, 1996; Wakefield *et al*., 2000; Wartenberg, 2001). For examples, Knox (1989) defines a cluster as being a geographically and or temporarily bounded group of occurrences (i) of a disease already known to occur characteristically in clusters, or (ii) of sufficient size and concentration to be unlikely to have occurred by chance, or (iii) related to each other through some social or biological mechanism, or having a common relationship with some other event or circumstance. Wakefield *et al* (2000) state that a cluster corresponds to an area and time period in which the risk surface is elevated, implying that the number of cases is in excess to that expected in the area and time period.

It should be noted that clusters can occur out of chance. In such a case, a more thorough epidemiological investigation of the disease cluster alarm may not be warranted. It is however necessary to test the statistical significance of cluster alarms using appropriate statistical methods. For such testing, there are over 100 methods available in the peer-reviewed literature.

Kulldorff (2001) has recently defined a class of more than 50 new tests for spatial randomness based on many possible permutations of a general framework proposed. One is therefore curious about the reason for the multiplicity of disease cluster methods. Expectedly, given their large number, some of the tests are identical with one another (Ross and Davis' Test, 1990 is the same as Esseen's Test, 1983) and some are special cases of others (Cuzick-Edward's k-Nearest Neighbor Test, 1990 is a special case of the Weighted Moran' I Test, 1981) (see Kulldorff 2001 for more examples).

Most of the disease cluster detection tests can be classified as space, time and space-time tests (Table 1-1):

- Space tests, identify clusters in space, (i.e. when cases of disease tend to aggregate over particular locations or sub-regions).
- Time tests, when they test for temporal clustering within a single time series or in several time series simultaneously.
- Space-time tests, when they detect clustering in space, time and space-time.
- Furthermore, the space tests can also be referred to as:
- Global investigate whether there is clustering throughout the study area regardless of their specific locations or spatial extent, i.e. the research questions are: Is the spatial distribution of cases within the study area random or not? If not, where are the regions of spatial aggregation?
- Local detect clustering limited to geographically restricted regions within the study area.
- Focused detect clustering around a point source exposure to factors that are proposed to increase risk of disease (i.e. that takes place around a suspected cause for the elevated risk).

Space			Time	Space - Time
Global	Local	Focused		
Moran's I (1950)	Moran's I (1950)	Fixed Cut-Off, Lyon et al (1981)	Empty Cell, Mathen & Chakraborty (1950)	Ederer-Myers-Mantel Method (1964)
Horn's Ro (1966)	Turnbull's CEEP (1990)	Isotonic Regression, Stone (1988)	Ederer-Myers-Mantel Method (1964)	Knox's method (1964)
Mantel & Bailar (1970)	Besag & Newell's R (1991)	Stone MLR (1988)	Larsen's test (1973)	Mantel's method (1967)
Ripley's K Function (1980)	Grimson's MAX (1993)	Hills & Alexander's Z (1989)	Dat's 0-1 matrix Method (1982)	k-NN, Cuzick & Edwards (1990)
Esseen's Test (1983)	Spatial Scan, Kulldorff and Nagarwalla (1995)	Focused k-NN, Cuzick & Edwards (1990)	CuSum Test (Levin & Kline, 1985)	Grimson's U (1993)
Whittemore et al. (1987)	Anderen-Titterington (1997)	Focused Besag & Newell (1991)	Grimson's U (1993)	Diggle et al. (1995)
k-NN, Cuzick & Edwards (1990)	Spatial Scan, Kulldorff (1997)	Score Test, Waller et al (1992), Lawson (1993)	Scan Test (see Jacques, 1994)	Jacquez (1996)
Alexander's NNA (1991)	Bithell's M with uniform kernel (1999)	Bithell's Linear Rank Score (1995)		Kulldorff Space and Space-Time Scan Statistics (1998)
Alt & Vach (1991)	Isotoni Spatial Scan, Kulldorff (1999)	Maximum X_2, Lagazio et al. (1996)		
Grimson's U (1993)		Cumulative X_2, Lagazio et al. (1996)		
Tango's Excess Events Test (1995)		Diggle et al. (1999)		
Anderson & Titterington's (1997)				

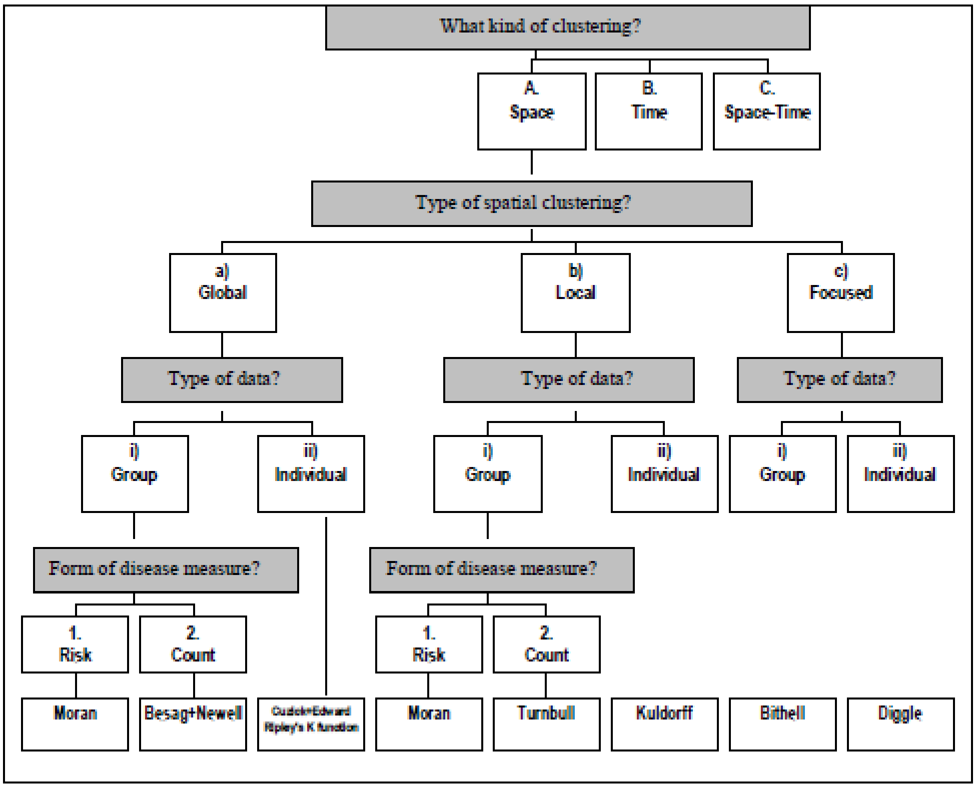
Table 1-1 Lists a selection of relevant disease cluster detection tests in the various categories.

The tests are usually based on an area (at which level data are aggregated, like villages, towns, districts and sub-regions) and a centroid (used as a reference point to determine the coordinates of the area).

The available cluster detection tests are based on either the Poisson probability model (Mantel and Bailar, 1970; Besag and Newell, 1991; Tango, 2000) or the Bernoulli probability model (Esseen, 1983; Cuzick and Edwards, 1990; Diggle *et al.*, 1999). For some tests, one can choose to apply either the Poisson or the Bernoulli model (Kulldorff, 1997; Kulldorff, 1999; Turnbull, 1990; Stone, 1980). Furthermore, the tests are based either on rates or population counts of disease or mortality, depending on which probabilistic model is used. In the Poisson model, the cases in each area are under the null hypothesis assumed to be generated from an inhomogeneous Poisson process, and the expected number of cases in each area is taken to be proportional to its population size, or to the person-years. In the Bernoulli model, a finite number of individuals is considered, usually as cases and non-cases (or controls) as a binary variable. They may represent people with or without a disease. Methods based on the Bernoulli model require that the locations of all individuals are known and they test whether there is a random distribution of the cases given these locations.

Osman A., Sankoh and Heiko Becher (2002) showed the general characteristics of the various groups of tests in a way that facilitates a quick decision on which test to use.

They demonstrate a recommended selection of appropriate disease cluster detection tests by asking and answering a series of questions which yields the flow-chart is given (Figures 1-2a and 1-2b).



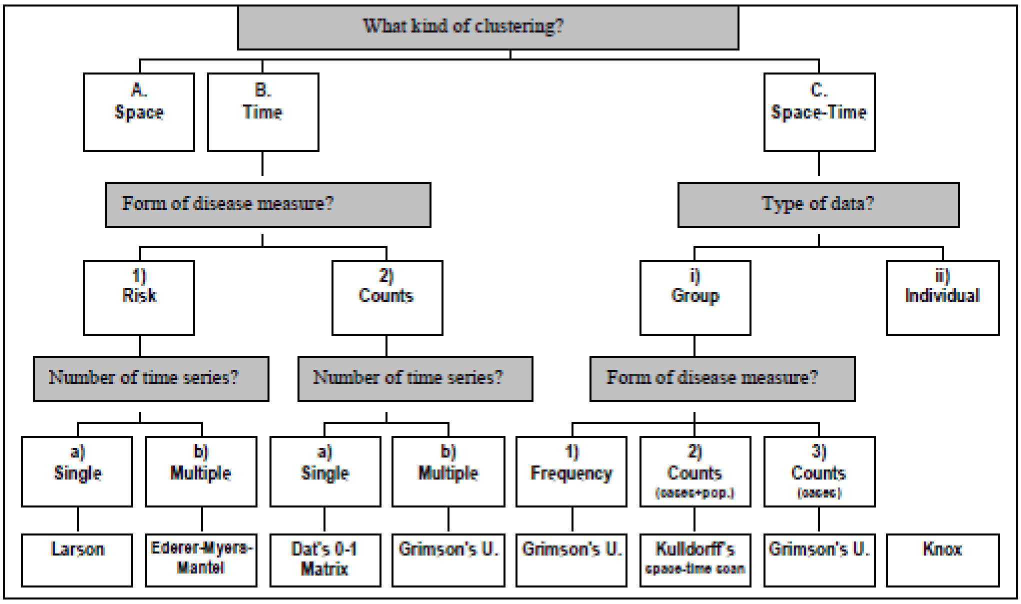


Figure 1-2a and 1-2b Flow-chart for determining the appropriate test

1.5.2 Objects Ranking and Prioritization methods

Over the last century multivariate statistics have become an important tool to perform data analysis and, in recent years, its development has been mainly oriented towards the technical aspects of data analysis. With the advent of computers and the 'information age', statistical problems have grown in both size and complexity, and new fields have arisen, like data mining.

Two main aspects are faced by statistics: data exploration, which means learning from data, and data modelling.

Experiments and measurements are performed with the aim of analysing the variance of elements, measuring the distance among the elements and investigating their order relationships. Several techniques are now available for data exploration purposes and several Clustering methods are available to study the distance between elements or their similarity. Different criteria can be used to establish whether elements are close enough (i.e. similar enough) to be located within the same group or cluster, and different definitions of cluster are provided by different cluster measures.

Another way to perform data exploration is by rank methods which analyse the order relationship among elements.

The different kinds of order methods available can be roughly classified as total (called evenscoring) and partial-order ranking methods, according to the specific order they provide.

These methods are the ones needed to support and solve decision problems, setting priorities. Besides sophisticated multivariate statistics, used mostly in pre-processing and modelling data, priority setting makes use of quite simple methodologies.

However the increasing of problem complexity (multicriteria decision problems) leads to the decision processes becoming more complex, requiring the support of new tools. Thus there has been increased interest in decision making strategies and several techniques have been proposed.

A decision problem is a situation where an individual has alternative courses of action available and has to select one, without any a priori knowledge of which is the best.

The decision process, which results in the selection of the best solution, is efficient if the procedure to reach the solution is optimal. The aims of a decision process are (a) to generate effective information on the decision problem from available data, (b) to generate effective solutions and (c) to provide a good understanding of the structure of a decision problem. Multi-Criteria Decision Making (MCDM) strategies are used to rank various alternatives (scenarios, samples, objects, etc.) on the basis of multiple criteria, and are also used to make an optimal choice among these alternatives. In fact, the assessment of priorities is the typical premise before a final decision is taken. Decision support systems are computer-based systems, which assist individuals in the decision process and support judgement decision, improving the effectiveness of Total Ranking Theory the decision process. Thus the focus is on the high quality of the strategy rather than on the quality of the final solution.

In recent years ranking strategies have been widely applied for different purposes in environmental sciences and chemistry (Brüggemann and Carlsen, 2006): evaluation of aquatic toxicological tests (Brüggemann *et al*., 1997a; Brüggemann *et al*., 1995a), analysis of waste disposal sites (Halfon, 1989), ranking chemicals for environmental hazard (Halfon and Reggiani, 1986; Newman, 1995), comparison among ecosystems (Brüggemann *et al*., 1994; Munzer *et al*., 1994; Pudenz *et al*., 1997; Brüggemann *et al*., 1999a; Pudenz *et al*., 2000), exploration of habitat diversity (Myers *et al.*, 2001; Myers *et al.*, 2005; Myers et al., 2006), chemicals prioritization (Brüggemann *et al*., 1993a), evaluation of on-line databases (Brüggemann *et al*., 1997b; Voigt *et al*., 1999; Voigt *et al*., 2000), ranking of contaminated sites (Brüggemann *et al*.,1995b; Sørensen *et al*., 1998), ranking of near-shore sediments (Brüggemann *et al*., 2001), evaluation of materials in car production (Pudenz *et al*., 1999).

Most scientific concepts are multi-faceted and can be quantified in a variety of ways. In the complex systems evaluated by ranking strategies, elements (chemical substances, chemical processes, regions, etc.) are described by several attributes, referred to also as the criteria; thus the system must be analysed by more than one criterion, and decisions must be made by taking several criteria into account contemporaneously. The criteria are any set of attributes which must reliably represent the system required properties and which must be orientable, (i.e. for each criterion it is necessary to explicitly ascertain whether the best condition is satisfied by a minimum or maximum value of the criterion).

Let us now consider an R-dimensional system, with an associated (N x R) data matrix X. To each of the N elements a set of R attributes, criteria relevant to the decision making procedure is associated.

The strategies to reach the optimal choice require the development of a ranking of the different options. Within a set E ($s, t, w, z \in E$) an evaluation method can generate:

- a complete or total ranking: $s > t > w > z$ also called a linear order;
- the best option: $s > (t, w, z)$;
- a set of acceptable options: $(s, t, w) > z$;
- an incomplete ranking of options $s > (t, w, z)$ or $(s, t) > (w, z)$.

1.5.2.1 Total Ranking Theory and Methods (Additive Aggregation methods)

Total order ranking methods are multicriteria decision making techniques used for the ranking of various alternatives on the basis of more than one criterion. A criterion is a standard by which the elements of the system are judged. Criteria are not always in agreement, they can be conflicting, motivating the need to find an overall optimum that can deviate from the optimum of one or more of the single criterion.

The different ways of quantifying a single underlying concept will be referred to as views or indicators. While there is generally a positive association among different views, the association is not perfect and different indicators can provide different comparative assessments. Although in many ways these views are neither comparable nor combinable, it remains a strong and almost irresistible human urge to combine them into a single view and a corresponding linear ordering of the objects under consideration.

Total order ranking methods are based on an aggregation of the criteria yr,

where r = 1, ..R: $\Gamma = f(y_1, y_2, ...y_R)$
Thus, if an element is characterised by R criteria, then a comparison of different elements needs a scalar function (i.e. an order or ranking index), to sort them according to the numerical value of Γ.

Most common aggregation methods use additive and geometric aggregation, as stated in the Handbook on Constructing Composite Indicators (OECD, 2008) The simplest additive aggregation method entails the calculation of the ranking of each object according to each individual indicator and summation of the resulting rankings, e.g. Information and Communication Technologies Index (Fagerberg, 2001). The method is based on ordinal information (the Borda rule). It is simple and independent of outliers. However, the absolute value of information is lost.
The second method is based on the number of indicators that are above and below a given benchmark. This method uses nominal scores for each indicator to calculate the difference between the number of indicators above and below an arbitrarily defined threshold around the mean, e.g. the Innovation Scoreboard (European Commission, 2001).
By far the most widespread linear aggregation is the summation of weighted and normalised individual indicators.
When using a linear additive aggregation technique, a necessary and sufficient condition for the existence of a proper composite indicator is *preference independence*: given the individual indicators$\{x_1, x_2,..., x_Q\}$, an additive aggregation function exists if and only if these indicators are mutually preferentially independent (Debreu, 1960; Keeney and Raiffa, 1976; Krantz *et al*., 1971).
An undesirable feature of additive aggregations is the implied full compensability, such that poor performance in some indicators can be compensated for by sufficiently high values in other indicators.
If multi-criteria analysis entails full non-compensability, the use of a geometric aggregation is an in-between solution.

Several evaluation methods which define a ranking parameter generating a total order ranking have been proposed in the literature (Keller and Massart, 1991; Hendriks *et al*., 1992; Lewi *et al*., 1992) with the application in many different context; those more frequently used are Pareto Optimality, Desirability functions, Utility functions, Dominance functions, Preference functions, Concordance Analysis and Absolute Reference method.

Most of these methods require the definition of the values and situations of optimum, i.e. for each criterion it is necessary to ascertain explicitly if the best condition is satisfied by a minimum or a maximum criterion value, and the trend from the minimum to the maximum must also be established. The attribute setting is a crucial point in ranking methods since it requires the “mathematization” of decision criteria which are often not completely defined or explicit. Total order ranking results are strictly dependent on the criteria setting and thus can be completely different for different settings.

- **Pareto Optimality**

The Pareto optimality technique selects the so-called Pareto-optimal points and the points that are not Pareto-optimal points are inferior to the Pareto optimal points with respect to at least one criterion. Let us consider a two-dimensional criterion space (Figure 1-3).

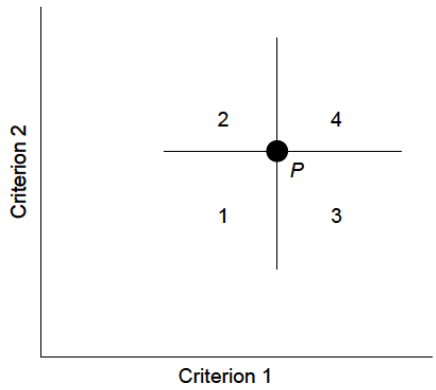


Figure 1-3 Representation of the four quadrants in a two-dimensional criterion space around the point P.

A point corresponds to one setting of two criteria, the criterion values of which are plotted against each other. The space around the point P can be divided in four quadrants. In the case of two criteria both to be maximised, the points in the first quadrant are inferior to point P, while points in the fourth quadrant are superior to point P. The points in the second and third quadrants are incomparable with point P since they are superior to P for one criterion and inferior for the other.
In other words, a point is a Pareto optimal point if no other points are found in the upper right quadrant. According to Pareto optimality, at least one point must be Pareto optimal, and all the non-inferior and incomparable points together form a set of Pareto-optimal points. If the system under study is described by more than two criteria, the R-dimensional criterion space (R > 2) containing the Pareto optimal points must be projected onto a two dimensional plane (using for example the Principal Component Analysis technique).

- ***Desirability and Utility functions***

The Desirability approach is based on the definition of a desirability function for each criterion in order to transform values of the criteria to the same scale.

Each criterion is independently transformed into a desirability dir by an arbitrary function which transforms the actual value of each element into a value between 0 and 1.

Once the kind of function and its trend for each criterion is defined, the global desirability D of each i-th element can be evaluated as follows:

$D_i = \sqrt[R]{d_{i1} \times d_{i2} ..... \times d_{iR}}$ with $0 \leq D_i \leq 1$ (1.2)

The overall desirability is calculated combining all the desirabilities through a geometrical mean.

It must be highlighted that the desirability product is very strict: if an element is poor with respect to one criterion, its overall desirability will be poor, and in the case limit if one element is zero the overall desirability becomes zero.

In addition each criterion can be weighted in order to take into account criterion importance in the decision rule.

Once D for each element has been calculated, all the elements can be ranked according to their D value and the element with the highest D can be selected as the best one.

The critical feature of this approach to multicriteria decision making problems is the establishment of the relation between criteria and desirability values which must be performed by the decision maker

The Utility approach is very similar to the desirability functions; each criterion is independently transformed into a utility or by a function which transforms the actual value of each element into a value between 0 and 1.

In this case the overall utility is calculated less severely: in fact the overall quality of an element can be high even if a single utility function is zero.

Like the desirability functions, the utility functions are affected by arbitrariness related to the a priori selection of the functions and corresponding upper and lower limits.

- ***Dominance functions***

This method is based on the comparison of the state of the different criteria for each pair of elements. This approach does not require the transformation of each criterion into a quantitative function, it has only to be established whether the best condition is satisfied by a minimum or maximum value of the selected criterion.

For each pair of elements (i, j) three sets of criteria are determined:
$R^+(i,j)$ is the set of criteria w+ where i dominates j (i.e. where i is better than j), $R^0(i,j)$ is the one where i and j are equal, and $R^-(i,j)$ is the set of criteria w^- where i is dominated by j.
The dominance function (called C_{ij}) between two elements i and j is calculated considering the weights. A C_{ij} value equal to 1 means equivalence of the two elements; $C_{ij} > 1$ means that the element i is, on the whole, superior to the element j, whereas $C_{ij} < 1$ means that the element i is, on the whole, inferior to the element j. The obtained values can be normalised in the closed interval 0-1 and then a global score can be calculated as the sum of these normalized values.

- ***Preference functions***

The preference function ranking method was developed by Brans, Vincke and Mareschal (Brans and Vincke, 1985; Brans *et al*., 1986). This approach uses subjective preference functions for each separate criterion to rank the different elements. However, differently from the desirability and utility functions, the preference function trend does not directly model the element values for each criterion; it models the difference values between each pair of elements. Thus for each r-th criterion, a preference function $P_r(i.j)$ must be defined for the difference between the function values of two elements ($\delta_{ij} = f(i) - f(j)$). The preference function Pr(i.j) defines the degree to which the i-th element is preferred to the j-th element.
If the difference between the two elements, i and j, is greater than or equal to the δ_r value, then the i¬th element is strictly preferred to the j-th element; if it is less than 0, no preference exists and the two elements do not differ. In the other cases the preference value is provided by the function itself.
In a second step, a preference index $\Pi(i,j)$ of element i over j for all the criteria, is calculated and finally In a third step, the positive flow and negative flow outranking for each element is calculated.
The global quality, called net flow outranking, of the i-th element is then calculated and normalized

- ***Concordance Analysis***

The main difference between Concordance Analysis and Desirability, Utility and Dominance functions is the introduction of a reference element to which each element is compared. The reference element can be a real element or a fictitious one: the centroid (i.e. the vector of the means) is frequently used as the fictitious reference element.

Because of the different dimensions of the criteria, each criterion first undergoes normalisation, and each is weighted according to its importance in the decision process. For each criterion the normalised value is compared with the normalised value of the reference element. For each element Concordance (composed by those criteria for which the i-th element has values higher than those of the reference element i^*) and Discordance (composed by those criteria for which the i-th element has values lower than or equal to those of the reference element i^*) sets are defined. For each element a Concordance Indicator CI_i (measures the number of criteria for which the i-th element is preferred to the reference element) and correspondingly a Discordance Indicator DI_i (which quantifies not only the number of criteria with a worse i-th element than the reference element but also how much worse it is) is calculated.

The elements are ranked according to the global score Γi:

$$\Gamma i = CI_i - DI_i \qquad (1.3)$$

In its usual form, the Concordance indicator is a measure of the number of criteria for which each element is preferred to the reference element, since the Indicator is defined as the sum of the weights belonging to the criteria of the Concordance set, however no account is taken of the real quantitative distance between the two elements. Pavan (2003) proposed a new and quantitative Concordance Indicator CI'_i which measures not only for how many criteria the i-th element is preferred to the reference element but also how much it is preferred, is proposed here as the sum of the weighted differences between the criteria of the Concordance set and those of the reference element.

- ***Absolute Reference method***

The absolute reference method is based measuring the distance between each element and a reference element, which is supposed to represent the overall optimum of all the considered criteria. This method requires the definition of the values and situations of optimum, i.e. for each criterion it is necessary to explicitly ascertain not only whether the best condition is satisfied with a minimum value or a maximum value of the criterion, but also the specific optimum values. To get rid of different criterion dimensions, each criterion first undergoes normalisation and weighting to account for its importance.

Once a distance measure (i.e. Euclidean, Mahalanobis, Manhattan) has been selected, the Absolute reference method calculates the entire N distances between the elements and the reference element. An example in ecological problems is given by Ideal Vector method (Rossi P. *et al*., 2008)

For each element a measure of its similarity with the reference element is derived from the Euclidean distance according to the following expression:

$S = 1 - d_{ii*}\ 0 \leq S_i \leq 1$ (1.4)

This similarity measure is used to rank the elements. It ranges from 0 (no similarity exists between the considered element and the reference one) and 1 (there is complete similarity between the considered element and the reference one).

1.5.2.2 Pros and cons (arguments for and against) of composite indicators

In general terms, an indicator is a quantitative or a qualitative measure derived from a series of observed facts that can reveal relative positions (i.e. of an object) in a given area. When evaluated at regular intervals, an indicator can point out the direction of change across different units and through time. In the context of policy analysis (Brand *et al*., 2007), indicators are useful in identifying trends and drawing attention to particular issues. They can also be helpful in setting policy priorities and in benchmarking or monitoring performance. A composite indicator is formed when individual indicators are compiled into a single index on the basis of an underlying model. The composite indicator should ideally measure multidimensional concepts which cannot be captured by a single indicator. The main pros and cons of using composite indicators are the described in Table 1-2 (Saisana and Tarantola, 2002).

Pros:	Cons:
• Can summarise complex, multi-dimensional realities with a view to supporting decision-makers. • Are easier to interpret than a battery of many separate indicators. • Can assess progress of countries over time. • Reduce the visible size of a set of indicators without dropping the underlying information base. • Thus make it possible to 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 (*i.e.* citizens, media, *etc.*) and promote accountability. • Help to construct/underpin narratives for lay and literate audiences. • Enable users to compare complex dimensions effectively.	• May send misleading policy messages if poorly constructed or misinterpreted. • May invite simplistic policy conclusions. • May be misused, *e.g.* to support a desired policy, if the construction process is not transparent and/or lacks sound statistical or conceptual principles. • The selection of indicators and weights could be the subject of political dispute. • May disguise serious failings in some dimensions and increase the difficulty of identifying proper remedial action, if the construction process is not transparent. • May lead to inappropriate policies if dimensions of performance that are difficult to measure are ignored.

Table 1-2 Pros and Cons of Composite Indicators

The aggregators believe there are two major reasons that there is value in combining indicators in some manner to produce a bottom line. They believe that such a summary statistic can indeed capture reality and is meaningful, and that stressing the bottom line is extremely useful in garnering media interest and hence the attention of policy makers. The second school, the non-aggregators, believes one should stop once an appropriate set of indicators has been created and not go the further step of producing a composite index. Their key objection to aggregation is what they see as the arbitrary nature of the weighting process by which the variables are combined. (Sharpe, 2004) According to other commentators: […] it is hard to imagine that debate on the use of composite indicators will ever be settled […] official statisticians may tend to resent composite indicators, whereby a lot of work in data collection and editing is “wasted” or “hidden” behind a single number of dubious significance. On the other hand, the temptation of stakeholders and practitioners to summarise complex and sometime elusive processes (e.g. sustainability, single market policy, etc.) into a single figure to benchmark country performance for policy consumption seems likewise irresistible. (Saisana *et al*., 2005).

1.5.2.3 Partial Ranking Theory and Methods

Ordering is one of the possible ways to analyse data and to get an overview over the elements of a system. The elements are commonly characterised by more than one quantity, i.e. they are described by several variables. As a consequence of the multivariate property of the elements, their ordering requires specific techniques as “conflict” among the criteria is bound to exist. Total order ranking methods, being scalar methods, combine the different criteria values into an index, the ranking index Γ, and element comparison and ordering is performed according to the numerical value of Γ. In this way the elements are always ranked in a total or linear ordered sequence, but the information on conflict among criteria is inevitably lost.

Partial order ranking (Brüggemann and Patil, 2010) is a vectorial approach that recognizes that not all elements can be directly compared with all other elements because, when many criteria are used, contradictions in the ranking can be present.

Obviously the higher the number of criteria, the higher the probability that contradictions in the ranking exists. The partial ranking approach not only ranks elements but also identifies contradictions in the criteria used for ranking: some "residual order" remains when many criteria are considered and this motivates the term "partial order". Thus the more known concept of order is the one demanding that all elements be comparable (i.e. linear or total order), while partial order is the one in which elements can be “not comparable”. If many elements are to be investigated, and especially if many criteria are to be considered, the parallel coordinates become complex and confusing.

In this paragraph the issues, challenges, and difficulties encountered in trying to combine multiple indicators into a single index are examined (Patil and Taillie, 2004a).

A collection S of objects where each object has an associated suite, (I_1, I_2, ..., I_p), of real-valued indicators has been considered. We suppose that all indicators are consistently oriented so that small values indicate “poor" conditions and large values indicate “good" conditions.

The elements in S will be denoted by a, b, c, ... We would like to make comparative statements about two given objects a and a' based on their indicator values (I_1, I_2, ..., I_p and I'_1 ,I'_2, ...,I'_p), respectively. If it happens that $I'_j \geq I_j$ for all j, then we say that a' is intrinsically “better” or “bigger” than a (in the loose sense) and we write a' ≥ a or a ≤ a'.

When, on the other hand, the indicators are not unanimous in comparing a and a', we have an ambiguous situation in which different investigators might rank a and a' differently. Here there is no consensus ranking. The possibilities are indicated in Fig. 1-4 in the case of p =2 indicators. Object a divides indicator space into four quadrants. Objects a' falling in the first quadrant (including its boundary) are intrinsically better than a and those falling in the third quadrant are intrinsically worse than a. The second and fourth quadrants (excluding their boundaries) are regions of ambiguity; objects falling here are not intrinsically comparable with a.

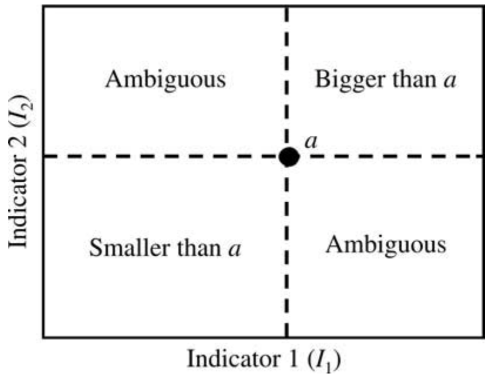


Figure 1-4. With two indicators, each object a divides indicator space into four quadrants. Objects in the second and fourth quadrants are ambiguous in making comparisons with a.

Resolution of ambiguity can be accomplished (mathematically) by combining the indicators into an index:

index = $H(I_1, I_2, ..., I_p) = H(a)$.

H denote such combination and the simplest combination is linear, $H = w_1I_1 + w_2I_2 +\ldots+ w_pI_p$.

The induced linear ordering can be displayed pictorially in terms of the contour of H that passes through a. The contour divides indicator space into two regions; objects in the upper right-hand region are intrinsically bigger than a while those in the lower left-hand region are intrinsically smaller than a (Fig. 1-5).

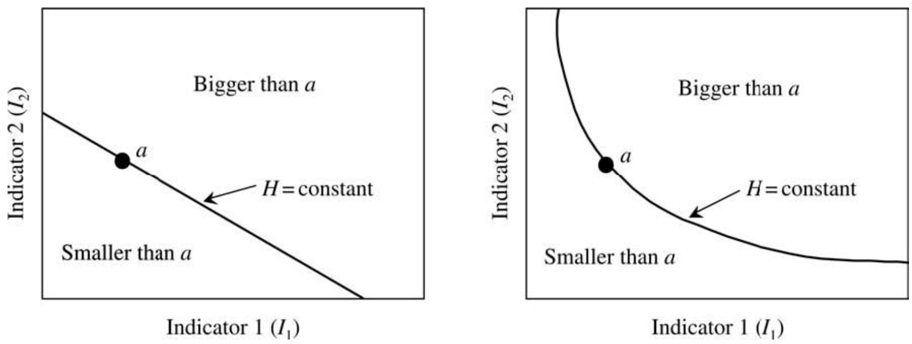


Figure 1-5. Contour of index H passing through object a. A linear index is shown on the left and a non-linear index on the right.

However, for an index H to be considered valid, its induced ordering should be consistent with the intrinsic ordering and this request pictorially, means that the contour of H that passes through object a must lie entirely within the ambiguous regions for a. Fig. 1-6 shows some valid contours and also some invalid contours.

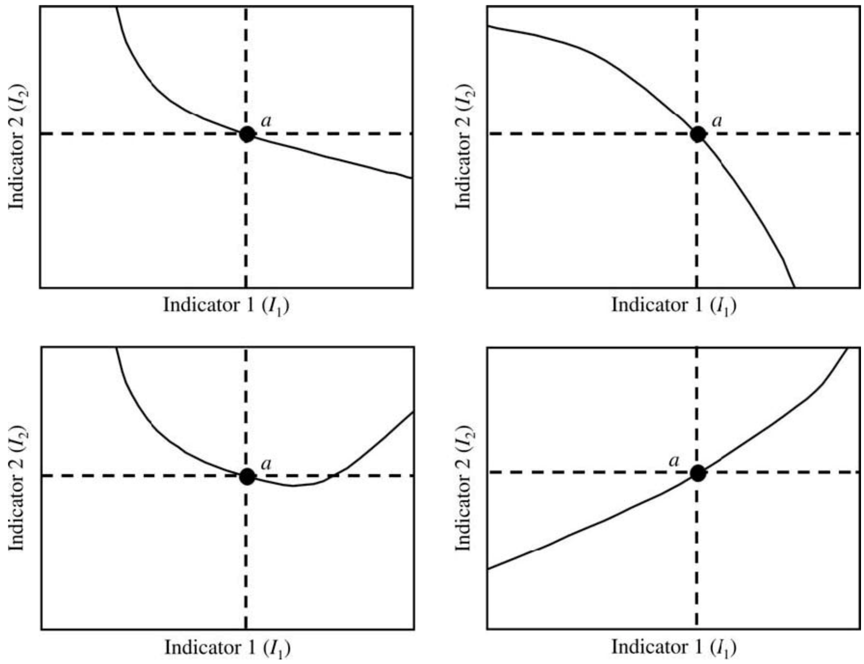


Figure 1-6. The top two diagrams depict valid contours while the bottom two diagrams depict invalid contours.

The mathematical conditions for an index to be valid are very simple and Fig. 1-6 suggests that validity is related to monotonicity of the contours when p = 2.

Validity is thus a mild restriction and still leaves a lot of freedom in choosing an index. Any proposed choice has to be considered in light of the “tradeoffs” or “substitutions” that are implied by the index’s contours.

If one can argue persuasively for specific trade-off value(s), then it makes a lot of sense to use the corresponding index. Typically, though, an index is adopted on grounds of mathematical convenience or simplicity (e.g., an average) with little effort to justify or even discuss the implied tradeoffs.

Two objects x, y belonging to E are characterized by their attributes’ values ($q_1(x)$, $q_2(x)$,...,$q_n(x)$ and ($q_1(y)$,$q_2(y)$,...,$q_n(y)$)).

We say x and y are comparable, if $q_i(x) \leq qi(y)$ or $q_i(y) \leq qi(x)$, for all i = 1,2,..,n.

If $q_i(x) \leq q_i(y)$ for all i, then we write $x \leq y$.

If $q_i(x) \leq q_i(y)$ not for all i (i.e., if there exists at least one i^* with $q_i^*(x) > q_i^*(y)$ and one i^{**} with $q_i^{**}(x) < q_i^{**}(y)$) then the two objects x, y are incomparable (with respect to the considered set of attributes). In that case we write x // y.

The demand "for all" to set up an order relation we call the generality principle. Sets equipped with an order relation are called **partially ordered sets (posets)**. It is convenient to speak of an attribute set. Brüggemann *et al*. (1995a) introduced the concept, information base, IB, which is the set of attributes used in the data matrix. Therefore we will either write $(X,\{q_1, q_2,\ldots q_n\})$ if it is important to refer to the attributes or write (X, IB).

A total order is a set, whose order relation leads to complete comparability (i.e., each object is comparable with each other).

We need one further relation in a poset. Object b is said to cover object a provided (i) a < b and (ii) there is no object x for which a < x < b. Note that all the inequalities in this definition are strict.

There are three ways of portraying partially ordered sets:

- hasse diagrams;
- zeta matrices;
- cover matrices.

The Hasse diagram is a planar graph whose vertices are in one-to-one correspondence with the objects in S and whose pattern of edges determines the order relation. On the other hand, the zeta matrix is better for analytic purposes-in fact many of the operations on posets can be expressed by matrix multiplication. The cover matrix is a variant of the zeta matrix.

The Hasse Diagram Technique (HDT) is a useful tool to perform partial order rankings with an easy visualisation of the obtained results. They are excellent for visualization purposes-provided S is not unduly large.

1.5.3 Other useful statistical tools

1.5.3.1 Principal Component Analysis

Principal Component Analysis (Rossi O. *et al.*, 2009) is one of the best known procedures in multivariate statistics. Proposed by Pearson (1901) and developed by Hotelling (1933) it is one of the main methods for performing data analysis and exploration.

It allows the examination of the correlation pattern among variables and an evaluation of their relevance, the visualization of the elements by analyzing their inter-co-relationships (outliers, clusters), the synthesis of data description discarding noise, the reduction of data dimensionality by discarding unnecessary variables, and the finding of principal properties in multivariate systems. From a mathematical point of view the aim of principal component analysis is to transform a certain number of (possibly) correlated variables into a (smaller) set of orthogonal (i.e. uncorrelated) variables which reproduce the original variance/covariance structure. This means rotating a p-th dimensional space to achieve independence between variables. The new variables, called principal components, are linear combinations of the original variables along the direction of maximum variance in the multivariate space, and each linear combination explains a part of the total variance of the data. Being orthogonal the information contained in each PC is unique. A maximum of p principal axes can be derived from the original data containing p variables. The new variables are defined by calculating eigenvalues and eigenvectors of the correlation matrix C(or the covariance matrix S) obtained from the original data matrix X.

Because of their properties, principal components can often be used to summarize most of the variability of a dispersion matrix of a large number of variables, providing a measure of the amount of variance explained by a few independent principal axes. The objective is to reduce the dimensionality (number of variables) retaining most of the original variability in the data. The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible.

In particular, the first two principal components define a plane, which represents the largest amount of variance. The elements are projected in this plane in such a way as to preserve, as much as possible, the relative Euclidean distances they have in the multidimensional space of the original variables. Principal component analysis is a reduced space ordination method which starts from a scaling of the elements in full-dimensional space, representing them in a few dimensions while preserving the distance relationships among the elements.

1.5.3.2 Cluster Analysis

A general question facing researchers in many areas of inquiry is how to organize observed data into meaningful structures, that is, to develop taxonomies (Jardine and Sibson, 1971, Sneath and Sokal, 1973).

Cluster analysis, also called data segmentation, (first used by Tryon, 1939) is an exploratory data analysis tool that encompasses a number of different algorithms and methods for grouping objects of similar kind into respective categories.

All relate to grouping or segmenting a collection of objects into subsets or “clusters”, such that those within each cluster are more closely related to one another than objects assigned to different clusters. Central is the notion of degree of similarity (or dissimilarity) between the individual objects being clustered.

The main goal of clustering (Rossi O. *et al.*, 2009) is to reduce the amount of data by categorizing or grouping similar data items together. In other words it aims at sorting different objects into groups in a way that the degree of association between two objects is maximal if they belong to the same group and minimal otherwise. Given the above, cluster analysis can be used to discover structures in data without providing an explanation/interpretation (i.e. cluster analysis simply discovers structures in data without explaining why they exist).

Cluster analysis methods are mostly used when we do not have any a priori hypotheses, but are still in the exploratory phase of our research. In a sense, cluster analysis finds the “most significant possible solution”. Therefore, statistical significance testing is really not appropriate here, even in cases when p-levels are reported (as in k-means clustering).

Clustering methods (Anderberg, 1973, Hartigan, 1975, Jain and Dubes, 1988, Jardine and Sibson, 1971, Sneath and Sokal, 1973, Tryon and Bailey, 1973) can be divided into two basic types: hierarchical and partitional (k-means) clustering.

Partitional clustering attempts to directly decompose the data set into a set of disjoint clusters.

The criterion function that the clustering algorithm tries to minimize may emphasize the local structure of the data, as by assigning clusters to peaks in the probability density function, or the global structure. Typically the global criteria.

The typical approach is to specify a desired numberof k clusters, then assign each case (object) to one of k clusters minimizing some measure of dissimilarity in the samples (dispersion) within each cluster, while maximizing the dissimilarity of different clusters. A very common measure is the sum of distances or sum of squared Euclidean distances from the mean of each cluster. Computationally, clusters are often computed using a fast, heuristic method that generally produces good (but not necessarily optimal) solutions. The k-means algorithm is one such method.

K-means training starts with a single cluster with its centre as the mean of the data. This cluster is split into two and the means of the new clusters are iteratively trained. These two clusters are again split and the process continues until the specified number of clusters is obtained.

When the user specifies random start the algorithm generates the k cluster centres randomly and goes ahead by fitting the data points in those clusters. This process is repeated for as many random starts as the user specifies and the Best value of start is found.

Hierarchical clustering, on the other hand, data are not partitioned into a particular cluster in a single step series of partitions takes place successively by either merging smaller clusters into larger ones, or by splitting larger clusters. Usually what happens is starting from a single cluster containing all objects to n clusters each containing a single object. At each particular stage the method joins together the two clusters which are closest together (most similar). The clustering methods differ in the rule by which it is decided which two small clusters are merged or which large cluster is split.

Hierarchical Clustering is subdivided into agglomerative methods, which proceed by series of fusions of the n objects into groups, and divisive methods, which separate n objects successively into finer groupings.

Differences between methods arise because of the different ways of defining distance (or similarity) between clusters. Several agglomerative techniques will now be described in detail.

Single linkage clustering: it is one of the simplest and is also known as the nearest neighbour technique. The defining feature of the method is that distance between groups is defined as the distance between the closest pair of objects, where only pairs consisting of one object from each group are considered.

Complete linkage clustering: also called farthest neighbour, it is the opposite of single linkage. Distance between groups is now defined as the distance between the most distant pair of objects, one from each group.

Average linkage clustering: here the distance between two clusters is defined as the average of distances between all pairs of objects, where each pair is made up of one object from each group.

Average group linkage: with this method, groups once formed are represented by their mean values for each variable, that is, their mean vector, and inter-group distance is now defined in terms of distance between two such mean vectors.

Ward's method: Ward in 1963 proposed a clustering procedure seeking to form the partitions P_n, P_{n-1},..., P_1 in a manner that minimizes the loss associated with each grouping, and to quantify that loss in a form that is readily interpretable. The distance between two clusters, A and B, is how much the sum of squares will increase when we merge them So at each step in the analysis, the union of every possible cluster pair is considered and the two clusters whose fusion results in minimum increase in 'information loss' are combined. Information loss is defined by Ward in terms of an error sum-of-squares criterion (minimizing the merging cost of combining the clusters).

Hierarchical clustering may be represented by a two dimensional diagram known as dendrogram which illustrates the fusions or divisions made at each successive stage of analysis. By cutting the dendrogram at a desired level a clustering of the data items into disjoint groups is obtained.

A problem with the clustering methods is that the interpretation of the clusters may be difficult. Most clustering algorithms prefer certain cluster shapes, and the algorithms will always assign the data to clusters of such shapes even if there were no clusters in the data. Therefore, if the goal is not just to compress the data set but also to make inferences about its cluster structure, it is essential to analyze whether the data set exhibits a clustering tendency.

Another potential problem is that the choice of the number of clusters may be critical: quite different kinds of clusters may emerge when K is changed.

1.5.3.3 Multiple Discriminant Analysis

Discriminant Analysis (Rossi O. *et al.*, 2009) may be used for two objectives: either we want to assess the adequacy of classification, given the group memberships of the objects under study; or we wish to assign objects to one of a number of (known) groups of objects. Discriminant Analysis may thus have a descriptive or a predictive objective.

The main purpose is to predict group membership based on a linear combination of the interval variables. The procedure begins with a set of observations where both group membership and the values of the interval variables are known. The end result of the procedure is a model that allows prediction of group membership when only the interval variables are known. A second purpose is an understanding of the data set, as a careful examination of the prediction model that results from the procedure can give insight into the relationship between group membership and the variables used to predict group membership.

In both cases, some group assignments must be known before carrying out the Discriminant Analysis. Such group assignments, or labelling, may be arrived at in any way. Hence

Discriminant Analysis can be employed as a useful complement to Cluster Analysis (in order to judge the results of the latter) or Principal Components Analysis. Alternatively, in star-galaxy separation, for instance, using digitised images, the analyst may define group (stars, galaxies) membership visually for a conveniently small training set or design set.

Multiple Discriminant Analysis (MDA) is an extension of Discriminant Analysis and is also termed Discriminant Factor Analysis and Canonical Discriminant Analysis. It adopts a similar perspective to PCA: the rows of the data matrix to be examined constitute points in a multidimensional space, as also do the group mean vectors. Discriminating axes are determined in this space, in such a way that optimal separation of the predefined groups is attained. As with PCA, the problem becomes mathematically the eigenreduction of a real, symmetric matrix. The eigenvalues represent the discriminating power of the associated eigenvectors. The g groups lie in a space of dimension at most g-1. This will be the number of discriminant axes or factors obtainable in the most common practical case when $n > m > g$ (where n is the number of rows, and m the number of columns of the input data matrix). There is one eigenvalue for each discriminant function. The ratio of the eigenvalues indicates the relative discriminating power of the discriminant functions. For example, if the ratio of two eigenvalues is 1.6, then the first discriminant function explains 60% more between-group variance in the dependent categories than does the second discriminant function. The relative percentage of a discriminant function equals a function's eigenvalue divided by the sum of all eigenvalues of all discriminant functions in the model. Thus it is the percent of discriminating power for the model associated with a given discriminant function. Relative percentage is used to decide how many functions are important. Usually, the first two or three eigenvalues are important.

1.5.3.4 Fuzzy Partial Order

Complexity of the partial order has its counterpart in messy Hasse diagrams with too many lines hiding the structure. What may be the reason for complexity in such diagrams? The number of objects |X| is not necessarily causing messy Hasse diagrams. There is another reason for complexity: In partial orders we obtain either $x < y$ or $x \parallel y$ even if the numerical difference between attribute values is small. This ordinal interpretation of the data matrix causes the lines in the Hasse diagram, although they are representing irrelevant incomparabilities or comparabilities. Irrelevant incomparabilities or comparabilities may better be interpreted as equivalence relation.

The following question arises: How can we manipulate Hasse diagrams to draw useful information, without losing the connection to the original data matrix? One possible answer can be given in an efficient way applying the concept of fuzzy logic to partial order (Brüggemann and Patil, 2010).

The very idea of fuzzy partial order is to replace the crisp < relation by a fuzzy subsethood as follows (Kosko, 1992; Van der Walle *et al.*, 1995).

Kosko fuzzy subsethood*:* Let a, b be two objects characterized by m dimensionless (normalized) attributes, then:

$$SH(a,b) = \frac{\sum_{i=1}^{m} \min(q_i(a), q_i(b))}{\sum_{i=1}^{m} q_i(a)} \qquad (1.5)$$

SH(a,b) is the membership function, describing to which extent object a can be considered as being below object b. If a < b, then SH(a,b) = 1 and 0 ≤ SH(b,a) < 1, if a || b, then both SH(a,b) and SH(b,a) $\in [0,1)$.

Relational matrix: Application of SH for all objects pairs leads to a matrix R (labeled by object identifiers) with entries between 0 and 1. The matrix R cannot be considered as being an expression for partial order. The crucial point is the transitivity. The transitivity axiom as formulated in chapter 2 refers to crisp relations which can be written as R(a,b) = 1 and R(b,c) = 1 implies R(a,c) = 1. In the setting of fuzziness, three fractional numbers are to be compared and for fuzzy-transitivity it is convenient to require

min(R(a,b), R(b,c)) ≤ R(a,c). (1.6)

The matrix R, obtained from the Kosko-measure, does not necessarily obey to Eq. (1.6). Hence an approach is needed to find a transitive closure for R, i.e. to replace some entries in R such that Eq. (1.6) is fulfilled.

Transitive closure: De Baets and De Meyer (2003) found an approach which guarantees fuzzy transitivity by replacing minimal entries of R as possible. They propose the “matrix method”: There the essential step is to calculate $R^{(n)}$ from $R^{(n-1)}$ as follows:

$R^{(n)}(x,y) = \max[\min(R^{(n-1)}(x,w), R^{(n-1)}(w,y)]$ for all $w \in X$, (n) (1.7)

indicating the n^{th} step in the iteration loop.

When the matrices $R^{(n)}$ and $R^{(n-1)}$ do no more differ by a certain threshold ε, the iteration stops, say at R.

α-cut: The final matrix R is transitively closed, hence consistent with partial order. It may have at most n^2 different values. For defuzzification of R, it is appropriate to rank order its entries and call them α-cuts: $\alpha_1 \leq \alpha_2 \leq .... \leq \alpha_{n^2} = 1$, so that we can perform the transformation:

$$R^{crisp}(x,y) = \begin{cases} 1 \; if \;\; R(x,y) \geq \alpha \\ 0 \qquad\qquad else \end{cases} \qquad (1.8)$$

Arbitrary choice can be made for the threshold α. Three cases arise in the application of Eq. 1.8:

1. $R^{crisp}(x,y) = R^{crisp}(y,x) = 0$: x and y are incomparable
2. $R^{crisp}(x,y) = 1$, $R^{crisp}(x,y) = 0$: $x < y$ or $R^{crisp}(x,y) = 0$, $R^{crisp}(y,x) = 1$: $x > y$
3. $R^{crisp}(x,y) = R^{crisp}(y,x) = 1$: $x \cong y$.

Tolerance: If α has a low value, then almost all entries of R will get a 1, hence there is little differentiation among the objects. If however $\alpha = 1$, then only the entries having value 1 in the original SH-matrix (Eq. 1.5) will be retained, and the order relations of the original data matrix are reproduced. If α is varied, we find:

- for $\alpha \in (\alpha_i, \alpha_{i+1})$, the crisp matrix R does not depend on α
- for α-values from different intervals of α-cuts will induce different crisp matrices R and therefore different equivalence classes and partial orders.

It is convenient to call α a tolerance level.

Extraction: The matrix $R^{(crisp)}$ contains not only the order relations but also equivalence relations. In order to obtain a Hasse diagram, equivalent elements must be identified and the order relations of the quotient set extracted.

Advantages: The partial orders, indexed by α are order preserving:

$(X, IB)_{\alpha 1} \subseteq (X, IB)_{\alpha 2}$, $\alpha_1 > \alpha_2$ (Van der Walle *et al*., 1995) (1.9)

Hasse diagrams evolve in a systematic manner, depending on α.

Disadvantages: Equation (1.5) implies that a sum is to be performed over different attributes. A sacrilege in the eyes of partial order theory! Furthermore, an objective selection of the α-value is difficult. Annoni *et al*. (2008) propose a measure for selecting a suitable α-value.

1.5.3.5 Partially Ordered Scalogram Analysis with Coordinates (POSAC)

Given a poset and its visualization by a Hasse diagram, a question arises: Can we find a smaller set of attributes from which we can get the same Hasse diagram? This question directs towards a possible representation of the ordinal properties of the data matrix in a lower dimensional space. Let us imagine that a data matrix has five attributes. If we can find a set of two attributes, which generate the same Hasse diagram (i.e. which lets the original order relations remain invariant), then we can represent the objects in a two-dimensional scatter plot. This will considerably simplify the ordinal analysis.

For convenience, we introduce POSAC but for more details, see Borg and Shye (1995), Voigt *et al.* (2004a,b), Brüggemann *et al.* (2003). POSAC is a method to reduce the attributes into a smaller number of dimensions, with the goal of correctly preserving as many of the comparabilities that exist in the original model as possible. The goal of the POSAC method is to reduce an N-dimensional data matrix by plotting it into two-dimensional space. The two-dimensional coordinate representation of objects with observed profiles, the data row of object x, $(q_1(x), q_2(x),...,q_m(x))$, should best preserve profile order relations as POSAC constructs new axes, which correctly presents as many of the order relations as possible. POSAC is similar to Principal Components Analysis (PCA) in that they are both dimension reduction methods, but while PCA tries to preserve distances, POSAC tries to preserve comparabilities.

POSAC helps the stakeholder by representing the objects in a two-dimensional plane, however by a more or less severe approximation, because some order relations will be ignored. The poset dimension can help to predict, whether by POSAC an exact presentation in a two-dimensional plane is possible.

As we have seen before, there are three possible order relations in a two-dimensional Cartesian coordinate space. The possibilities are indicated in Figure 1-7 A given object a divides the attribute space into four quadrants. The objects $y \in X$ that fall in the first quadrant are intrinsically better than a (i.e. $y > a$), and those that fall in the third quadrant are intrinsically worse than a ($y < a$). The second and fourth quadrants are regions of ambiguity (Figure 1-7), objects falling here are incomparable with object a (i.e. $y \parallel a$).

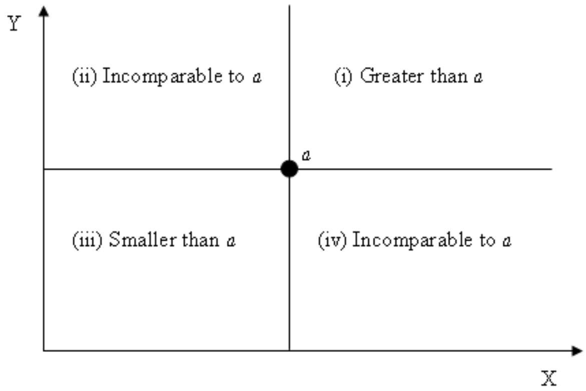


Figure 1-7 Two dimensional ordering

In a data matrix of m columns, we want to form a partially ordered set by comparing their profiles, provided by the rows of the data matrix. In the partially ordered set, some pairs of profiles may be ordered or comparable while some pairs of profiles are incomparable.

The POSAC algorithm can result in some profiles being unable to be accurately located in the two-dimensional coordinate space. With a large number of profiles, misrepresentation becomes a potential liability of POSAC. In order to measure how well POSAC retains comparabilities from the original data set, we compute the proportion of comparabilities correctly represented, if a pair of objects were comparable in the original data set, then they would have to be comparable with the correct orientation in the POSAC diagram in order to be considered correctly represented. Similarly, if a pair of objects is incomparable in the original data set, then they would have to be incomparable in the POSAC diagram as well. We would like the proportion of comparabilities correctly represented to be as high as possible, and a proportion above 0.75 is considered rather good for large data sets.

Here the program package SYSTAT has been used. The POSAC program produces a two-dimensional diagram with the objects represented and also provides the proportion of comparabilities that are correctly represented.

1.6 Other available instruments

1.6.1 The Geographical Information Systems (GIS)

Most of the necessary information to proceed to an environmental-ecological evaluation and to a territorial planning has a spatial component. Consequently the best tools to acquire and implement these data are the Geographical Information Systems (GIS).

The term Geographical Information System characterizes all types of software that are able to georeference the spatial information and so to give answer to territorial problems. GIS are able to treat and manage territorial data having a geographical basis. More in detail, GIS are settled to acquisition, management, processing, analysis, modelling and representation of data having a geographical position (Burrough *et al.*, 1998). Further than the geographical positioning of objects, the database contains attributes and information useful to distinguish objects themselves each others and to underline relations in order to solve management problems and territorial planning.

GIS can be distinguished on the basis of the digital representation type of the geographical field. Are available GISs that work in vectorial and in raster format even if currently the most popular and utilized of them allows managing both structures of data.

In our specific case, existing habitat cartographies as much as the administrative ones in the given study areas, which represent the basic layers in order to carry out the ecological-environmental analysis (i.e. the subject of this Thesis), are examples of digital cartography in vectorial format of polygonal type

For their intrinsic characteristics, and for available extensions and possible customizations that can be obtained, GIS use in ecological studies is widely popular in many operational fields (Young *et al.*, 1988; Campbell *et al.*, 1989; Bian and West, 1997; Rossi P. *et al.*, 2002). Among them environmental monitoring, territorial planning and Ecological Network design and management can be cited (Swetnam *et al.*, 1998; Weiers *et al.*, 2004).

1.6.2 The Ecological Networks

The topic of Ecological Networks (E.N.) is now established as focal in environmental politics, starting programmes and initiatives corresponding to a logic of integration (i.e. of network) among individual actions on the environment (Kati *et al.*, 2004; Opdam *et al.*, 2006). The knowledge concerning the E.N. theme has been partly acquired at a planning level, and not only at a normative one, and included in International Conventions

(European Landscape Convention, 2000), in Council Directives of the EEC, in pan-European strategies and in national guidelines.

The term E.N. has assumed different meanings in different areas according to the functions to be favoured and focused on (APAT, 2003; Bennett, 2004; Jongman *et al*., 2004; Jongman and Pungetti, 2004; Opdam *et al*., 2006): (a) a linked habitat system; (b) a Parks and Reserves system; (c) an enjoyable landscape units system; (d) a multipurpose ecosystemic scenario based on the realization of an integrated system of areas where it is possible to promote sustainable socio-economic development processes. It is convenient to consider that the four above-listed approaches do not exclude, but rather complement and interpenetrate each other because they correspond to complementary targets of land management.

Even though all the concepts mentioned earlier are in some way related to biodiversity conservation, the best definition of an E.N. that explicitly relates to conservation on a landscape scale states that E.N.s are "systems of nature reserves and their interconnections that make a fragmented natural system coherent, so as to support more biological diversity than in its non connected form" (Jongman *et al*., 2004). These systems are composed of "core areas, (usually protected by) buffer zones and (connected through) ecological corridors" (Bischoff and Jongman, 1993; Jongman *et al.*, 2004). We focused on this type of E.N., which is one of the potential applications of the structural perspective offered by landscape ecology (Noss and Harris, 1986), but excluded consideration of large-scale continental "green backbones" and small-scale corridors.

These three essential elements (core areas, buffers, and corridors) may sometimes be associated with "restoration areas" for the recovery of damaged elements of ecosystems, habitats, and landscapes (Cook and van Lier, 1994) and with "sustainable-use areas where sufficient opportunities are provided within the landscape matrix for both exploitation of natural resources and the maintenance of ecosystem functions" (Bennett and Witt, 2001; Bennett, 2004). Although there are many variations in the definition of E.N.s, the most common goal of an E.N. is "to maintain the biological and landscape diversity of a region".

An E.N. is meant to ensure biodiversity conservation by protecting areas of assumed or known high species richness (core areas) and connecting them through corridors that should enable species to move across unsuitable areas.

The logical flow of justifications is as follows (Bennett, 1998): (1) land-use patterns have increased landscape fragmentation; (2) connections among fragments and the resulting exchange of individuals, genes, nutrients, and ecosystem processes are important for species to survive and ecosystem processes to remain functional; and (3) landscape linkages are needed to restore connectivity and ensure long-term survival of species and functionality of the ecosystem processes.

The theoretical background for these justifications for E.N.s is in the theory of island biogeography (MacArthur and Wilson, 1967), in metapopulation theory with its paradigm of source-sink dynamics (Hanski, 1999), and in the broader perspective of landscape ecology (Turner, 1989; Turner, 2005; Turner *et al*., 2001). It is also supported by the undisputable evidence that habitat fragmentation is among the primary threats to species survival (Wilcove *et al*., 1998; but see Fahrig, 2003 for further research).

2 Study Areas and Materials

2.1 Study Area “A”: Baganza Valley (Parma)

The Baganza River Valley is situated on the Emilian side of the Northern Apennines, between the River Parma Valley to the east and the River Taro Valley to the west. From an administrative point of view, the valley is under the Province of Parma in the Emilia-Romagna region. It covers an area of about 17500 hectares (ha) with a difference in altitude of over 1400 m - rising from 57 m above sea level (a.s.l.) up to 1493 m a.s.l. (Mount Cervellino). The basin, oriented in the South West – North East direction, is very long in shape. The main mountain reliefs are placed along the spur beginning from Mount Borgognone, marking off the Baganza Valley from the Parma Valley.

The study area is included between the Municipalities of Langhirano (4.08%), Sala Baganza (8.26%) Terenzo (8.72%), Corniglio (8.72%), Felino (9.96%), Berceto (25.18%), Calestano (32.58%), Collecchio (0.84%) and Parma (1.60%), and the boundaries are marked by an administrative boundary Map (Fig. 2-1).

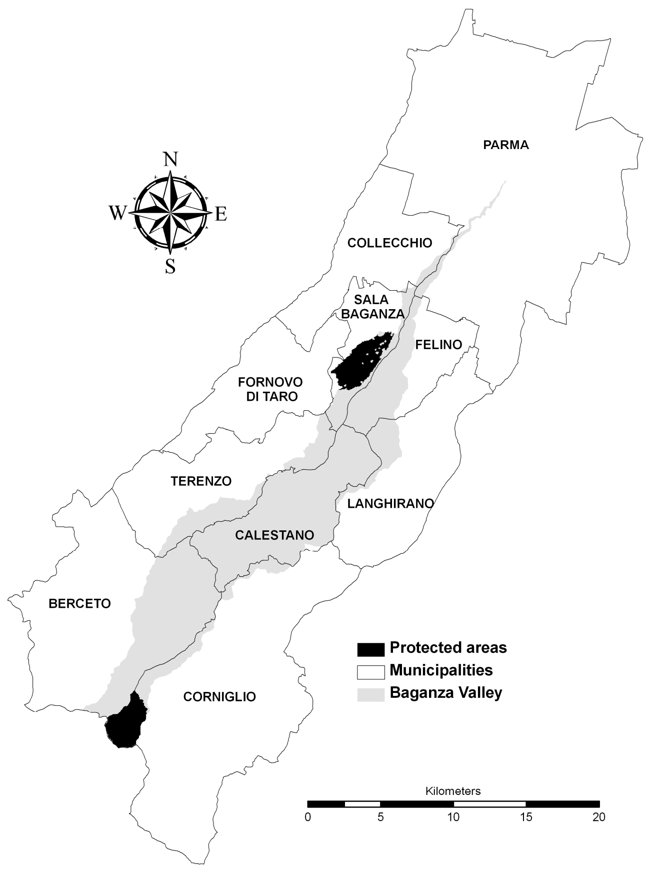


Figure 2-1 Geographical and administrative location of the Baganza Valley. The protected areas are highlighted.

Two protected areas are present in the valley, for a total 1411.30 ha, equal to about 8% of the area: the Crinale Park (average altitude 1164.4 m a.s.l.) and Carrega Woods Regional Park (average altitude 286.6 m a.s.l.), which are about 25 km apart with a medium altimetric drop of about 878 m.

A wide series of data and information has been used in order to plan the Baganza Valley E.N. This information first refers to the Map of Italian Nature Project database, particularly to the habitat cartography. The habitats are classified according to the CORINE Biotopes (C.B.) methodology (C.E.C., 1991) at the scale 1:25000 (Figure 2-2).

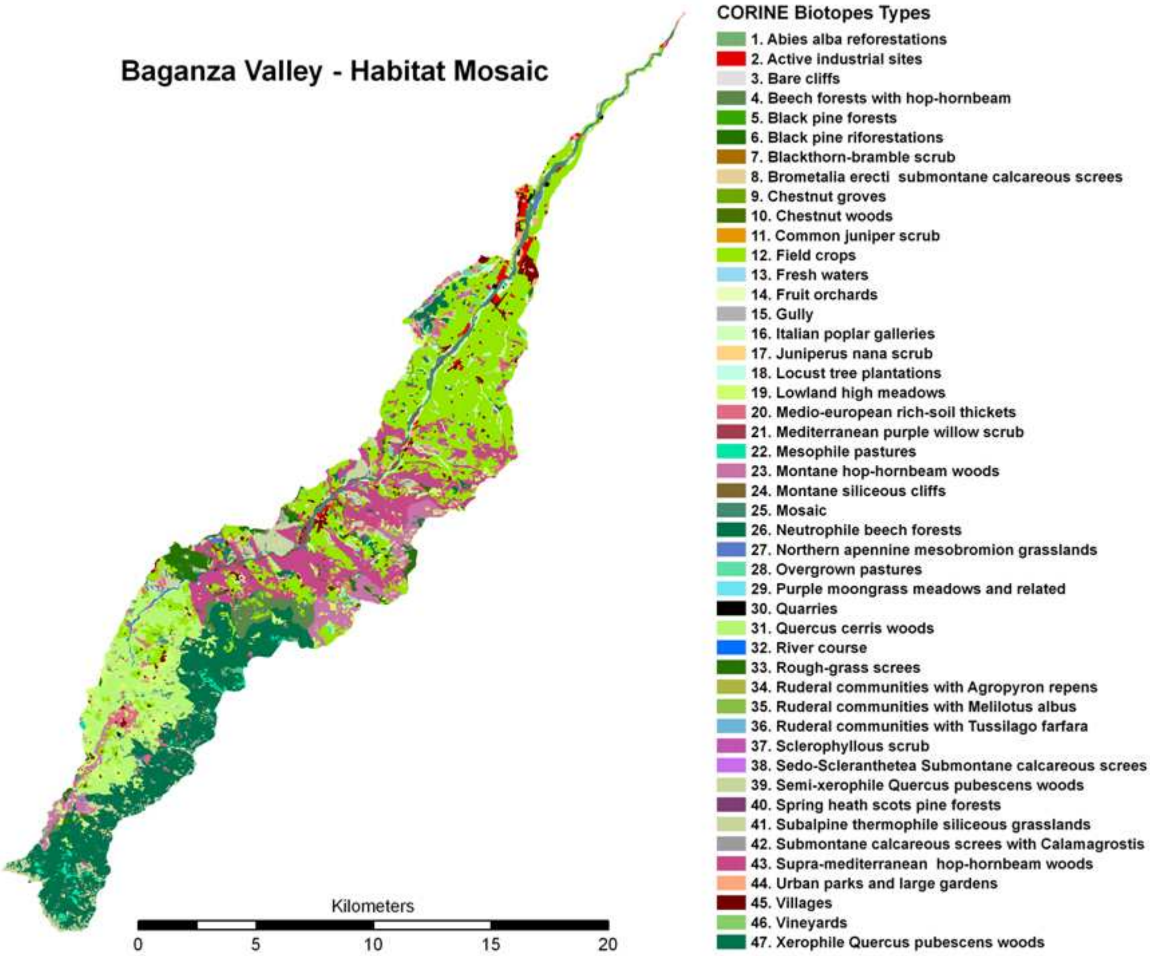


Figure 2-2 Spatial distribution of the 47 types of CORINE Biotope habitats within the study area "A".

The environmental units identified in the Valley belong to 47 different types (codes) of C.B. habitats, including natural, semi-natural and anthropized (i.e. towns, industrial sites and caves) zones (Fig. 2-2). The total amount of habitat is 2387 (where 2189 are natural/semi-natural, and 198 are anthropized).

The statistical distribution of the different C.B. types is shown below (Figure 2-3):

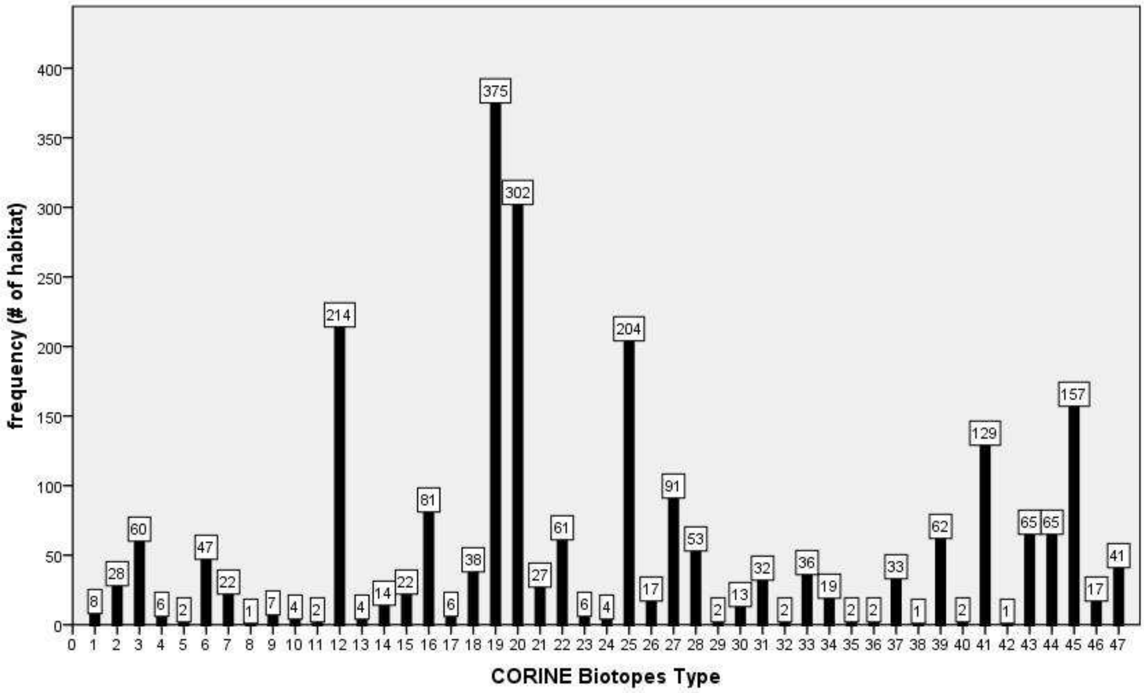


Figure 2-3 Histogram of frequencies of the 47 types of CORINE Biotope habitats within the study area “A”.

C.B. habitat types have been recognized (Rossi P., 1999; Rossi O., 2001) according to vegetation covers, physiognomy and abiotic factors. This habitat classification is hierarchically structured in categories identified by codes, comprising wide sintaxa at landscape level down to alliance and associations.

All this information, together with the Digital Elevation Model and the hydrographical stream network at the scale 1:50000, has been used to outline the ecological-naturalistic traits and structure of the area.

Recent official data concerning the Municipalities of the area and carried out by ISTAT, have been utilized in order to measure human pressure on the Valley.

Other materials used in the study include the Regional and National Park Map, the Natural Regional Reserve Map, the Map of the Sites of Community Importance for Nature Conservation, the Special Protection Area Map, the geographic range of distribution of the Italian Vertebrates, the Suitability Italian Vertebrate, the Digital Elevation Model (DEM) at scale 1:50000 and a Landsat 5 TM image dated 2003.

All the data and information concerning the study area belong to the Map of the Italian Nature Data Base.

2.2 Study Area "B": Oltrepò Pavese and Ligurian-Emilian Apennine

The study area covers 321 815 hectares in northern Italy, stretching over the Provinces of Parma (40% of the area), Piacenza (23.3%), Pavia (18.8%), Genoa (6.5%), La Spezia (6.2%), and Massa Carrara (5.2%). The territory is characterized by elevated morphologic and vegetation diversity, correlated with its heterogeneous lithological composition, the vastness of the area and the wide range in height. Parks and Reserves included in the study area are the Regional Park of Aveto, the Regional Park of the Parma and Cedra Valleys and the Natural Reserve of Prinzera Mountain (Figure 2-4)

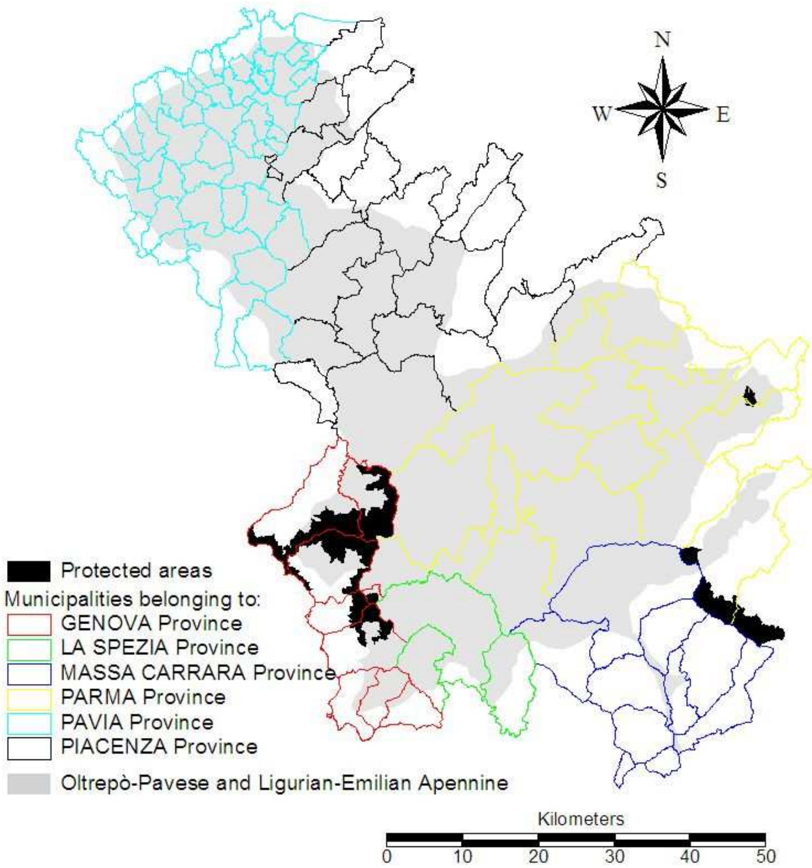


Figure 2-4 Geographical and administrative location of the study area "B". The protected areas are highlighted.

The area is included in the Map of the Italian Nature Project (Rossi *et al*., 1998) which aims at identifying, mapping and evaluating landscape units for biodiversity conservation and management. The basic maps produced are mosaics of different habitat types according to the CORINE Biotopes Project Habitat Classification (C.E.C., 1991). CORINE Biotopes (C.B.) habitat types are recognizable according to vegetation covers, physiognomy and

abiotic factors. This habitat classification is hierarchically structured in categories identified by codes, comprising wide sintaxa at landscape level down to alliances and associations.
The digital map of the study area is produced as GIS coverage in polygonal format of 34 different C.B. habitat types identified through satellite, airborne and terrain data at 1:50000 scale (Figure 2-5).

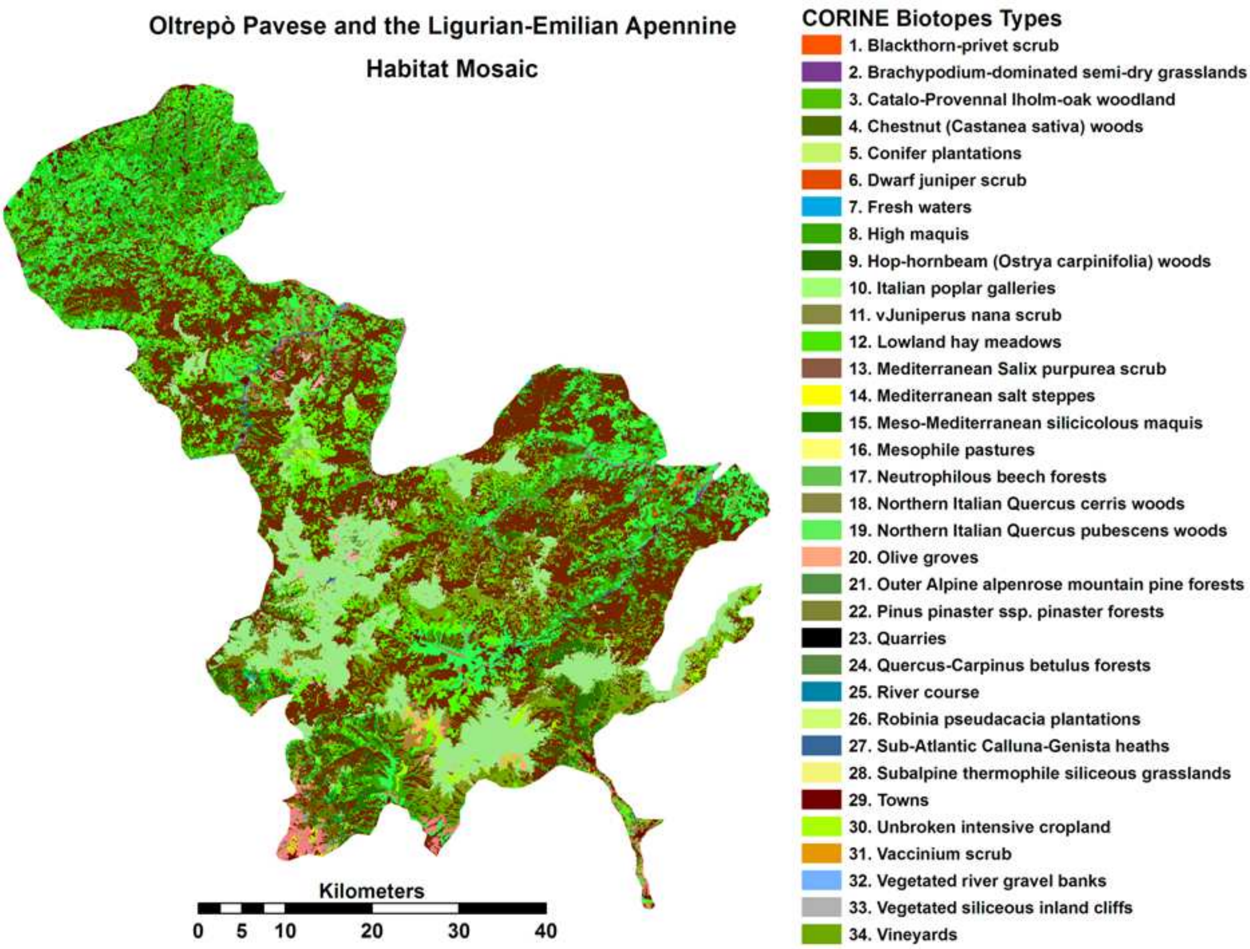


Figure 2-5 Spatial distribution of the 34 types of CORINE Biotope habitats within the study area “B”.

The resulting total number of C.B. habitats was 25318 (where 21010 are natural/semi-natural, and 4308 are anthropized) (Tomaselli, 2004).

The statistical distribution of the different C.B. types is shown below (Figure 2-6):

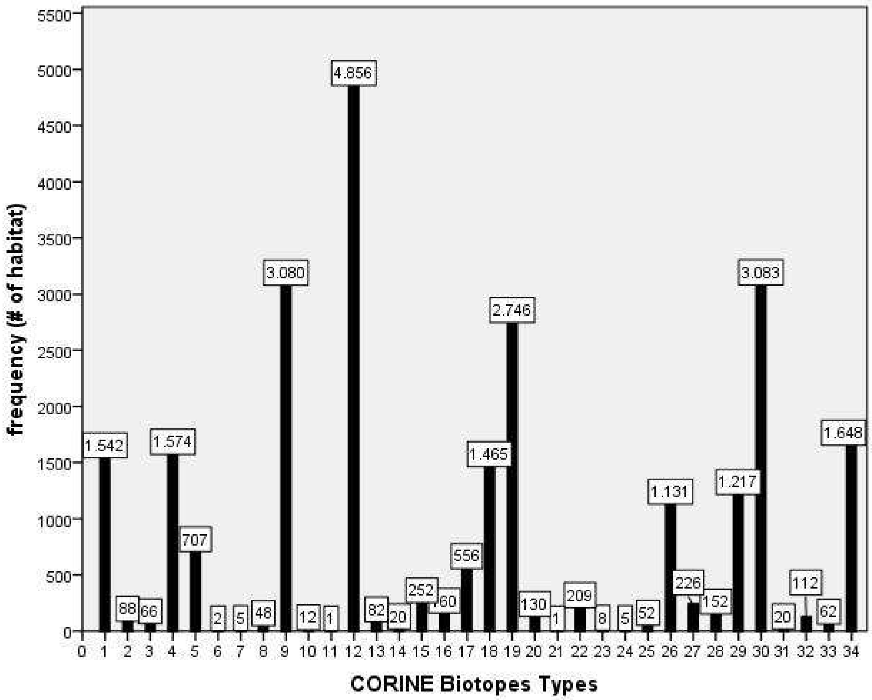


Figure 2-6 Histogram of frequencies of the 34 types of CORINE Biotope habitats within the study area “B”.

Quercus ilex woods and Mediterranean maquis prevail on the mountainside; they are replaced at higher altitudes by Quercus cerris and Quercus pubescens forests. In the remaining part of the study area, starting from 1000 -1100 meters and in correspondence of higher relieves, wide, densely wooded areas of Fagus sylvatica prevail, while Ostrya carpinifolia forests are to be found between 100 and 1000 meters, and Quercus pubescens communities on the southern slopes up to approximately 700 meters of altitude. Urban areas and industrial sites are concentrated in the lowland, and the landscape presents an agricultural character with cereal crops, vineyards and grasslands.

The study area includes 108 Communes whose boundaries are marked by an administrative boundary Map. The demographic data of the 108 Communes derives from the Italian Institute of Statistics (ISTAT).

Other materials used in the study were provided by the Italian Ministry of the Environment. These data include the Map of Regional and National Parks, the Map of Natural Regional Reserves, the Map of the Sites of Communitarian importance for Nature Conservation, the map of Special Protection Zones, the Map of Ramsar Zones, the geographic range of distribution of Italian Vertebrates, the Suitability Map of Italian Vertebrates, the Digital Elevation Model (DEM) at scale 1:50000 and a Landsat 5 TM image dated 2003.

All the data and information concerning the study area belong to the Map of the Italian Nature Data Base.

2.3 The Ecological Indicators

Ecological Value and Ecological Sensitivity are concepts of relevant importance in environmental analysis, because both play an essential role in spotting critical zones in a given study area.

From a methodological point of view, both EV and ES are multidimensional and their quantitative evaluation is “difficult” because requests the use of a certain number (i.e. a set) of suitable environmental indicators.

2.3.1 Ecological Value indicators

As regards Ecological Value, 9 different indicators are listed in Table 2-1 (from 1.1 to 1.9) and grouped according to 5 different criteria.

CRITERIA	INDICATORS
BIODIVERSITY	1.1 Size
	1.2 Vertebrate Species richness
	1.3 Soil roughness
RARITY	1.4 Habitat rarity within the area
	1.5 Presence of rare vertebrates
PROTECTIVE ASPECTS	1.6 Suitability for vertebrates at risk (IUCN)
HUMAN BENEFITS	1.7 Percentage of surface included in Protected Areas
	1.8 Normalized Difference Vegetation Index (NDVI)
INSTITUTIONAL ASPECTS	1.9 Involvement in conservation areas (SAC, SPA, Ramsar)

Table 2-1 Criteria and corresponding indicators for the comparative evaluation of the overall Ecological Value of CORINE Biotopes habitats.

Biodiversity concerns biotic and abiotic features which characterize a given C.B. habitat and are correlated with biodiversity. It includes habitat size (Lee *et al.*, 2001; Margules and Usher, 1981; Rosenzweig, 1995), species richness (Eiswerth *et al.*, 2001; Smith and Theberge, 1986; Van der Ploeg and Wlijim, 1978) and terrain complexity (Pressey *et al.*, 2000; Roy *et al.*, 2000).

The indicator of species richness (1.2) is expressed as number (or alternatively and in a better way as density dividing the amount of present species in a habitat divided by its surface expressed in hectares) of Italian vertebrates whose distribution ranges overlap a given C.B. habitat. The geographical ranges are free by the REN-GISBAU project (Boitani *et al*. 2002) and refer to a total of 422 Italian vertebrate species present in the study area. Each habitat which is included by at least 50% of its area in the vertebrate range is graded with 1, otherwise with 0.

Terrain complexity (1.3) is expressed as soil roughness. The irregular topography of a given habitat has been computed using a 1:50000 Digital Elevation Model (DEM) in grid format and quantitatively assessed as Coefficient of Variation (CV) of the altitude:

$$CV = \frac{\text{altitude(std.dev.)}}{\text{altitude(mean)}} \times 100 \qquad (10)$$

The numerator is the standard deviation and the denominator is the mean altitude of the C.B. habitat.

Rarity criterion includes both habitat and vertebrate rarity indicators, assigning a score to each degree of rarity (Csuti *et al*., 1997; Gaston, 1994).

The presence of rare habitats or rare species in a given area sets ecological value to the same area (Gaston, 1994).

Concerning the habitat rarity indicator (1.4) at the scale of the study area, habitat types which cover less than 1% of the study area are defined as very rare C.B. (they have score 2), they are rare if between 1% and 5% (score 1), common if above 5% (score 0).

Rarity of vertebrate species (1.5) within the C.B. habitat mosaic is related to the extent of vertebrate range in the study area. Species which have a limited distribution, i.e. below 1% within the study area are considered very rare, thus C.B. habitats involved in their spatial distribution are graded 2. Species that inhabit areas between 1% and 5% of the study area are considered rare, and the C.B. habitats included score 1. Finally, species that occur over an area wider than 5% are common and their corresponding habitats are graded 0.

Protective criterion describes (Table 2-1) the protective aptitude of habitats towards some species of relevant ecological attention.

Habitat suitability indicator (1.6) with respect to vertebrates (or alternatively of all existing vertebrate species) included in the IUCN Red List categories evaluates the relative importance of a C.B. habitat depending on its inclusion in or exclusion from areas suitable for the normal needs or survival of critical, endangered or vulnerable species. The used data set of Habitat Suitability Models are produced and diffused by REN-GISBAU project

(Boitani *et al*. 2002). Habitat suitability maps, produced in raster format at 300x300 meter resolution, summarize vertebrates' environment relationships for each species with different suitability classes, comprising unsuitable, not very suitable, fairly suitable and very suitable environments. Grade 0 is assigned to a habitat placed in either unsuitable areas or outside the vertebrate suitability map, while habitats overlapping not very suitable, fairly suitable and very suitable environments are graded 1, 2, and 3 respectively. A C.B. habitat that falls within different suitable areas for a given vertebrate has the score of the widest suitability category with respect to the habitat area as a whole.

Human benefits are concerned with the use of the C.B. habitats by humans (de Groot *et al*., 2004). Recreational-educational indicator (1.7) is focused on the use of Protected Areas for public education and green tourism and is quantitatively assessed as percentage of C.B. habitat included in the Protected Areas (Parks, Reserves).

Primary productivity of habitat (1.8) provides information on the energetic basis for the food web on the land and is measured by the Normalized Difference Vegetation Index (NDVI) of natural and semi-natural habitats (Rouse *et al*., 1973). NDVI is calculated through Landsat TM satellite image dated 2003 and available in the Map of the Italian Nature Project. For each C.B. habitat, NDVI is derived by averaging the NDVI values of pixels overlapping the C.B. habitat.

Indicator 1.9 has legal-institutional significance and is related to the implementation of the EU Habitat Directive (92/43/EEC), the EU Birds Directive (49/409/EEC), and the Ramsar Convention on Wetlands (1971). The degree of ecological value given to a C.B. habitat can be evaluated according to its inclusion in or exclusion from the so called Conservation Zones: Special Areas of Conservation (SACs) (formerly defined Sites of Community importance (SCIs)), Special Protection Areas (SPAs), and Ramsar Sites. Indicator 1.9 ranks the habitat by taking into account whether it occurs or not in the SIC, ZPS and Ramsar Zones. A habitat is graded 0 if it is placed outside the boundaries of the Conservation Zones, and 1, 2, 3 depending on the number of different Conservation Zones in which it is included. Alternatively, this indicator can be estimated as C.B. habitat area percentage included in SACs, SPAs and Ramsar Sites.

In both cases, the value is not influenced by the possible inclusion in more than one zone belonging to the same type of Conservation zones (i.e. if a habitat belongs to two SPAs, its final score will be 1, not 2).

2.3.2 Ecological Sensitivity indicators

Habitat ecological sensitivity is defined as habitat proneness to environmental change involving a combination of intrinsic and extrinsic factors (Nilsson and Grelsson, 1995; Ratcliffe, 1977). In order to effectively develop this multidimensional concept a set of 9 indicators (Rossi, 2005) has been used (Table 2-2). All these indicators are correlated with the risk of a habitat of being damaged or losing its ecological identity/integrity.

Ecological Sensitivity indicators from 2.1 to 2.9 are grouped into 4 different criteria (Table 2-2).

CRITERIA	INDICATORS
STRUCTURAL ASPECTS	2.1 Fractal Coefficient of perimeter
	2.2 Circularity Ratio of area
	2.3 Average slope
COMPOSITIONAL ASPECTS	2.4 Presence of vertebrate species at risk (IUCN)
	2.5 Presence of vegetal species at risk (IUCN)
ABIOTIC RISKS	2.6 Landslide Index
	2.7 Fire Potential Index (FPI)
	2.8 Orientation compared to the main wind direction
ISOLATION	2.9 Nearest Neighbour Index

Table 2-2 Criteria and corresponding indicators for the comparative evaluation of the overall ecological sensitivity of CORINE Biotopes habitats.

Risks deriving from structural factors comprises habitat features such as perimeter convolution (2.1), shape compactness (2.2), terrain slope (2.3).

Regarding the perimeter convolution, literature suggests that ecosystems receiving several kinds of inputs from many directions are the ones more likely to be at risk of losing their identity (Ratcliffe, 1977). Uneven boundaries encourage interactions with many and different external factors (environments), thus they can influence habitat sensitivity. The indicator used is represented by Fractal Coefficient of habitat perimeter ranging between 1 and 2 (Forman, 1995):

$$\mathrm{FC} = 2 \times \frac{\ln(\mathrm{Perimeter})}{\ln(\mathrm{Area})} \qquad (11)$$

All other things being equal, the more irregular the perimeter of a C.B. habitat, the greater it’s opening to the dynamic external forces which press on its identity and/or its integrity (FC close to 2).

Like perimeter convolution, shape compactness (2.2) of a habitat is a structural characteristic which has ecological involvements (Forman, 1995). Indeed, compact shapes are functional to maintaining habitat resources because they minimize perimeter exposure and contact with surrounding environment. Habitat compactness has been quantified by Circularity Ratio Index (CR) as follows:

$$CR = \frac{\text{Area}}{\text{Area}_c} \qquad (12)$$

where Area is the habitat area and Area_c is the area of the minimum circle comprising the habitat.

All other things being equal, a value close to 1 implies great power to preserve the internal abiotic and biotic resources; a value close to 0 (zero) describes the opposite situation.

Terrain slope (2.3) affects soil quality and depth implying a change in habitat integrity. The indicator has been derived from DEM (150x150 m^2 cell resolution) and quantitatively assessed as the average percentage of slope of the pixels overlapping the C.B. habitat.

Risks from biotic factors include 2 indicators concerning the presence of species of vertebrates and plants at risk of extinction within a C.B. habitat (Ratcliffe, 1977; Smith and Theberge, 1986).

The presence of species of vertebrates listed on the 2000 IUCN Red List is quantified (2.4) as number (or alternatively and in a better way as density) of distribution ranges that extend over a CORINE habitat for not less than 50%.

The occurrence of plants classified by reference to the IUCN Red data Book is calculated by summing the number of plants (or alternatively and in a better way as density) at risk placed in a CORINE habitat (2.5).

Important Abiotic risks which can involve C.B. habitats are risk of landslide (Restrepo *et al*., 2001), risk of fire (Vila *et al*., 2001) and wind impact (Visser *et al*., 2004).

Landslide risk of a CORINE habitat can imply a change in species abundances and in species composition. This risk (2.6) has been computed according to the Ambalagan method (Ambalagan, 1992), by which a score has been assigned to each habitat, accounting for the type of soil, the land cover category and the slope level. The information was derived from a 1:250000 lithological map, the CORINE habitat map and DEM respectively. The indicator assumes continuous values ranging from 0 to infinity.

The risk of fire (2.7) is not the same for all habitats, but some factors make them more susceptible to this risk. Fire exposes a habitat to a chance of loss or damage of its ecological integrity, therefore it is closely connected to ecological sensitivity. The risk of fire indicator is computed using Fire Potential Index (FPI) (Burgan, 1988), which is calculated as:

$$FPI = (1 - GVI) \times (1 - WI) \qquad (13)$$

GVI, i.e. Greenness Index (Crist and Cicone, 1984), is a function of vegetation vigor and biomass, and it measures processes such as primary production, while WI represents Wetness Index (Crist and Cicone, 1984), which is related to vegetation moisture. FPI has been derived from Landsat TM remote sensing image dated 2003 and refers to a 30x30 m^2 pixel. This indicator is expressed as an integer value ranging from 0 to 255.

Wind impact upon habitat is measured (2.8) as a floating value ranging from 0 to 1, where 0 represents the orthogonality between the prevailing wind and the habitat orientation, and 1 represents the parallelism between the prevailing wind and the habitat orientation involved. Wind carries parallel accelerated soil erosion, damage to vegetation, and changes in biological communities, and affects more habitats which are oriented parallel to prevailing wind.

Habitat isolation risk is represented by nearest neighbor distance (2.9) from one patch to another of the same CORINE type. The Nearest Neighbor Index (NNI) indicator provides an estimate of the connectivity inherent in the landscape and measures the degree of spatial dispersion in the distribution based on the minimum of the inter-feature distances (Forman and Godron, 1986; Taylor *et al.*, 1993).

All the indicators are calculated for each habitat by means of Remote Sensing and GIS technologies using ESRI's ArcView GIS software and ENVI software.

2.4 Demographical indicators

All the Communes of the area were submitted to a Demographic Analysis using six main indicators derived from the official ISTAT data. The official data utilized in the analysis were provided by ISTAT and refer respectively to 2005 (for Study area “B”) and 2008 (for Study area “A”).

The Demographic Analysis is a useful instrument to reveal both the current and, especially, the trends of the short and middle term Anthropic Pressure. The demographic indicators referring to each Commune and suggested by ISTAT are the following:

1. Population density: number of residents per hectare of Commune territory;
2. Mean age;

3. Ageing rate expressed by the formula:

$$\frac{\text{Residents} \geq 65}{\text{Residents} \leq 14} \times 100 \qquad (14)$$

i.e. percentage ratio between Resident population aged 65 and over, and Resident population aged 0-14;

4. Dependency Ratio expressed by the formula:

$$\frac{(\text{Residents aged} \leq 14) + (\text{Residents aged} \geq 65)}{15 \leq \text{Residents aged} \leq 64} \times 100 \qquad (15)$$

i..e. percentage ratio between Resident population aged 0-14 plus resident population aged 65 and over, and Resident population aged 15-64;

5. Population Rate Of Natural Increase expressed with the formula:

$$\frac{(\text{Resident live births}) - (\text{Residents deaths})}{\text{Average resident population}} \times 1000 \qquad (16)$$

i.e. per thousand ratio between Residents' live births minus residents' deaths and the Average resident population;

6. Net Migration Rate expressed by the formula:

$$\frac{(\text{Foreigners registered}) - (\text{Foreigners cancelled})}{\text{Average resident population}} \times 1000 \qquad (17)$$

i.e. per thousand ratio between the Foreigners coming from abroad registered in the population register minus Foreigners cancelled from the population register because of moving abroad, and the Average resident population.

3 Methods

3.1 Ranking and Prioritization Methods utilized

In the study areas, accordingly to biodiversity protection and conservation aim, two types of objects, referred to two different levels of analysis (ecological-naturalistic and administrative) has been investigated. Ecological partitions (i.e. habitats), described by 9 indicators concerning Ecological Value and 9 indicators concerning Ecological Sensitivity, and administrative partitions (i.e. Communes or Municipalities) described by a further set of 6 demographical indicators.

According to these indicators, and to the level of the analysis, different types of ranking methods have been tested.

3.1.1 Ideal Vector Distance

For both Ecological Value (EV) and Ecological Sensitivity (ES) indicators, there is a level that can be said to have the best environmental condition for that particular indicator in that particular study area. This level is the ideal score for that indicator. This way of proceeding is a typical application of total ranking theory: the absolute reference method.

Each C.B. habitat of the study area is described by a vector of 9 elements (indicators) for its overall ecological value and 9 elements (indicators) for its overall ecological sensitivity.

All these indicators are expressed on different scales; before using them together in a classification or ordination procedure they must be brought to the same common scale. Of the methods which allow simultaneous adjustment of the magnitude and the variability of the different indicators we used the method of ranging proposed by Sneath and Sokal (1973) and recommended by Milligan and Cooper (1988) and Legendre and Legendre (1998):

$$y_i^{'} = \frac{(y_i - y_{min})}{(y_{max} - y_{min})} \qquad (18)$$

where y_i is the current value of the C.B. habitat, y_{min} is the minimum value among the y_i, y_{max} is the maximum value, and $y_i^{'}$ is the transformed value.

This transformation reduces the value of each indicator to the close interval 0-1.

The ordination procedure of all the C.B. habitats in terms of overall ecological value (or overall ecological sensitivity) is based on the Ideal Vector Method (Rossi P. *et al.*, 2008).

The vector whose elements (indicators) represent the best performances in the area is called Ideal Vector. Regarding ecological value, each element of the ideal vector is given the maximum observed value for that environmental indicator; after the transformation, that element is represented by the value 1.

Regarding ecological sensitivity, we have the opposite. The elements of the ideal vector, after the transformation, become equal to 0 (zero) (minimum value of sensitivity).

Consequently, the multidimensional Euclidean distance of a given C.B. habitat (represented by its specific vector) from the Ideal Vector is a measurement of its overall ecological value or its overall ecological sensitivity. In formal terms:

$$\mathrm{Dist}_k = \sqrt{[\sum_{i=1}^{n} (y'_{i,k} - \mathrm{VETT}_{ID})^2]} \qquad (19)$$

Dist_k refers to the C.B. units k, n is the number of indicators utilized, and VETT_{ID} represents the Ideal Vector.

Clearly, the smaller the distance from the Ideal Vector, the higher the overall ecological value; for the ecological sensitivity we have the opposite.

Even if this method has been developed specifically for ecological aspects of the habitat, it can be, without particular difficulties, also for Human Pressure concept.

Similarly to Ecological Value and Ecological Sensitivity indicators, for each Demographical indicator referred to a single different Commune (i.e. administrative partition of the territory), there is a level that can be said to have the best (or similarly the worst) spin-off on habitat condition. This level is the ideal score for that indicator. The vector whose elements (indicators) represent the best performances in the area can be called Ideal Vector of Human Pressure.

The analysis of these demographical indicators will be shown in a dedicated paragraph because their singular contribute of each of them to the overall Human Pressure is not so evident as for Ecological Value and Ecological Sensitivity indicators.

3.1.2 Hasse Diagram Theory (HDT): Basic concepts, Linear Extensions and Posets Linearization

Basic concepts

At the basis of the Hasse diagram technique (HDT) is the assumption that we can perform a ranking while avoiding the use of an ordering index. Hasse diagrams not only present information on the ranking but, most important, also show whether the criteria, characterizing the objects, lead to ambiguities in the ranking. For example, an object might be ranked higher according to one criterion but lower according to another. These two objects are not ordered because their data are “contradictory”. This ambiguity is hidden when we use an index for ranking.

The Hasse diagram technique is a partial order ranking technique (Brüggemann and Patil, 2010) introduced in environmental sciences by Halfon (Halfon and Reggiani, 1986) and refined by Brüggemann (Brüggemann and Bartel, 1999c; Brüggemann and Carlsen, 2006). It is based on a specific order relation, named product order, and it provides a diagram, which visualises the results of the sorting. To implement Hasse Diagram Technique ca be used WHASSE (Brüggemann *et al.*, 1999) and PhyHasse software (Brüggemann *et al*., 2008).

Some facts must be briefly repeated to introduce in Hasse Diagram Theory in order to understand how an Hasse Diagram is built and how extract from this type of visualization useful information among the data set.

In this approach the basis for ranking is the information collected in the full set of criteria. With the term criteria are included both quantitative and qualitative properties. An attribute is a numerical quantity logically related to a criterion. We denote these attributes as q_1, q_2, ..., q_n. It is convenient to denote the full attribute set as A. Each subset of attributes A is denoted by A_i, and is used to perform a sensitivity analysis (see later).

The concept “tuple” generalizes from the following: pair of data, triple of data. We avoid the concept “vector”, because the properties of a linear space are not needed.

Data are the numerical values corresponding to each criterion by which a given object is characterized. An object is the item of interest. Each object, x, is characterized by a tuple of data ($q(x) = (q_1(x), q_2(x),..., q_n(x))$). The set of m objects is called E. We also write the following: an object x is an element of a set. Hasse diagrams are used to rank graphically these objects, applying a partial order relation (see paragraph 1.5.2.3) which is called the “information basis” of the comparative evaluation of elements.

Hasse Diagram visualizes the results of the partial order ranking and is constructed as follows:

1. each element is represented by a small circle;
2. within each circle the element name, or the equivalence class, is given. Equivalent elements are different elements that have the same numerical values with respect to a given set of attributes. The equality according to a set of attributes defines an equivalence relation;
3. cover-relation is a situation that comes true if there is no element “a” of E, for which $s \leq a \leq t$, then s is covered by t, and t covers s. If an order or cover relation exists then a line between the corresponding pairs of elements is drawn, the elements belonging to an order relation are "comparable". In other words, a line in the Hasse Diagram indicates that the two objects connected by that line are “comparable” with each other;
4. being s and t two objects belonging to E, if $s \leq t$ then s is drawn below t, therefore the diagram has orientation, consequently a sequence of lines can only be read in one direction either upwards or downwards. Hasse diagrams are oriented acyclic graphs (digraphs); instead of drawing arrows, indicating that object a is “greater” than object b, the object a is located above b in the plane;
5. if $s \leq t$ and $t \leq z$ then $s \leq z$ according to the transitivity rule; however a line between s and z is not drawn because this connection can be deduced from the lines between s and t and t and z. In other words, lines due to transitivity are omitted;
6. if either $s \leq t$ or $t \leq s$ then s and t are not connected by a line; thus they are called “incomparable”;
7. “incomparable” elements are located at the same geometrical height and as high as possible in the diagram, resulting in a structure of levels. Elements belonging to a given level are incomparable’. Note, however, that a location of elements at different levels does not imply comparability.

In the Hasse Diagram, the elements at the top of the diagram are called maximals and there are no elements above them; instead elements which have no elements below are called minimals and they do not cover any further element. If there is only one maximal/minimal element, then this is called greatest/least element.

Therefore, by this convention, the maximal elements are the most hazardous, and are selected to form the set of priority elements. Elements that are not comparable with any other element are called isolated elements, and can be seen as maximals and minimals at once: according to the caution principle they are located at the top of diagram within those elements that require priority attention. A chain is a set of comparable elements, therefore levels can be defined as the longest chain within the diagram. An antichain is a set of mutually incomparable elements. In finite data matrices, chains and antichains contain a finite number of objects. Therefore, we can speak of chains or antichains having a certain length, according to the number of elements they contain. We can find chains of maximal length, or antichains of maximal length. Within a partial order in general, there are several chains of maximal length and several antichains of maximal length. Height of the poset is the number of elements of the longest chain, while width of the poset is the number of elements of the maximum of antichains.

Incomparability is due to contradictory attributes: for each incomparable pair of elements there must be at least one pair of attributes of counteracting values. Such attributes are called antagonistic. The key diagram interpretation is provided by the meaning of chain and antichain. A chain indicates that the values of the attributes increase synchronously, whereas antichains correspond to diverse patterns. Thus if attributes describe the hazard caused by chemicals which are toxic to different species, then maximals are those elements of highest priority, the most toxic ones, whilst incomparability expresses a diverse pattern of toxicity e.g. toxicity to different species. In this case maximal elements are, in the same way, of priority attention, being toxic but in a different way.

Methods to Obtain Linear or Weak Order by Means of Partial Order

Obtaining linear orders that relates to the heart of prioritization and ranking (Patil and Taillie, 2004a): If we can obtain a linear order for all objects just from the data matrix, this will provide the stakeholder with an alternative ranking, and he may check the role of subjective preferences.

Thus partial order provides a method to obtain a linear order without the need of making additional assumptions like weights. The main computational problem, however, is the huge number of linear extensions which some times makes the calculation of the linear order difficult. Different procedures actually exist to rank objects.

First it is necessary to define what a level is. Levels are a means to derive from posets a weak order, because objects x can be ordered due to their level number lev(x). Let us introduce the equivalence relation

$\Re$: $x,y \in X$

$$x \,\Re\, y :\Leftrightarrow lev(x) = lev(y) \qquad (20)$$

Typically, the equivalence classes due to $\mathfrak{R}$ are large.

Therefore the disadvantage of ordering by lev is that there are many ties. The advantage however is its simplicity.

Cumulative rank frequency method.

A possible method is the follow and concerns with the concept of linear extension (Patil and Taillie, 2004a).

Each of the many possible ways of ranking the elements of a poset is referred to as a linear extension. A linear extension is a linear order, which preserves the order relations of a poset The Hasse diagram of each linear extension appears as a vertical graph (Figure 3-1). Enumeration of all possible linear extensions can be accomplished algorithmically as follows. The top element of a linear extension can be any one of the maximal elements of the Hasse diagram. Select any one of these maximal elements and remove it from the Hasse diagram. The second ranked element in the linear extension can be any maximal element from the reduced Hasse diagram. Select any of these and proceed iteratively. The procedure can be arranged as a decision tree (Figure 3-1) and each path through the tree from root node to leaf node determines one linear extension.

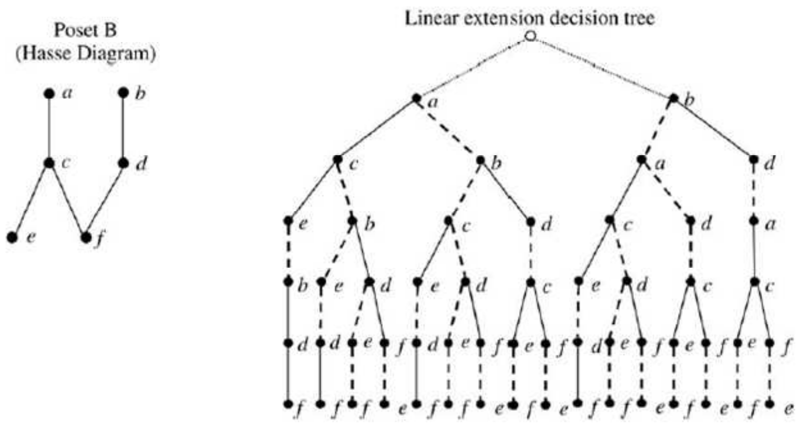


Figure 3-1 Hasse diagram of a hypothetical poset (left), some linear extensions of that poset (middle), and a decision tree enumerating all 16 possible linear extensions (right). Links shown in dashed/red (called jumps) are not implied by the partial order. The six members of the poset can be arranged in 6!=720 different ways, but only 16 of these orderings are valid linear extensions.

The suite of indicators determines only a partial order on the objects, but it is human nature to ask for a linear ordering of those hotspots. Is there some objective way of smoothing the partial order into a linear one? A clever solution treats each linear extension in Figure 3-1 as a voter and the principle of majority rule is applied. Focus attention on some member of the poset, say element a, and ask how many of the voters give *a* a rank of 1? Rank of 2? Rank of 3? Etc.

The results are displayed in Table 3-1 and Figure 3-2, where each row of the table is called a rank-frequency distribution. The cumulative forms of these rank-frequency distributions form a new poset with stochastic ordering of distributions as the order relation. For this example, the new poset is already a linear ordering (see Figure 3-2).

	Rank						
Element	1	2	3	4	5	6	Totals
a	9	5	2	0	0	0	16
b	7	5	3	1	0	0	16
c	0	4	6	6	0	0	16
d	0	2	4	6	4	0	16
e	0	0	1	3	6	6	16
f	0	0	0	0	6	10	16
Totals	16	16	16	16	16	16	

Table 3-1 Rank-frequency table for the poset of Figure 3-1. Each row gives the number of linear extensions that assign a given rank r to the corresponding member of the poset. Each row is referred to as a rank-frequency distribution.

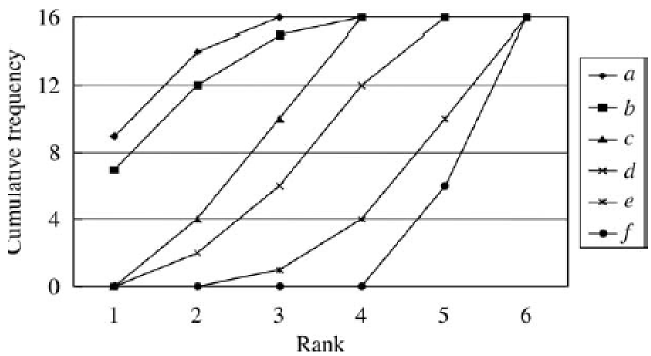


Figure 3-2 Cumulative rank-frequency distributions for the poset of Figure 3-1. The curves are stacked one above the other giving a linear ordering of the elements: a > b > c > d > e > f .

We refer to the above procedure as the cumulative rank-frequency (CRF) operator. In general, it does not transform a partial order into a linear order in a single step; instead, multiple iterations may be required (Figure 3-3).

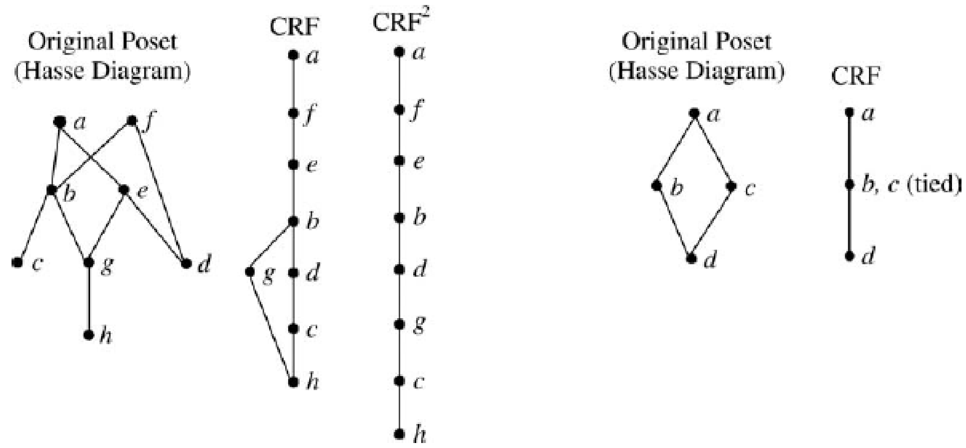


Figure 3-3 (Left) Two iterations of the CRF operator are required to transform this partial order into a linear order. (Right) A poset for which the CRF operator produces ties.

The CRF operator can also produce ties in the final linear ordering. When several objects have identical indicator values, they coincide in indicator space and are said to be tied. Note that the CRF operator can produce ties even if there are no ties according to the original suite of indicators.

The set of all linear extensions of a partially ordered set X, LE(X), allows the following applications:

1. Let x be an element of the partially ordered set X. Compare the number of linear extensions where x has a certain height, H (i.e. position) with the total number of linear extensions, LT. This may be interpreted as the probability for x to have height H. Varying H we obtain the height probability function of object x.
2. Let x ‖ y in X. The number of linear extensions in which x > y is #LE(x>y). The proportion #LE(x>y)/LT is called the mutual probability of x to have a higher height than y
3. By taking the average (or the median) of all heights of an object x over all linear extensions we obtain the “averaged height (rank)”, hav(x), by which for all objects a linear or weak order can be found. Also the symbol Rkav(x) for averaged rank is used in the literature. For the concept of averaged heights, see Winkler (1982).

Unfortunately, except for very small posets, it is computationally impossible to enumerate all the linear extensions because their number is too large.

As an alternative to full enumeration, Markov Chain Monte Carlo (MCMC) methods can be used to estimate the (row-normalized) rank-frequency table. This entails sampling from the uniform distribution on the set Ω of all linear extensions of a given poset. If $\omega \in \Omega$ is the current linear extension, the MCMC transition to the next (proposed) linear extension is accomplished by randomly selecting a jump (see Figure 3-1) from ω and interchanging its two endpoints. See Aldous (1987), Brightwell and Winkler (1991) and Haggstrom (2002) for further elaboration of MCMC methods applied to discrete data structures.

Local Partial Order Model (LPOM)

Let us select an object x. We investigate objects that have all attributes with smaller values. We are seeking those elements y of the partially ordered set, for which $y \leq x$ holds. In technical terms:

$O(x) := \{y \in X : y \leq x\}$ (21)

As O(x) depends on the element x, O(x) is called the principal down set, generated by x.

$y \in O(x)-\{x\}$ is a successor. (22a)

$S(x) := O(x)-\{x\}$ is the set of successors. (22b)

Similarly, it is of interest to select an element x and find elements y with $x \leq y$.

In technical terms: $F(x) := \{y \in X : y \geq x\}$ (23).

As F(x) depends on the element x, F(x) is called the principal up set, generated by x.

$y \in F(x) - \{x\}$ is a predecessor (24a)

$P(x) = F(x) - \{x)$ is the set of predecessors. (24b)

Finally, it is of interest to select two elements x and y , $x \leq y$, and to determine elements z with $x \leq z \leq y$. The set $I(x,y) := \{z: z \in X, x \leq z \leq y\}$ is called the interval of x and y.

Down sets, up sets and intervals are interesting, because they:

- provide order theoretical tools to get simpler Hasse diagrams (as mentioned above, we speak of “navigation through a Hasse diagram”);
- are needed for several counting tools.

$|O(x)|$, $|F(x)$, $|I(x,y)|$ can be easily determined by evaluating their definitions.

In Figure 3-4, the concepts of down sets and up sets are exemplified.

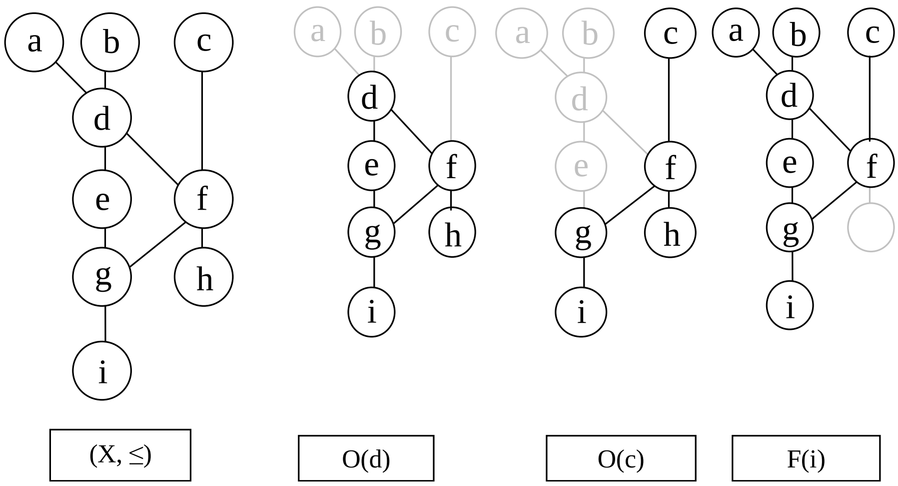


Figure 3-4 Two principal down sets and one principal up set, taken from the poset (X, ≤)

Let us now introduce the set U(x): $U(x) := \{y \in X, y||x \text{ in } (X,IB)\}$ (25)

The idea behind the "Local Partial Order Model" (LPOM) is to select an object x and to characterize its order theoretical environment (i.e. is to look at O(x), F(x) and U(x)). Because we focus on one single object, for which we want to estimate its averaged height, hav (sometimes also called Rkav) we call the method Local Partial Order Model. As we have to do with partial order, the environment cannot be understood only by considering the objects covering x and the objects covered by x, but also objects incomparable to x. The principal down set O(x), the principal up set F(x), and the set of incomparables U(x) need to be considered as determining quantities to estimate hav(x). For details of the method see Brüggemann and Patil (2010).

Sensitivity and Stability Analysis

The fundamental basis of our analysis is the data matrix: The attributes define its columns and the objects its rows. We pose three questions:

1. What role does any single attribute play? Can we for example save time and money, because some attribute has little discriminatory power?

2. What can be said about the attribute set? Is the attribute set complete? Should we delete any attribute? Should we add more attributes to the data matrix?

An analysis of the influence of each attribute on the ranking is called **Sensitivity Analysis (**Brüggemann and Patil, 2010).

The intention behind an attribute related sensitivity measure is not to contextually evaluate the attributes. Here it is of interest to examine as to how an attribute influences the position of objects in a Hasse diagram. We want to know the impact of the removal of a column from the data matrix. Hence we have to compare the partial order, induced by the original data matrix with that of the modified data matrix in order to find out the impact of the modification (i.e. the sensitivity to a Hasse diagram). We will measure the sensitivity by defining a suitable distance measure. Large impact of the removal of a column of the data matrix will need large distance between initial poset and modified poset. The distance will be conceptualized by counting the ordinal change (mismatch) between the pairs $(x,y) \in (X, IB)$ and $(x,y) \in (X, IB(i))$ with $IB(i) = IB - \{q_i\}$. There are several methods counting the pairwise mismatch, a) using down sets or up sets or b) using the ζ - matrix.

We focused on the first method.

We restrict our analysis to down sets, using up sets would follow the same logic.

There are two information bases, the original one, IB, and the modified one which is called IB(i). $IB(i) \subset IB$, hence any comparability of (X, IB) must be reproduced in (X, IB(i)). Therefore:

$(X, IB(i)) \supseteq (X, IB)$ and $O(x, IB(i)) \supseteq O(x, IB)$ (26)

To count the ordinal mismatch between the two down sets, we use the symmetric difference of sets Δ

($A \Delta B := (A \cup B) - (A \cap B)$, A, B being two arbitrary sets), count its content and call the result W(x, IB, IB(i)):

$W(x, IB, IB(i)) = |O(x, IB(i)) \Delta O(x, IB)|$ (27)

As the complete object set X is of interest, we sum up:

$W(X, IB, IB(i)) = \Sigma\ W(x, IB, IB(i))\ x \in X$ (28)

One can show that W(X, IB, IB(i)) is indeed a “distance” between both posets:

W(X, IB, IB) = W(X, IB(i), IB(i)) = 0, W(X, IB, IB(i)) = W(X, IB(i), IB) and the triangle inequality is fulfilled. Equation 4.2 can be simplified applying simple set-algebraic relations:

$W(x, IB, IB(i)) = |O(x, IB(i)| - |O(x, IB)| \geq 0$ (29)

Furthermore W(X, IB, IB(i)) can be normalized by the denominator n*(n-1)/2, n being the number of objects:

$\sigma(X, IB, IB(i)) = W(X, IB, IB(i))/(n*(n-1)/2)$ (30)

Generally $W(q_i)$ is used and we this quantity the sensitivity measure of the partial order to the attribute q_i deleted from the data matrix.

So, suppose to compare 3 different posets of the elements of a set X given by 3 different attributes (IB_1, IB_2 and IB_3) and suppose that the comparison of (X, IB) with (X, IB(1)), (X, IB(2)) and (X, IB(3)) gives the following values for $W(q_i)$:

W(X, IB, IB(1)) = 0, W(X, IB, IB(2)) = 3 and W(X, IB, IB(3)) = 1.

So we conclude that deletion of attribute q_2 has the most impact on the Hasse Diagram.

Now we want to measure the **Ordinal Stability** due to augmentation of the information base.

We define $U_X := \{(x,y)\ ,\ x,y \in X \text{ with } x \parallel y\}$ (31)

and $U_{X/\cong} := \{(x,y)\ ,\ x,y \in X/\cong \text{ with } x \parallel y\}$ (32)

They measure the ambiguity in ranking (Brüggemann and Patil, 2010). In order to obtain a measure in the scale [0,1] we normalize U_X by n*(n-1)/2 being the number of objects and $U_{X/\cong}$ by n_K*(n_K-1)/2, n_K being the number of elements in the quotient set. We call the normalized quantities P(IB) and take care whether the object – or the quotient set is of interest. If P(IB) is "near" 1 then addition of an attribute cannot change the partial order severely as in the exteme case of P(IB)=1 the poset (X, IB) is an antichain and (X, IB $\cup$ $\{q_{m+1}\}$) remains an antichain. In the case of P(IB) = 0 the poset (X, IB) is a chain and adding an attribute may lead to an antichain, which we consider as a strong change of the poset!

Therefore P(IB) is a measure of the ordinal stability of the poset due to augmentation of the information base.

Comparison of two partial orders as a multivariate problem (Proximity analysis)

Here we want to count what is different between any two pairs (x,y) obtained from the one and the other partial order. These counts we aim to visualize in a histogram-like diagram.

Proximity analysis furnishes detailed information about the matchings arising from two partial orders. A PyHasse software module (Brüggemann *et al*., 2008) is available.

Let us take two elements x, y of X then the following constellations appear while comparing two empirical posets. Counts of some matchings like (<, <) and (> , >) as well as (> , <) and (< , >) separately is not meaningful if we have a comparison in mind. Therefore instead of taking care for all 16 matchings we group them in "behaviour classes", B_1,..,B_5 as follows: (Figure 3-5) .

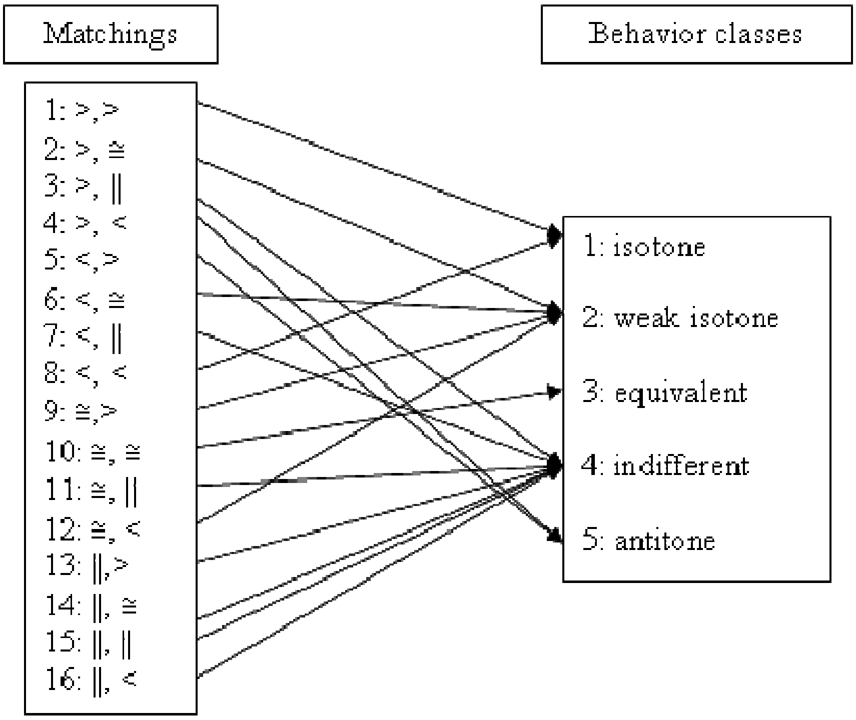


Figure 3-5 Assignment of matchings m_i to behaviour classes B_i.

In order to describe the behavior of two partial orders in a compact way we use the wording:

- isotone: matchings (<,<) and (>,>);
- antitone: the matchings (>,<) and (>,<);
- weak isotone: the following matchings:(< , ≅) , (>,≅), (≅ , <), (≅ , >);
- indifferent: all matchings where || is part of the pair;
- equivalent: matching (≅ , ≅).

It is convenient to present the comparison of two partial orders by a bar diagram of f(Bi). This multivariate consideration of the comparison of partial orders we call “proximity analysis”.

Antagonism and Separability Analysis

The concept of separability goes the other way round: Instead of trying to find separated subsets it is supposed that two candidate subsets are found and we want to assess their degree of separation.

A natural question is: How many and which attributes out of the total test-battery explain that separation? The interest is what properties of the data matrix is responsible for this separation.

Let us identify two disjoint subsets of $X/_{\cong}$: X_1 and X_2 . The possible number of relations (i.e. of < or ||-relations) $N(X_1,X_2)$ between X_1 and X_2 is:

$N(X_1,X_2) = |X_1|*|X_2|$. (33)

Let $x \in X_1$ and $y \in X_2$, then $x \parallel y$ or $x < y$ or $y < x$. We count the ||-relations:

$U(X_1,X_2) = \{(x,y): x \parallel y, x \in X_1, y \in X_2, X_1 \cap X_2 = \emptyset\}$ (34)

We define the separability, $Sep(X_1,X_2)$ as follows:

$Sep(X_1,X_2): = |U(X_1, X_2)| /N(X_1,X_2)$, $Sep(X_1,X_2) = Sep(X_2,X_1)$ (35)

Sometimes we write $Sep(X_1, X_2, IB)$ to specify the partial order.

The separability allows to characterize any disjoint pair of subsets X_i, $X_j \subset X$ and allows to find separated subsets without checking the Hasse diagram for articulation points (Figure 3-6).

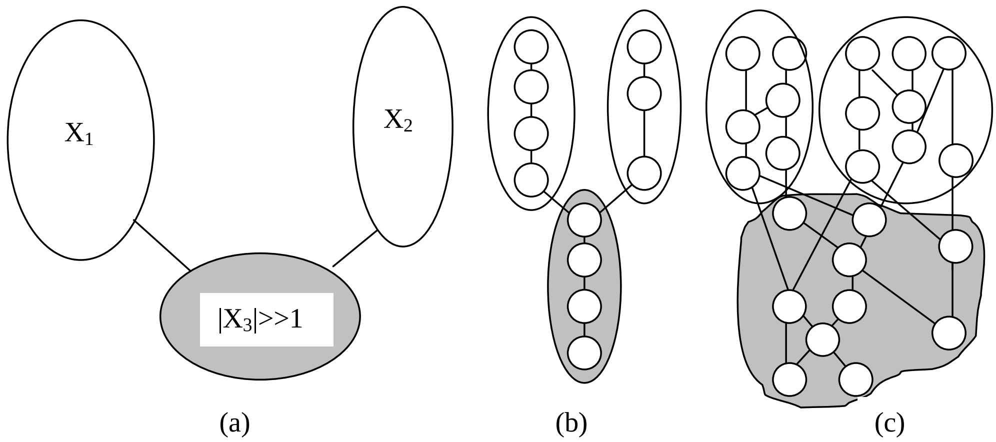


Figure 3-6 (a): Separated subsets in a schematic presentation of Hasse diagrams. (b) and (c): Examples for which the scheme (L.H.S.) may stand.

It should be possible to relate structural properties of the Hasse diagram, like the appearance of separated object subsets to properties related to the data matrix.

Let us consider $x, y \in X$ and $x \parallel y$. The singletons {x} and {y} are the simplest example of separated object subsets. In case of $x \parallel y$, there are two attributes q_i and q_j $i \neq j$ such that $q_i(x) < q_i(y)$ and $q_j(x) > q_j(y)$. We say: The separation of x and y is due to q_i and q_j.

Let us now consider two separated object subsets X_1 and X_2 with $|X_1|$ or $|X_2|>1$, then it may be possible that not just one pair of attributes breaks simultaneously all comparabilities among the (unordered) pairs of $X_1 \times X_2$. Hence **we have to search for the smallest subset of attributes which simultaneously breaks all comparabilities of (x,y) $\in$ $X_1 \times X_2$**:

If IB' exist such that $x \parallel_{IB'} y$ for all $x \in X_1$ and all $y \in X_2$ with $X_1, X_2 \subset X$ and $Sep(X_1, X_2) = 1$ and $IB' \neq \emptyset$, $IB' \subseteq IB$ then we call IB' the set of antagonistic attributes/indicators and abbreviate it by $AIB(X_1, X_2)$ (antagonistic information base) and we often write AIB if there is no confusion possible (Simon (2003), Simon and Brüggemann (2004a, b)). AIB contains those attributes which are causing the separation of subsets X_1 and X_2: while some attributes of AIB may have large values for objects of X_1 and small values for those of X_2, some other attributes have low values for objects of X_1 and large ones for X_2. The attributes of AIB separate X_1 and X_2 because they are "antagonistic".

The smallest possible AIB is a pair $\{q_i, q_j\}$ such that for all $x \in X_1$ and all $y \in X_2$ we obtain $x \parallel y$.

This is the most desirable result of antagonism study because then a reasonable graphical display by a two-dimensional scatter plot may be possible. We also write: the attributes of AIB "explain" the separation of X_1 and X_2. The search for AIB is a computational task. For example, analysis for antagonistic attributes WHASSE software (Brüggemann *et al*., 1999) and/or PhyHasse software (Brüggemann *et al*., 2008) can be used; for the procedure see Patil and Brüggemann (2010).

Two attributes are sufficient to explain the separation of two subsets. Suppose to have two subsets X_1 and X_2. We realize that $Sep(X_1, X_2) = 1$. Suppose that AIB contains only two attributes q_1 and q_3 among all attributes available, so we are able to construct a scatter plot (Figure 3-7):

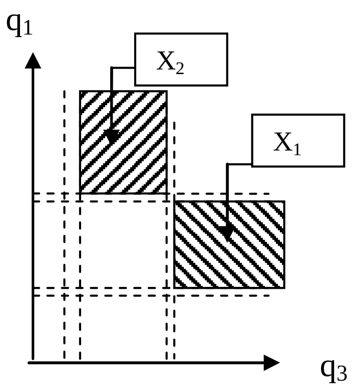


Figure 3-7 |AIB| = 2. A scatter plot of X_1 and X_2.

Figure 3-7 demonstrates the usefulness of the concept of antagonistic attributes: We see that q_1 has large values for X_2 and low values for X_1 whereas q_3 has low values for X_2 but large values for X_1, thus explaining the separation of the two subsets. It may however be possible that we need more than two attributes to explain the separation of object subsets.

3.1.3 Salience and Primacy

Patil and Taillie (2004a) consider partially ordered sets (posets) in environmental contexts from the perspective of political contention whereby there is need for inferential extension of the observed data on multiple indicators in order to obtain a single induced ordering that resolves contentious issues (e.g. Simon et al., 2004). There are, however, numerous environmental contexts in which incomplete orderings become directly useful from management perspectives without forcing a single induced ordering by inferential extension.

In particular, incomplete orderings can answer four important questions pertaining to conservation and potential for remediation:

1. the first question is which ones among a disparate population of n cases (landscape units) have consistency of expression (concordance) relative to a suite of p indicators. Subsets of the cases having consistent expression are subject to direct comparative ordering to address further questions;
2. how to sort out superior cases for priority attention in conservation and protection and/or to serve as reference standards for comparative assessment;
3. how can cases (landscape units) be recognized that are severely degraded in all relevant respects to the degree that preservation and protection concerns are effectively absent;
4. among the remaining cases that lack concordance in varying degree, are there cases of landscape units that could be elevated to superior status by remedial attention in some particular regard. These are the better cases for which there is consistency of expression among p-1 of the p indicators. The degree to which consistency is improved by deleting the most discordant indicator shows both the benefit that would accrue to targeted remediation and the level of effort that remediation would entail.

Our primary focus here is on these questions where partial or incomplete orderings are directly informative to conservation, remediation, or allocation issues of environmental management.

Conflicts in rankings can be viewed from two major perspectives.

One perspective is that any conflict of rankings makes the units intrinsically incomparable.

A second perspective attempts to resolve some of the conflicts on the basis of more liberal criteria.

Adopting the first perspective allows us to segregate subsets of landscape units (i.e. habitats) whereby there is intrinsic ordering between the subsets but not within a subset among its members. These subsets are partially ordered sets (posets) corresponding to the levels that would be depicted on Hasse diagrams (Neggers and Kim, 1998). If the positive direction for each indicator is better, then the primary (number 1) subset consists of units that are not dominated by any other unit. There is domination if some unit is equal to or better than another on all indicators. The secondary (number 2) subset is found by removing the primary subset and then finding the nondominated subset of the remaining units. The tertiary (number 3) and subsequent subsets are found by applying the process recursively.

Multiple units with identical values on all indicators are precluded if the subsets are to be posets in the mathematical sense because of the anti-symmetry condition (Patil and Tallie, 2004a). Anyway, for practical purposes, identical units can be re-introduced retrospectively by placing identically.

Partial progression pattern is a sequence of ordering relations that pertains to a subset of observational units on the basis of a (sub)set of indicators or statistically summarized indicators.

In particular, with multiple criteria, there are two complementary views of absolute precedence. One view is domination and the other is subordination. These complementary views are not equivalent in proclamations of precedence.

In the ***Domination perspective*** (Myers *et al*., 2006). on partial order one case can be said to dominate another if it is at least as good on all indicators, and better on at least one indicator. In other words, an observational unit can be said to dominate another if its values on all indicators are as good or better, with at least one being better. In this perspective, there is complete lack of evidence to refute at least some superiority for the dominating case.

Conversely, in the ***Subordination perspective*** (Myers *et al*., 2006). on partial order, one case is said to be subordinate to another if it is at least as poor on all indicators and poorer on at least one indicator. In other words, one unit is subordinate to another if its values on all indicators are less than or equal to those of the other, with at least one being less. In this perspective, there is complete lack of evidence to refute at least some inferiority for the subordinate case.

Determining domination is a recursive process which proceeds through a series of levels. The process begins with determining all of the cases that are not dominated by any other case, and assigning these to dominance level one. After excluding all of the level one cases, the process repeats to find those among the remaining cases that are not dominated and assigning them to level two. The process recycles with increasing level number until there are no dominations among the remainder. **Among the members of a particular level there is conflict (disagreement) among the indicators, thus effectively precluding comparisons within the level.**

Computing subordination is a similarly recursive process, but from a different perspective. The first pass finds cases that have no subordinates and designates them as level one. The second pass works with the remainder and finds cases having no subordinates if level one cases are excluded from consideration, with these being designated as level two. This continues until there are no subordinates among the remaining cases.

It is important to understand the implications of levels for precedence with respect to domination and subordination.

With regard to domination, there are no cases that are clearly better than those in level one. However, these cases are not necessarily uniformly good on all indicators. They can be superior on one indicator while being more or less mediocre on most indicators, as long as they are not particularly inferior on any indicator. As the level number gets larger, the best can get worse along with degradation on most. Thus, a larger level number for dominance is indicative of increasing consensus on overall inferiority, as more and more dominating cases have previously been removed from the pool.

In the progression for subordination, there are no cases that are subordinate to those in level one; so there are no cases that are clearly worse than those in level one, with these being worse than the remainder. As the level number for subordination increases, more clearly worse cases have been segregated as previous levels. Thus, a larger level number for subordination is indicative of increasing consensus on overall superiority. Domination status puts most dominant units at status 1, and increasing status implies greater consensus on inferiority.

In other words, in the successive subordination all units that have no subordinate units are designated as level 1 and removed, with the process then being iterated. In this case, the units having level 1 are not necessarily low on all indicators and increasing status scores (non-subordination level or NSL) imply greater consensus among the indicators on superiority. Members of the same status level have a sense of intrinsic incomparability. Subordination status puts the most subordinate units at status 1, and increasing status implies greater consensus on superiority.

Domination and subordination are complementary constructs, but do not generally give equivalent results in partial ordering. As a consequence, neither the domination view alone nor the subordination view alone gives sufficient discrimination to have great practical utility, but joining the two views is considerably more revealing. Toward coupling the domination and subordination views, we first plot domination level (inferiority) on the horizontal axis and subordination level (superiority) on the vertical axis (Figure 3-8).

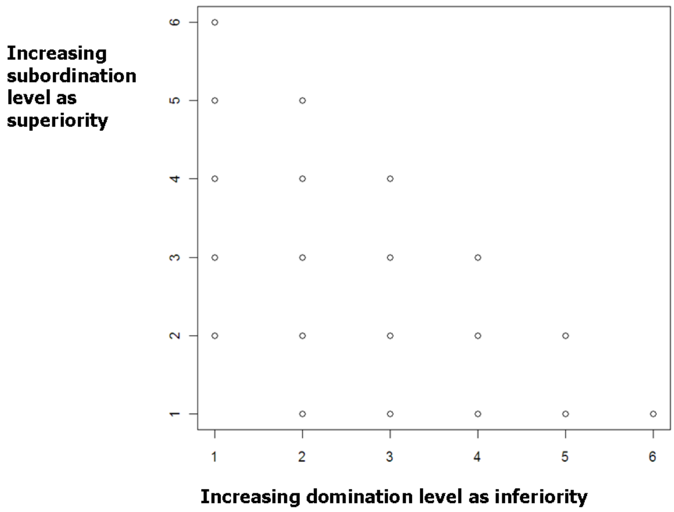


Figure 3-8 Scattered plot obtained coupling domination (horizontal axis) and subordination (vertical axis) views.

The more superior occupy the upper-left corner with high superiority and low inferiority, whereas the more inferior occupy the lower-right corner. Sets having complete consistency for the two views appear on the upper-left to lower-right diagonal. The greater the departure from a diagonal position, the more conflict (less consensus) among the indicators arises. A logical sequence of precedence (which we call ***Salience***) is to start numbering at the upper-left and move to the right across a row before dropping down to the left side of the row below. Any vacant positions are skipped (not incrementing the numbers).

Computations of domination and subordination are deeply nested, highly cyclic, and combinatorial. Lack of consensus among the indicators will lead to salience sets that are large and few in numbers, thus giving relatively low discriminatory power.

An alternative approach is to work with rank range relations, which relaxes the comparative criteria to obtain more discriminatory power.

In this new approach, each indicator is (separately) converted to ranks in a place-based manner such that rank 1 is best (first-place). Each data case than has a range of ranks among the multiple indicators. Comparatives are made in terms of the range of ranks within a data case.

If one case has a better best rank along with an equal or better worst rank, then that case has superiority in a rank range sense. Likewise, if one case has a better worst rank along with an equal or better best rank, then it has superiority in a rank range sense. Note that the worst ranks and best ranks are now not required to be on the same indicators for the two cases. Thus, a particular indicator could have the best rank for one case while having the worst rank for the other case.

A companion to the salience idea can also be constructed for rank range comparisons (and we call this companion as ***Primacy***). One case has rank range superiority over another if the low rank is lower and the high rank is equal or lower, or if the high rank is lower and the low rank is equal or lower. A superior rank range will be said to be below (B) the inferior one. Similarly, one case has rank range inferiority relative to another if the low rank is higher and the high rank is equal or higher, or if the high rank is higher and the low rank is equal or higher. An inferior rank range will be said to be above (A) the superior one. For each case, we can tabulate the number of inferior (A) cases and the number of superior (B) cases when compared to the case in question.

Note that the sum of A and B will often be less than the total number of cases because there may be advantage on the low rank coupled with disadvantage on the high rank (or vice versa). Being neither A nor B, which we will call C for confounded, is the rank range analog of being in the same salience set such that there is lack of clarity in comparing cases. Plotting inferior frequency (A) on the vertical axis against superior frequency (B) on the horizontal axis gives a plot that is a range relational counterpart to domination and subordination such that the upper left is the prime position (Figure 3-9).

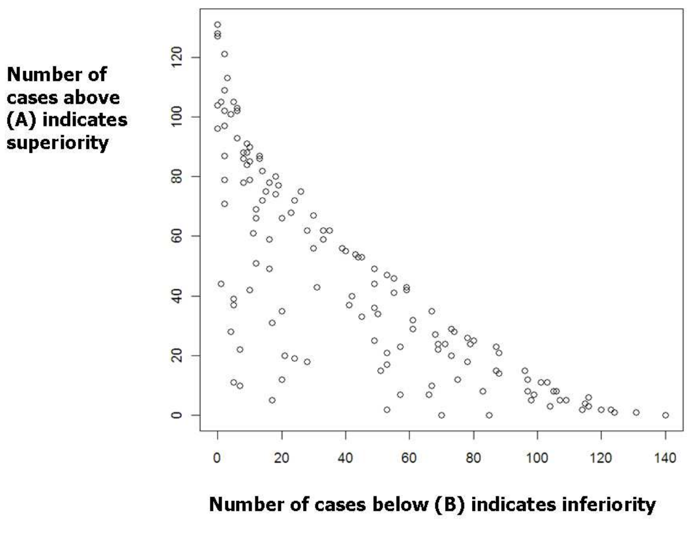


Figure 3-9 Scattered plot obtained coupling superior frequency (horizontal axis) and inferior frequency (vertical axis).

Sequential numbering for primacy starts in the upper-left (prime) position and proceeds in the same manner as was done for salience.

A primacy plot (Figure 3-10) orders the cases by primacy, showing the respective rank ranges as vertical lines along with the numbers of cases above A (inferior to current case) and below B (superior to current case).

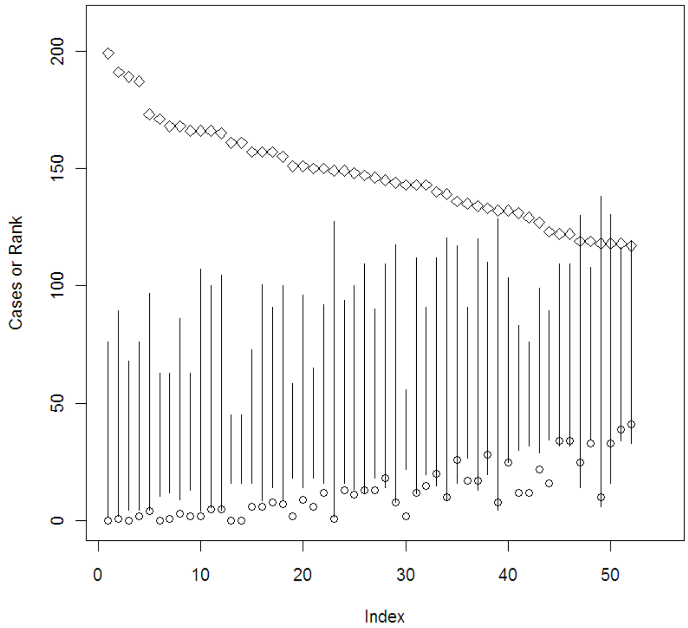


Figure 3-10 An example of possible primacy plot. The cases are ordered showing the rank ranges as vertical lines along with the numbers of cases above A (inferior to current case) and below B (superior to current case).

Horizontal ordering is by primacy. In Figure 3-10, diamonds show number of cases with rank range above (less favourable) while circles show number of cases with rank range below (more favourable).

Plotting reduced ranges with vertical line spanning second best to second worst will show the influence of the end members (Figure 3-11).

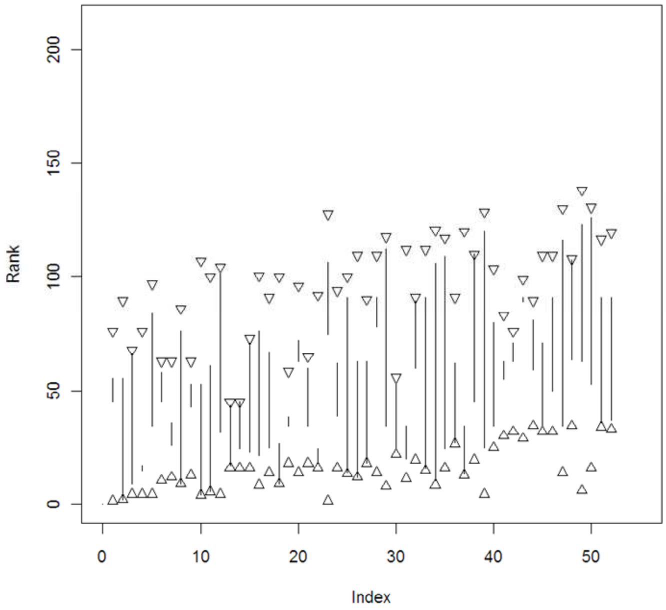


Figure 3-11 Primacy plot obtained using reduced ranges as vertical lines (spanning second best to second worst).

Reduced range plot with vertical line showing reduced range, upward triangle showing minimum range, and downward triangle showing maximum range.

3.2 Upper Level Set Scan Statistic for HotSpot Detection

Three central problems arise in geographical surveillance for a spatially distributed response variable. These are (i) identification of areas having exceptionally high (or low) response, (ii) determination of whether the elevated response can be attributed to chance variation (false alarm) or is statistically significant, and (iii) assessment of explanatory factors that may account for the elevated response. Although a wide variety of methods have been proposed for modeling and analyzing spatial data (Cressie, 1991), the spatial scan statistic (Kulldorff and Nagarwalla, 1995; Kulldorff, 1997) has quickly become a popular method for detection and evaluation of disease clusters and is now widely used by many health departments, government scientists, and academic researchers.

Two books (Glaz and Balakrishnan, 1999; Glaz *et al.*, 2001) cover the scan statistic, although their emphasis is on the one-dimensional version.

When applied in space-time, the scan statistic can provide early warning of disease outbreaks and can monitor the spatial spread of an outbreak.

Basic ingredients of the scan statistic are the geometry of the area being scanned, the probability distribution generating responses under the null-hypothesis of chance variation, and the shapes and sizes of the scanning window. Depending on the application, different response distributions are chosen and the test statistic is evaluated through Monte Carlo simulation (Dwass, 1957).

The spatial scan statistic deals with the following situation:

A region R of Euclidian space is tessellated or subdivided into cells (that will be labeled by the symbol a). Data are available in the form of a count Y_a (non-negative integer) on each cell a. In addition, a "size" value A_a is associated with each cell. The cell sizes A_a are regarded as known and fixed, while the cell counts Y_a are independent random variables.

Two distributional settings are commonly studied: Binomial and Poisson.

Each distributional model has a simple interpretation. For the binomial, N_a people reside in cell a and each has a certain disease independently with probability p_a. The cell count Y_a is the number of diseased people in the cell. For the Poisson, A_a is the size (perhaps area or some adjusted population size) of the cell a, and Y_a is a realization of a Poisson process of intensity λ_a across the cell. In each scenario, the responses Y_a are independent; it is assumed that spatial variability can be accounted for by cell-to-cell variation in the model parameters.

The spatial scan statistic seeks to identify "hotspots" or "clusters" of cells that have an elevated response compared with the rest of the region. Elevated response means large values for the rates (or intensities),

$$G_a = Y_a / A_a \qquad (36)$$

instead of for the raw counts Y_a. Cell counts are thus adjusted for cell sizes before comparing cell responses. The scan statistic easily accommodates other adjustments, such as for age or for gender.

A collection of cells from the tessellation should satisfy several geometrical properties before it could be considered as a candidate for a hotspot cluster. First, the union of the cells should comprise a geographically connected subset of the region R. Second, the zone should not be excessively large-for, otherwise, the zone instead of its exterior would constitute background (i.e. search for hotspots to zones that do not comprise more than fifty percent of the region).

The notion of a hotspot is inherently vague and lacks any a priori definition. There is no "true" hotspot in the statistical sense of a true parameter value. A hotspot is instead defined by its estimate-provided the estimate is statistically significant.

The spatial scan statistic seeks to identify "hotspots" or clusters of cells that have an elevated rate compared with the rest of the region, and to evaluate the statistical significance (p-value) of each identified hotspot. These goals are accomplished by setting up a formal hypothesis testing model for a hotspot. The null hypothesis asserts that there is no hotspot, i.e., that all cells have (statistically) the same rate. The alternative states that there is a cluster Z such that the rate for cells in Z is higher than for cells outside Z. An essential point is that the cluster Z is an unknown parameter that has to be estimated. Likelihood methods are employed for both the estimation and significance testing.

Candidate clusters for Z are referred to as zones. Ideally, maximization of the likelihood should search across all possible zones (in order to identify the Maximum-Likelihood Estimated (MLE) Zone), but their number is generally too large for practical implementation. Various devices (e.g., expanding circles) are employed to reduce the list of candidate zones to manageable proportions. Significance testing for the spatial scan statistic employs the likelihood ratio test; however, the standard chi-squared distribution cannot be used as reference or null distribution—in part because the zonal parameter Z is discrete. Accordingly, Monte Carlo simulation (Dwass, 1957) is used to determine the needed null distributions.

Explication of a likelihood function requires a distributional model (response distribution) for the response Y_a in cell a. This distribution can vary from cell to cell but in a manner that is regulated by the size variable A_a . Thus, A_a enters into the parametric structure of the response distribution. In disease surveillance, response distributions are generally taken as either binomial or Poisson, leading to comparatively simple likelihood functions.

Currently available spatial scan statistic software suffers from several limitations:

- first, circles have been used for the scanning window, resulting in low power for detection of irregularly shaped clusters (Figure 3-12). Alternatively, an irregularly shaped cluster may be reported as a series of circular clusters. Mostashari *et al.* (2003) explore the potential of elliptical scanning windows;
- second, the response variable has been defined on the cells of a tessellated geographic region, preventing application to responses defined on a network (stream network, highway system, water distribution network, etc.);

- finally, reflecting the epidemiological origins of the spatial scan statistic, response distributions have been taken as discrete (specifically, binomial or Poisson).

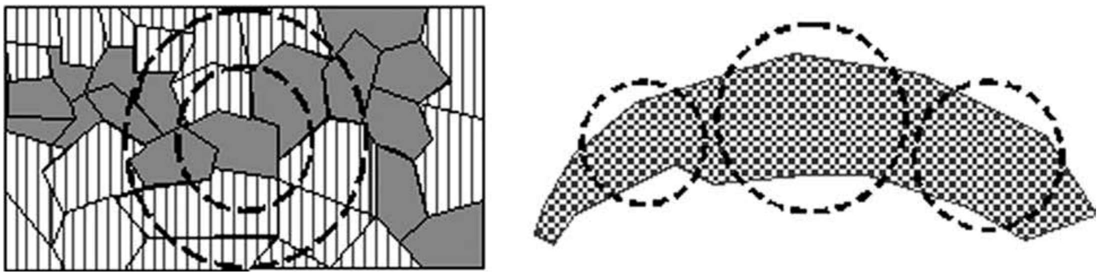


Figure 3-12 Limitations of circular scanning windows. (Left) An irregularly shaped cluster-perhaps a cholera outbreak along a winding river foodplain. Small circles miss much of the outbreak and large circles include many unwanted cells. (Right) Circular windows may report a single irregularly shaped cluster as a series of small clusters.

With suitable modifications, the scan statistic approach can be used for critical area analysis in fields other than the health sciences. In particular some promising developments for generalizing the spatial scan statistic to make it applicable to hotspot-related issues encountered by environmental scientists has been applied.

Upper level set (ULS) Scan Statistic is a new version of the spatial scan statistic designed for detection of hotspots of arbitrary shapes and for data defined either on a tessellation or a network (Patil and Taillie, 2004b). It looks for hotspots from among all connected components of upper level sets of the response rate and is therefore called ULS scan statistic. The method is adaptive with respect to hotspot shape since candidate hotspots have their shapes determined by the data rather than by some a priori prescription like circles or ellipses. This data dependence will be taken into account in the Monte Carlo simulations used to determine null distributions for hypothesis testing. We will also compare performance of the ULS scanning tool with that of the traditional spatial scan statistic.

Although the traditional spatial scan statistic is applicable only to tessellated data, the ULS approach has an abstract graph (i.e., vertices and edges) as its starting point. Accordingly, this approach can also be applied to data defined over a network, such as a subway, water or highway systems.

In fact in ULS scan statistic approach a tessellation determines such a graph: vertices are the cells of the tessellation and a pair of vertices is joined by an edge whenever the corresponding cells are adjacent. A network determines such a graph directly. Each vertex in the graph carries three items of information: (i) a size variable that is treated as known and nonrandom, (ii) a response variable whose value is regarded as a realization of some probability distribution, and (iii) the probability distribution itself, which is called the response distribution.

Parameters of the response distribution may vary from vertex to vertex, but the mean response (i.e., expected value of the response distribution) should be proportional to the value of the size variable for that vertex. The response rate is the ratio Response/Size and a hotspot is a collection of vertices for which the overall response rate is unusually large.

The key element here is enumeration of a searchable list of candidate zones Z (among which MLE-Zone must be searched). A zone is, first of all, a collection of vertices from the abstract graph. Secondly, those vertices should be connected (Figure 3-13) because a geographically scattered collection of vertices would not be a reasonable candidate for a "hotspot".

Even with this connectedness limitation, the number of candidate zones is too large for a maximum likelihood search in all but the smallest of graphs.

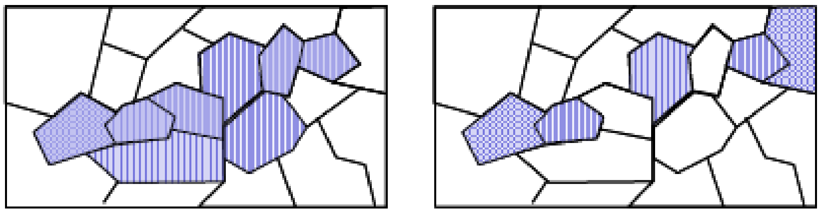


Figure 3-13 Connectivity for tessellated regions. The collection of shaded cells on the left is connected and, therefore, constitutes a zone. The collection on the right is not connected.

ULS approach reduces the list of zones to searchable size in the following way. The response rate at vertex a is $G_a = Y_a / A_a$. These rates determine a function $a \rightarrow G_a$ defined over the cells in the tessellation (i.e the vertices in the abstract graph). This function has only finitely many values (called levels) and each level g determines an upper level set U_g defined by $U_g = \{a: G_a \geq g\}$. Upper level sets do not have to be geographically connected (Figure 3-14) but each upper level set can be decomposed into the disjoint union of connected components.

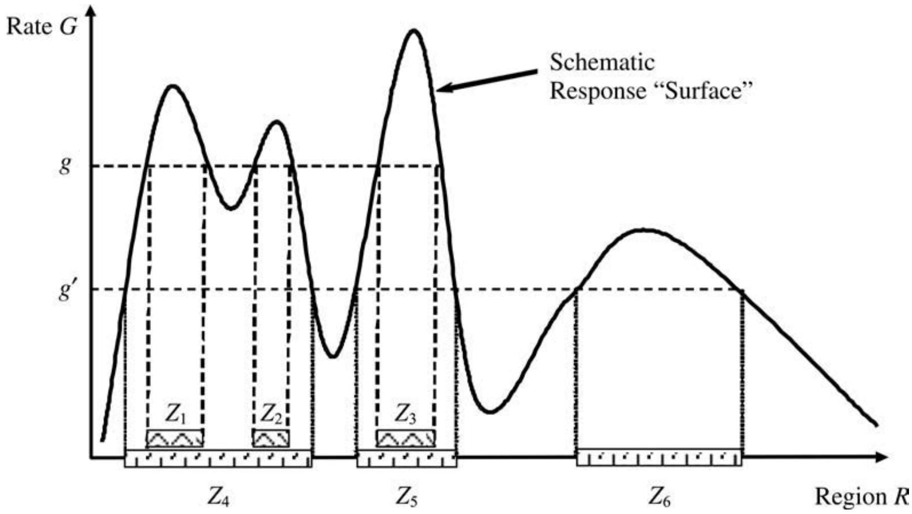


Figure 3-14 Schematic response surface with two response levels, g and g'. The upper level set determined by g has three connected components, Z_1, Z_2 and Z_3; that determined by g' has Z_4, Z_5 and Z_6 as its connected components. The diagram also illustrates the three ways in which connectivity can change as the level drops from g to g': (i) zones Z_1 and Z_2 grow in size and eventually coalesce into a single zone Z_4, (ii) zone Z_3 simply grows to Z_5, and (iii) zone Z_6 is newly emergent.

The list of candidate zones Z for the ULS scan statistic consists of all connected components of all upper level sets. This list of candidate zones is denoted by Ω_{ULS}. The zones in Ω_{ULS} are certainly plausible as potential hotspots since they are portions of upper level sets. Their number is small enough for practical maximum likelihood search—in fact, the size of Ω_{ULS} does not exceed the number of vertices in the abstract graph (e.g., the number of cells in the tessellation). Finally, Ω_{ULS} becomes a tree under set inclusion, thus facilitating computer representation. This tree is called the ULS-tree (Figure 3-15); its nodes are the zones $Z \in \Omega_{ULS}$ and are therefore collections of vertices from the abstract graph. Leaf nodes are (typically) singleton vertices at which the response rate is a local maximum; the root node consists of all vertices in the abstract graph.

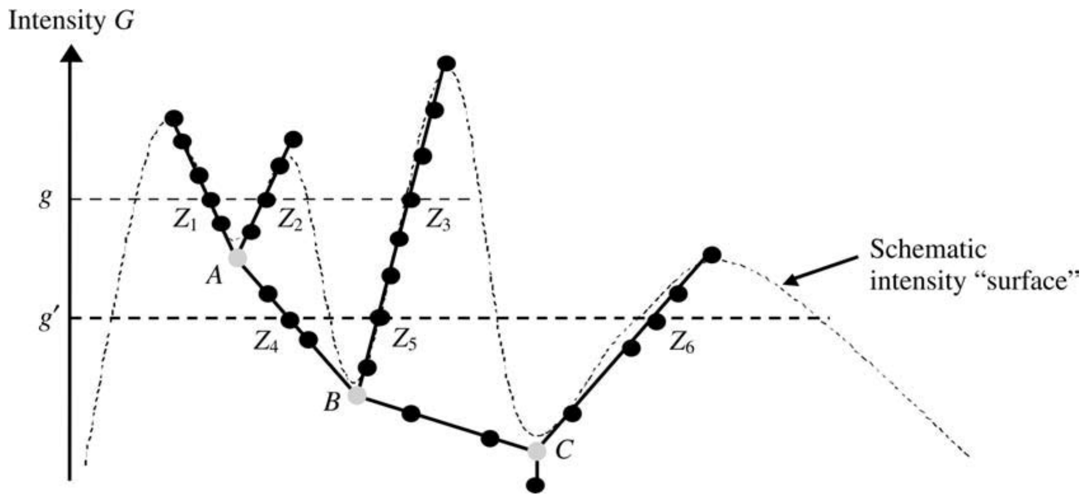


Figure 3-15 ULS connectivity tree for the schematic surface displayed in Figure 3-14. The four leaf nodes correspond to surface peaks. The root node represents the entire region. Junction nodes (A, B and C) occur when two (or more) connected components coalesce into a single connected component.

Finding the connected components for an upper level set is essentially the issue of determining the transitive closure of the adjacency relation defined by the edges of the graph. Several generic algorithms are available in the computer science literature (Cormen *et al*. 2001, for depth first search; Knuth 1973, or Press *et al*. 1992, for transitive closure).

An important aspect is that in ULS approach the scan statistic methodology will be extended to include continuous response distributions (Patil *et al*., 2009a; Patil *et al*., 2009b). Three parametric families of distributions has been chosen: gamma distribution, lognormal distribution, and scaled beta distribution. The first two families apply to responses that can range from zero to infinity, while the third is for bounded responses. The overall approach is to model the mean and relative variance in terms of the size variable. These moments are functions of the parameters of the response distribution, so that a likelihood function can be written down and parameters estimated by maximum likelihood.

A further aspect must be underlined. The hotspot MLE is just that - an estimate. Removing some cells from the MLE and replacing them with certain other cells can generate an estimate that is almost as plausible in the likelihood sense. We will express this uncertainty in hotspot delineation by a confidence set of hotspot zones - a subset of the ULS tree (Figure 3-16).

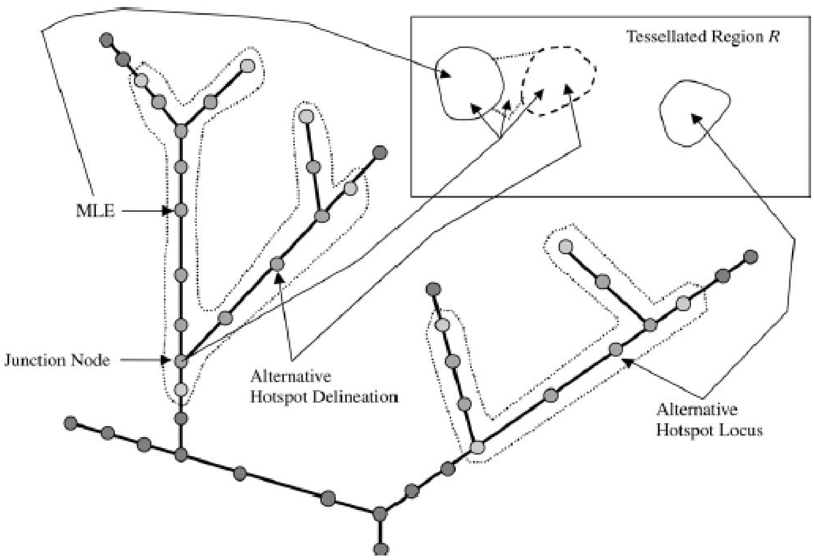


Figure 3-16 A confidence set of hotspots on the ULS tree. The different connected components correspond to different hotspot loci while the nodes within a connected component correspond to different delineations of that hotspot - all at the appropriate confidence level.

We will determine the confidence set by employing the standard duality between confidence sets and hypothesis testing (Lehmann, 1986) in conjunction with the likelihood ratio test. The hotspot confidence set also lets us assign a numerical rating to each cell for inclusion in the hotspot. The rating is the percentage of zones (in the confidence set) that includes the cell under consideration (Fig. 3-17). The inner envelope consists of cells receiving a100% rating while the outer envelope contains the cells with a nonzero rating. A map of these ratings, with superimposed MLE, provides a visual display of uncertainty in hotspot delineation.

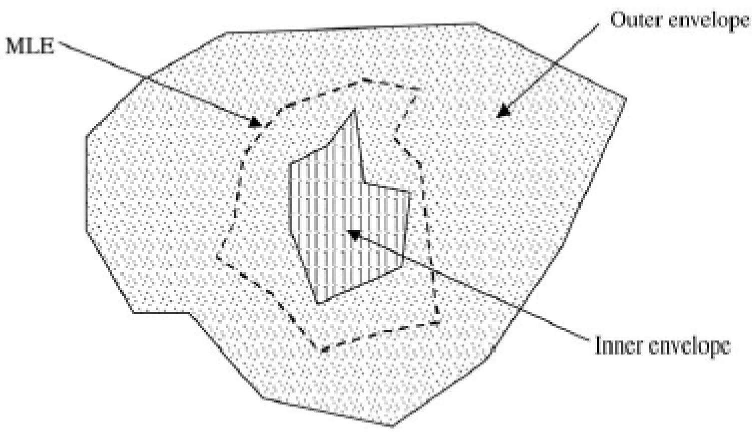


Figure 3-17 Hotspot-membership rating (i.e. estimation uncertainty in hotspot delineation). Cells in the inner envelope belong to all plausible estimates (at specified confidence level); cells in the outer envelope belong to at least one plausible estimate. The MLE is nested between the two envelopes.

3.3 Systematic Conservation Planning

In biodiversity conservation, two are the priority goals that must be achieved:

- The representativeness, i.e. the need to include in protected areas a representative sample of all the existing habitat and species;
- The persistence, which implies the conservation of biological and evolutionary processes that ensure a long term survival of habitat and species allowing them to withstand to threats and pressures belonging to the external environment or the human system;

In order to attain these objectives of representativeness and persistency, it is necessary to study adequately the location, the shape and the connectivity level of the areas to be protected, identifying the necessary constrains for each of them. The establishment of conservation areas must not be the only one aim of planning actions: in fact alternative types of protection can be effectively utilized, in order to involve the users of that areas, promoting sustainable management techniques outside the institutional reserves.

Biodiversity conservation is important not only in wild and yet unspoilt areas, but also in fragmented ones which are immersed in an anthropic matrix and even in urban areas.

If the location of protected areas is not appropriately examined, the chosen areas can reveal to be not completely suitable to biodiversity conservation, especially in presence of clashing interests regarding the land use.

Opposite needs can clash each others and, social economical and political priorities can deeply modify the requests of conservation raised by ecologists. For this reason it is important to compute costs and benefits deriving from conservation and exploiting in the most possible effective way the available economical resources.

Conservation policies must be based on scientific knowledge and utilize suitable methodologies: the systematic approach on the selection of areas to be protected provides a clear and flexible mechanism to identify possible conservation options.

In Ecological Network Planning Systematic Conservation Planning methods stand out for scientific attention, developed and applied first of all in South Africa (Cowling and Pressey, 2003) and Australia (Stewart and Possingham, 2003), but also in north America (Carroll, 2005) and Canada (Warman *et al*., 2004).

The Systematic Conservation Planning methods (Margules and Pressey, 2000) allow identifying a set of suitable representative sites whose protection is crucial to achieve high percentages of biodiversity (in terms of habitat, species, etc.) at a minimum cost (not only in the economic sense).

Therefore, Systematic Conservation Planning outlines a strategy that allows identifying basic areas in order to reach the objectives of representativeness and persistency, explaining clearly the reasons of choices and utilized criteria for selection. Consequently, it will be possible to focus the protective actions on that priority areas mapping out an implementational sequence useful in case it is not immediately possible to preserve all the selected areas. This procedure permits to use in an efficient way the available resources in order to obtain the maximum biodiversity protection using a fixed budget, or to detect the minimum cost to reach the established targets focusing the actions of conservation only in zones where the effectiveness will be higher.

Conservation Planning (Margules and Pressey, 2000, Margules and Sarkar, 2007) was used, exploiting MARXAN software potentialities (Ball and Possingam, 2000). This software is considered the most suitable for our planning needs, even if there are others which are equally effective and frequently utilized in international scientific works (Sarkar *et al*., 2006) – i.e. ZONATION (Moilanen, 2007; Gordon *et al*., 2009), ResNet (Sarkar *et al.*, 2007), C-Plan (Pressey *et al*., 2009), etc..

In its simplest form the reserve planning problem is concerned with the site spatial allocation for biodiversity conservation, so that certain representation and design targets are met in the least number of available sites. (Possingham *et al*., 2000).

Easy and explicit methods in order to locate and localize new reserves to be established that, together with the existing ones, must reach some minimum conservation targets are utilized. As a consequence, the new areas that should be preserved are complementary to the actual ones.

Systematic Conservation Planning can be separated into six fundamental stages (Margules and Pressey, 2000):

1. Compile data on the biodiversity of the planning region

First, it requires clear choices about the features to be used as surrogates for overall biodiversity in the planning process.

- Review existing data and decide on which data sets are sufficiently consistent to serve as surrogates for biodiversity across the planning region.
- If time allows, collect new data to augment or replace some existing data sets.
- Collect information on the localities of species considered to be rare and/or threatened in the region (these are likely to be missed or under-represented in

conservation areas selected only on the basis of land classes such as vegetation types).

2. Identify conservation goals for the planning region

Second, it is based on explicit goals, preferably translated into quantitative, operational targets.

- Set quantitative conservation targets for species, vegetation types or other features (e.g., at least three occurrences of each species, 1500 ha of each vegetation type, or specific targets tailored to the conservation needs of individual features). Despite inevitable subjectivity in their formulation, the value of such goals is their explicitness.
- Set quantitative targets for minimum size, connectivity or other design criteria.
- Identify qualitative targets or preferences (e.g., as far as possible, new conservation areas should have minimal previous disturbance from grazing or logging).

3. Review existing conservation areas

Third, it recognizes the extent to which conservation goals have been met in existing reserves.

- Measure the extent to which quantitative targets for representation and design have been achieved by existing conservation areas.
- Identify the imminence of threat to under-represented features such as species or vegetation types, and the threats posed to areas that will be important in securing satisfactory design targets.

4. Select additional conservation areas

Fourth, it uses simple, explicit methods for locating and designing new reserves to complement existing ones in achieving goals.

- Regard established conservation areas as ‘constraints’ or focal points for the design of an expanded system.
- Identify preliminary sets of new conservation areas for consideration as additions to established areas. Options for doing this include reserve selection algorithms or decision-support software to allow stakeholders to design expanded systems that achieve regional conservation goals subject to constraints such as existing reserves, acquisition budgets, or limits on feasible opportunity costs for other land uses.

5. Implement conservation actions

Fifth, it applies explicit criteria for implementing conservation action on the ground, especially with respect to the scheduling of protective management when not all candidate areas can be secured at once (usually).

- Decide on the most appropriate or feasible form of management to be applied to individual areas (some management approaches will be fallbacks from the preferred option).
- If one or more selected areas prove to be unexpectedly degraded or difficult to protect, return to stage 4 and look for alternatives.
- Decide on the relative timing of conservation management when resources are insufficient to implement the whole system in the short term (usually).

6. Maintain the required values of conservation areas

Sixth and finally, it adopts explicit objectives and mechanisms for maintaining the conditions within reserves that are required to foster the persistence of key natural features, together with monitoring of those features and adaptive management as required.

- Set conservation goals at the level of individual conservation areas (for example, maintain several habitats for one or more species for which the area is important). Ideally, these goals will acknowledge the particular values of the area in the context of the whole system.
- Implement management actions and zonings in and around each area to achieve the goals.
- Monitor key indicators that will reflect the success of management actions or zonings in achieving goals. Modify management as required.

Working in this context, hereafter are reported the choices made to analyze the territory aimed to the E.N. planning of the study area.

At first, the *conservation features***,** working as “surrogates” to represent and estimate the biodiversity of the area, must be identified: in this article the C.B. habitat typologies have been chosen as conservation features.

The use of higher ecological levels, like biocoenosis or habitat, allows the more effective representation of the whole biological and ecosystemic functions present in the area, providing a better surrogate of biodiversity than data of species distribution. Adequate data can be easier available and uniform all over the study area. In effect the use of a single specie as indicator, even if represents a direct measure of biodiversity, doesn't provide information on the quality of ecological existing processes. The use of a single specie also arises the question of its effective representativeness in showing the real presence of other connected species or of environments suitable for its persistency as well as the completeness and reliability of the available data concerning its spatial distribution.

Secondly, being Systematic Conservation Planning a target driven process (Margules and Pressey, 2000), the conservation goals (*targets*) were defined *a priori*. These targets are the minimum surface with which each C.B. type should be represented in the E.N..

The area investigated (*planning region*) was divided into discrete areas, called *planning units*: it was decided to operate on a grid of hexagonal regular cells (in order to maximize possible edges among units) (Hobson *et al*., 2002, Noss, 2003; Oom *et al*., 2004; Pagnutti *et al.,* 2005) of fixed dimension (0.28 ha), habitat representation scale permitting (1:25000 corresponding to a minimum habitat dimension of 0.1 ha), giving a total amount of 61459 cells.

In Systematic Conservation Planning each planning unit can be included in the selection sites to be protected in order to reach the conservation target fixed in advance or be excluded if not providing a significant contribution to reach the target. The basic principle of planning unit inclusion is the complementarity: a new unit can be added if and only if it improves the biodiversity level of the previously selected unit system, favoring the achievement of the settled conservation target. MARXAN software allows to evaluate the contribution of each planning unit to the entire system. The contribution must be intended as probability that the unit is necessary and/or essential to achieve the target (*irreplaceability*) (Pressey *et al.,* 1994; Ferrier *et al*., 2000).

The irreplaceability/conservation value concept is widely utilized in scientific literature not only in terrestrial applications of systematic conservation planning (Carwardine *et al*., 2007), but also in fresh water (Linke *et al.,* 2008) and in marine context (Leslie *et al*., 2003).

The lowest number of cells (*portfolio*) represents the part that can be added to the fixed elements of the E.N., i.e. the zones essential for their ecological-environmental significance.

Analytically, the problem of minimizing the amount of complementary areas results in defining an *objective function* present in every systematic planning algorithm.

When, as in our case study, there are many planning units (n = 61) and conservation features (m = 44), the problem solution is complex and it is necessary to have recourse to an algorithm. The most modern and efficient among them, adopted in the present research, is included in MARXAN (Ball and Possingham, 2000). It makes use of an algorithm based on the following simulation (*simulating annealing*) in order to optimize the problem solution (Kirkpatrick *et al.*, 1983).

The objective function used in MARXAN is designed so that the lower the value, the better the reserve (function minimization). It takes the following form:

$$\sum_{\text{sites}} \text{Cost} + \text{BLM}\sum_{\text{sites}} \text{Boundary} + \sum_{\text{cons.feat.}} \text{CFPF} \times \text{Penalty} + \text{Cost Treshold Penalty(t)} \qquad (37)$$

where:

Cost is some measure of the cost, area, or opportunity cost of the reserve system. It is the sum of the cost measure of each of the n planning units within the reserve system. The cost must be interpreted as an ecological cost and evaluated, for each planning unit, according to the following formula:

$$\text{Cost}_i = \frac{1}{\text{EV}_i} \times \frac{1}{\text{ES}_i} \qquad (38)$$

where: EV_i is the Overall Ecological Value and ES_i is the Overall Ecological Sensitivity of the planning unit *i*. In our case study, each planning unit is composed by different C.B. habitat types overlapping its areas: consequently each planning unit is assigned the area weighted mean value of Ecological Value and Ecological Sensitivity of all the C.B. habitat types present in it.

Boundary is the length of the border surrounding the reserve system. The *boundary length modifier* (BLM) is a parameter that directs the model to clusters of planning units together rather than selecting several disconnected planning units. If a value equivalent to 0 is given to BLM, then the boundary length is not included in the objective function.

The method by Stewart and Possingham (2005) was used to determine an efficient BLM: it proposes a choice on the basis of the trade-off analysis and of the perimeter length of every single E.N. planned starting from a certain BLM value.

Penalty term is a penalty associated with each underrepresented conservation feature. It is expressed in terms of cost and boundary length, and is roughly the cost and additional modified boundary needed to adequately reserve a conservation feature which is not adequately represented in the current system (i.e. the conservation target is not reached).

Cost threshold penalty is a penalty applied to the objective function if the target cost is exceeded. It is a function of the cost and possibly the boundary of the system, and in some algorithms will change as the algorithm progresses (i.e. *t* in the (37) formula).

4 Results and Discussion

This section is organized in 3 parts.

The first two (paragraph 4.1 and 4.2) investigate study areas on habitat level, proposing and testing quantitative methods to individuates habitat most worthy to be protected and to manage for their conservation. The third part (paragraph 4.3) focuses the attention on administrative partition of the territory, being the correct level at which funds for environmental policies are distributed for the protection and conservation policies. In this third part the aim is to suggest useful guidelines to environmental stakeholders and, on the other side, to rank administrative units according to an environmental funding preference.

4.1 Natural Habitat Level Analysis: Individuation of Habitat of Ecological Attention

Basically, attention of ecological scientists is on habitat. Preserving in a correct way natural habitats is the fundamental step for biodiversity conservation. Ecological parameters like Ecological Value and Ecological Sensitivity play a strategic role in habitat analysis but it is necessary to take into account that they are multidimensional. Results of experimenting different quantitative methodologies to identify ecologically critical habitats and to rank habitats are presented.

4.1.1 Redundancy degree of the proposed ecological indicators

By using the indicators of Tables 2-1 and 2-2, and Eqs. (18) and (19), we obtained a vector of nine measurements for both ecological value and ecological sensitivity for each one of the 2189 habitats in the Study area “A” (Baganza Valley) and for each one of the 21010 C.B. habitats in the study area “B” (Oltrepò Pavese and the Ligurian-Emilian Apennine).

The presence of possible high degree of redundancies among the indicators of Ecological Value and of Ecological Sensitivity was assessed subjecting correlation matrices of the same indicators to a Principal Component Analysis.

For study area “B” the results of the Principal Component Analysis carried out on the two correlation matrixes (Tables 4-1 and 4-2) are given in Table 4-3 and Table 4-4.

	Indicator	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9
1.1	Size	1	0.012	0.177	0	-0.009	0.032	0.003	-0.007	0.011
1.2	Vertebrates richness	0.012	1	-0.022	0.004	-0.014	0.1542	0.012	0.1007	0.024
1.3	Soil roughness	0.1771	-0.022	1	-0.025	0.078	0.029	-0.035	0.071	-0.009
1.4	Rarity	0	0.004	-0.025	1	-0.007	0.063	0.15	-0.068	0.1347
1.5	Vertebrates rarity	-0.009	-0.014	0.078	-0.007	1	-0.259	-0.047	-0.051	-0.082
1.6	Suitability for vertebrates at risk	0.032	0,1542	0.029	0.063	-0.259	1	0.081	0.1625	0.0951
1.7	Involvement in Protected Areas	0.003	0.012	-0.035	0.15	-0.047	0.081	1	-0.071	0.2993
1.8	NDVI	-0.007	0.1007	0.071	-0.068	-0.051	0.1625	-0.071	1	-0.024
1.9	Involvement in Conservation Areas	0.011	0.024	-0.009	0.1347	-0.082	0.0951	0.2993	-0.024	1

Table 4-1 Correlation matrix between the indicators of Ecological Value.

	Indicator	2.1	2.2	2.3	2.4	2.5	2.6	2.7	2.8	2.9
2.1	Fractal Coefficient of perimeter	1	-0.638	-0.003	-0.016	0.000	0.019	-0.022	0.006	-0.003
2.2	Circularity Ratio of area	-0.638	1	-0.027	-0.005	0.004	-0.043	0.001	-0.06	0.043
2.3	Average slope	-0.003	-0.027	1	0.1083	0.017	-0.072	-0.111	0.051	0.007
2.4	Species of vertebrates at risk (IUCN)	-0.016	-0.005	0.1083	1	0.047	-0.02	-0.007	0.013	0.014
2.5	Species of vegetation at risk (IUCN)	0	0.004	0.017	0.047	1	-0.002	0.013	-0.002	0.056
2.6	Landslide index	0.019	-0.043	-0.072	-0.02	-0.002	1	-0.269	0.003	-0.038
2.7	FPI	-0.022	0.02	-0.111	-0.007	0.013	-0.269	1	-0.018	0.009
2.8	Orientation compared to the main wind direction	0.006	-0.06	0.051	0.013	-0.002	0.003	-0.018	1	-0.016
2.9	Nearest Neighbour Index	-0.03	0.043	0.007	0.014	0.056	-0.038	0.009	-0.016	1

Table 4-2 Correlation matrix between the indicators of Ecological Sensitivity.

Component	Eingenvalue	% of Variance	Cumulative % of Variance
1	1.658	18.425	18.425
2	1.436	15.956	34.381
3	1.258	13.973	48.354
4	1.000	11.110	59.464
5	0.897	9.967	69.431
6	0.860	9.551	78.982
7	0.709	7.880	86.863
8	0.621	6.901	93.764
9	0.561	6.236	100.000

Table 4-3 Results of the Principal Component Analysis carried out on the correlation matrix of Table 4-1.

Component	Eigenvalue	% of Variance	Cumulative % of Variance
1	1.655	18.391	18.391
2	1.269	14.096	32.486
3	1.204	13.374	45.860
4	1.048	11.640	57.500
5	0.982	10.915	68.416
6	0.948	10.537	78.952
7	0.865	9.608	88.560
8	0.672	7.466	96.026
9	0.358	3.974	100.000

Table 4-4 Results of the Principal Component Analysis carried out on the correlation matrix of Table 4-2.

In both cases it is necessary to take into account at least six eigenvalues to explain a reasonable percentage (over 75%) of the total variability. Indeed, a careful observation of the matrixes of Tables 4-1 and 4-2 reveals that the degree of interdependence (correlation) among these indicators is, on average, very low (Tables 4-3 and 4-4).

For study area “A” the results of the Principal Component Analysis carried out on the two correlation matrixes (Tables 4-5 and 4-6) are given in Table 4-7 and Table 4-8.

	Indicator	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8
1.1	Vertebrates concentration	1	-0.381	-0.141	-0.056	0.121	-0.006	0.169	0.101
1.2	Soil Roughness	-0.381	1	0.146	-0.028	0.011	0.070	-0.099	-0.110
1.3	Rarity	-0.141	0.146	1	0.017	0.057	-0.075	-0.427	-0.062
1.4	Vertebrates rarity	-0.056	-0.028	0.017	1	-0.389	0.032	-0.140	0.096
1.5	Suitability for Vertebrates at risk	0.121	0.011	0.057	-0.389	1	-0.122	0.300	0.028
1.6	Involvement in Protected Areas (%)	-0.006	0.070	-0.075	0.032	-0.122	1	-0.066	0.433
1.7	NDVI	0.169	-0.099	-0.427	-0.140	0.300	-0.066	1	0.102
1.8	Involvement in Conservation Areas (%)	0.101	-0.110	-0.062	0.096	0.028	0.433	0.102	1

Table 4-5 Correlation matrix between the indicators of Ecological Value.

	Indicator	2.1	2.2	2.3	2.4	2.5	2.6	2.7	2.8
2.1	Convolution	1	-0.590	0.268	-0.003	0.027	0.008	-0.006	0.005
2.2	Compactness	-0.590	1	0.323	0.027	0.044	0.113	0.005	-0.005
2.3	Vertebrates at risk (IUCN) concentration	0.268	0.323	1	-0.002	0.067	0.094	-0.025	0.034
2.4	Slope	-0.003	0.027	-0.002	1	0.183	0.095	0.046	-0.033
2.5	Landslide Index	0.027	0.044	0.067	0.183	1	0.079	0.087	-0.027
2.6	FPI	0.008	0.113	0.094	0.095	0.079	1	0.065	-0.120
2.7	Orientation compared to the main wind direction	-0.006	0.005	-0.025	0.046	0.087	0.065	1	-0.036
2.8	Nearest Neighbor Index	0.005	-0.005	0.034	-0.033	-0.027	-0.120	-0.036	1

Table 4-6 Correlation matrix between the indicators of Ecological Sensitivity.

Component EV	Eigenvalue	% of variance	Cumulative % of variance
1	1.8248	22.810	22.810
2	1.559	19.491	42.302
3	1.268	15.851	58.153
4	1.098	13.730	71.884
5	0.753	9.410	81.294
6	0.616	7.704	88.998
7	0.456	5.699	94.697
8	0.424	5.303	100.000

Table 4-7 Results of the Principal Component Analysis carried out on the correlation matrix of Table 4-5.

Component ES	Eigenvalue	% of variance	Cumulative % of variance
1	1.615	20.185	20.185
2	1.359	16.990	37.175
3	1.200	15.004	52.179
4	1.036	12.955	65.134
5	0.958	11.976	77.110
6	0.849	10.617	87.727
7	0.791	9.8840	97.611
8	0.191	2.3889	100.000

Table 4-8 Results of the Principal Component Analysis carried out on the correlation matrix of Table 4-6.

It is to be noted that in both cases 5-6 components are necessary to explain a portion of dispersion greater than 75% of the total. This result suggests that redundancy among indicators is on the average low. This conclusion is also confirmed by the very low value of the mean value of correlations between the indicators (-0.015 for the Ecological Value, and 0.026 for the Ecological Sensitivity).

4.1.2 Habitat ranking: Ideal Vector Vs Salience

In both study areas, ranking of habitats according to Ecological Value and Ecological Sensitivity has been performed using the Ideal Vector Method (see paragraph 3.1.1). The Salience methodology (see paragraph 3.1.3) has been applied in study area “B” in order to compare the obtained results between ranking methods that aggregates indicators in an overall index (Ideal Vector distance) and methods that leaves indicators separated (Salience).

To derive more legible and useful maps of the overall Ecological Value and the overall Ecological Sensitivity, the numerous distances from the Ideal Vector have been divided into five groups comprising the same number of C.B. habitats (quintiles).

The first quintile of habitats, closer to the ideal vector situation, has been marked as (habitats of) “Elevated Value”, while the second and the third as (habitats of) “High Value” and “Median Value”, respectively. Finally, the names “Modest Value” and “Low Value” have been assigned to the fourth and the fifth groups of habitats.

For what concerns Ecological Sensitivity, the label “Low Sensitivity” has been assigned to the first group of habitats that is the closer to the ideal situation of the smallest Ecological Sensitivity. The labels “Modest Sensitivity”, “Median Sensitivity”, “High Sensitivity”, and “Elevated Sensitivity” have been assigned progressively to the second, third, fourth and fifth groups of habitats. Thus, maps of the overall Ecological Value and overall Ecological Sensitivity classified into five categories were obtained both for Study area “A” (Figures 4-1a and 4-1b) and for study area “B”. (Figures 4-2a and 4-2b).

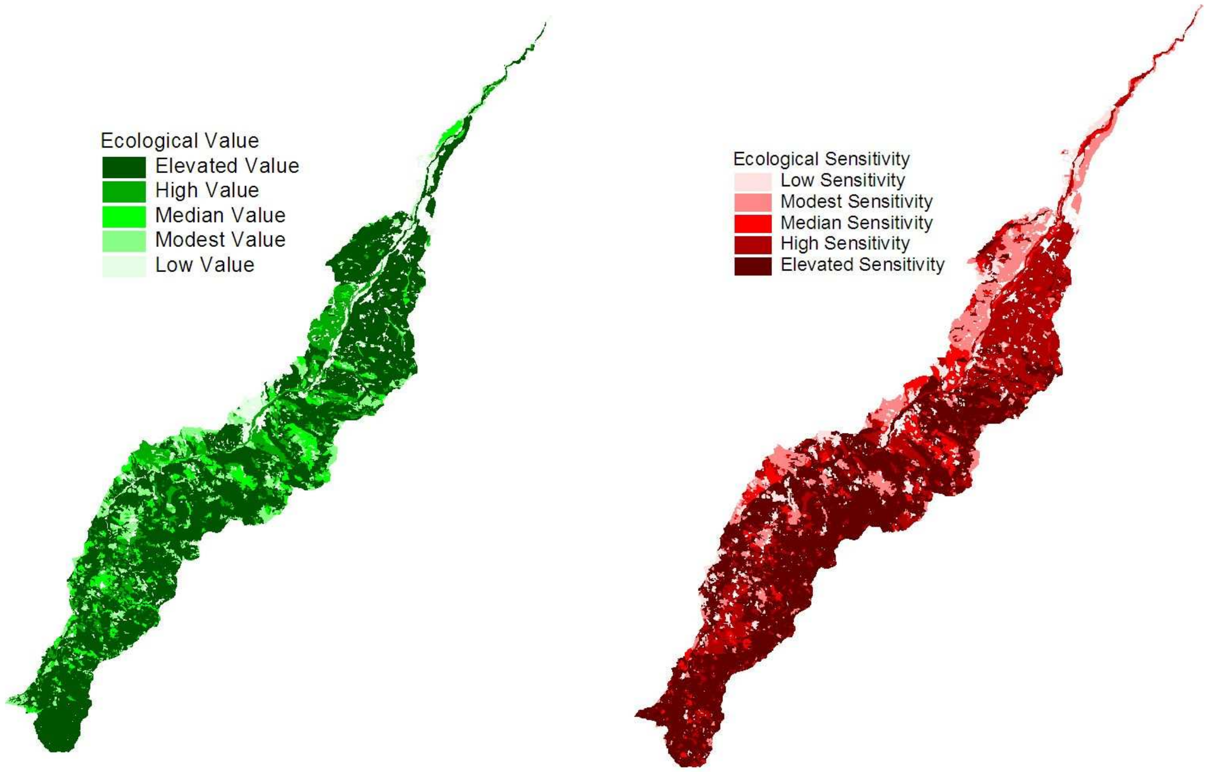


Figure 4-1a and 4-1b Distribution of Ecological Value and Ecological Sensitivity of Study Area "A" according to Ideal Vector Method.

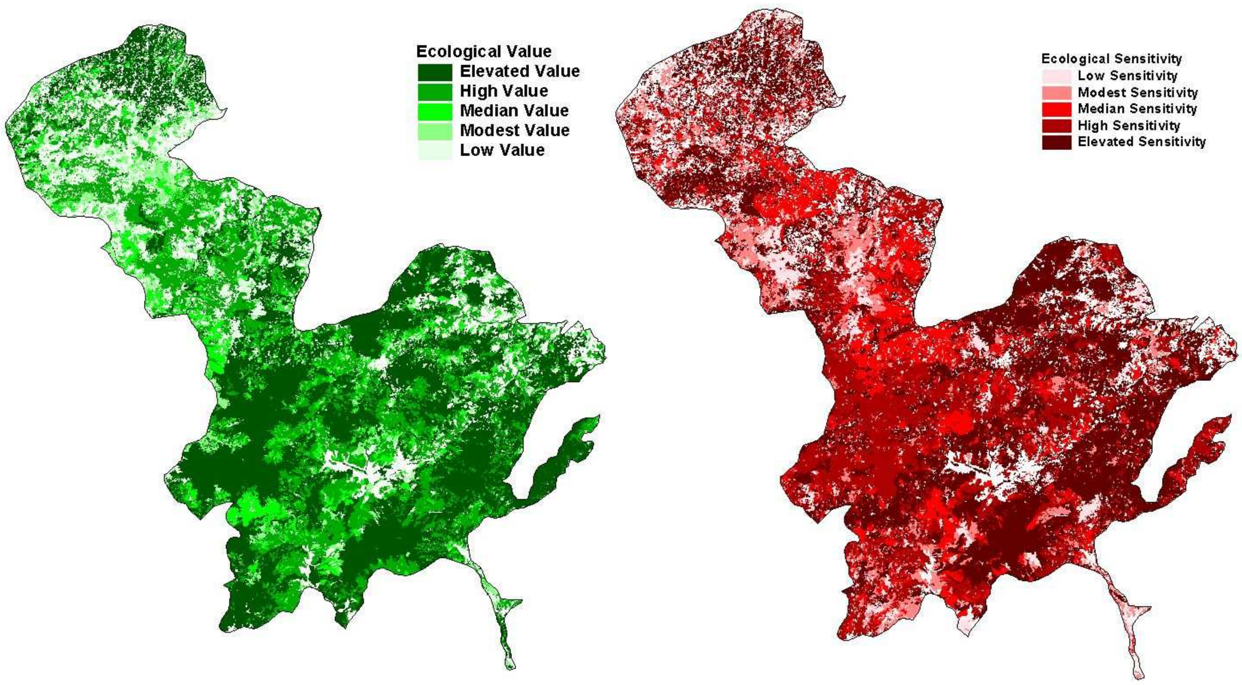


Figure 4-2a and 4-2b Distribution of Ecological Value and Ecological Sensitivity of Study Area "B" according to Ideal Vector Method.

The contribution of each indicator to the observed gradient of Ecological Value (as well as of that of Ecological Sensitivity) can be clarified by the technique of the Multiple Discriminant Analysis carried out on the five groups. This analysis has been performed both for the two study areas.

The results obtained for study area "B" regarding overall Ecological Value are given in Tables 4-9 and 4-10. The analysis shows that the first discriminant function explains over 91% of the total dispersion (Table 4-9).

Functions	Eigenvalues	% of Variance	Cumulative % of Variance	Canonical Correlation
1	5.467	91.3	91.3	0.919
2	0.425	7.1	98.4	0.546
3	0.081	1.3	99.8	0.273
4	0.012	0.2	100.0	0.110

Table 4-9 Results of the Multiple Discriminant Analysis carried out on the 5 groups (quintiles) of overall Ecological Value.

Indicator	Function			
	1	2	3	4
1.1 Size	0.028	-0.041	-0.131	0.064
1.2 Vertebrates richness	0.089	0.129	-0.044	-0.055
1.3 Soil roughness	0.398	0.066	0.588	-0.469
1.4 Rarity	1.185	-0.289	0.008	-0.121
1.5 Vertebrates rarity	0.873	0.097	0.395	-0.131
1.6 Suitability for vertebrates at risk	0.495	0.273	0.598	0.769
1.7 Involvement in Protected Areas	0.117	0.022	-0.089	0.009
1.8 NDVI	0.835	0.692	-0.455	-0.207
1.9 Involvement in Conservation Areas	0.802	-0.374	-0.305	0.149

Table 4-10 Standardized coefficients of the Discriminant Function (see Table 4-9).

The results obtained suggest that the indicators of Ecological Value which mostly influence the gradient of overall value among the five groups are in order of importance (Table 4-10): the degree of habitat rarity (1.4), the number of rare vertebrates (1.5), the NDVI values (1.8), and the degree of belonging to the Conservation Zones (1.9). Their importance in ecological sensitivity gradient is confirmed looking at the mean values of their values among the quintiles.

Regarding the gradient of Ecological Sensitivity among the five groups (quintiles), it is interesting to notice that the first discriminant function (Table 4-11) explains almost 99% of the total variation. Table 4-12 reveals that there are five main indicators affecting the gradient of ecological sensitivity of the C.B. habitats among the groups (quintiles), i.e. number of vertebrates at risk of extinction present in the habitat (2.4), habitat orientation to the prevalent winds (2.8), fire risk (2.7), landslide risk (2.6) and degree of habitat compactness (2.2).Their importance in Ecological Sensitivity gradient is confirmed looking at the mean values of their values among the quintiles.

Functions	Eigenvalues	% of Variance	Cumulative % of Variance	Canonical Correlation
1	5.596	98.9	98.9	0.921
2	0.057	1.0	99.9	0.232
3	0.003	0.0	100.0	0.051
4	0.000	0.0	100.0	0.021

Table 4-11 Results of the Multiple Discriminant Analysis carried out on the 5 groups (quintiles) of overall Ecological Sensitivity.

Indicator	Function			
	1	2	3	4
2.1 Fractal Coefficient of perimeter	0.171	0.237	0.399	0.353
2.2 Circularity Ratio of area	-0.726	-0.092	0.416	0.710
2.3 Average slope	0.319	0.045	0.122	0.164
2.4 Species of vertebrates at risk (IUCN)	1.256	-0.592	0.113	0.070
2.5 Species of vegetation at risk (IUCN)	0.138	0.342	0.787	0.106
2.6 Landslide index	0.880	0.032	0.195	-0.266
2.7 FPI	0.946	0.270	0.130	-0.464
2.8 Orientation compared to the main wind direction	1.113	0.421	-0.324	0.489
2.9 Nearest Neighbour Index	0.078	0.086	0.022	-0.236

Table 4-12 Standardized coefficients of the Discriminant Function (see Table 4-11).

Summarizing, the C.B. habitats with elevated overall Ecological Value are the ones that: (1) are very rare within the study area; (2) host a large number of rare vertebrates; (3) are characterized by large green zones revealed by high NDVI values and (4) belong to the Conservation Zones.

The C.B. habitats with elevated overall Ecological Sensitivity are the ones that: (1) are characterized by a high number of vertebrates at risk of extinction; (2) are more open to the negative influence of the prevalent winds; (3) are more open to fire risk; (4) are more open to landslide risk and (5) have a low degree of compactness.

Similarly, the results obtained for study area "A" regarding overall Ecological Value are illustrated in Tables 4-13 and 4-14. Also in this case, the analysis shows that the first discriminant function explains over 88% of the total dispersion (Table 4-13).

Functions	Eigenvalues	% of Variance	Cumulative % of Variance	Canonical Correlation
1	6.205	88.3	88.3	0.928
2	0.755	10.7	99.1	0.656
3	0.051	0.7	99.8	0.220
4	0.014	0.2	100.0	0.117

Table 4-13 Results of the Multiple Discriminant Analysis carried out on the 5 groups (quintiles) of overall Ecological Value.

Indicator	Function			
	1	2	3	4
1.1 Vertebrates concentration	0.574	0.858	0.229	-0.600
1.2 Soil Roughness	0.644	0.578	0.319	-0.404
1.3 Rarity	-0.457	0.251	0.463	0.355
1.4 Vertebrates rarity	0.389	-0.020	-0.021	-0.130
1.5 Suitability for Vertebrates at risk	0.537	-0.145	0.542	0.265
1.6 Involvement in Protected Areas (%)	0.760	0.370	-0.237	0.310
1.7 NDVI	1.080	-0.242	0.058	0.085
1.8 Involvement in Conservation Areas (%)	0.046	0.466	-0.157	0.405

Table 4-14 Standardized coefficients of the Discriminant Function (see Table 4-13).

The results obtained suggest that the indicators of Ecological Value which mostly influence the gradient of overall value among the five groups are in order of importance (Table 4-14): the NDVI values (1.7), the percentage of inclusion in protected areas (1.6), the soil roughness (1.2) and the concentration of vertebrates (1.1).

Their importance in Ecological Value gradient is confirmed looking at the mean values of their values among the quintiles.

Regarding the gradient of Ecological Sensitivity among the five groups (quintiles), it is interesting to notice that the first discriminant function (Table 4-15) explains more than 99% of the total variation.

Functions	Eigenvalues	% of Variance	Cumulative % of Variance	Canonical Correlation
1	5.565	99.1	99.1	0.921
2	0.040	0.7	99.8	0.197
3	0.007	0.1	100.0	0.085
4	0.002	0.0	100.0	0.043

Table 4-15 Results of the Multiple Discriminant Analysis carried out on the 5 groups (quintiles) of overall Ecological Sensitivity.

Indicator	Function			
	1	2	3	4
2.1 Convolution	0.470	0.139	-0.088	0.761
2.2 Compactness	-0.806	-0.036	0.432	0.643
2.3 Vertebrates at risk (IUCN) concentration	0.310	0.065	0.036	-0.282
2.4 Slope	0.215	0.264	0.776	-0.057
2.5 Landslide Index	0.653	-0.265	-0.285	0.128
2.6 FPI	1.195	-0.552	0.125	-0.317
2.7 Orientation compared to the main wind direction	1.160	0.502	0.067	0.099
2.8 Nearest Neighbor Index	0.194	0.322	-0.126	-0.769

Table 4-16 Standardized coefficients of the Discriminant Function (see Table 4-15).

Table 4-16 reveals that there are four main indicators affecting the gradient of Ecological Sensitivity of the C.B. habitats among the groups (quintiles), i.e. fire risk (2.6), habitat orientation to the prevalent winds (2.7), degree of habitat compactness (2.2) and landslide risk (2.5).

Their importance in Ecological Sensitivity gradient is confirmed looking at the mean values of their values among the quintiles.

Summarizing, the C.B. habitats with elevated overall Ecological Value are the ones that: (1) are characterized by large green zones revealed by high NDVI values; (2) shown an actual greater inclusion in Protected Areas; (3) are characterized by great ecological variations (which potentially positively affect faunal and floristic richness) due to terrain morphological complexity and (4) host a large number of vertebrates;

The C.B. habitats with elevated overall Ecological Sensitivity are the ones that: (1) are more open to fire risk; (2) are more open to the negative influence of the prevalent winds; (3) have a low degree of compactness and (4) are more open to landslide risk;

This similar condition that affect the results both for the two study areas are reasonable considering that Baganza Valley is geographically inserted in the south-east part of the Oltrepò-Pavese and Ligurian-Emilian Apennine.

For what concerns the Salience method, we investigate directly, both for Ecological Value and Ecological Sensitivity, the structure of indicators, maintaining them separated, in order to organize and rank the habitats with different level of agreement in superiority and different level of consensus in inferiority.

In fact, there are two different ways that we can obtain such levels, one is by finding non-domination (inferiority) levels and the other by finding non-subordination (superiority) levels. Habitat A is dominated by habitat B if habitat B is better or equal to habitat A for all the indicators, and habitat B is strictly better than A for at least one indicator. Intuitively, habitat A is non-dominated by habitat B, if A is better than B in at least one indicator. In the non-domination scheme, the habitats in the first level are the habitats that are not dominated by any other habitat. Similarly, habitats in Level k are those which are dominated by at least one element in Level (k-1), but not dominated by any element not in levels less than k.

Subordination works in the same manner, here we look for which habitats are worse than other habitats, as habitat A is subordinated by habitat B if habitat B is worse than or equal to A for all indicators. The levels for non-subordination can be computed similarly.

By using the subordination program developed by Myers, we can determine superiority and inferiority levels for all the habitats. We do this once for the 9 indicators of Ecological value and once for the 9 indicators of Ecological Sensitivity referring to study area “B” which has a greater number of natural habitats to be compared.

Scatter plot of habitats has been produced with non-subordination levels on the y-axis and non domination levels on the x-axis once for the 9 indicators of Ecological value and once for the 9 indicators of Ecological Sensitivity (Figures 4-3a and 4-3b).

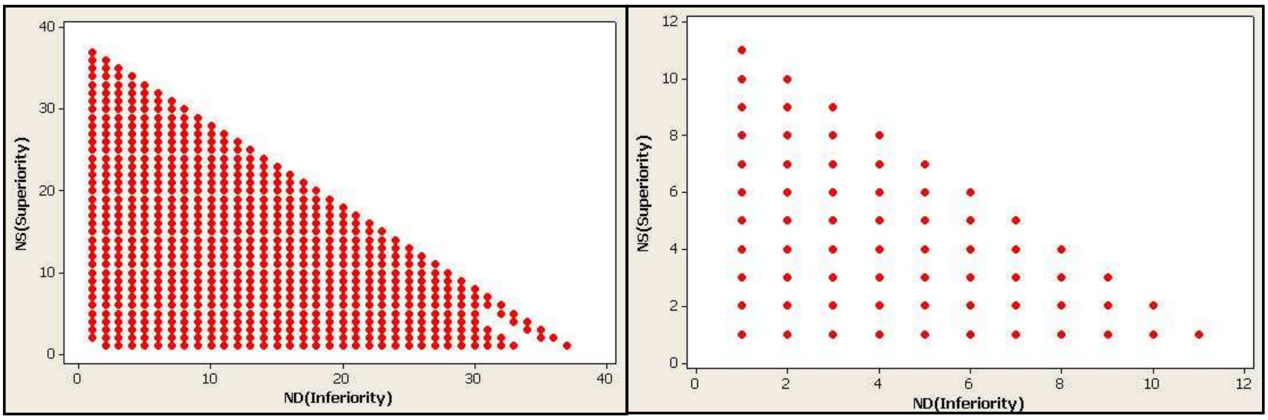


Figure 4-3a and 4-3b Scatter plot of C.B. habitats ranking using subordination for Ecological Value and Ecological Sensitivity

In these scatter plots, the upper left hand corner contains respectively the habitats having elevated Ecological Value and elevated Ecological Sensitivity. On the other side, the lower right corner contains respectively habitats having low ecological value and low Ecological Sensitivity.

In fact, going down to the scatter plot decrease the consensus in superiority of the habitat (i.e. habitat that are non subordinated to the others) and moving on the right part of the scatter plot increase the consensus in inferiority (i.e. habitat that are dominated by the others).

It will be useful to show, also using this method, more legible and useful maps of the overall ecological Value and the overall Ecological sensitivity, dividing into quintiles the C.B. habitat. Contrary to Ideal Vector results (i.e. multidimensional distances), the Salience method produce directly a ranking avoiding the concept of distance among the elements (i.e. habitats). This aspect generates trouble.

The message of the scatter plot (Figures 4-3a and 4-3b) is clear only in the corners. Outside of these two regions, the message given by Salience method begins to be less clear and it is not so simple to understand the ecological situation of habitats. In effect this method (as like many partial ordering methods) generates many ties. The ties problem is due to the restrictive request of the procedure in deriving levels of superiority and inferiority and perhaps this tendency is emphasized by the increasing number of used indicators.

To understand the spatial distribution of Ecological Value and Ecological Sensitivity using Salience method two maps has been produced even if among the 5 groups habitats are not equally distributed (Figures 4-4a and 4-4b).

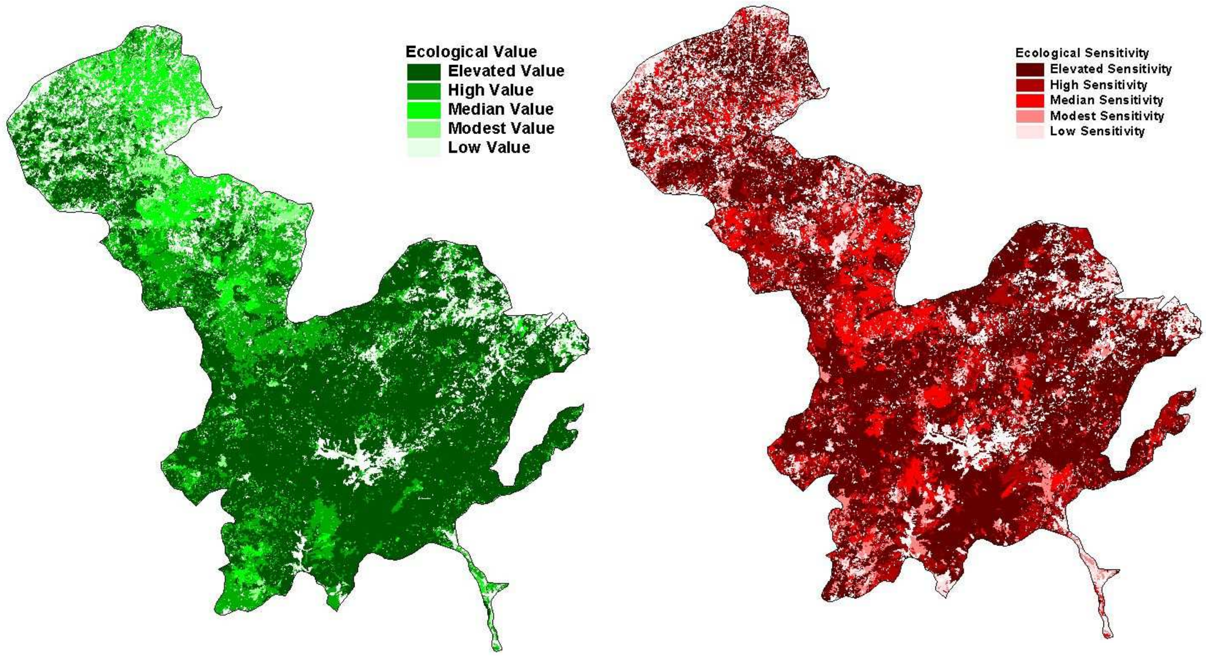


Figure 4-4a and 4-4b Distribution of Ecological Value and Ecological Sensitivity according to Salience Method

Being not possible to derive quintiles using Salience method, we cannot compute the Multiple Discriminant Analysis in the same way it has been performed using Ideal Vector method.

To understand how differently the original indicators of Ecological Value and Ecological Sensitivity contributed in determining ranking of habitats has been carried out a Discriminant Analysis using only two groups for both methods: Group 1 contains habitat with elevated Ecological Value (or Ecological Sensitivity) while Group 2 is composed by all the rest of habitats of the study area. For Ideal Vector method habitat with elevated Ecological Value (or Sensitivity) means habitats in the corresponding quintile previously mapped. For Salience method, these habitats belong to the upper left corner of the scatterplots.

Being compared only two groups of habitats, there is only one discriminant function that explains the total dispersion (100%).

Results obtained, for Ideal Vector and Salience methods regarding overall ecological value and overall ecological sensitivity, are illustrated in Tables 4-17 and 4-18.

Indicator of Ecological Value	Discriminant Function	
	Ideal Vector	Salience
1.1 Size	0.055	-0.010
1.2 Vertebrates richness	0.007	0.442
1.3 Soil roughness	0.162	0.528
1.4 Rarity	0.953	-0.053
1.5 Vertebrates rarity	0.504	0.003
1.6 Suitability for vertebrates at risk	0.163	0.498
1.7 Involvement in Protected Areas	0.081	0.005
1.8 NDVI	0.378	0.571
1.9 Involvement in Conservation Areas	0.750	-0.048

Table 4-17 Comparison of standardized coefficients of the Discriminant Function of Ecological Value obtained (see text)

Indicator of Ecological Sensitivity	Discriminant Function	
	Ideal Vector	Salience
2.1 Fractal Coefficient of perimeter	0.172	0.294
2.2 Circularity Ratio of area	-0.388	-0.491
2.3 Average slope	0.180	0.435
2.4 Species of vertebrates at risk (IUCN)	0.563	0.193
2.5 Species of vegetation at risk (IUCN)	0.195	0.045
2.6 Landslide index	0.467	0.303
2.7 FPI	0.560	0.304
2.8 Orientation compared to the main wind direction	0.706	0.702
2.9 Nearest Neighbour Index	0.063	0.151

Table 4-18 Comparison of standardized coefficients of the Discriminant Function of Ecological Sensitivity obtained (see text).

The results correlated to Ideal Vector method essentially confirm the importance of the same indicators of Ecological Value already seen in Table 4-10. In effect the C.B. habitats with elevated overall Ecological Value are the ones that (1) are very rare within the study area; (2) host a large number of rare vertebrates; (3) are characterized by large green zones revealed by high NDVI values and (4) belong to the Conservation Zones.

Also the results associated to the Ideal Vector method regarding Ecological Sensitivity mainly confirm the same indicators of Table 4-12. Indeed the C.B. habitats with elevated overall Ecological Sensitivity are the ones that: (1) are characterized by a high number of vertebrates at risk of extinction; (2) are more open to the negative influence of the prevalent winds; (3) are more open to fire risk; (4) are more open to landslide risk; and (5) have a low degree of compactness.

Discriminant Analysis correlated to Salience method ranking shows results somewhat different from the Ideal Vector ones. The analysis individuates a different set of indicators that affect the determination of elevated ecological performance of habitats regarding ecological Value. These results don't confirm the Ideal Vector ones but, working the two methods in a different way, the obtained rankings and particularly the selection of habitat having elevated performance can be reasonably influenced in a different manner by ecological indicators. Using Salience method of ranking, the C.B. habitats with elevated overall Ecological Value are the ones that (1) are characterized by large green zones revealed by high NDVI values; (2) are characterized by great ecological variations (which potentially positively affect faunal and floristic richness) due to terrain morphological complexity; (3) are very suitable for vertebrates at risk of extinction and (4) host a large number of vertebrates.

The Discriminant Analysis for Salience method of ranking regarding Ecological Sensitivity mainly confirms the results obtained using Ideal Vector individuating basically the same group of indicators affecting the determination of high ecological performance of habitats (only indicator 2.4 is replaced by indicator 2.1). Indeed, the C.B. habitats with elevated overall ecological sensitivity are the ones that: (1) are more open to the negative influence of the prevalent winds; (2) have a low degree of compactness (3) are more open to fire risk; (4) are more open to landslide risk; and (5) are characterized by more convoluted boundaries.

Ecological Value and Ecological Sensitivity are two main ecological parameters of habitats. Each of them alone is not sufficient to define completely the ecological situation of a habitat in order to define an effective biodiversity conservation plan.

In this perspective we define as Highspots of Ecological Attention (HSEA) the small fraction of C.B. habitats characterized, at the same time, by the greatest overall Ecological Value and the greatest overall Ecological Sensitivity.

The C.B. habitat defined as HSEA needs ecological attention and should be protected. In fact, having a habitat elevated ecological value means that it is ecologically relevant, but only if it is characterized at the same time by elevated sensitivity it is potentially at risk; otherwise stakeholders should not focus their attention on it.

A threshold of 20% of C.B. habitats with the greatest overall Ecological Value and 20% of C.B. habitats with the greatest overall Ecological Sensitivity was considered in order to identify the HSEAs in both the study area. It is to be noted that in this application of the methodology we preferred not to be "conservative"; instead of using 15% of the C.B.

habitats with the elevated overall Ecological Value (or elevated Ecological Sensitivity), we used 20% because often happens to have habitat with similar ecological value and sensitivity and we want to prevent the exclusion of some of them in this research. Clearly, for the reasons explained before in this chapter, this threshold can be precisely extracted only with the Ideal Vector methods, while using Salience method, the presence of many ties avoid the precise extraction of this fixed percentage of habitat. The choice of 20% as cutting threshold helps in Salience method to avoid the exclusion of possible ties with elevated ecological characteristics.

The histograms below show all the distances from the Ideal Vector for ecological value and sensitivity in study area “A” (Figures 4-5a and 4-5b) and “B” (Figures 4-6a and 4-6b). The distances are reduced in the close interval 0–1.

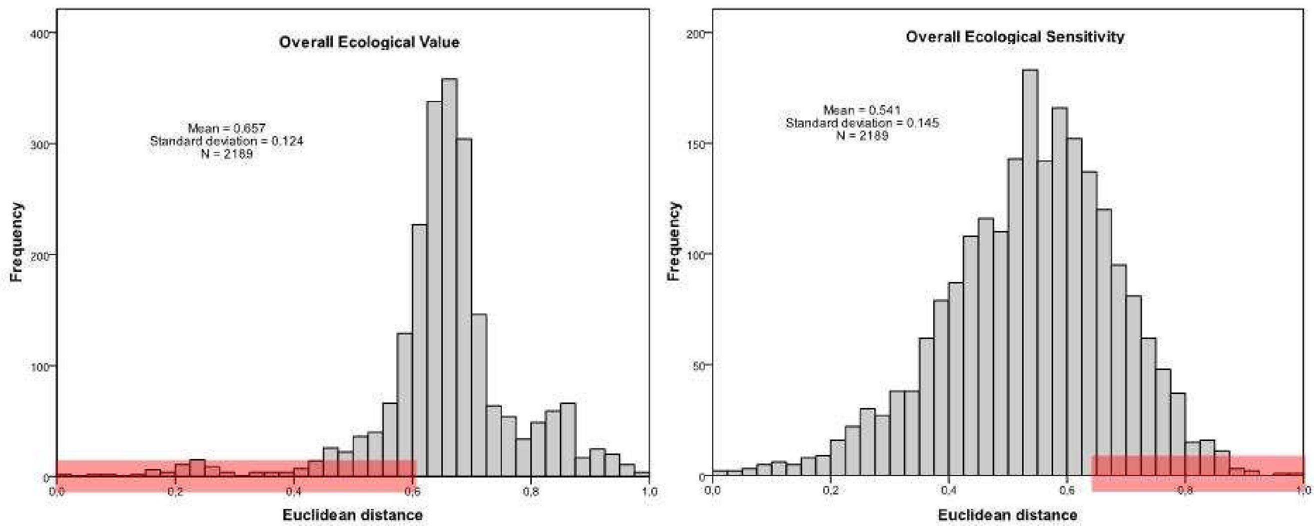


Figure 4-5a and 4-5b: Histograms of frequencies of CORINE Biotopes habitats referred to their distance from the Ideal Vector in study area “A”.

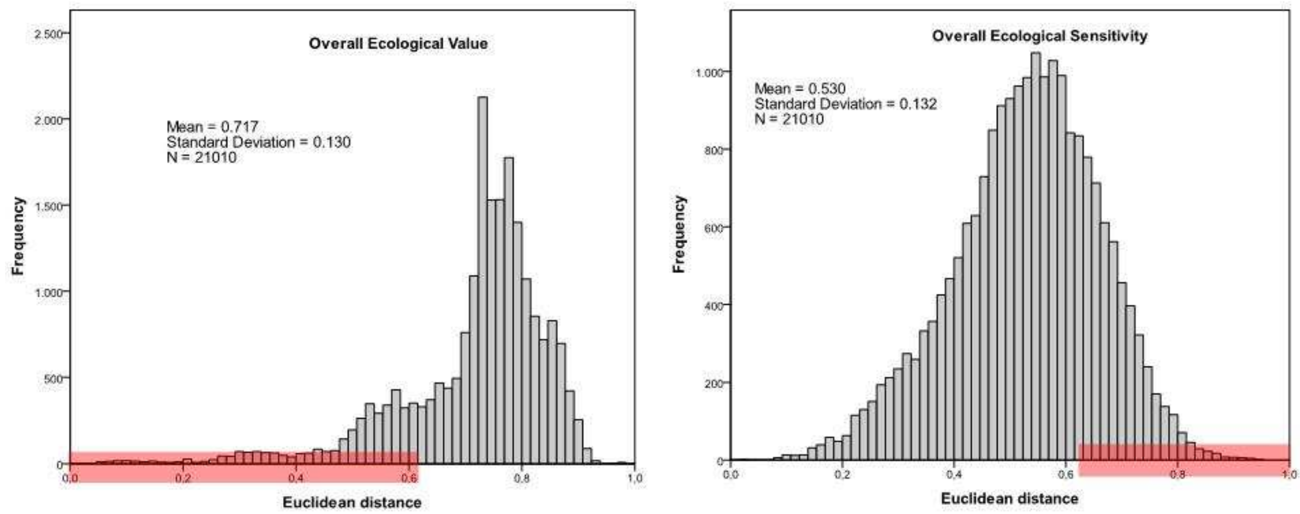


Figure 4-6a and 4-6b: Histograms of frequencies of CORINE Biotopes habitats referred to their distance from the Ideal Vector in study area “B”.

In study area “A” the threshold values are 0.604 and 0.659, respectively for the overall Ecological Value and the overall Ecological Sensitivity. There are 130 HSEA, which is 5.9%, as expected.

The study area covered by HSEAs is 7162.08 ha, i.e. 58.52% of the total area. The spatial distribution of the HSEAs in the study area is shown in Figure 4-7.

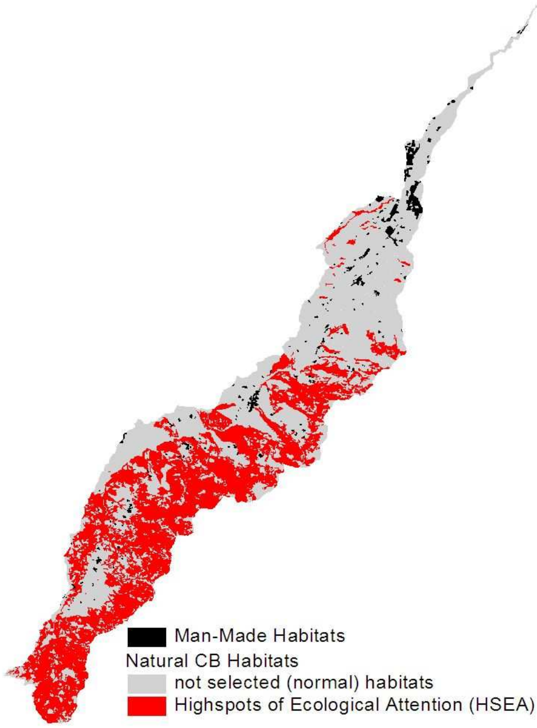


Figure 4-7 Spatial distribution of the HSEAs individuated using Ideal Vector Method in the study area “A”.

Similarly, in study area “B” the threshold values are 0.636 and 0,641, respectively for the overall Ecological Value and the overall Ecological Sensitivity. There are 892 HSEAs, which is 4.25%, as expected.

The study area covered by HSEAs is 63847 ha, i.e. 22.56% of the total area. The spatial distribution of the HSEAs in the study area is shown in Figure 4-8.

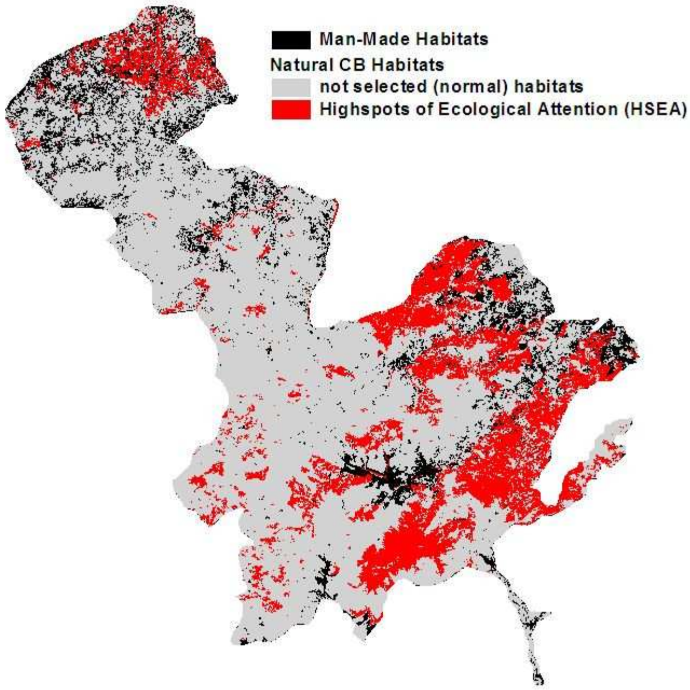


Figure 4-8 Spatial distribution of the HSEAs individuated using Ideal Vector Method in the study area “B”.

In study area “B” using Salience method we compute approximately 20% of the habitats in this way: we start with the highest level of superiority and starting with the lowest level of inferiority (moving from left to right), we accept all habitats with that level of superiority, then the same with the next level of superiority. We continue accepting habitats until we have reached the 20% of them.

In practice, for Ecological Value, the cut-off level chosen for superiority is 22. For all levels of superiority greater than 22, we accepted those habitats. For habitats with superiority level 22, we accepted all habitats with inferiority level smaller than or equal to 13. Similarly for ES, we accepted all habitats that have superiority level greater than 7, and for habitats with superiority level 7, we accepted habitats with inferiority level smaller or equal to 2. To find the HSEA, we chose the habitats that were accepted for both EV and

ES. We find the habitats which have been accepted for both sets of indicators. We call these habitats as HSEA for the Salience method.

There are 1228, which is 5.84%, as expected. The study area covered by HSEA is 81829 ha, i.e. 28.92% of the total area. The spatial distribution of the HSEA in the study area is shown in Figure 4-9.

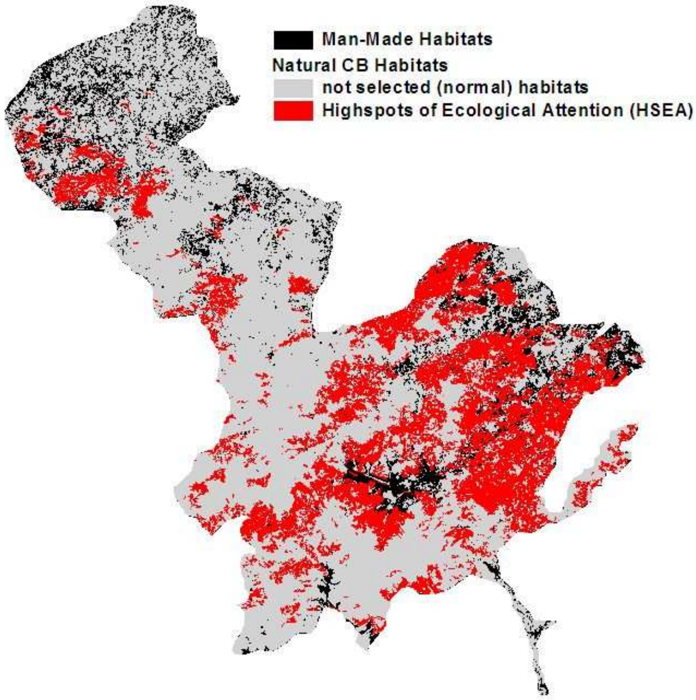


Figure 4-9 Spatial distribution of the HSEAs individuated using Salience Method in the study area “B”.

In order to compare the results in these two methods, a graphical display of the highspots (of Ecological Attention, i.e. HSEAs) using both methods is shown. The Salience method results in more highspots than the Ideal Vector method. In addition, HSEAs from Salience and from the Ideal Vector method agree only partially in their results, being HSEA in both methods only 214 habitats.

These results suggest that there is a large difference in the choice of highspots selected between the two methods. This may be due to the different approaches taken by the methods, with the Ideal Vector method using aggregation in an index and the subordination method leaving indicators separated (Figure 4-10).

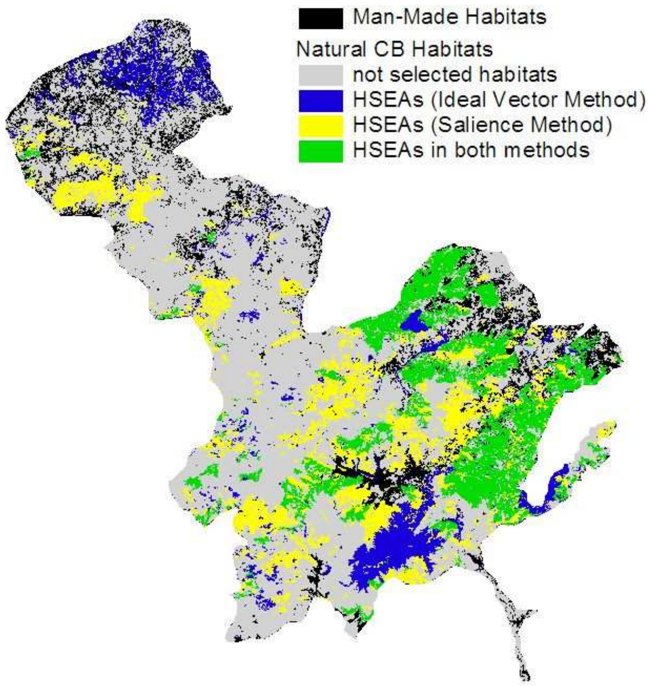


Figure 4-10 Spatial distribution of highspots (HSEAs) in study area “B” using both ranking methods.

4.2 Planning and analysing a habitat Network with some optimal ecological characteristics

Until now we concentrated on methodologies useful to rank environmental units (i.e. habitats). The goal has been to identify which fraction of habitats is most worthy to be protected (the so called HSEA).

The next step is to use this acquired capability to achieve a further and more complex goal that is to provide a methodology to plan a Network of habitats which satisfy some optimal ecological characteristics. In other words, starting from the discovery of the geographical location of HSEA, it is necessary and useful to design an interconnected system of habitats which satisfy simultaneously many other environmental-management criteria with the aim to preserve in an efficient and effective way the biodiversity of a given region.

In E.N. planning some essential aspects that characterize the environmental mosaic structure of the Valley (compactness degree, fragmentation degree, isolation degree of each natural and seminatural habitat type) has been taken into due account, in quantitative terms. In detail, the E.N. design aims to:

- “maximize” the biodiversity of the Valley (in terms of natural habitat types). In fact a high habitat diversity entails necessarily a high diversity of species;

- “minimize” the territorial fragmentation and the space involved in the E.N.;
- As last point has been considered important to evaluate the effect of diffuse anthropic pressure acting on the optimal characteristic of the above mentioned E.N.

The region subjected to the Habitat Network design is the Baganza River Valley (area “A”). It has been chosen because it is complex from an ecological-naturalistic point of view, and also diffusely anthropized. In this area it is necessary to achieve an E.N. that mainly considers the first and the fourth interpretative model (see paragraph 1.6.2), beause it is able to contribute towards the maintenance of the actual high biodiversity but also to induce or to redress a landscape overall balance in the Valley.

The basic steps to plan an E.N. with ecological-environmental features which should be desirable are shown during this paragraph. A specific goal achieved in the analysis correspondes to each step.

The environmental units identified in the Valley amount to 2387 and they belong to 47 different types of C.B. habitats. Having habitats different shape and dimension, they are not the best elements on which operate in a planning perspective. For this reason the *planning region* was divided into 61459 *planning units*: generating a grid of hexagonal regular cells of fixed dimension (0.28 ha), habitat representation scale permitting (1:25000 corresponding to a minimum habitat dimension of 0.1 ha). These cells are the basic elements of E.N. planning.

Preliminary Step 1. Individuation of a possible relationship between biodiversity and investigated area

In a sustainable development perspective, guidelines for the territorial planning are essential to allow maximizing biodiversity conservation, at the same time minimizing costs and spaces assigned to its protection (***objective 1***). The possible quantitative relationship between the investigated area of the Valley and the actual biodiversity level has been empirically studied, in order to establish the minimum area to be preserved in order to protect the majority of biodiversity present in the Baganza Valley itself.

From the statistical universe of 2189 natural and semi-natural C.B. habitats covering the Valley, habitat samples of growing *n* dimension have been drawn, completely randomly (and with reintroduction). At first *n* was set equal to 50, then to 100, 200, 400, 500, 550, 600, 650, 700, 750, 800, 850, 1000, each time counting both the whole area covered by C.B. habitats and the corresponding number of different CORINE typologies present (biodiversity level). This procedure was repeated several times to obtain the pattern shown in Figure 4-11.

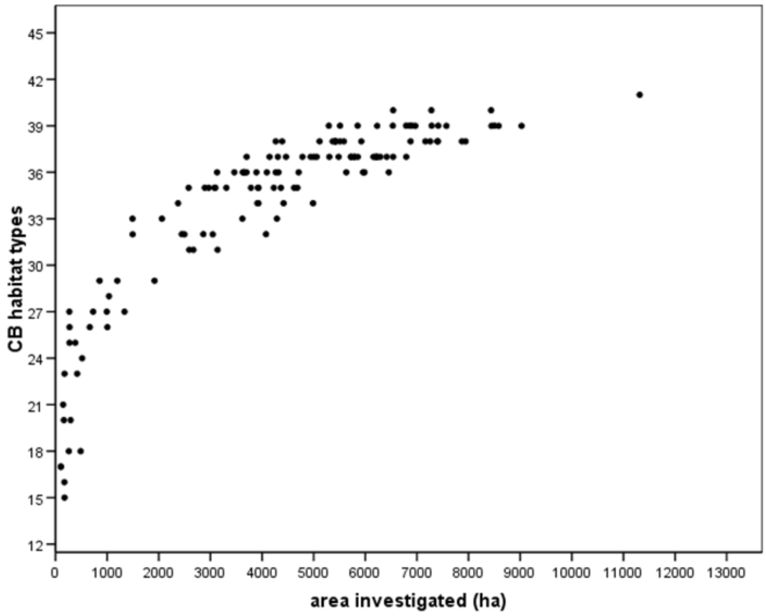


Figure 4-11 Cumulative Curve showing the pattern between the investigated area (in hectares) and the number of CORINE Biotopes habitat types, obtained by conducting increasing (in terms of number of habitats) random sampling.

Observing the graph, it can be inferred, as expected, that the number of different habitats does not grow in a linear way with the investigated area quantity, i.e.: it first grows very quickly, then ever more slowly, towards a threshold value represented by the 44 C.B. habitat typologies (excluding the anthropized ones).

A first interesting result is represented in Figure 4-12 deduced from Figure 4-11.

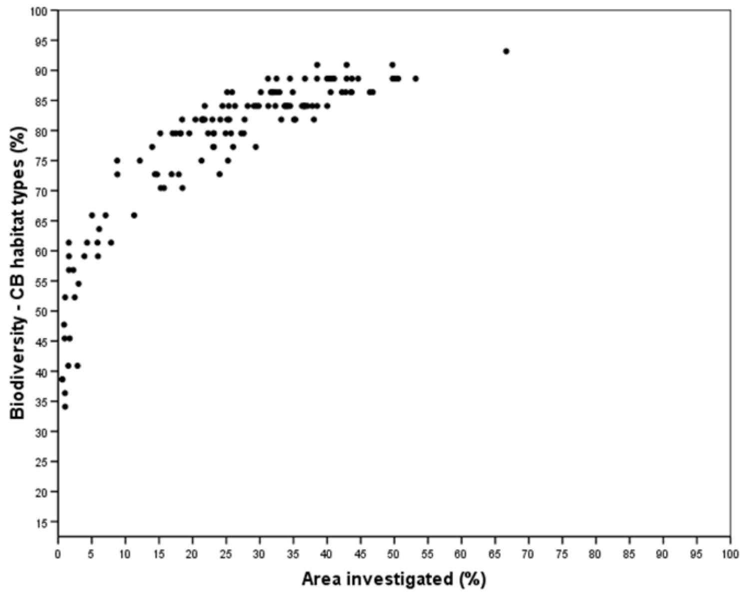


Figure 4-12 Cumulative Curve, derived from Figure 4-11, showing the pattern between the percentage of investigated area and the corresponding percentage of CORINE Biotopes habitat types, obtained by conducting increasing (in terms of number of habitats) random sampling.

It is to be noted that the biodiversity percentage (meant as percentage of different C.B. habitat) grows very quickly with the percentage of the area explored in the Valley up to a value of about 18-20%; then it grows more slowly up to a value of 30-35%, and finally grows very slowly towards the asymptote identifying the total (100%) biodiversity (44 habitat).

Around 18-20% of the area explored, the biodiversity rate of the Baganza Valley seems to reach over 80%; around 30-35% values of the area, this biodiversity value reaches over 90%.

Preliminary Step 2. Representativeness of different habitat types within the Ecological Network

The ecological network planning must necessarily aim to reduce the fragmentation level of the territory, possibly maintaining its physiognomy and its basic features. (***objective 2***). The area assessment of each C.B. habitat type to include in the Network must basically take into account both the overall area that the C.B. habitat type covers in the Valley and its fragmentation degree.

After fixing the whole network area A_N, and laying down $A_N = p \times \sum A_i$ with $0 < p < 1$, the following relation can be derived:

$$A_i^* = \frac{A_i \times f_i \times \bar{d}_i}{\sum_i A_i \times f_i \times \bar{d}_i} \times A_N \qquad (39)$$

Where:

A_i^* = area of the C.B. habitat type *i*, to be included in the Network (*target*);

A_i = area of the Valley covered by C.B. habitat type *i*;

f_i = total number of Valley habitats belonging to the same C.B. habitat type *i*;

$\bar{d}_i$ = mean distance between all the f_i habitats belonging to the same C.B. habitat type *i*.

The *p* value (area Valley proportion within the Ecological Network) is chosen with reference to the quantitative relation represented by the chart shown in Figure 4-11.

The values f_i and d_i represent two core components of the fragmentation process which depends on both the f_i number of fragments composing A_i and, A_i being equal, the mean distance $\bar{d}_i$ between them.

It is a well-known fact (Davies, 2001; Fahrig, 2003) that, generally, the higher the habitat type fragmentation the greater the habitat risk of losing its own characteristic traits.

From the Ecological Network design point of view, it becomes essential that habitat types characterized by a high fragmentation degree are adequately represented.

Consequently, a second important result is underlined in Table 4-19.

Conservation Feature (CF)	Feature Name	Target (ha)	Amount Held (ha)	Target Met (TM)
47	Xerophile *Quercus pubescens* woods	409522.7849	1283473.951	yes
46	Vineyards	41129.4702	96304.8643	yes
45	Villages	0	190966.8121	yes
44	Urban parks and large gardens	379129.871	379145.0524	yes
43	Supra-mediterranean hop-hornbeam woods	1678516.272	7246635.887	yes
42	Submontane calcareous screes with *Calamagrostis varia*	0.7389	90.5716	yes
41	Subalpine thermophile siliceous grass	467821.4492	1279301.229	yes
40	Spring heath scots pine forests	2898.9268	36973.8147	yes
39	Semi-xerophile *Quercus pubescens* woods	827128.0566	1838534.802	yes
38	*Sedo-Scleranthetea* submontane calcareous screes	0.2391	22100.4388	yes
37	Sclerophyllous scrub	31496.4178	106511.9257	yes
36	Ruderal communities with *Tussilago farfara*	1611.353	17811.2843	yes

CF	Feature Name	Target (ha)	Amount Held (ha)	TM
35	Ruderal communities with *Melilotus albus*	12642.2207	13133.2644	yes
34	Ruderal communities with *Agropyron repens*	82089.6983	334143.9857	yes
33	Rough-grass screes	35738.971	184589.2491	yes
32	River course	67704.4977	244508.5894	yes
31	*Quercus cerris* woods	1754727.835	3828686.795	yes
30	Quarries	0	930.3001	yes
29	Purple moongrass meadows and related	26.9986	5025.1503	yes
28	Overgrown pastures	328832.3315	431893.0367	yes
27	Northern apennine mesobromion grasslands	508433.9373	508570.0217	yes
26	Neutrophile beech forests	203135.5141	7835731.978	yes
25	Mosaic	5817615.326	5817645.762	yes
24	Montane siliceous cliffs	1100.5305	35124.2301	yes
23	Montane hop-hornbeam woods	134759.2123	2089683.648	yes
22	Mesophile pastures	134516.319	376936.6683	yes
21	Mediterranean purple willow scrub	51084.482	802019.944	yes
20	Medio-european rich-soil thickets	3183858.751	3184019.209	yes
19	Lowland high meadows	3701080.433	3701090.765	yes
18	Locust tree plantations	151259.633	190431.516	yes
17	Juniperus nana scrub	604.227	1766.1047	yes
16	Italian poplar galleries	602558.6036	2977836.635	yes
15	Fruit orchards	43925.1876	78420.519	yes
14	Fresh waters	6430.1006	18693.9668	yes
13	Field crops	7866567.995	7866596.873	yes
12	Common juniper scrub	5067.7462	5600.0026	yes
11	Chestnut woods	21177.9436	22397.088	yes
10	Chestnut groves	3426.7779	24650.6742	yes
9	Gully	56497.6029	193138.2109	yes
8	*Brometalia erecti* submontane calcareous screes	0.1914	17688.1307	yes
7	Blackthorn-bramble scrub	78423.0372	78528.1753	yes
6	Black pine reforestations	885504.9386	886013.8914	yes
5	Black pine forests	155.4354	19976.42	yes
4	Beech forests with hop-hornbeam	395174.178	396589.3585	yes
3	Bare cliffs	130652.7465	130659.2245	yes
2	Active industrial sites	0	23255.6857	yes
1	*Abies alba* reforestations	10701.2953	11969.64	yes
	Total (ha)	3011.473	5483.580	
	Total (%)	17.2	31.3	

Table 4-19 Target requested to be included in the E.N. and corresponding amount held obtained using MARXAN for each of the 47 CORINE habitat types in the Baganza Valley.

The third column of this table shows the minimum value, in terms of area, that is considered desirable to be included in the E.N. for each C.B. type (i.e. *target*). The minimum requested area was estimated using Eq. 1, setting a value of $p = 0.18$ to all natural and semi-natural habitat categories and removing the anthropic habitats. The chosen p value is suggested by looking at the curve in Figure 4-12 where around 18% of the area explored, corresponds to a high biodiversity level, over 80%. It is to be noted that the sum (Table4-19) of all the minimum areas requested by the targets is 3011 ha (about 17.2% of the Valley), while the result obtained using MARXAN ("amount held" column) gives a higher area value in the E.N. because at the same time it must satisfy other criteria (compactness, cost, etc.).

Peliminary Step 3: Detection of Valley zones with both elevated ecological value and elevated ecological sensitivity

The habitats presenting at the same time high Ecological Value and high Ecological Sensitivity require Ecological Attention and are therefore central in conservation strategies and essential to maintain the biodiversity of a region. These critical habitats should be included preferentially in an Ecological Network (***objective 3***).

Applying the Ideal Vector method (see paragraph 3.1.1) both the overall Ecological Value and the overall Ecological Sensitivity were calculated for each C.B. habitat.

The measure interval of the Ecological Value and the Ecological Sensitivity was divided into deciles, each containing 218 C.B. habitats. The same score on a scale ranging from 1 to 10 was assigned to the habitats belonging to the same decile. Habitats scoring 9 and 10 (i.e. 20% of the total, or quintile) are characterized by either elevated overall Ecological Value, or elevated overall Ecological Sensitivity. C.B. habitats falling at the same time in the quintile with elevated Value and in the one with elevated Sensitivity deserve more attention and protection. This is the reason why these habitats must be included in the E.N.

Preliminary Step 4: The measurement of current human pressure on the environment and its possible trend in the near future

In the Ecological Network planning, the management must take into account human pressure acting on the habitat mosaic and its foreseeable trend (***objective*** 4). Therefore, it is clearly necessary to analyze the current demographic situation, but mainly its future tendency too.

So far, the area has been analyzed from an ecological point of view.

The Ecological Network is designed taking into account mainly and only essential ecological parameters of the habitats (and consequently of the cells). After defining the network, the Human Pressure is introduced. In particular the demographical analysis developed on the administrative units of the area (The Communes) allows to give them useful suggestions regarding the management of habitats inside the Ecological Network. With this analysis it is possible to reveal management macro-criticalities. With this term we consider not only all the situations (a Commune or cluster of them) in which human presence (i.e. Human Pressure) tends to increase in conditions of actual elevated pressure (overpopulation and so soil overexploitation) but also all the situations in which an actual low human presence is associated to a further trend population decrease (depopulation) because also this type of trend, probably more than the first one, produces negative effects on habitat conditions and quality.

Step 5: Individuation of the Ecological network

All the information relating to preliminary step 1, 2, 3, 4 was utilized in order to design the E.N. of Baganza Valley using the methodological approach of Systematic Conservation Planning through the MARXAN software (see paragraph 3.3).

Ecological Networks is characterized by a typical fundamental structure which constitute a sort of “skeleton” of it: Primary Knots, Secondary Knots and Connecting Corridors.

HSEA habitats must be included in the E.N.. These habitats represent about 4% of the Valley and they make up the Secondary Knots of the network.

Primary Knots of the E.N. are the areas already under nature conservancy. Within the Valley there are two protected areas: the Carrega Woods Regional Park in the hilly region, and the Crinale Park (which incorporates a SCI too) in the mountain area.

The hydrographical network of the Baganza river together with its tributaries and the riparial habitats make up the Connecting Corridors of the E.N..

In total these three areas, whose presence is *a priori* considered fundamental, cover about 16.94% of the Baganza Valley.

MARXAN software, on the basis of the above-explained ties and requirements, produced a set of Network scenarios. Among them, the Scenery with a BLM value equal to 1 was chosen (best-case scenario). In fact, next to BLM value equal to 1 the rate (*trade off*) between the area and the perimeter of the E.N. is optimal. In Figure 4-13 is shown the trade-off.

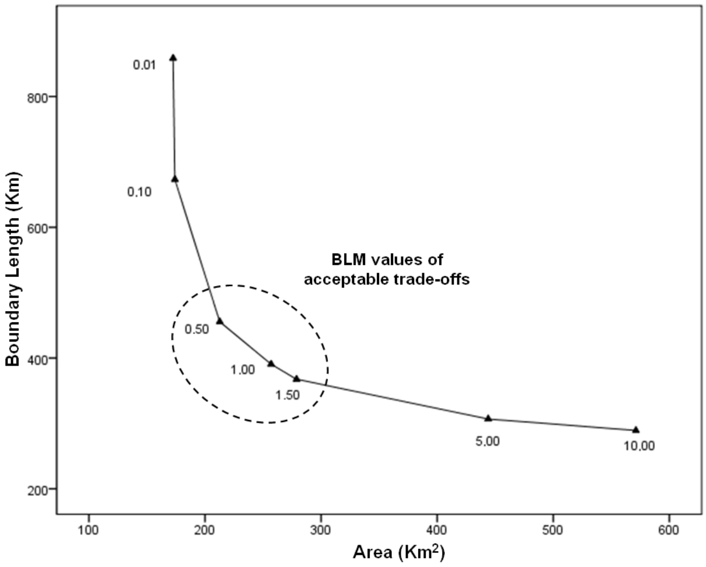


Figure 4-13 The trade-off between minimizing boundary length (perimeter) and minimizing area for various boundary length modifiers (BLM). The scenarios with a BLM between 0.50 and 1.50 achieve spatial compactness with acceptable trade-offs.

The Ecological Network obtained using ecological parameters (Eqs. 37 and 38) is shown in Figure 4-14.

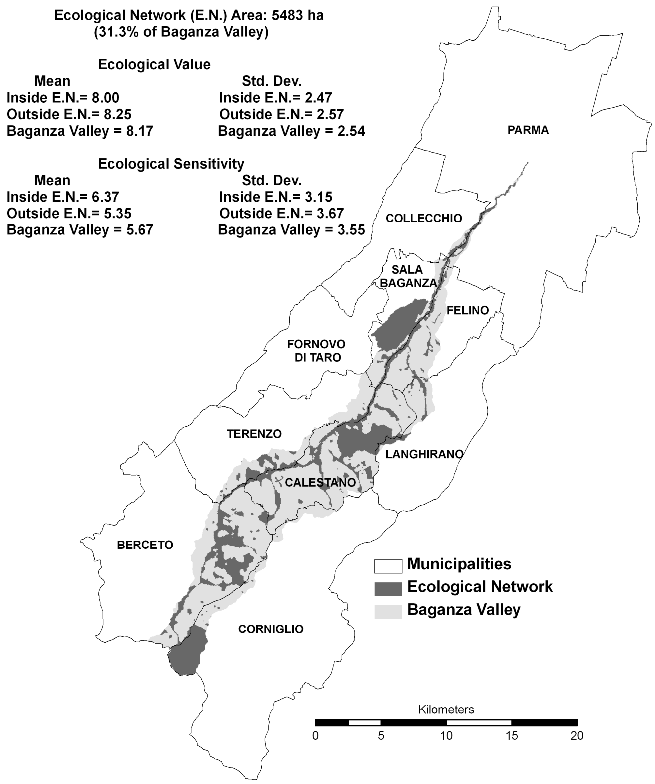


Figure 4-14 The planned Ecological Network (BLM =1), its basic ecological features (Ecological Value and Ecological Sensitivity) and its spatial distribution within the Municipalities comprised in the Baganza Valley.

As a whole, the E.N. covers an area of 5483 ha, equal to 31.3% of the Baganza Valley. Furthermore the E.N. concerns the territory of all the Municipalities involved in the area.

MARXAN generated an E.N. with a mean Ecological Value (calculated referring to the hexagonal cells) basically in line with the Valley one, which already is high. Otherwise, the mean Ecological Sensitivity of the habitat comprised in the E.N. is definitely higher (+20.7%) than the habitats outside (Figure 4-14).

It should be noted that for each type of natural and semi-natural C.B. habitat the pre-established minimum conservation target was reached (Table 4-19). The thus obtained Network includes all the habitat typologies, assuring great protection to the biodiversity currently present in the Valley.

Comparing the habitat composition of the E.N. with the composition in the Baganza Valley, an increase of more valuable typologies appears clear (Figures 4-15a and 4-15b).

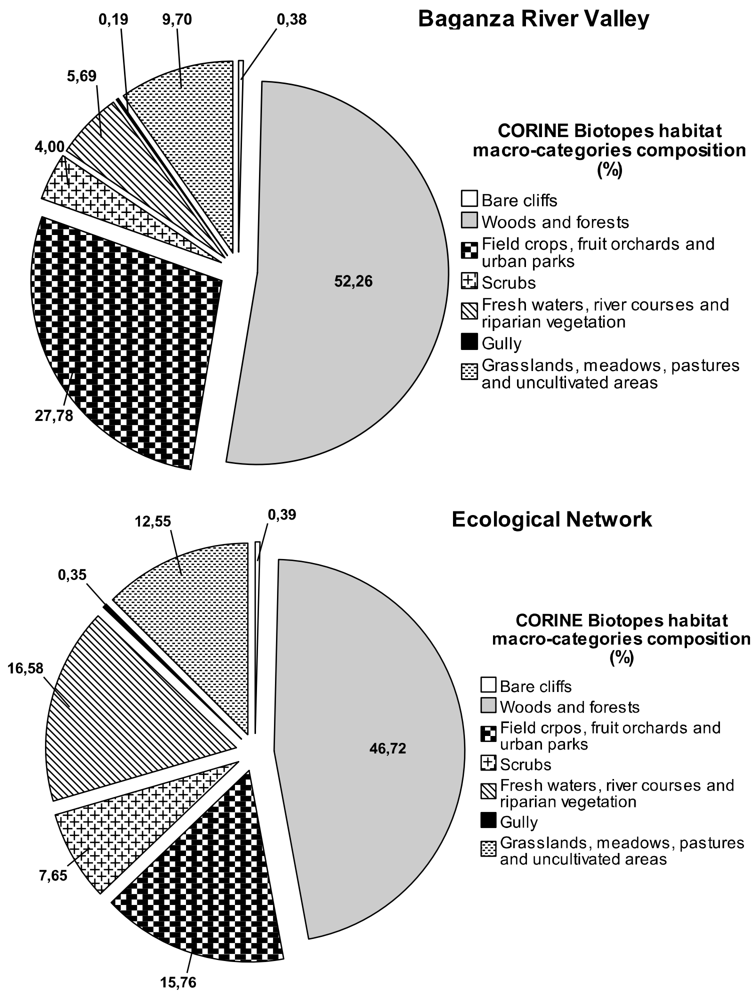


Figure 4-15a and 4-15b Pie charts that show the composition (%) in terms of 7 CORINE Biotopes habitat macro-categories respectively of the designed Ecological Network and of the overall Baganza Valley.

In particular, the presence of cultivated fields, orchards and urban parks is strongly reduced (-12%), favouring water bodies (+11%), brushes and shrubs (+3.65%), meadows and pastures (+3%), with only a modest loss in woods and forests (-5.5%), however well represented in the Network.

This interesting result is confirmed by a Cluster Analysis (*k*-means method) carried out on the whole 61459 cells constituting the Baganza Valley, each of them characterized by a specific Ecological Value and a specific Ecological Sensitivity (paragraph 3.3, Eq. 38). The statistical analysis has identified three groups of cells (clusters) on the basis of the ecological characteristics examined (Table 4-20).

Indicator	Cluster		
	1 (N=33253)	2 (N=17921)	3 (N=10285)
EV	8.965	9.377	3.497
ES	8.624	1.569	3.299

Table 4-20 Amount (in terms of hexagonal cells), and related mean Ecological Value (EV) and mean Ecological Sensitivity (ES) of 3 groups carried out by Cluster analysis.

The first group (Cluster 1) is characterized by elevated Ecological Value and elevated Ecological Sensitivity. The second group (Cluster 2) is characterized by elevated Ecological Value and low Ecological Sensitivity. The third group (Cluster 3) is characterized by low Ecological Value and low Ecological Sensitivity (Figure 4-16).

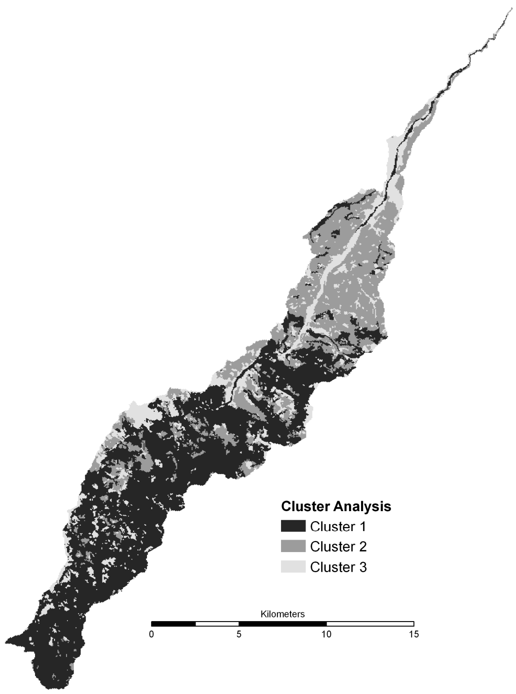


Figure 4-16 Spatial Distribution of the 3 Clusters (of hexagonal cells) in the Baganza Valley.

Cluster 1, depending on its intrinsic features of elevated Value and elevated Sensitivity, represents the Baganza Valley areas of higher interest in environmental protection: for this reason they can be called areas of Ecological Attention (Rossi *et al.* 2008).

The highly significant χ^2 value (Table 4-21) confirms the high number of Network cells included in Cluster 1.

Zone	Cluster 1	Cluster 2	Cluster 3	Total
Inside E.N.	11869	4098	3625	19592
	(60.58%)	(20.92%)	(18.50%)	(100%)
Outside E.N.	21384	13823	6660	41867
	(51.07%)	(33.02%)	(15.91%)	(100%)
Total	33253	17921	10285	61459
	(54.11%)	(29.16%)	(16.73%)	(100%)
χ^2 = 946.65 with 2 degree of freedom				

Table 4-21 Frequency matrix (event table) underlying the composition (number and percentage of hexagonal cells) in terms of the 3 clusters of Table 4-20, of the Ecological Network (inside E.N.), of areas outside E.N. and of the Baganza Valley in toto. The χ^2 value of the matrix is reported.

Out of 19592 hexagonal cells in the E.N. (i.e. more than 60%), 11869 belong to Cluster 1. The expected frequencies of cells in this cluster, under hypothesis H_o, currently are 10600 (about -12% of the ones observed (11869) under the same hypothesis). The wholeness of cells of the E.N. falling in Cluster 1 and Cluster 2 (both with high Ecological Value), represents more than 80% (exactly 60.58+20.92 = 81.5%) of the total amount of cells in the Network.

Berceto, Calestano, Felino, Sala Baganza, Terenzo, Corniglio, Langhirano, Collecchio and Parma are the Municipalities whose territory is more or less included in E.N..

Referring to preliminary step 4, the evaluation of the 6 above-mentioned indicators allow to establish the current demographic structure and its trend in these Municipalities (Table 4-22).

MUNICIPALITY	STRUCTURE at 01/01/2008					TREND (on period ’04 - ‘07)		
	Population	Population Density (1)	Mean age (2)	Ageing rate (3)	Dependency ratio (4)	Rate of natural increase (5)	Net migration rate (6)	Total rate
Berceto	2292	17	51	427	65	-14.83	4.56	-10.27
Calestano	2006	35	46	220	60	-4.90	16.23	11.33
Felino	8075	208	43	143	52	1.00	16.96	17.96
Sala Baganza	5206	168	43	138	50	-0.91	27.12	26.21
Terenzo	1210	17	51	454	66	-11.89	1.43	-10.46
Corniglio	2101	13	53	522	84	-14.99	2.84	-12.15
Langhirano	9341	132	43	142	51	-0.58	17.91	17.33
Collecchio	13300	226	44	159	52	-0.63	22.69	22.06
Parma (provincial capital)	178718	685	45	191	54	-1.68	22.83	21.15
Parma (Province)	425702	123	45	185	55	-2.53	18.44	15.91
Emilia Romagna (Region)	4275802	193	44	177	55	-1.60	13.36	11.76

Table 4-22 Indicator values describing the demographic structure (from 1 to 4) and the demographic trend (5 and 6) in the Municipalities of the Baganza Valley, in the Province and Region of reference.

Demographical structure indicators (the firsts 4) give an essential description to characterize the current demographic situation (2008) in the Municipalities of the Valley. The natural and migration rates (averaged from 2004 to 2007) provide an essential estimate to identify the human pressure trend in the short and medium term. Comparing the values obtained with the general situation in the Province of reference (Parma), 3 different situations stand out:

1. Mountain Municipalities (Corniglio and Berceto) and sub-mountain ones (Terenzo) show, if compared with the whole Province, a much lower population density(up to 89% less), a much more aged population (up to 17.8% more), with a much slower generational replacement (until 182% more). The high value of dependency ratio (up to 52.7% more) confirms the small presence of workforce in the area. The furthest situation from the provincial mean can be found in Corniglio, which the above-mentioned percentage gaps refer to. The presence of a strongly negative rate of natural increase is only in minimum part mitigated by a positive migration rate, increasing, in this way, the general trend to depopulation and land abandonment.
2. Even if Calestano (placed in the hilly belt of the Valley) presents demographic structure indices on average lower than the provincial ones, it shows a population

density definitely higher (double) of the Municipalities in Cluster 1 accompanied with a population not only with a higher number of inhabitants in working-age, but also with a stronger presence of young people. This observation is proven by the ageing rate and the mean age definitely lower and more in line with the provincial mean value. The Municipality shows a strongly positive migration rate, with a foreseeable high increase in human pressure on the land.

3. The plain Municipalities (Felino, Sala Baganza, Langhirano and Collecchio) show a highly populated land with a slightly lower mean age than the Province (up to 4.4% less) and a much lower ageing rate (up to 25.4% less). The ratio between working-age and retired people, or people not yet working by the law, is in line with the provincial mean value, and is high as in the rest of the Emilia Romagna region. In addition, because of a high migration rate, a considerable population increase can be foreseen.

The Ecological Network shown in this study covers, in a variable proportion, all the Baganza Valley Municipalities (Table 4-23).
Municipalities.

Municipality	Cluster 1	Cluster 2	Cluster 3	Total	% on E.N.
Berceto	3506	193	614	4313	22.01
Calestano	4064	544	785	5393	27.53
Collecchio	54	35	100	189	0.96
Corniglio	2374	103	18	2495	12.73
Felino	101	425	472	998	5.09
Langhirano	373	166	157	696	3.55
Parma	227	176	149	552	2.82
Sala Baganza	565	2361	640	3566	18.20
Terenzo	605	95	690	1390	7.09
Total	11869	4098	3625	19592	100
% on E.N.	60.58	20.92	18.50	100	

Table 4-23 Distribution (hexagonal cell number) of the 3 clusters within the Baganza Valley.

This table underlines how more interesting areas from an ecological point of view (i.e. belonging to Cluster 1) fall in the mountain and sub-mountain Municipalities (Berceto, Corniglio, Terenzo and Calestano). However, Cluster 2 areas have a certain environmental interest because of their high ecological value, and mainly concern the plain zone occupied by Sala Baganza and Felino.

Step 6: Deriving useful considerations for environmental stakeholders

The analysis of the E.N. defined only on the basis of ecological considerations and the next demographical analysis of the Communes involved in it allows to identify different possible management scenarios and to provide useful suggestions regarding the choice and adoption of conservation policies.

Table 4-23 shows that the Municipalities significantly involved in the management of Ecological Attention areas present in the E.N. (Cluster 1 in Figure 4-17) are mountain and sub-mountain ones (Berceto, Corniglio, Terenzo and Calestano). The first three Municipalities contain 54.64% of high Ecological Value and high Ecological Sensitivity cells present in the E.N.. However, they are characterized by very low current human pressure which may be added to its clear decreasing trend. Due to the growing depopulation and the high mean age of resident population, it seems necessary that these Municipalities form a consortium to compensate for the lack of local resources, eventually requesting economic help to the upper administrative bodies (Region and Province). They can propose agreed defence and mitigated interventions to maintain the integrity and connectivity of the E.N. as a whole. In a mountain region characterized by high presence of woods and steep slopes, the depopulation and the progressive land use abandonment, though promoting the widespread naturalness, could increase landslide and fire risk on the territory.

Areas belonging to Cluster 2 present high Ecological Value, too. Most of these zones belong to Sala Baganza Municipality (57.6%), and are located in the lower part of the Valley. Sala Baganza, also characterized by the presence of a fair number of cells belonging to Cluster 1 (4.8%), is in a condition of a high and growing current human pressure in the presence of habitats with modest Ecological Sensitivity. The pre-existence in the Sala Baganza territory of an important regional park (Carrega Woods Park), should recall attention for an economic development compatible with biodiversity protection.

Even if in small measure, the remaining municipalities located in the plain belt of the Valley (Felino, Collecchio, Langhirano and Parma) include zones belonging to Cluster 1 in their territory (6.36% of the total). These Municipalities have a current demographic situation characterized by strong and constantly growing pressure. Because of this the local administrators should pay ‘early’ attention to the appearance of those phenomena that might induce continuity breaks in the E.N. connections. This is very important because of the presence in these areas of many Vertebrate species at risk of extinction (i.e. the Sardinian grass snake, the garden dormouse, the Italian agile frog and various bat species). The reassuring current financial situation of these Municipalities allows them to provide all the territorial protection and control measures that seem to be suitable for an immediate recognition and a sensible management of risk areas (i.e. HSEAs).

4.3 Administrative Level Analysis: Communes

Thus far, the areas have been analyzed at habitat scale from an ecological point of view.

The paragraph 4.2 faces a very actual conservation tool adopting in many parts of the world and recently absorbed by National environmental regulation (i.e. Ecological Network).

However, since the conservation actions and environmental policies are taken by decision-makers at different administrative scales, it is necessary to interpret the ecologically relevant habitats in terms of administrative partitions of the Italian territory. In particular we refers to the lowest level: the Communes (i.e. Municipalities).

In order to implement a correct and efficient conservation policy, it is necessary to move from a naturalistic unit to an administrative institution, keeping knowledge of environmental situation and human needs in a view of sustainable land use planning of biodiversity conservation (Kim and Pauleit, 2007).

Since any form of environmental policy in practice finds expression in funds to spend in local administrative partitions involved in ecologically critical situations, there is the primary necessity to find quantitative methodologies to identify environmental criticality in order to guide public stakeholders in allocating funds only where it is truly necessary.

For this reason, ecological information integrated in the human context is an essential aspect to make environmental evaluations and provide guidelines for conservation action and planning (Rookwood, 1995;Wyant *et al*., 1995).

Two types of questions and relative problems arise when you move from the naturalistic unit to the corresponding administrative one:

1. In which reasonable/realistic way is it possible to allocate habitats (and as a consequence also HSEAs) into Communes? Our basic choice, that represents the easiest way, is to allocate completely each natural habitat in the Commune in which its centroid belongs to. According to this logic the total number of habitat is preserved avoiding any further split of habitats in more than one Commune. However, other possible choices of assignation can been considered and one (i.e. habitat area fraction) has been explored in deriving some possible guidelines in conservation planning.

2. The physical boundaries of the study area overlap or not the corresponding administrative boundaries? In our specific case, but also in general, the answer is negative because the boundaries of the study area are chosen using a naturalistic approach (i.e. watersheds) and not administrative ones (Figure 4-17), being the declared interest of Map of Italian Nature in mapping habitats.

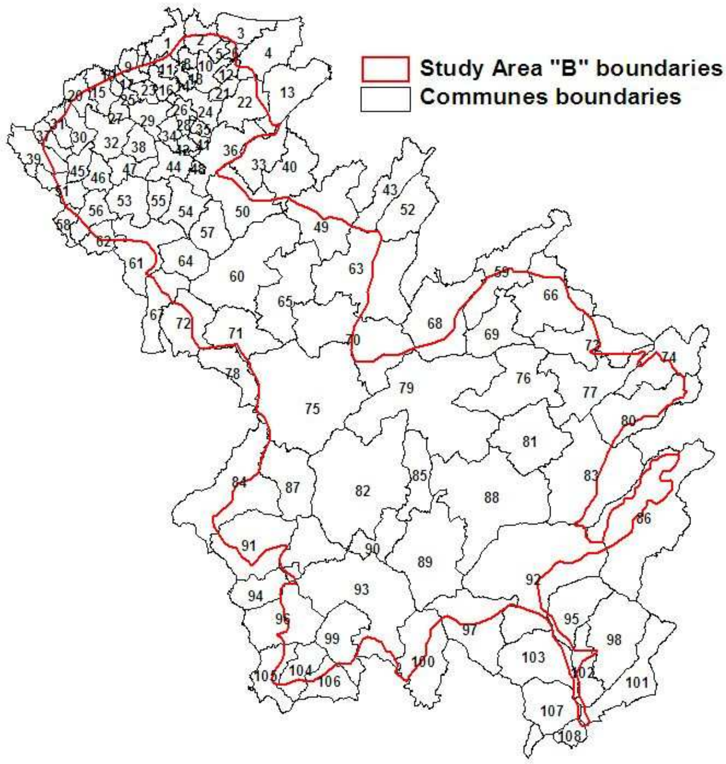


Figure 4-17 Communes involved in the study area “B”.

We considered in our analysis all Communes which overlap the study area, either in part or in total, and which also contain at least one habitat in order to preserve the total ecological information of the area. The limitation of this approach is that we cannot have a complete ecological situation (i.e. habitat distribution) in the Communes located at borders of the area, penalizing them. As a consequence of these choices, the results cannot be considered realistic for any type of environmental decision, but the attention must be focused on methods and use of quantitative tools to develop useful guidelines.
From this paragraph all the results shown are referred to the Study area “B” which involved 108 Communes (Figure 4-17). This choice is due to the simple consideration that in study area “A” the number of involved Communes is very small (9) so that all the results cannot be considered generally valid from a scientific point of view, and perhaps cannot be useful and relevant in a biodiversity conservation perspective.

4.3.1 Demographical analysis of Communes

The demographic indicators are not directly available at a habitat level but the assumption that the human pressure in a Commune reflects the real pressure on its habitats (causing fragmentation, reducing their dimensions etc) is realistic.

It is reasonable to determine which Communes are most under human pressure (overpopulation). It is also of great ecological interest to show in which Communes the opposite tendency (i.e. depopulation) is acting.

All the Municipalities in the area were submitted to a demographic analysis using six main indicators derived from the official ISTAT data of year 2008 (see paragraph 2.4). The demographic analysis is a useful tool to reveal both current human pressure and, especially, its trend in the short and medium term.

First of all we need to identify in which way each one of those 6 indicators contribute to determine the Human Pressure level of each Commune (that reflects the Human Pressure level on habitats that are within).

The only one indicator having a clear positive orientation (i.e. contribution) to Human Pressure level is the Population Density (indicator 1), because it is reasonable to assume that increasing the population on a certain area will increase proportionally the Pressure on it, increasing the request in infrastructures and in spaces with a consequent soil consumption. The other five don’t show a clear orientation and for this reason it is necessary a preliminary investigation on their contribution in composing Human Pressure levels. We have analyzed their relative trend compared to the indicator 1.

Scatter plots of each of the 5 indicators, in terms of their actual values and relative ranks produced on 108 Communes, according to the rank determined by the indicator 1 has been investigated (see Figures 4-18 and 4-19.).

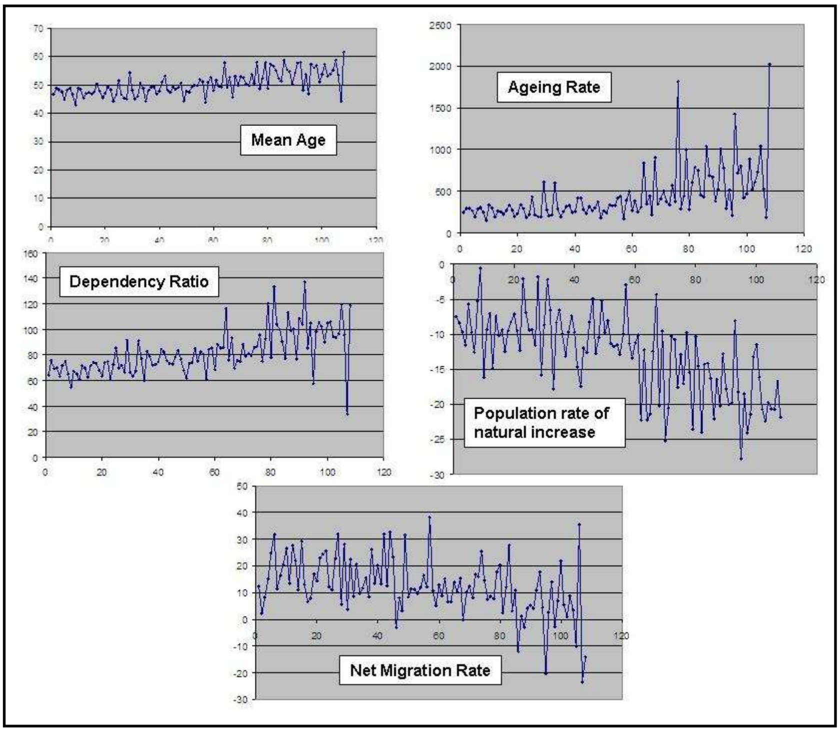


Figure 4-18. Scattered plots using actual values of indicators 2, 3, 4, 5 and 6 according to rank determined by indicator 1

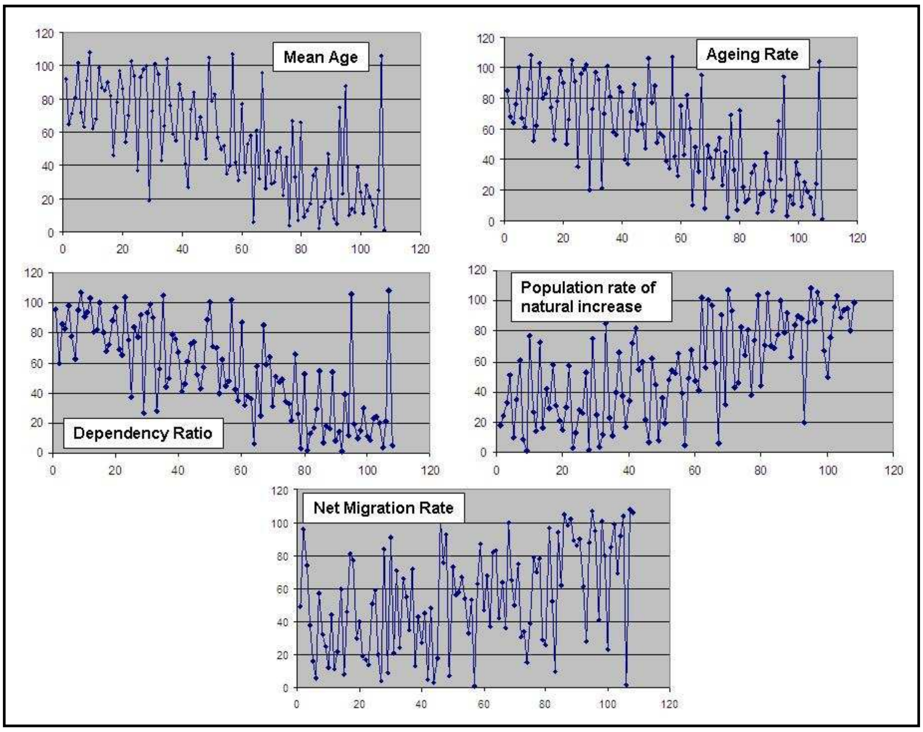


Figure 4-19 Scattered plots using ranks given by indicators 2, 3, 4, 5 and 6 according to rank determined by indicator 1.

Further, to make the results more clear, the correlation matrix on original values and on the relative ranks have been carried out as shown below (Tables 4-24 and 4-25):

Ranking	**Ind 1**	**Ind 2**	**Ind 3**	**Ind 4**	**Ind 5**	**Ind 6**
Ind 1	1					
Ind 2	-0.424	1				
Ind 3	-0.331	**0.860**	1			
Ind 4	-0.415	**0.910**	**0.716**	1		
Ind 5	**0.407**	-0.757	-0.614	-0.632	1	
Ind 6	**0.184**	-0.369	-0.375	-0.250	**0.381**	1

Table 4-24 Correlation matrix of actual values given by each of the 6 demographic indicators (see text).

Ranking	**Ind 1**	**Ind 2**	**Ind 3**	**Ind 4**	**Ind 5**	**Ind 6**
Ind 1	1					
Ind 2	-0.668	1				
Ind 3	-0.642	**0.982**	1			
Ind 4	-0.700	**0.922**	**0.889**	1		
Ind 5	**0.656**	-0.781	-0.770	-0.719	1	
Ind 6	**0.438**	-0.407	-0.399	-0.364	**0.342**	1

Table 4-25 Correlation matrix of ranks given by each of the 6 demographic indicators (see text).

From Tables 4-24a and 4-24b joined with the analysis of the scatter plots (Figures 4-18 and 4-19), we can clearly see that Indicators 2, 3 and 4 are very strongly positively correlated, and are negatively correlated to Indicators 1, 5 and 6. There appears to be a fairly strong correlation between Indicators 1 and 5, but a weak positive correlation between Indicator 6 and Indicators 1 or 5. Due to these observations, we computed the Poset rankings (Patil and Taillie, 2004a) of Indicators 2, 3 and 4, as well as the set of Indicators 1, 5 and 6. Since the orientation of Indicator 6 is not as clear as the other 5 Indicators, we also computed the orientation of Indicator 1 and 5 alone. From Table 4-26, we confirm our idea that Indicator 1 and 5 clearly increase with an increase in anthropic pressure, since we know that an increase in population density implies an increase in anthropic pressure, and Indicators 2, 3 and 4 have the opposite orientation and the increase of these indicators implies a decrease in the anthropic pressure. Indicator 6 has a positive orientation with anthropic pressure, but the relationship is not that strong.

Ranking	**Ind 1,5,6**	**Ind 2,3,4**	**Ind 1**	**Ind 2**	**Ind 3**	**Ind 4**	**Ind 5**	**Ind 6**
Ind 1,5,6	1	-0.769	**0.850**	-0.762	-0.740	-0.748	**0.808**	**0.728**
Ind 2,3,4	-0.769	1	-0.687	**0.984**	**0.971**	**0.968**	-0.771	-0.399
Ind 1,5	0.903	-0.800	0.898	-0.795	-0.773	-0.779	0.914	0.405

Table 4-26 Correlation matrix of ranks of groups of indicators using POSET.

At the end, to confirm the relative orientation of each demographic indicator concurring in Human Pressure level, we have analyzed all possible Hasse Diagrams (based on original values for each couple of indicators investigating both the possible orientation for indicator 2, 3 and 4 (Table 4-27). The relative ratio of comparabilities/incomparabilities shows in a clear way how each indicator works better if compared to indicator 1 (higher the ratio better is the agreement of the relative orientations).

Case	Comparabilities (count)	Incoparabilities (count)
1 (I1;I5)	4208	1570
2 (I1;I6)	3762	2016
3 (I1;I2)	1493	4285
4 (I1;I-2)	4291	1487
5 (I1;I3)	1549	4229
6 (I1;-I3)	4233	1545
7 (I1;I4)	1375	4403
8 (I1;-I4)	4406	1372
9 (I1;I5;I6)	2898	2880
10 (I2;I3;I4)	4875	903
11 (I1,I2,I3,I4,I5,I6)	212	5566
12 (I1,-I2,-I3,-I4,I5,I6)	2456	3322

Table 4-27 Total number of comparabilities and incomparabilities in Hasse Diagrams due to different combinations of demographical indicators (see text).

The results obtained by these several analyses seem reasonable looking at the nature of each of the other 5 indicators.

Indicators 5 and 6 are, like indicator 1, directly referred to the amount of population, taking care respectively of the internal increase of population (due to births-deaths in the year) and the external one (due to migration flux) showing the future short and middle-term tendencies of the actual population density. According to this, their positive correlation to indicator 1 is reasonable because if this internal/external balance is high (positive) we can reasonably expect in the near future an increase in population density and so an increase in Human Pressure.

Otherwise, indicators 2, 3 and 4 are structural indicators that show us the population composition in terms of age in each Commune, and all them have showed an opposite orientation (negative correlation) to indicator 1.

Indicator 4 (dependency ratio) shows the ratio between people outside working age (children or retired) and people in working age (in between) and it seems reasonable its opposite orientation because in a condition of high population density we usually expect a lot of competition to work and so the basic wage should be lower and more people must work to maintain people not in age to work. Otherwise, less population means less competition and a consequent increase in the basic wage with an opposite tendency. So at decreasing levels of this indicator it is reasonable to expect increasing values in indicator 1 and so in Human Pressure.

The indicator 3 (ageing rate) which provides, investigating deeply people outside working age, the ratio between retired and children, can be subjected to such considerations than indicator 4. It shows again an opposite orientation to indicator 1. It is already reasonable because looking at the situation in Developing Countries, high levels of population density are generally related to high number of children compared to old people. So at decreasing levels of this indicator, it is reasonable to expect again an increasing value in indicator 1 and so in Human Pressure.

Finally for indicator 2 (mean age) shows an opposite orientation to indicator 1. Lower values of this indicator mean that there is an increasing number in young people or in people that are in working age (and will remain in it for more years), that usually request more needs from the territory (spaces, infrastructures) generating higher levels of impact, while high values mean a population with a lot of old people and so less demanding. So in presence of decreasing levels of indicator 2 is reasonable to expect an increasing value in Human Pressure.

A further analysis has been conducted to individualize which ones among the 6 demographic indicators mostly affect the demographic ranking of the 108 Communes in the study area. The Partial Order theory through the WHASSE software (Brüggemann *et al.*, 1999) or PhyHasse software (Brüggemann *et al.*, 2008) has been used: a partial order ranking using the 6 demographical indicators and the corresponding Hasse Diagram has been obtained and then we extract the w-values for each indicator from the overall w-matrix. This value is a sensitivity measure that gives evidence of the total number of changes (i.e. total mismatch) in the Hasse Diagram due to the removal of each indicator from the original indicator' set. In a certain way, this value give us information about how much each indicator affect (i.e. contributes to) the definition of the final Hasse diagram (i.e. the partial order ranking). Particularly, higher is the number of changes generated by each indicator (i.e. higher the associated w-value) and more it has influence in the final ranking of elements (i.e. the Hasse Diagram is more sensitive to that specific indicator). Looking at the following w-matrix (Table 4-28) appears clearly which are the most important indicators.

	Ind 1	Ind 2	Ind 3	Ind 4	Ind 5	Ind 6
W-value	379	10	36	100	302	977

Table 4-28 Sensitivity values (w-values) in Hasse Diagrams due to each of the 6 demographic indicators.

Indicators 1, 5 e 6 contribute mainly to the Communes demographic ranking. Therefore we decided to “abandon” indicators 2, 3 and 4. This choice is justified by demographic considerations. In effect, first of all is more useful to establish the amount of people pushing on a certain area (see indicators 1, 5 and 6) and after it is possible and useful to investigate the internal structure of the same population (see indicators 2, 3 and 4).

This preliminary analysis has been concluded applying the ideal vector method (that has been thought basically to rank habitats measuring their distance from an ideal habitat representing the best environmental possible condition in the area). In fact, knowing the contribution of each indicator to the Human Pressure, it is now possible to apply this methodology in order to rank Communes. In this specific context, and considering always the consequences on habitats belonging to a specific Commune, the Ideal Vector is represented by a six-dimensioned vector showing the lowest possible level of Pressure. For each indicator being positively correlated with level of Pressure, the Ideal value is represented by the lowest possible value among the 108 Communes, while for each indicator inversely correlated the right choice is the opposite (highest value).

In Figure 4-20 are shown the result of Ideal Vector application, dividing the Communes in quintiles of increasing Human Pressure.

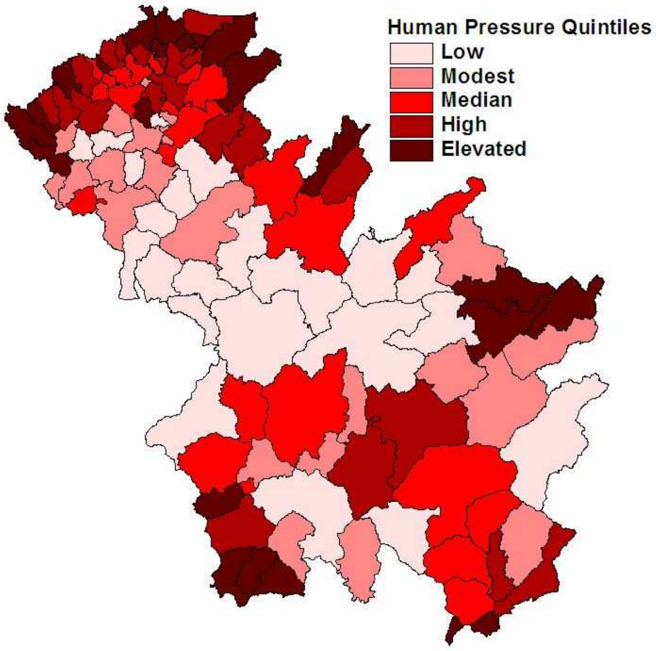


Figure 4-20 Distribution Human Pressure levels (i.e. quintiles) in Study Area “B” according to Ideal Vector Method.

4.3.2 Deriving possible guidelines for the Hotspots of Ecological Attention (HSEAs) management

The analysis at administrative scale refers basically to the preservation of the HSEAs. This type of habitats is very important for the conservation policies. The aim is to derive possible and simply readable guidelines for decision-makers at different administrative scales involved in biodiversity protection.

First, it is necessary to transfer the HSEAs to administrative partition of the Italian territory. In this case the assignation rule defined is the following: an HSEA can be referred to a single Commune only if the Commune contains at least 50% of the habitat surface, otherwise it must be assigned to all the Communes that contain part of it. For this reason a habitat can belong to one Commune, or shared by several Communes. As a consequence, in an administration based analysis, the amount of HSEAs for each Commune is characterized not only by entire habitats, but also by parts of it. This type of rule has been explored in order to obtain more realistic guidelines, even if it requests more computational work.

Aiming to derive guidelines easy to be implemented, a threshold of 15% of C.B. habitats with the greatest overall ecological value and 15% of C.B. habitats with the greatest overall ecological sensitivity was considered to identify the HSEAs in the study area.

The 528 HSEAs identified are actually included in 64 different Communes.

As the 64 Communes are widely spread in the study area, a Cluster Analysis (using the K means technique in SPSS software) was carried out on the demographic data.

The results in Table 4-29 suggest that the 64 Communes which contain HSEAs are not homogeneous for what concerns the current and medium-term Human Pressure and can be divided into three different groups (Figure 4-21).

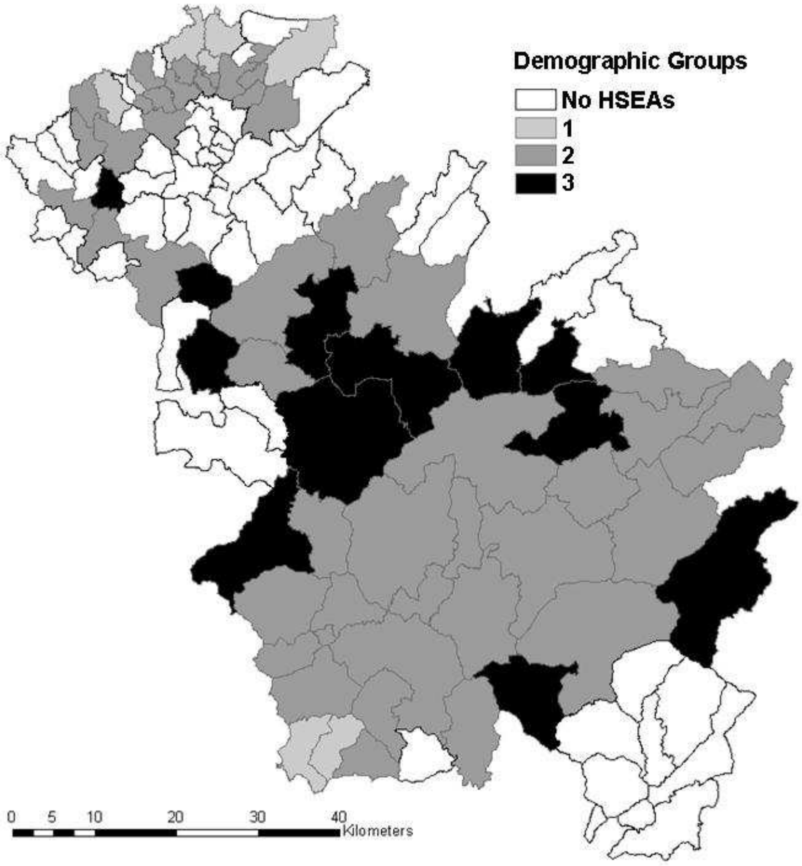


Figure 4-21 Spatial distribution of the 3 demographic groups of Communes containing HSEAs inside the study area "B".

Demographic indicators	Groups		
	1 (N=8)	2 (N=44)	3 (N=12)
1	365.96	60.99	15.96
2	46.76	49.37	56.6
3	246.76	330.66	797.4
4	66.68	78.56	106.49
5	-7.29	-11.27	-20.16
6	16.45	13.75	1.97

Table 4-29 Results of the Cluster Analysis carried out on the demographic indicators of the 64 Communes which contain HSEAs.

In group 1 (eight Communes), the Human Pressure is basically growing because the current negative population rate of natural increase is more than balanced by the net migration rate. These Communes are mainly located in the Provinces of Pavia and Genoa.

The opposite situation is represented by group 3, whose 12 Communes, mainly in the Provinces of Massa Carrara and Piacenza are characterized by a strong negative rate of natural increase which is not counterbalanced by the immigration rate.

Group 2 (44 Communes) is in between and is diffusely distributed in the Provinces of Parma, Piacenza, Pavia and Genoa.

Concerning the overall Ecological Value of the habitat mosaic in the study area, the corresponding map (Figure 4-2a) shows that groups 1, 2 and 3 are more expanded than the others. By looking at the entire area, many zones (situated) in the mountain and hilly regions of the Provinces of Parma, La Spezia, Massa Carrara and Genoa appear to be characterized by elevated ecological value. In particular, they are represented by wide beech forests above 1000 meters, and Quercus cerris and Ostrya carpinifolia woods frequently included in Sites of Community Importance. At lower altitudes, , the landscape in the Parma Province is characterized by remarkable agricultural connotation, increasing urban population density and industrial sites. Nevertheless, frequent contacts between agricultural areas and natural or semi-natural habitats lead to a notable vertebrate's diversity increase and moderately high ecological value. C.B. habitats with modest and low ecological value are found in the lowland of the Provinces of Piacenza and Pavia, and are represented by rural areas which derive from the ancient anthropic presence with meadows, and Quercus Pubescens woods. On the whole, the high ecological value that characterizes most of the study area links up with the so-called diffused naturalness, arising from the interpenetration of natural and anthropic components.

The Ecological Sensitivity map (Figure 4-2b) shows that the landscape is evenly spread over the five groups. A wide cluster of areas with elevated overall Ecological Sensitivity stands out around the villages of Bedonia and Borgo Val di Taro in the Province of Parma. These habitats mainly correspond to Apennine meadows, characterized by high fire hazard and limited size, Ostrya Carpinifolia and Quercus cerris woods holding over 10 species of vertebrates at risk of extinction (Table 4-30) and subjected to high landslide risk. Further highly sensitive areas are discovered near the boundaries between the Provinces of Parma and Massa Carrara and are represented by beech forests and chestnut woods including up to 14 species of vertebrates at risk of extinction (IUCN, 2007) (Table 4-30).

Class	Order	Genus	Species	Red List IUCN (2007)
Amphibia	*Anura*	*Rana*	*Latastei*	VU
Mammalia	*Chiroptera*	*Myotis*	*Bechsteini*	VU
Mammalia	*Chiroptera*	*Barbastella*	*Barbastellus*	VU
Mammalia	*Chiroptera*	*Rhinolophus*	*Euryale*	VU
Mammalia	*Chiroptera*	*Myotis*	*Capaccinii*	VU
Mammalia	*Rodentia*	*Eliomys*	*Quercinus*	VU
Mammalia	*Chiroptera*	*Myotis*	*Emarginatus*	VU
Anphibia	*Squamata*	*Natrix*	*Natrix*	CR

Table 4-30 Vertebrate Species at risk of extinction (IUCN 2007) present in the study area. The acronyms identify respectively, Critical (CR) and Vulnerable (VU) species.

These observations on the C.B. habitat mosaic are necessary because they give an up-to-date insight into the ecological value of the study area but also yield essential information on the current risks and the potential impact on the landscape due to the diffuse presence of human activities.

Considering the increasing difficulties in finding sufficient financial resources for nature conservation, environmental decision-makers must focus their attention and the few funds available, on those ecological environmental situations which, more than others, merit considering and defending. In this sense, the individuation of the HSEAs and their close examination in an ecological and demographic background can help landscape-planning choices. Our definition of HSEA considers two different, yet essential dimensions which make a C.B. habitat worthy of being defended and protected: its great overall ecological value but, also, its great overall ecological sensitivity.

The HSEA covers 11107.90 hectares (3.92% of the study area), but 3243.60 hectares (29.20%) are already within the existing protected zones and the remaining 7864.30 hectares (70.80%) are not included in the protected network yet.

The necessity to protect these new areas and connect them to the national network poses important and different problems of environmental policy because it is necessary to consider not only the first two dimensions (ecological value and ecological sensitivity), but also a third dimension, i.e. anthropic pressure trend.

In this specific case the three groups of Communes are really different as regards this trend (Table 4-29).

The first group of Communes (Canneto Pavese, Stradella, Casteggio, Torricella Verzate and Castel San Giovanni in the Province of Pavia, Casarza Ligure and Sestri Levante in the Province of Genoa) is characterized by very limited size and a strong foreseeable increase in human pressure in a context of current very high density (365.96 inhab/km^2, almost double the figure for the whole of Italy, equal to 189.1 inhab/km^2). The need for further space for new infrastructures (houses, schools, roads, etc) will inevitably clash with the need to conserve habitats of relevant value because of the presence of many rare vertebrates which will risk extinction due to the foreseeable increase in fragmentation, pollution, noise, etc. (Table 4-29). Moreover, the further growth may deplete the resources available, and the biodiversity values, which are considered a peculiar heritage for the local community and an important part of the quality of life, may be lost. The environmental policy that seems possible in all situations similar to this one might be of a compensatory kind: considering that these Communes are always self-sufficient from a financial point of view, they can attempt to convince the citizens to accept the “exchange”: “a new protected area in change of new necessary infrastructures”.

For the second group of 44 Communes, mainly located on the first hills of the Ligurian-Tuscan-Emilian Apennines in the Provinces of Parma, Genoa and La Spezia, the density is not high (60.99 inhab/Km^2) and very often the Commune territory is already covered by some conserved areas, in particular the Regional Park of Aveto and 16 SACs for the Nature Conservation. The presence of HSEAs is given by rare but isolated habitats of elevated ecological value (high maquis, Mediterranean salt steppes, Mediterranean Salix purpurea scrub). Many of the Communes (Castiglione Chiavarese, Ne, Ziano Piacentino, Borgo Priolo) are close to others Communes (Group 1) located on the plain and characterized by important economic activities. These Communes are an important source of work for the residents in this second group of Communes.

The policy to preserve the HSEAs of this group should not run into problems, but it would be useful to promote a better network of the new zones to be protected as they are rare and isolated. This network should reduce the territorial fragmentation, link the areas with greater biodiversity and at the same time protect the widespread biodiversity.

The Communes of the third group (among them Ferriere in the Province of Piacenza, Varsi in the Province of Parma, Menconico in the Province of Pavia) are located on the mountains (mean altitude 812 m), their territory is practically almost abandoned (14.96 inhab/Km^2), with the presence of many elderly people and children (Table 4-29). In consideration of the presence of many HSEAs given by rare but very isolated habitats (vegetated siliceous inland cliffs, brachipodium-dominated semidry grasslands) and of the poverty of these Communes, the environmental policy to be suggested must be based on a network of near Communes with the financial help of the Provinces (Parma, Piacenza, Pavia, Genoa and Massa Carrara) or/and of the Regions (Emilia Romagna, Lombardy, Liguria and Tuscany).

4.3.3 Providing a ranked list of Communes with Highest Funding Preference for biodiversity conservation purposes

The goal of this second point is to propose and test a quantitative methodology by which it is possible:

1) To identify which Communes have the Biodiversity Protection Funding priority.
2) To rank these selected Communes according to further conservation-management parameters.

The environmental decision-maker is aware of the general increasing difficulties in finding sufficient financial resources for nature conservation. He must focus his attention and, consequently, his few economical funds on ecological situations that more than the others merit considering and defending because of elevated value but also because of risk for their intrinsic characteristics and for human pressure acting on them.

From an operative point of view, after identifying a short list of Communes having the Biodiversity Protection Funding priority, this short-list can be further subjected to other criteria in order to rank the remained Communes.

Until now we have used only parameters that ecologists consider essential to determine the status of each Commune. Now we move to the perspective of a environmental decision maker which have to follow “other” criteria in a common view of reducing as much as possible the number of Communes to be funded (and so the total amount of spreaded resources).

To make this further choice, we must provide a rank of Communes in the short list on the basis of “other” criteria.

The 4 criteria, chosen at Commune level, are:

a. Species richness (i.e. number of C.B. types in each Commune).
b. Species abundance (i.e. total number of habitats in each Commune).
c. Abundance of the most abundant specie (i.e. total number of habitats for the most frequent C.B. type in each Commune).
d. Abundance of the least abundant (rare) specie (i.e. total number of habitats for the least frequent C.B. type in each Commune).

With these criteria it is obtained the double goal of maximizing C.B. habitat types and habitat frequencies, as well as minimizing the number of Communes.

4.3.3.1 Method "A": Hotspot Detection method

The main objective is in measuring the so called "**Funding Preference**" of each Commune. We are not able to measure it in a direct way. As a consequence, a set of surrogates variables which indirectly can "express" this Funding Preference is needed. Ecological parameters of habitats previously defined (i.e. Ecological Value, Ecological Sensitivity, Ecological Attention and Ecological Fragility) and demographic situation of Communes can better accomplish this role.

Having determined highspot habitats of Ecological Value (EV), Ecological Sensitivity (ES) and of Ecological Attention (EA) using Ideal Vector method, and having evaluated the Human Pressure levels (using demographic indicators) and the correspondent Ecological Fragility (EF) ones, we want to find out which Communes could be better targeted for funding preference in a perspective of biodiversity conservation. In particular, we are interested in identifying which Communes have an elevated number of highspot habitats or, better, an elevated fraction of area covered by each particular type of highspot habitats. This is a problem that is well suited for hotspot detection using the Upper Level Set (ULS) scan statistic (Patil, 2002; Patil *et al*., 2002; Myers *et al*., 2006b; Patil, Balbus *et al*., 2004a; Patil, Bishop *et al*., 2004b; Patil and Taillie, 2004b).

According to ULS methodology view (see paragraph 3.2), cells of the total tessellation (the study area itself) are the Communes to which is associated, each time, a variable size (i.e. total number of habitats or total habitat area), a variable response (i.e. total number of highspot habitats or their correspondent total area) as a realization of some probability distribution (binomial distribution in the discrete view of highspots' count and beta distribution in the continuous one using highspots' area) and the probability distribution, which is called the response distribution.

The response rate (G-values) that is the ratio Response/Size individuates a certain number of hotspot which is a collection of vertices (i.e. of Communes), arbitrary shaped, for which the overall response rate is unusually large. The method looks for hotspots from among all connected components of upper level sets of the response rate.

For each relevant ecological concept (Ecological Value, Ecological Sensitivity, etc.) a different Response rate that represents the G-value, and which describes on the tessellation of Communes of the area a sort of roof surface (i.e. G-value surface) has been computed.

The obtained values have been used as the level for each Commune (i.e. cell of the tessellation) for this specific concept.

Distinctly we computed the total number of highspots in each Commune, as well as the total number of habitats obtaining the proportion of habitats (G-value discrete surface) that are previously elected as highspots (respectively for EV, ES and EA) applying the ULS univariate approach using the binomial model of distribution. In that particular case the algorithm seeks contiguous sets of Communes which have an elevated proportion of highspots that is statistically significant, i.e. rejects the null hypothesis that the proportion of highspots inside the zone (potential hotspot) has the same proportion as the proportion of highspots outside the zone.

Moving to a continuous view of the same problem, has been computed the total area covered in each Commune by highspots obtaining again the proportion of highspots' area (G-value continuous surface) applying the ULS univariate approach using the beta model of distribution.

Summarizing the different approaches utilized each one of the ecological concepts:

1. Ecological Value analysis:
    a. Discrete approach: G-value = number of highspots / number of habitats
    b. Continuous approach: G-value = area of highspots/area of habitats
2. Ecological Sensitivity analysis:
    a. Discrete approach: G-value = number of highspots / number of habitats
    b. Continuous approach: G-value = area of highspots / area of habitats
3. Ecological Attention analysis:
    a. Discrete approach: G-value = number of highspots / number of habitats
    b. Continuous approach: G-value = area of highspots / area of habitats

Similarly the G-value surfaces on each Commune of the area according to the concept of Human Pressure and Ecological Fragility has been computed applying the ULS univariate approach using the gamma model.

Summarizing:

4. Human Pressure:
    a. Continuous approach "A_1" and "A_2": G-value = Multidimensional distance from Ideal Vector of Human Pressure (using all 6 or only indicators 1, 5 and 6);
    b. Continuous approach "B": G-value = population density

5. Ecological Fragility:

a. Continuous approach: G-value = ES (continuous) * HP (i.e. population density)

From the analysis of these G-value surfaces (representing a sort of "roof surface" upon each Commune), for EV, ES and EA, we can observe a great difference between the results of the discrete and continuous approach.

Figure 4-22, shows an example referring to Ecological Attention.

In each tridimensionale (3D) map the height of each Commune is given by its real values of the response ratio, while colours come out from a division in 10 equal intervals of the range of values (dark red is highest interval, light blue is the lowest one).

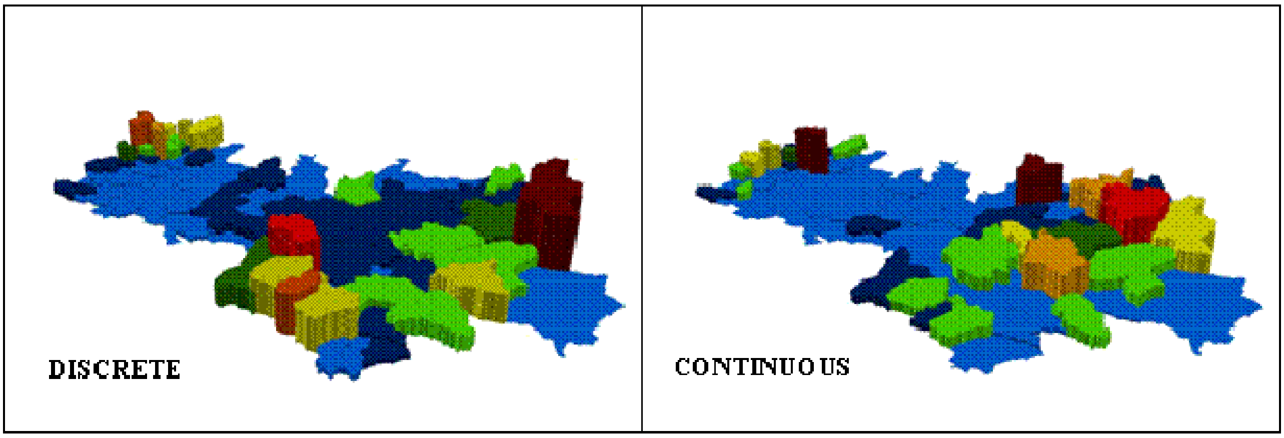


Figure 4-22 Tridimensional G-Value surfaces for discrete and continuous approach in Ecological Attention Hotspot Detection

Looking at the ULS results we decided to "abandon" the discrete approach since it produces less meaningful results. Ecologically it is reasonable, because we are interested in Communes rich in biodiversity, and this evaluation is better accomplished analysing the real area involved in worthy (i.e. high) habitats avoiding the less important ecological situation of funding Communes with a great number of very small habitats that totally covers a small fraction of the area.

Each hotspots zone is a cluster of Communes which have elevated statistically significant values of the Response ratio (G-value surface). Since Hotspots are intrinsically contiguous, we also need the adjacency matrix of the Communes in order to determine the neighbours of each.

Such Communes are the most plausible candidates to receive funding for environmental protection.

The result of each hotspot detection using ULS approach carried on these different G-value surfaces and representing different basic ecological parameters, produced a certain cluster of Communes. The identified clusters are the hotspots. We combined these hotspots of Communes in order to provide a short-list (or more equally reasonable) of most ecologically worthy Communes on which there should be focused the environmental attention. In fact they are the most suitable for biodiversity conservation in the area. In other words a short list of Communes with the highest Biodiversity Protection Funding Preference has been provided.

In practice the ULS software, using each time the most suitable model of distribution, identify High Response Zones (clusters of Communes) having the highest values of plausibility (i.e. highest values of Log-likelihood) and that are significant ($p < 0.05$).

The obtained results identify the Maximum Likelihood Zone (MLE-zone) and a certain number of Equivalent Zones (having less log-likelihood values but significant in any case).

Two possible approaches are reasonable in order to interpret the obtained results:

1) Considering only the Communes in the MLE-zone (that strictly talking identifies the hotspot).
2) Considering the Relative Hotspot Rating of each Commune (in a sort of Fuzzy logic view of the results) in all the possible Equivalent Zones (included the MLE one).

The comparison of the results of these 2 approaches with the G-value surface, reveal that each of them give only a partial evidence of all the peaks of values presents in the original response ratio surface and particularly, the Relative hotspot rating cover the possible usual lacks of the MLE-zone. So both the approaches must be taken into the due consideration joining their individual results.

We carried out a preliminary shortlist of Communes for each G-value surface that can be combined with the others to take into account the different useful surrogates that contributes to measure the Funding Preference levels.

Computationally we utilized the above mentioned two approaches at the ULS results to compose the preliminary shortlists in that way:

1) Considering the top 5 Communes in the MLE-zone having the maximum possible G-values;
2) Considering the relative hotspot rating of each Commune in all the possible Equivalent Zones (included the MLE-zone) and:
    a. Retaining only top 5 Communes having the highest hotspot rating.

b. Retaining only top 5 Communes having not only highest relative hotspot rating but also the highest G-value as possible. in practice there is an iterative procedure: sort cells using relative hotspot rating (i.e. start with the cells at point (a)); then look at the next one cell and if its G-Value is higher than the minimum of the 5 values actually in the list. remove the minimum and replace it with this sixth one; sort out the list and compare the values of new 5 elements with the seventh one and iteratively do it until the next G-value is smaller than the 5 ones in the actual short list.

c. Retaining the top 5 elements in the highest levels shown by the Hasse Diagram produced using both Hotspot Rating and original G-values.

According to this we can have 3 different preliminary shortlists given by: (1) 1+ 2a; (2) 1 + 2b and (3) 1 + 2c.

These 3 possible lists has been compared with the original G-value surface to identify the best one. Actually the comparison revealed a great consistency in their results allowing us to decide to retain the Communes present simultaneously in each of the 3 ones. The Communes retained compose our short-list for each ecological parameter investigated.

For each basic ecological surrogate (EV, ES, EA, EF and HP) of Funding Preference are provided maps of G-value, MLE-zone and of the 3 preliminary short-lists (Figures 4-23, 4-24, 4-25, 4-26, 4-27). The results for Human Pressure using multidimensional distance from Ideal Vector of Human Pressure (using all 6 or only indicators 1, 5 and 6) as G-Value have been omitted because no Hotspots have been identified.

Figure 4-23 Ecological Value maps of G-value, MLE-zone and of the 3 preliminary short-lists.

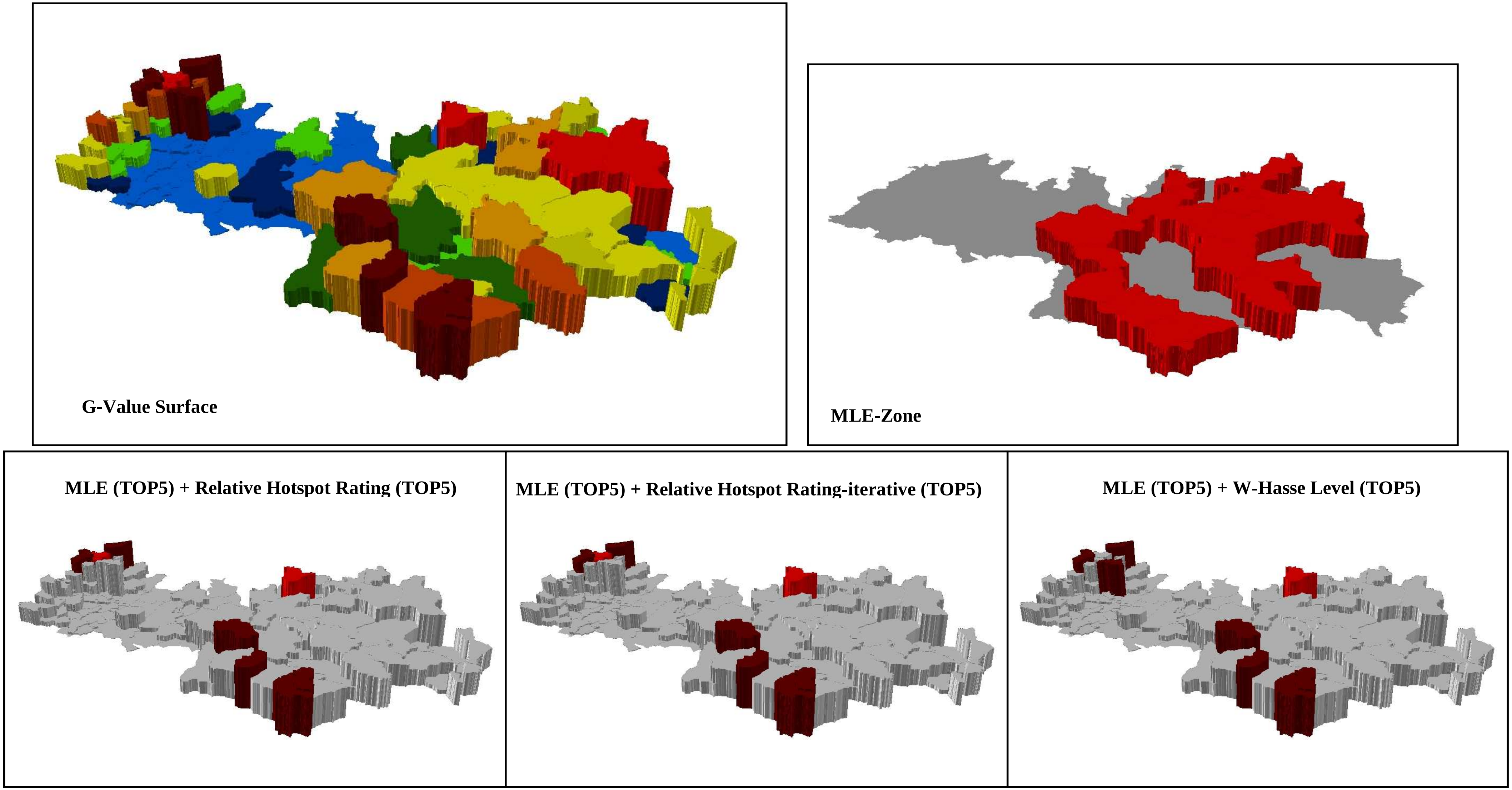


Figure 4-24 Ecological Sensitivity maps of G-value, MLE-zone and of the 3 preliminary short-lists.

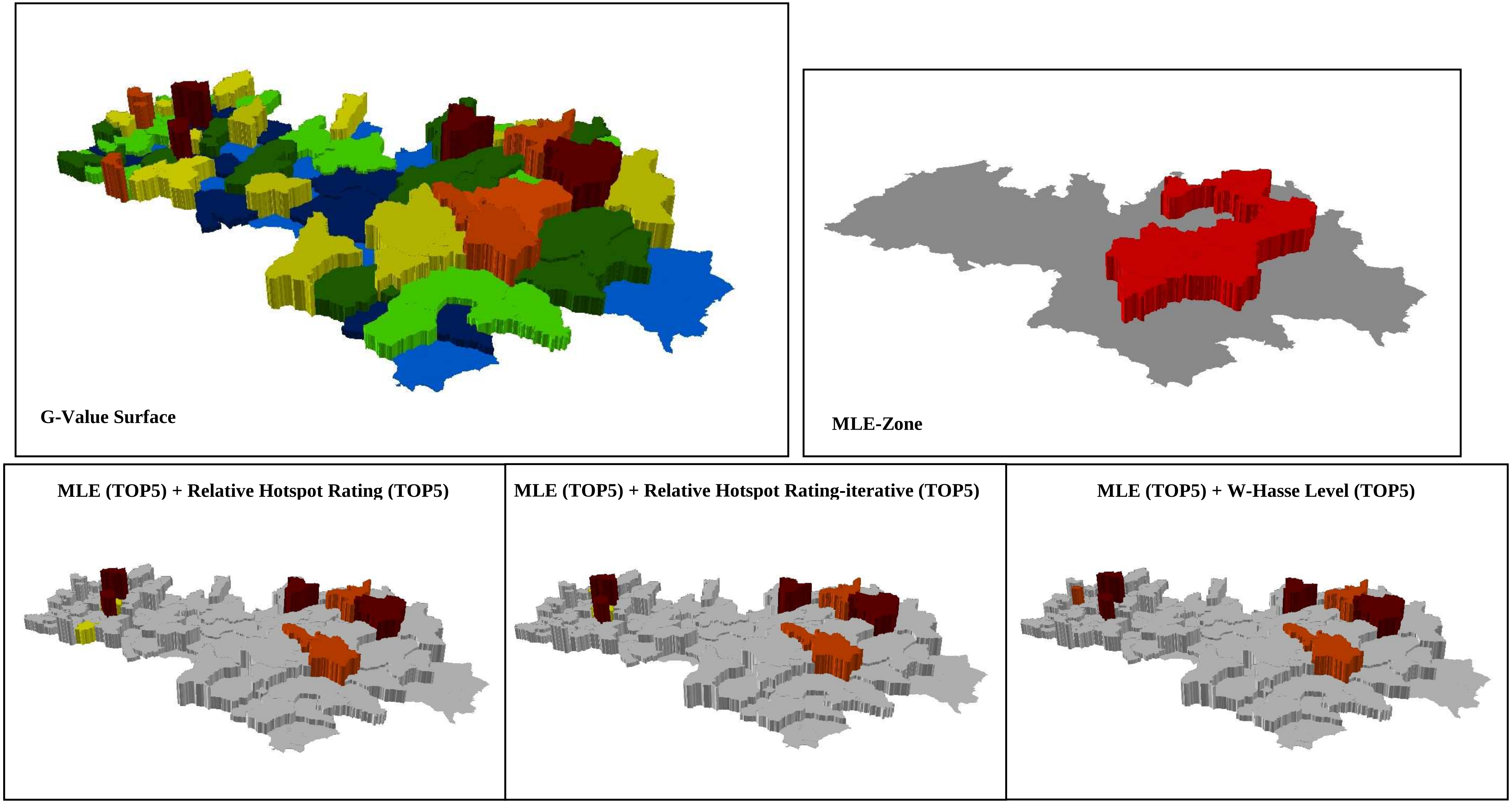


Figure 4-25 Ecological Attention maps of G-value, MLE-zone and of the 3 preliminary short-lists.

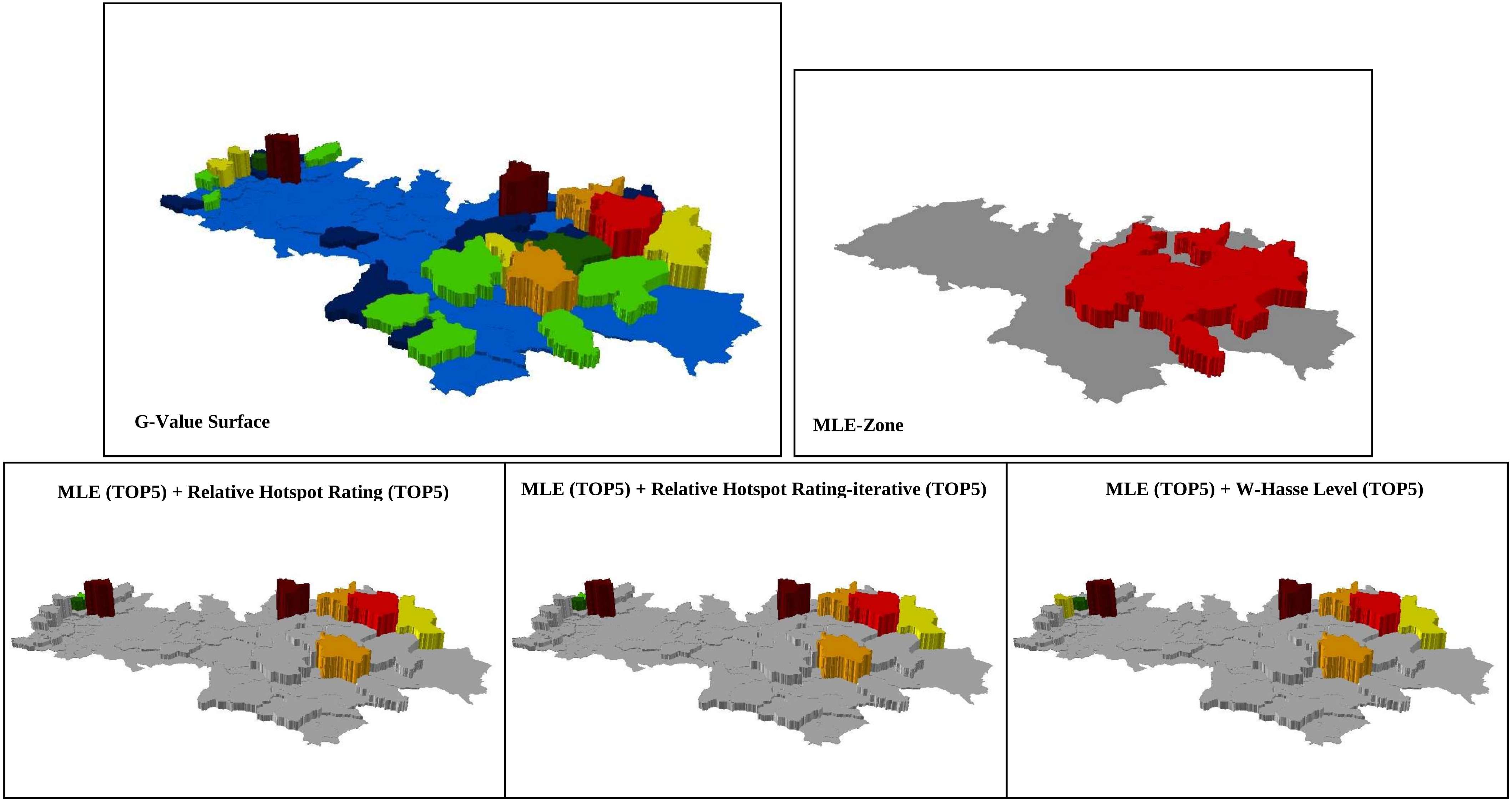


Figure 4-26 Human Pressure maps of G-value, MLE-zone and of the 3 preliminary short-lists.

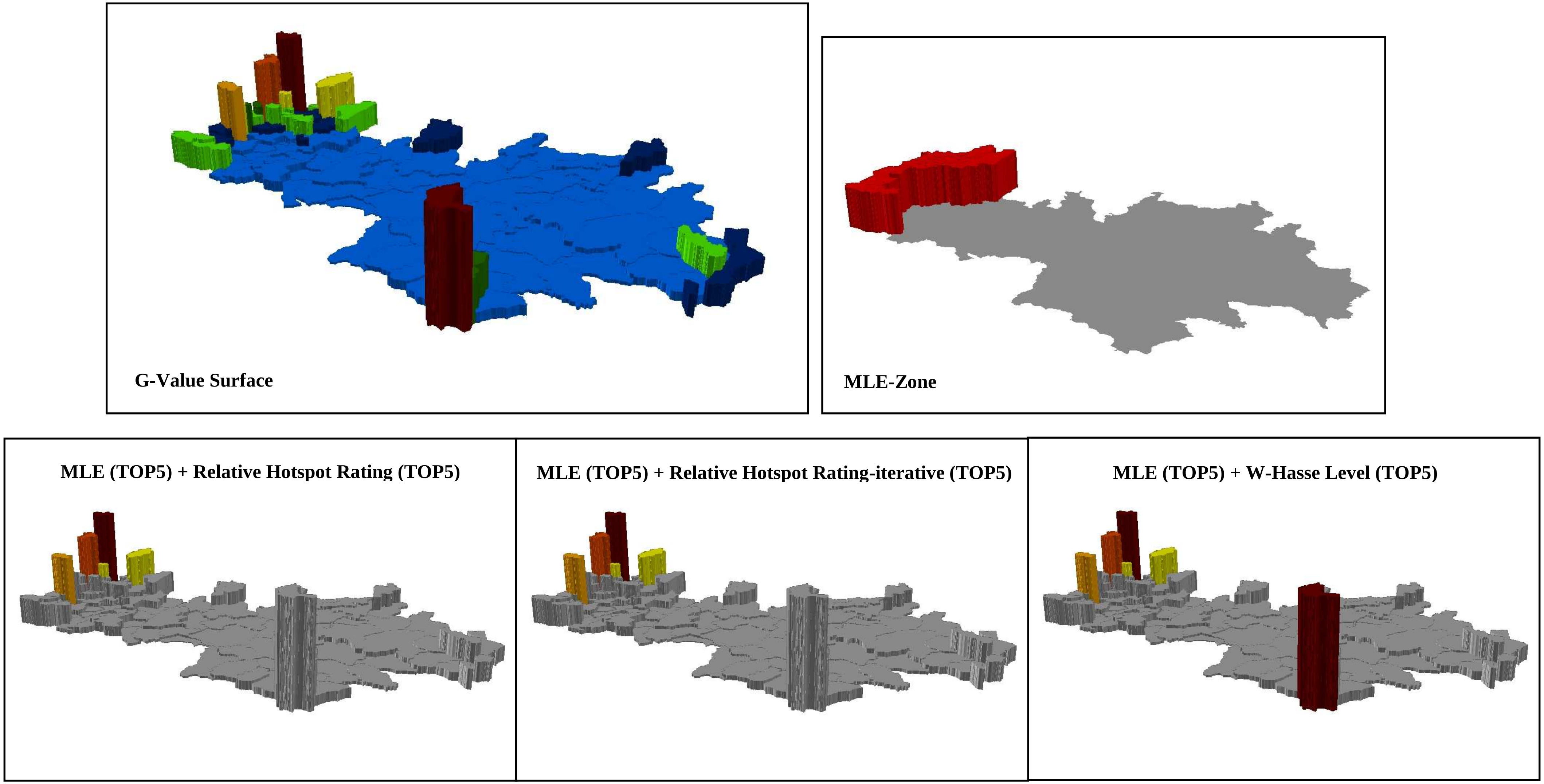


Figure 4-27 Ecological Fragility maps of G-value, MLE-zone and of the 3 preliminary short-lists.

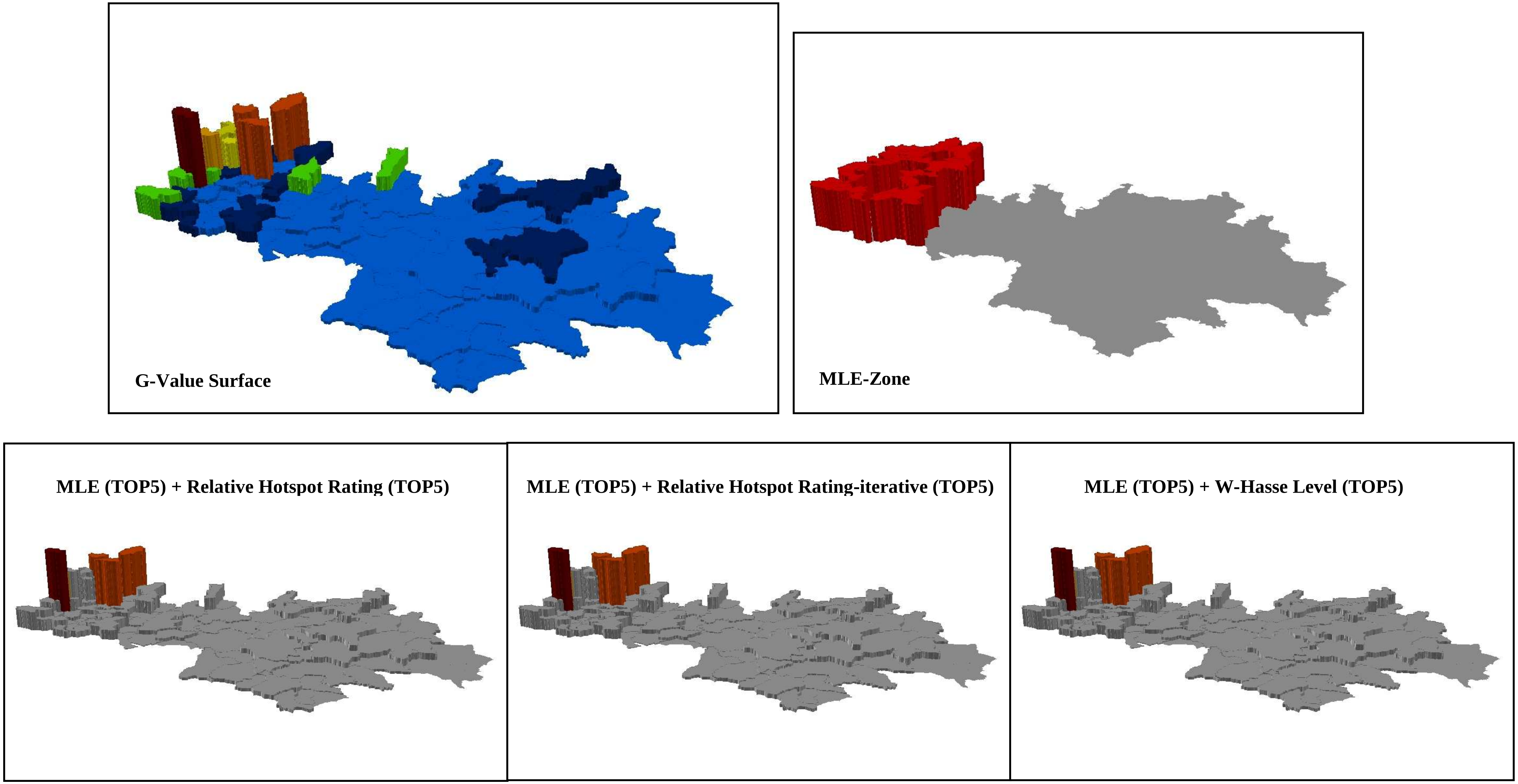


Table 4-31 shows the Communes (identified by a number) within each preliminary short list and in the final one for each ecological surrogate (i.e. parameter).

Ecological surrogate	1+2a	1+2b	1+2c	Preliminary Short -List
EV (continuous)	1-2-3-7-8-69-87-94-104-105	1-2-3-7-8-69-87-94-104-105	1-3-7-24-69-87-94-104-105	1-2-3-7-69-87-87-94-104-105
ES (Continuous)	18-24-44-55-62-69-77-83-85-89	14-18-24-44-55-69-77-83-85-89	18-24-25-55-69-77-83-85-89	18-24-44-55-69-77-83-85-89
EA (continuous)	2-8-11-18-24-69-77-83-86-89	2-8-11-18-24-69-77-83-86-89	9-11-18-24-69-77-83-86-89	11-18-24-69-77-83-86-89
HP	1-2-4-8-15	1-2-4-8-15	1-2-4-8-15-105	1-2-4-8-15
EF	2-4-15-19-24	2-4-15-19-24	2-4-15-19-24	2-4-15-19-24

Table 4-31 Composition of the five preliminary short-lists for each ecological surrogate (see the text).

Short-List 1: Ecological Attention short-list. Its analysis and ranking

The first suggested combination to provide the final short list of Communes is given directly using the Ecological Attention preliminary short-list. This list underline a certain number of Communes that are ecologically worth of attention because of a great part of their territory is covered by habitats having high EV but high ES (High Response Ratio). In particular this combination identifies 8 different Communes located in the northern part and in the south-eastern part of the study area (Figure 4-29).

Until now, these Communes has been detected only using strictly ecological parameters, but since the have high ES they are only potentially at risk. To be truly in danger they should be subjected to a relatively high Human Pressure. In other words we are particularly interested in protecting the candidate Communes that are under substantial external pressure, as the highspots in those Communes are ecologically fragile and in danger of substantial degradation.

For this reason we used the results of cluster analysis on demographical indicators previously described in order to filter among these 8 Communes which are really in danger and so worthy to be considered by environmental decision makers and subjected to further criteria of ranking.

The Cluster analysis revealed the presence of main six groups of Communes.

The spatial distribution of these clusters and their mean values for each indicator are shown below (Figure 4-28 and Table 4-32).

Cluster	number of Communes	Ind1	Ind2	Ind3	Ind4	Ind5	Ind6
outliers	1	6.39	61.70	2020.00	118.89	-21.86	-14.02
1	4	485.45	47.83	274.81	69.69	-9.25	9.55
2	50	101.95	47.39	259.02	70.57	-8.58	17.34
3	33	37.22	51.78	455.54	86.52	-15.37	12.76
4	2	19.40	57.72	1621.11	96.99	-17.81	5.13
5	16	17.46	56.71	787.89	110.74	-20.06	3.73
6	2	12.37	45.53	200.00	45.78	-22.23	-21.92

Table 4-32 Mean values of demographic indicators for each demographic cluster.

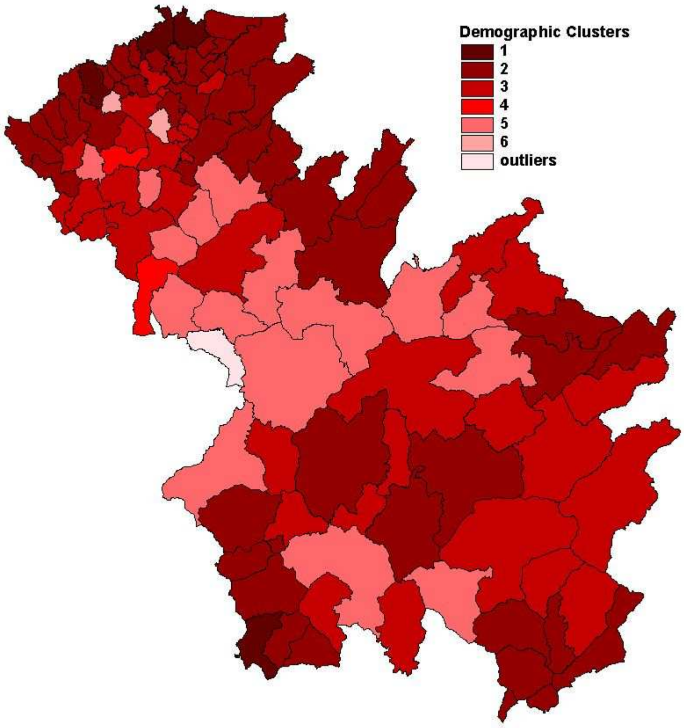


Figure 4-28 Spatial distribution of clusters according to all 6 demographic indicators.

From Table 4-32, we can observe some interesting characteristics. It is clear that for Indicator 1, Population Density, we can see a clear order of the clusters, the clusters are in order from highest to lowest. Further, the gradation is steep. In fact Cluster 1 has much higher Population Density than the remaining clusters, and Cluster 2 also has much higher Population Density than Cluster 3-6. Since Population density is considered by far the most important measure of anthropic pressure, we find the clear ordering of the clusters with respect to this indicator heartening. Furthermore, it justifies the removal of the outlier, since the outlier has a very small Population Density, and thus the Commune does not face a great amount of anthropic pressure. Indicator 5, Population Rate of Natural Increase, also has approximately the same ordering. Indicators 2, 3, and 4 seem to give a weak message, however, it does appear to show that there is an increase in the value of these indicators for the later clusters. Finally the analysis of clusters suggests us to consider only Communes involved in cluster 1 and 2.

According to this, only 5 Communes remains: 11, 18, 24, 77 and 89. Communes 69, 83 and 86 should be dropped out because, even if worthy of Ecological Attention, in their territory the ecologically relevant habitats are not truly in danger (Figure 4-29).

These 5 Communes can be subjected to the final rank using the 4 criteria described in the method section (Table 4-33).

ID	NAME	Ind 1	Ind 2	Ind 3	Ind 4
77	SOLIGNANO	7	413	237	1
89	ALBARETO	6	209	158	2
11	CIGOGNOLA	4	51	26	4
24	SANTA MARIA DELLA VERSA	5	128	47	1
18	MONTESCANO	3	14	8	1

Table 4-33 Values of the 4 further criteria for the 5 selected Communes in the first short-list.

Figure 4-29, shows their geographical location and ranks.

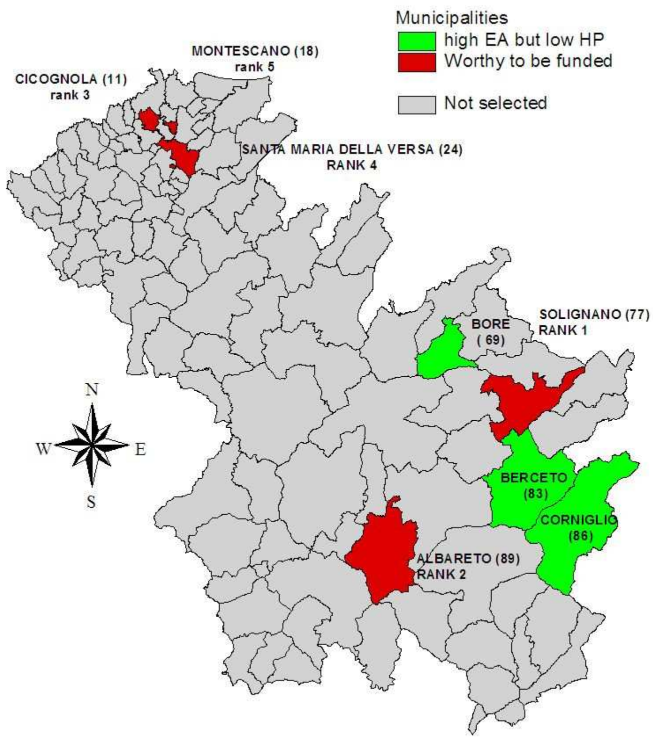


Figure 4-29 Geographical location and rank of the Communes in the first short-list.

The Cluster analysis technique carried out on indicators 1, 5 and 6 revealed the presence of main five groups. The spatial distribution of these clusters and their mean values for each indicator are shown below (Figure 4-30 and Table 4-34). In this case there are 3 outliers, two having a demographic situation of high pressure (Communes 2 and 105) and one showing the opposite one (Commune 27).

Cluster	Number of Communes	Ind1	Ind5	Ind6
1	2	401.56	-10.58	11.68
2	13	179.84	-6.66	19.21
3	21	75.97	-12.28	26.84
4	39	55.56	-10.08	10.10
5	30	18.62	-19.79	3.77

Table 4-34 Mean values of demographic indicators for each demographic cluster (using only indicators 1, 5 and 6).

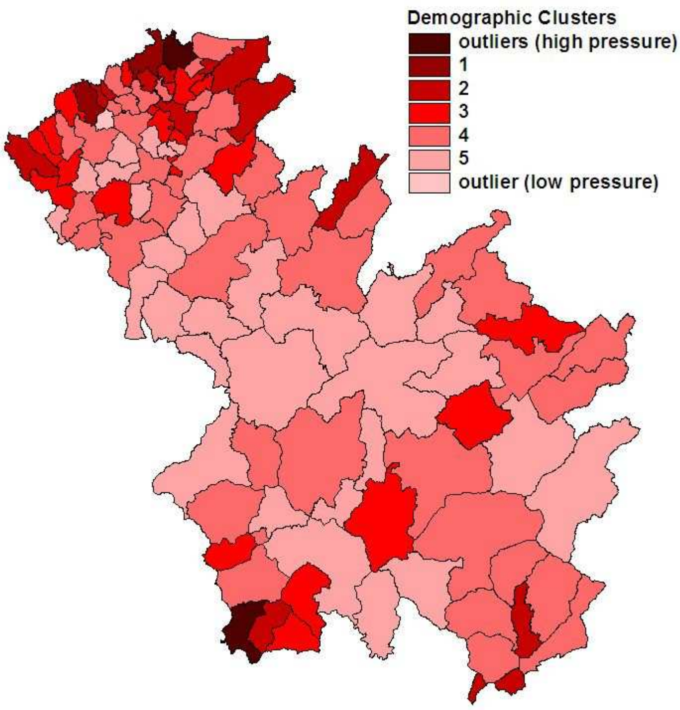


Figure 4-30 Spatial distribution of clusters according to the main 3 demographic indicators.

With similar considerations to the Cluster Analysis using all 6 indicators, this second analysis of clusters suggests us to consider only Communes involved in cluster 1, 2 and 3. According to this, only 4 Communes remains: 11, 18, 24 and 89. The only one difference with the previous Cluster Analysis consists in dropping out from the preliminary short-list Commune 77.

Short-List 2: Ecological attention and Ecological Fragility short-list. Its analysis and ranking

The second suggested combination to provide the final short list is given by the combination of the Ecological Attention and Ecological Fragility preliminary short-list. This obtained list underline a certain number of Communes that are or ecologically worth of attention because of great part of their territory is covered by habitats having high EV but high ES or because of great part of their territory is covered by fragile habitat. In other words this list contains Communes having at least two of the 3 basic ecological surrogates which are high and so interesting in a biodiversity conservation view. In particular this combination identifies 12 different Communes located always in the northern part and in the south-eastern part of the study area (Figure 4-31).

According to this logic, in some of these Communes there could be a lack in one of the 3 ecological dimensions and for this reason we subjected them to a 2 step ranking process using always Partial Order MCMC method. First we ranks Communes in the list using separately EV, ES and Human Pressure, and then we ranked them using these 3 ranks together. This last rank produced a further filter on the list which allows us to remove the lowest Communes, since they are not ecologically worthy considering all the 3 ecological surrogates. We selected top 9 Communes removing 19, 83 and 86 (Figure 4-31).

These 9 Communes can be subjected to the final rank using the 4 criteria described in the method section (Table 435).

ID	NAME	Ind 1	Ind 2	Ind 3	Ind 4
2	STRADELLA	4	113	56	9
4	CASTEL SAN GIOVANNI	5	29	11	2
11	CIGOGNOLA	4	51	26	4
15	CASTEGGIO	4	94	49	1
24	SANTA MARIA DELLA VERSA	5	128	47	1
69	BORE	7	155	84	2
77	SOLIGNANO	7	413	237	1
83	BERCETO	7	339	234	1
89	ALBARETO	6	209	158	2

Table 4-35 Values of the 4 further criteria for the 5 selected Communes in the second short-list.

Figure 4-31, shows their geographical location and ranks.

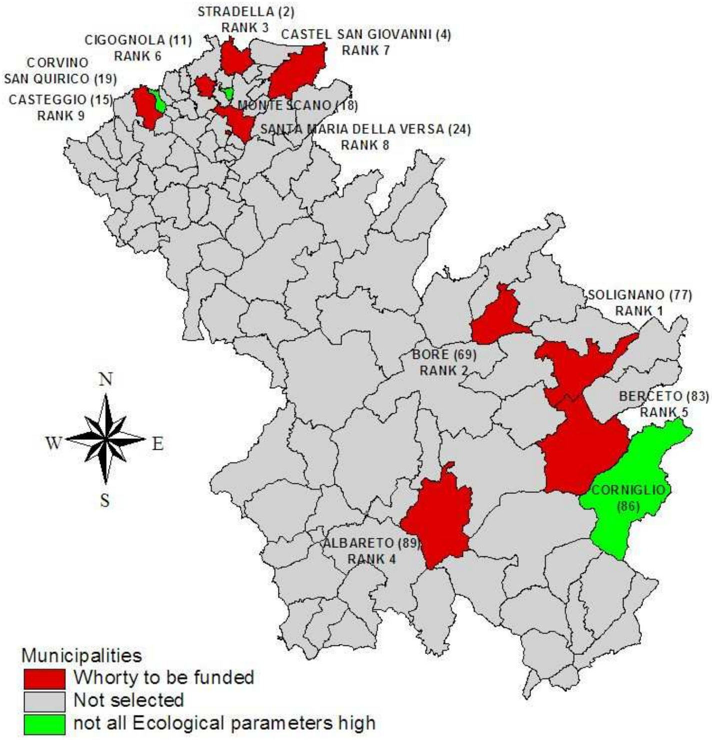


Figure 4-31 Geographical location and rank of the Communes in the second short-list.

Short-List 3: Overall Ecological Parameters short-list. Its analysis and ranking

The last suggested combination to provide the final short list is given by a two step process of combining and intersecting partial short-lists. First we combined in 3 different ways the 5 ecological surrogates, then we retained only the Communes in common to these 3. The procedure is shown below (Table 4-36):

Ecological surrogate	Preliminary Short -List	First Step	Second Step
EV	1-2-3-7-69-87-87-94-104-105	(1) EV-ES-HP	(1)-(2)-(3) intersection
ES	18-24-44-55-69-77-83-85-89	(2) EA-EF	
EA	11-18-24-69-77-83-86-89	(3) EV-ES-HP-EA-EF	
HP	1-2-4-8-15		
EF	2-4-15-19-24		

Table 4-36 Two-step procedure to carry out the third short-list.

This obtained list contains a certain number of Communes that are ecologically worth of attention according to the 3 basic ecological concepts simultaneously. In other words this list contains Communes having the 3 basic ecological surrogates which are high and so interesting in a biodiversity conservation view. In particular this combination identifies 12 different Communes located always in the northern part and in the south-eastern part of the study area (Figure 4-32).

These 9 Communes can be subjected to the final rank using the 4 criteria described in the method section (Table 4-37).

ID	Name	Ind 1	Ind 2	Ind 3	Ind 4
2	STRADELLA	4	113	56	9
4	CASTEL SAN GIOVANNI	5	29	11	2
15	CASTEGGIO	4	94	49	1
18	MONTESCANO	3	14	8	1
24	SANTA MARIA DELLA VERSA	5	128	47	1
69	BORE	7	155	84	2
77	SOLIGNANO	7	413	237	1
83	BERCETO	7	339	234	1
89	ALBARETO	6	209	158	2

Table 4-37 Values of the 4 further criteria for the 5 selected Communes in the third short-list.

Figure 4-32, shows again their geographical location and ranks.

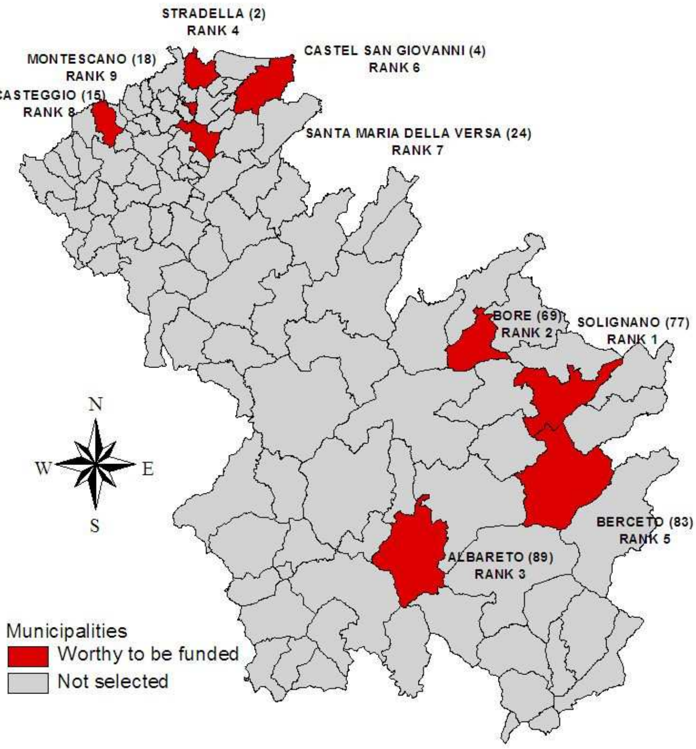


Figure 4-32 Geographical location and rank of the Communes in the third short-list.

Providing a final ranked list of Communes with Highest Funding Preference

The environmental decision-makers needs a final short-list composed of Communes that needs fund for biodiversity protection. Until now we have provided 3 different method to obtain this final list, but their composition are different.

What is needed it is to extract some elements among these 3 lists using a clear method. Suppose we want to select among these lists top 5 Communes. This is a reasonable request because 5 Communes correspond to around 5% of the entire number of Communes in the area (108). So providing a list of 5 we can considered the problem solved delivering a final list to the decision-makers.

What we can do is to threshold each of the 3 lists at the first 5 ranks. Then look at the 3 top five Communes of each list and see in how many lists they occur. First select elements that appears in all the 3 lists (Communes 77 and 89), then look at the elements that occur in two of them (69, 2 and 83). Consider that Commune 77 (Solignano), disappear in the first list using the Demographic Cluster Analysis on only the main 3 indicators: it remains in the other two lists and so will be retained in the final list of top 5 Communes. So the problem has been solved and the list has been provided.

In case a sixth Commune is needed to be chosen, it is not possible to find a solution among the remained Communes involved in the 3 short lists using this approach. To solve the problem a fuzzy logic approach can help. According to this approach a Fuzzy Partial Order method (Brüggemann and Patil, 2010; De Baets and De Meyer, 2003; Van de Walle, 1995) through PyHasse software (Brüggemann *et al*., 2008) on the remaining Communes (11, 15, 24, 4 and 18) and using the 4 criteria has been performed. Choosing an α-cut = 0.5 we obtained the following Hasse diagram (Figure 4-33) shows the presence of 3 equivalent Communes (11, 15 and 24).

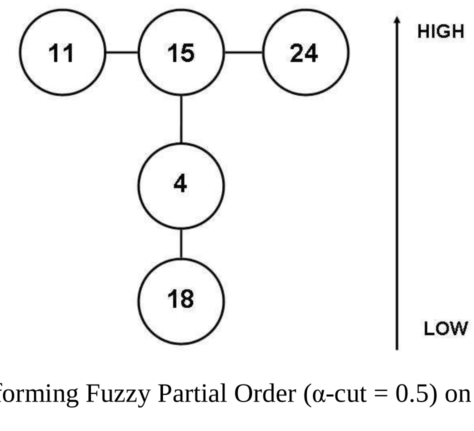


Figure 4-33 Hasse Diagram performing Fuzzy Partial Order (α-cut = 0.5) on 4 criteria.

Two possible candidates among the 5 have been removed. In order to individuate among the 3 remained Communes the most reasonable candidate for the sixth position:

1) Look at the values in the w-matrix (i.e. number of changes/mismatches determined by that specific indicator in the Hasse Diagram) to individuate the most important/influent criteria, and according to it rank these 3 Communes.
2) Consider all the 4 criteria, and define a resumptive index of them (i.e. the mean value of the unitized criteria).

Following the first method, the indicator 4 seems to be the most important one in ranking the Communes. Using only this indicator we obtained Cicognola (11) as the most plausible sixth Communed to be funded (having it the highest value among the remained 3 Communes).

Following the second method, the 4 criteria (ranged between 0-1) has been aggregated in an index (Table 4-38):

ID	NAME	Ind 1	Ind 2	Ind 3	Ind 4	Ind 1U	Ind 2U	Ind 3U	Ind 4U	Index
4	CASTEL SAN GIOVANNI	5	29	11	2	1.00	0.13	0.07	0.33	0.38
11	CIGOGNOLA	4	51	26	4	0.50	0.32	0.44	1.00	0.57
15	CASTEGGIO	4	94	49	1	0.50	0.70	1.00	0.00	**0.55**
18	MONTESCANO	3	14	8	1	0.00	0.00	0.00	0.00	0.00
24	SANTA MARIA DELLA VERSA	5	128	47	1	1.00	1.00	0.95	0.00	0.74

Table 4-38 Evaluation of the Resumptive Index for the 5 selected Communes in the third short-list.

Casteggio (15) has been individuated as the Commune having, among the 3 remained after fuzzy analysis, the highest value of the index.

4.3.3.1.1 Weighting methods

Until now, in all the applications of Ideal Vector Method, to all the indicators which contribute to the calculation of the distance from the Ideal Vector the same weight (equal to 1) has been given.

When the goal is the construction of an overall index, it is possible, and sometimes interesting, to give different weights to some groups of indicators in order to emphasize or to reduce their contribution. For example, in ranking many environmental units in terms of their overall ecological value (but it is similar for every multivariate ecological parameter) a decision-maker might retain and decide that some specific indicators, such as belonging to some official Conservation Zones, should receive greater consideration (weight) in comparison with all the other indicators.

Weights can be applied if there are in scientific literature enough studies that reveal a different degree of influence of the indicators on the multivariate phenomenon, parameter or characteristic investigated. Otherwise giving different weights means introducing a strong subjective interpretation to the analysis.

In biodiversity conservation issue (but usually in many other fields) there is not a quantitative evidence of this different influence of the indicators utilized, and consequently it is not possible, starting from literature, to assess different weights in calculating a summarized index for a specific ecological multivariate parameter (like Ecological Value, Ecological Sensitivity, etc.).

In this paragraph a certain number of methods to define different weights for indicators are described. In all these methods the weights are derived not using ecological considerations or evidences but directly from the analysis of the available data matrix.

In order to derive weights three different methods are shown:

1) Using partial order rankings and evaluating correlation values between the ranking due to the original variables and the MCMC (or LPOM) ranking;
2) Using PCA or POSAC technique and evaluating correlation values between the original variables and the reduced principal components;
3) Using w-values of Hasse Diagram established by the original value of the indicators (or the ranks due to the original values).

We referred to 108 Communes of Study area “B” and for each Commune it is used a set of 3 continuous indicators, eachone representing a specific ecological parameter:

- Area fraction of highspot habitats for Ecological Value;
- Area fraction of highspot habitats for Ecological Sensitivity;
- Population Density for Human Pressure.

The available dataset has the structure of a matrix with 108 rows (the Communes) and 3 columns (the 3 indicators). These methods can be simply applied using a different data matrix, with every number of elements described by any multiple set of indicators. For example to derive weights of each indicator describing the Ecological Value (or Ecological Sensitivity) of a certain number of habitats, in order to compute the Ideal Vector distance avoiding the use of same weights.

Method 1: MCMC (or LPOM) ranking

This first method has been used not only to derive different weights to be applied to the three indicators in the evaluation of Ideal Vector distance, but also to compare (by the evaluation of the correlation values) partial order ranking (due to MCMC or LPOM method) with Ideal Vector ranking without weights and giving different weights, and to compare the two Ideal Vector ranking themselves.

The idea is that if the correlation between the ranking due to the two different methods (Partial order and Ideal Vector) - in which scientists of Partial Order and Total Order theories believe - is high, there will be an agreement and so a confirmation in the goodness of these two methods. It is also of interest to see if the correlation between Ideal Vector ranking and partial order ranking increase using derived weights for indicators.

The weights have been evaluated as the fraction (or the percentage) of total correlation of the rank due to each specific indicator as regard the rank due to the 3 ranks using MCMC (or LPOM method). LPOM method (see paragraph 3.1.2) is an approximated method that can be used alternatively to MCMC method (that is an exact method to evaluate the ranking) when the number of elements is higher than 50.

This fraction (between 0 and 1) or percentage (between 0 and 100) is used as weight for each indicator. Iterating the method until the weights will stabilize (i.e. no significant modification of the weights occurs) it is possible to obtain more refined weights.

The analysis has been performed not only to the overall number of Communes, but also in detail for two Provinces of the area. The chosen Provinces are Parma and Piacenza. In particular the iterative method of deriving weights has been applied on Communes belonging to these two Provinces.

So, as an example, in the overall Area "B", the weight for Ecological Value (W_{EV}), has been computed in this way:

$$W_{EV} = \frac{\mathrm{Corr}(\mathrm{Rank}_{EV} - \mathrm{Rank}_{LPOM})}{\mathrm{Corr}(\mathrm{Rank}_{EV} - \mathrm{Rank}_{LPOM}) + \mathrm{Corr}(\mathrm{Rank}_{ES} - \mathrm{Rank}_{LPOM}) + \mathrm{Corr}(\mathrm{Rank}_{HP} - \mathrm{Rank}_{LPOM})}$$

With current values has been obtained:

W_{EV} = 0.645 / (0.645+0.579+0.604) = 0.645/ 1.828 = 0.353.

Similarly can be evaluated the weight for the other two indicators.

The results are shown in the 3 following Tables 4-39, 4-40 and 4-41:

Oltrepò Pavese (Area "B")						
	$Rank_{EV}$	$Rank_{ES}$	$Rank_{PD}$	$Rank_{LPOM}$	$Rank_{IVNoWeights}$	$Rank_{IVWeights}$
$Rank_{EV}$	1	0.129	0.216	0.645	0.831	0.850
$Rank_{ES}$	0.129	1	-0.037	0.579	0.550	0.524
$Rank_{PD}$	0.216	-0.037	1	0.604	0.390	0.387
$Rank_{LPOM}$	**0.645**	**0.579**	**0.604**	1	**0.891**	**0.882**
$Rank_{IVNoWeights}$	0.831	0.550	0.390	0.891	1	0.999
$Rank_{IVWeights}$	0.850	0.524	0.387	0.882	0.999	1

Table 4-39 Correlation matrix between the ranking due to the two different methods (Partial order and Ideal Vector) in study area "B".

Parma Province							
	$Rank_{EV}$	$Rank_{ES}$	$Rank_{PD}$	$Rank_{MCMC}$	$Rank_{IVNoWeights}$	$Rank_{IVWeights}$	$Rank_{IVWeightsStabilized}$
$Rank_{EV}$	1	0.382	-0.176	0.574	0.676	0.626	0.697
$Rank_{ES}$	0.382	1	0.456	0.779	0.815	0.888	0.876
$Rank_{PD}$	-0.176	0.456	1	0.629	0.518	0.535	0.447
$Rank_{MCMC}$	**0.574**	**0.779**	**0.629**	1	**0.935**	**0.929**	**0.909**
$Rank_{IVNoWeights}$	0.676	0.815	0.518	0.935	1	0.974	0.974
$Rank_{IVWeights}$	0.626	0.888	0.535	0.929	0.974	1	0.982
$Rank_{IVWeightsStabilized}$	0.697	0.876	0.447	0.909	0.974	0.982	1

Table 4-40 Correlation matrix between the ranking due to the two different methods (Partial Order and Ideal Vector) in Parma Province.

Piacenza Province							
	$Rank_{EV}$	$Rank_{ES}$	$Rank_{PD}$	$Rank_{MCMC}$	$Rank_{IVNoWeights}$	$Rank_{IVWeights}$	$Rank_{IVWeightsStabilized}$
$Rank_{EV}$	1	0.076	-0.171	0.531	0.479	0.374	0.182
$Rank_{ES}$	0.076	1	0.386	0.729	0.765	0.871	0.936
$Rank_{PD}$	-0.171	0.386	1	0.496	0.436	0.430	0.535
$Rank_{MCMC}$	**0.531**	**0.729**	**0.496**	1	**0.892**	**0.874**	**0.827**
$Rank_{IVNoWeights}$	0.479	0.765	0.436	0.892	1	0.968	0.907
$Rank_{IVWeights}$	0.374	0.871	0.430	0.874	0.968	1	0.956
$Rank_{IVWeightsStabilized}$	0.182	0.936	0.535	0.827	0.907	0.956	1

Table 4-41 Correlation matrix between the ranking due to the two different methods (Partial Order and Ideal Vector) in Piacenza Province.

The obtained results show a general high positive correlation (always more than 0.8) between Partial order ranking (due to LPOM or MCMC) and Ideal Vector ranking. Despite of our expectation, using weights the correlation between Partial Order ranking and Ideal Vector ranking remains high but decrease, also using the iterative procedure in the two analyzed Provinces.

Method 2: PCA and POSAC technique

Similarly to the method 1, PCA or POSAC techniques can be applied in order to reduce the number of variables essentially in two main coordinates (having different properties as explained in paragraphs 1.5.3.1 and 1.5.3.5). Using always the 3 continuous indicators for the total number of Communes in study area "B", these two coordinates using PCA and POSAC (Figures 4-34 and 4-35) have been evaluated and then the 2 values using these two new coordinates has been computed for each Commune. By using the two components values, for each Commune can be derived a mean value obtaining at the end 3 different values (component 1, component 2 and mean value of the two components). This set of triple values for all 108 Communes has been used to evaluate the 3 correlations with each original indicator. The correlation values are used to generate 3 different weights similarly to the procedure described in method 1 or, alternatively, can be chosen an average of the 3 obtained weights as the new weight for each original indicator.

The PCA and POSAC plots using main two coordinates are given (Figures 4-34 and 4-35):

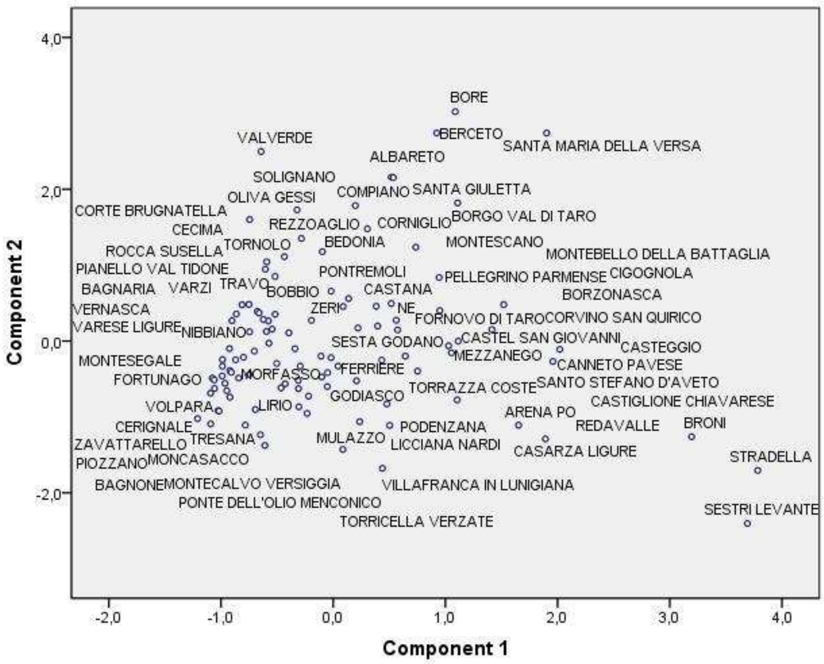


Figure 4-34 PCA Profile Plot.

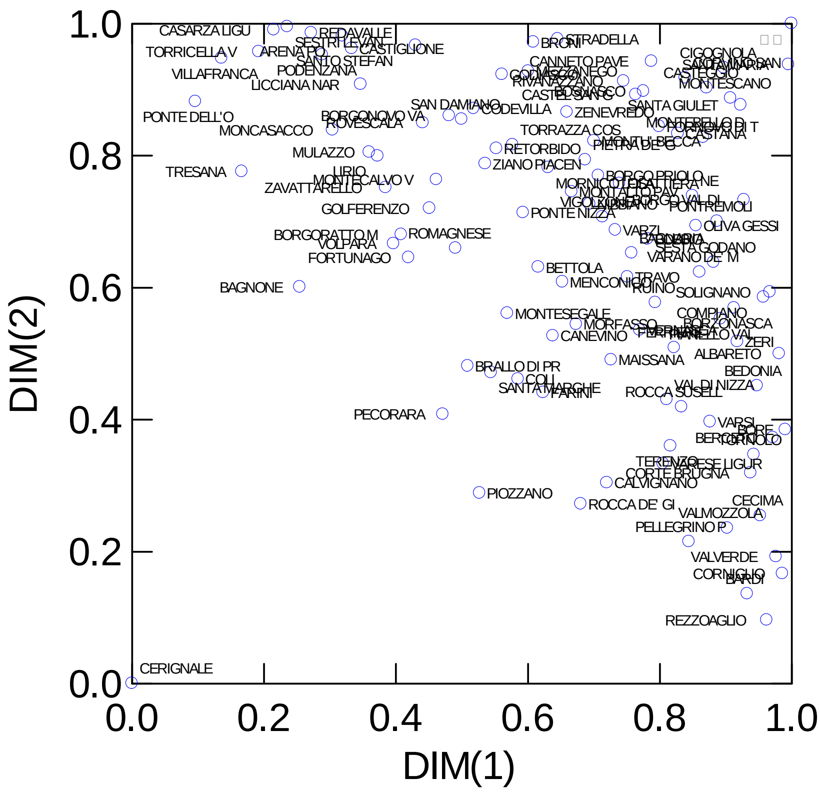


Figure 4-35 POSAC Profile Plot.

Method 3: Hasse Diagram method

A third possible method consists in using as weights the w-values (i.e. measure of mismatches/changes in the Hasse Diagram due to each indicator) of the indicator' set defining the Hasse Diagram. Similarly to the procedure followed in methods 1 and 2 (by using correlation values), in this case each w-value is divided by the sum of all the w-values due to each indicator (in our case are three) The w-values and weights for the 3 continuous indicators using the 108 Communes of Area "B" are provided (Table 4-42):

	ES	EV	HP	Total
w-value	1052	1545	1425	4022
weights	**0.26**	**0.39**	**0.35**	1

Table 4-42 W-values and weights for the 3 continuous indicators using all Communes of Area "B".

4.3.3.2 Method “B”: Partial Order Method using Hasse Diagram

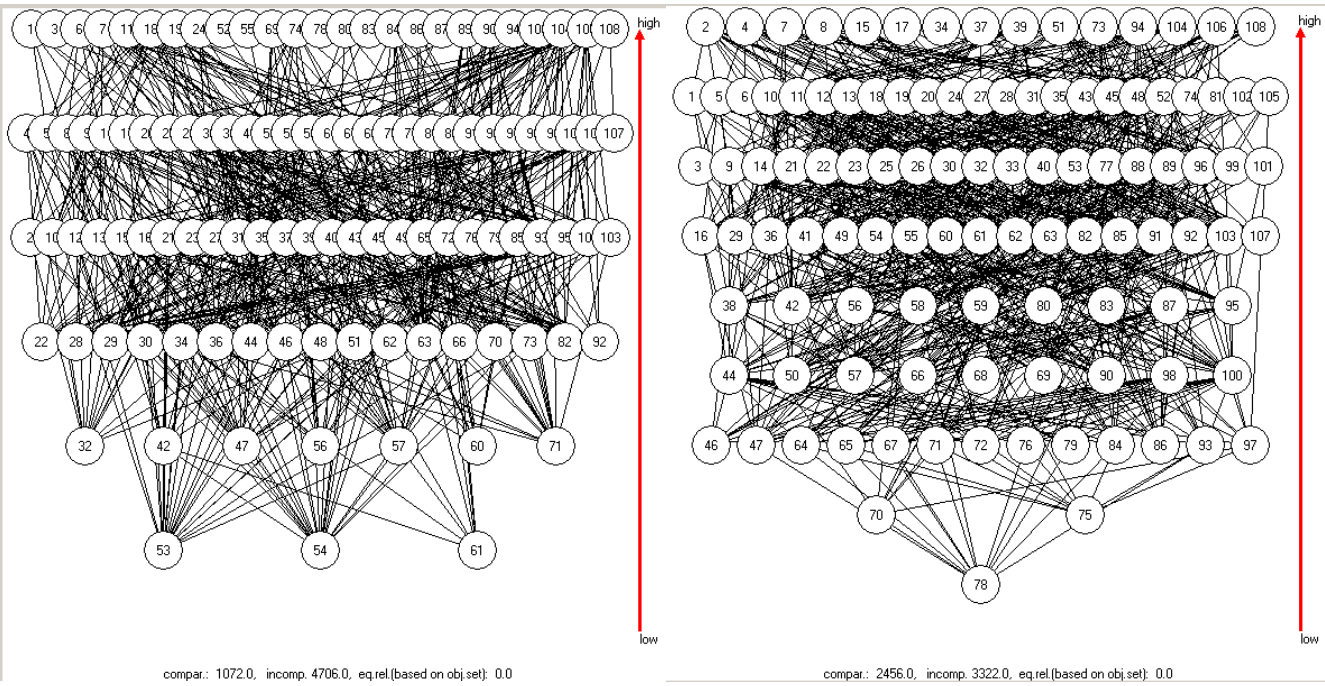
An alternative method to rank the 108 Communes of the Area “B”, defining their “Funding Preference” is described in this paragraph. At the end, it is interesting to extract the top 5 Communes (representing around the 5% of the total number) because they are the most worthy Communes to be funded for biodiversity conservation purposes.

In this case, and also in method “C” each Commune has been qualified by 3 different data matrices, in order to investigate Ecological Value, Ecological Sensitivity and Human Pressure levels of each Commune. In fact the interest is always in combinations of High Ecological Value, High Ecological Sensitivity and High Human Pressure.

In particular has been utilized:

- 9 indicators of Ecological Value (each of them evaluated as the mean value weigthed on area of all the habitat belonging to the Commune);
- 9 indicators of Ecological Sensitivity (each of them evaluated as the mean value weigthed on area of all the habitat belonging to the Commune);
- 6 demographical indicators to describe the Human Pressure on habitats of each Commune.

Determined for each indicator its contribution (positive or negative) respectively to its specific parameter (EV, ES and HP) and having oriented all the indicators in the same direction, eventually reversing some of them, 3 Hasse Diagram has been obtained using PyHasse software (Figure 4-36).



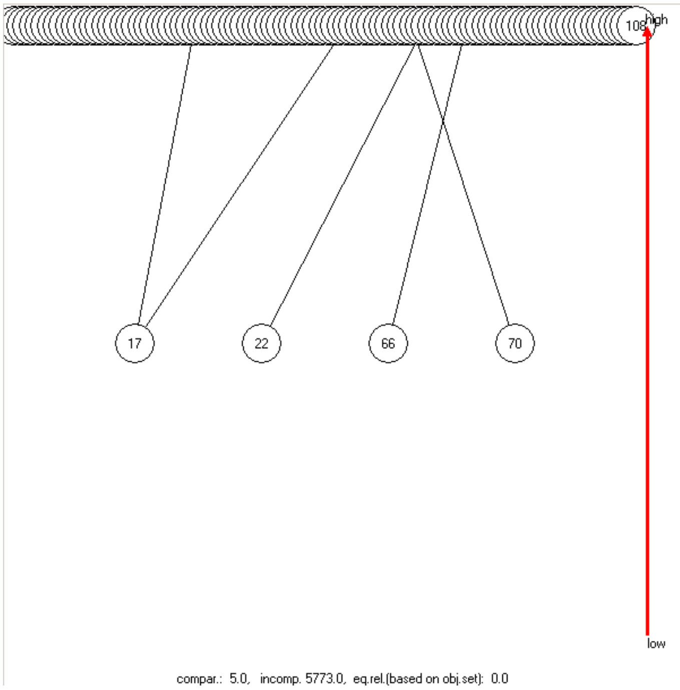


Figure 4-36 Hasse Diagrams obtained using indicators respectively of EV(9), of ES(9) and of HP(6).

For each Hasse Diagram a certain number of levels has been revealed. The top level contains Communes (i.e. maximal elements) with greatest interest in conservation purposes according to the specific ecological parameter considered. On the contrary, elements in the last level has the lowest ecological interest (minimal elements).

The Hasse Diagram due to ES is of interest. In fact it reveal a very low number of levels and it means that, among the Communes, the utilized 9 indicators produce a lot of ties (as a consequence of many incomparabilities).

The next step aims to put together the 3 ranks produced separately by indicators of each ecological parameter (using LPOM method). In this perspective an Hasse Diagram like the one obtained using all 9 indicators of Ecological Sensitivity will not affect in a consistent way the final Hasse Diagram that considers all the 3 parameters. In particular it means that, introducing the rank due to all ES indicators, the structure of the final Hasse Diagram doesn’t change too much compared with the Hasse Diagram produced only by rank of EV indicators and rank of HP indicators.

This structure of Hasse Diagram of ES suggested us that probably an indicator affected too much the Ecological Sensitivity system. Being the compactness the only one indicator that contributes negatively to Ecological Sensitivity has been tried to remove it. Two Hasse Diagrams of ES using all 9 indicators and using only 8 indicators (removing Compactness) has been compared to see if something change in the Communes order.

First of all the Hasse Diagram of ES using only 8 indicators has been derived (Figure 4-37).

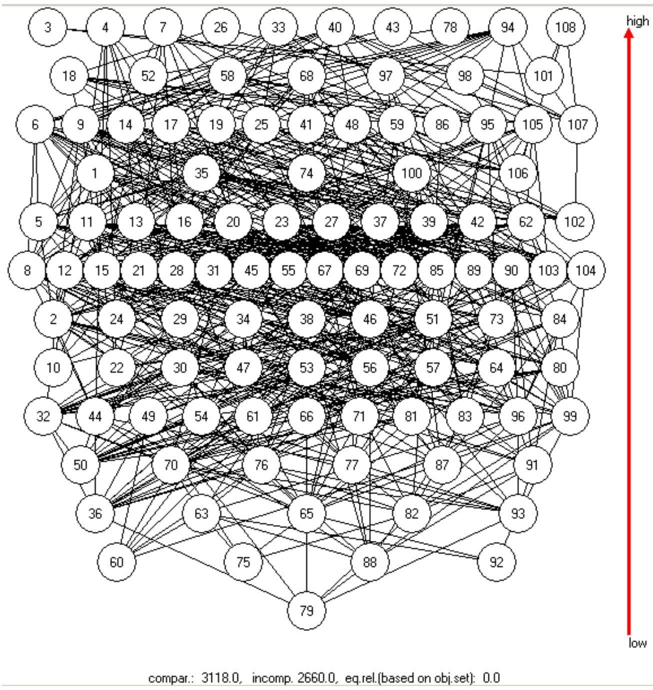


Figure 4-37 Hasse Diagram due to Ecological Sensitivity using only 8 indicators.

Comparing this new Hasse Diagram (HD) with the previous one it is graphically evident that the number of incomparabilities decrease generating an higher number of levels.

Probably this different configuration of HD due to eight Ecological Sensitivity indicators will affect more the configuration of the final HD derived using the 3 separated rank produced by each ecological parameter.

To quantitatively demonstrate this last assumption, proximity analysis has been performed (see paragraph 3.1.2).

Using the proximity analysis the structure of HD ($Rank_{EV}$; $Rank_{HP}$) has been compared with the HD ($Rank_{EV}$; $Rank_{ES(9)}$; $Rank_{HP}$) and the HD ($Rank_{EV}$; $Rank_{ES(8)}$; $Rank_{HP}$) ones.

To evaluate the similarity of these HDs, a specific tool in PyHasse software has been utilized. The software calculate, for each couple of compared HD, the matching previously described and divided in 4 behavior classes (isotone, antitone, weak isotone and indifferent) (see paragraph 3.1.2). In that case the interest is mainly in demonstrating that the isotone degree decrease comparing the HD ($Rank_{EV}$; $Rank_{HP}$) with the total HD in which the Compactness has been removed. Also the degree of antitone must be analyzed., because gives useful information about the general behaviour of ES indicators compared to EV and HP ones.

The HD of the 3 configurations and the results of proximity analysis are given (Figure 4-38).

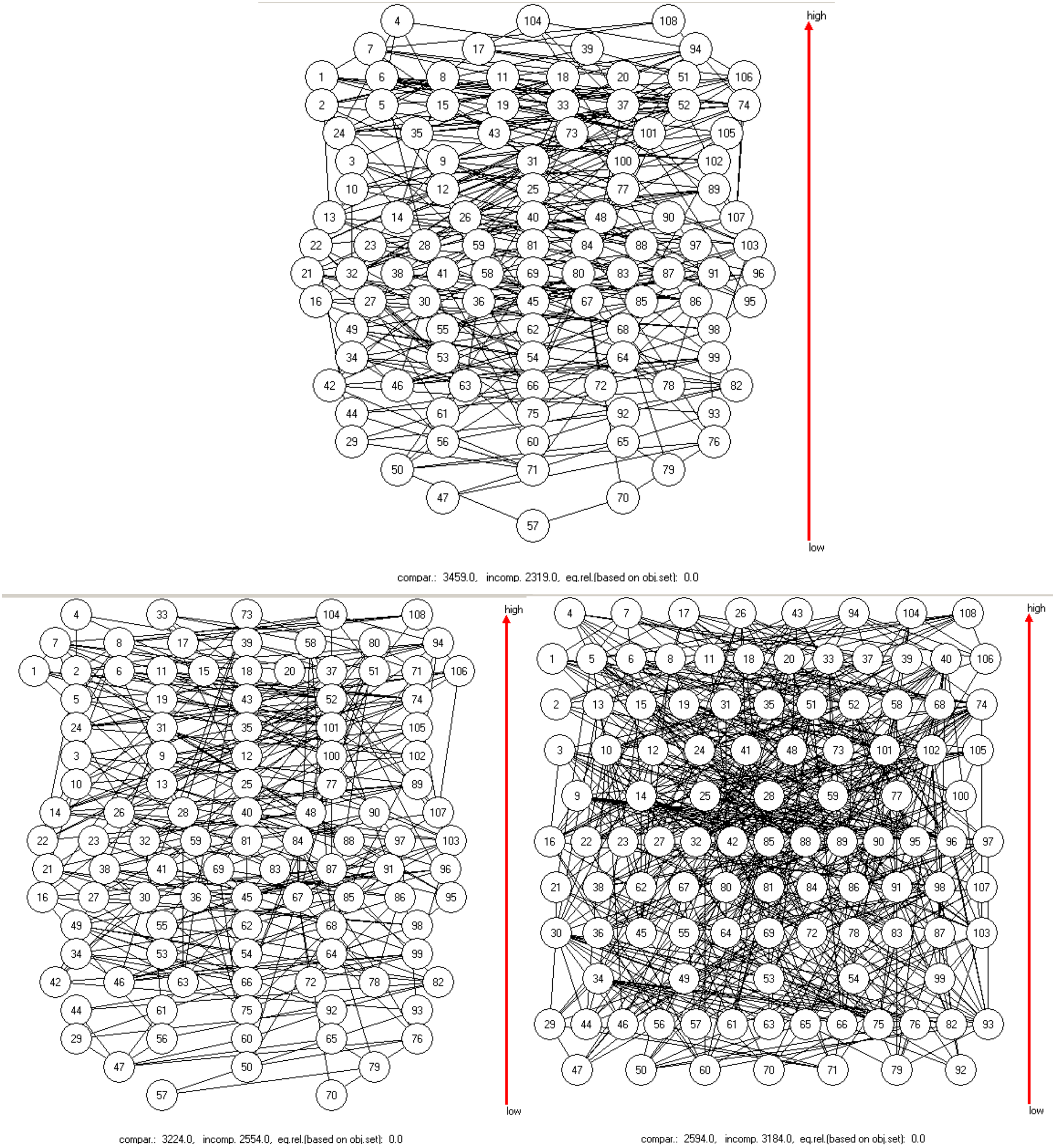


Figure 4-38 HD (Rank_{EV}; Rank_{HP}) comparison with the HD (Rank_{EV}; $\text{Rank}_{ES(9)}$; Rank_{HP}) and the HD (Rank_{EV}; $\text{Rank}_{ES(8)}$; Rank_{HP}).

Maximal elements (i.e. Communes identified by an univocal number) of HD (Rank_{EV}; Rank_{HP}) are: **4, 104** and **108**. Maximal elements of HD (Rank_{EV}; $\text{Rank}_{ES(9)}$; Rank_{HP}) are: **4**, 7, 17, 26, 43, 94, **104** and **108**. Maximal elements of HD (Rank_{EV}; $\text{Rank}_{ES(8)}$; Rank_{HP}) are **4**, 7, 17, 26, 43, 94, **104** and **108**. In bold are underlined the Communes presents in all the 3 Hasse Diagrams.

		Isotone	Antitone	Weak isotone	Indifferent	Identical (Equals)
HD (EV;HP)	Count	6448	0	0	5108	0
Vs						
HD (EV;ES(9);HP)	Fraction	0.56	0	0	0.44	0
HD (EV;HP)	Count	5188	0	0	0.55	0
Vs						
HD (EV;ES(8);HP)	Fraction	0.45	0	0	0.55	0

Table 4-43 Comparison of Isotone, Antitone, Weak isotone, Indifferent, Identical (Equals) degrees of Hasse Diagrams maintaining or removing the Compactness in the indicator set of Ecological Sensitivity.

The Table 4-43 quantitatively confirm what has been supposed. In fact removing the Compactness indicator in Ecological Sensitivity, the isotone degree decrease and it means that HD due to EV, HP and ES using only 8 indicators is less similar to than HD due to EV, HP and ES using all 9 indicator to the HD due only to EV and HP. In practice, the HD due to all the ES indicators not affected the final results because the Compactness indicators produced a lot of ties that have the consequences of countering the effect of ES parameter in the analysis.

Summarizing, the proximity analysis underlines two main aspects:

1. Ecological Sensitivity using all 9 indicators has very low influence in determining Communes ranking than EV and HP;
2. There are no conflicts (i.e. antitone degree is null) and so ES indicators doesn’t produce any contradiction on relations based on EV and HP alone.

In practice, the influence of an HD that shows a weak order with many ties (that is the case of using 9 indicators of ES) on an HD that shows a weak order with a low degree of ties – i.e. with many levels – (that is the case of using only EV and HP indicators), is more or less null and the resulting HD with all the 3 ecological parameters produce an HD similar than the one using only EV and HP indicators. On the contrary, having the HD due to only 8 ES indicators a low number of ties, the original order (i.e. HD) based only on EV and HP parameters is remarkably affected by ES.

As result of the proximity analysis, to extract the top 5 Communes in the study area, has been considered the Hasse Diagram derived using all indicators of EV, all indicators of HP but only 8 indicators of ES.

The candidates for the top list must be searched among the Communes in the top level of the generated Hasse Diagram. Candidates are 8 Communes having the following id number: 4, 7, 17, 26, 43, 94, 104, 108.

Similarly to the final step of method 1, it is necessary a further set of indicators (see paragraph 4.3.3) to order the remained 8 Communes. In that case only the first 3 (among 5) indicators has been utilized and the table with data is given (Table 4-44):

ID	C.B. Types	Total C.B.	Most frequent C.B.
4	5	29	11
7	2	6	4
17	3	24	14
26	3	7	4
43	4	13	6
94	3	12	7
104	7	174	79
108	4	7	3

Table 4-44 Matrix of maximal objects of the HD($Rank_{EV}$, $Rank_{ES(8)}$, $Rank_{HP}$) and three further ecological criteria.

The obtained Hasse Diagram (Figure 4-39), shows clearly that the best Commune is number 104.

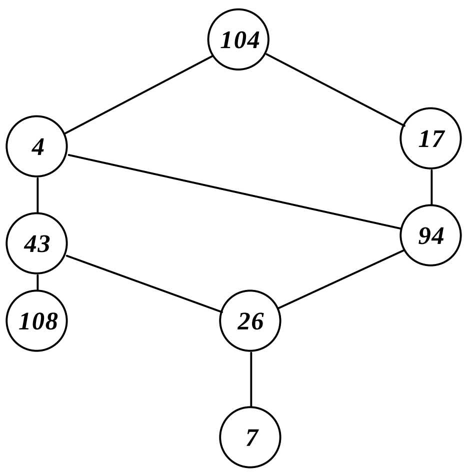


Figure 4-39 Hasse Diagram of the remained 8 Communes obtained using criteria in Table 4-43.

The relative sensitivity of the HD to the 3 indicators is given by the w-values that are: $W(ind_1)=4$, $W(ind_2)=0$, $W(ind_3)=4$.

It is to remember that higher values in the w-matrix means higher sensitivity in the final ranking due to that specific indicator having high w-value. In fact this w-value quantify the differences/changes (i.e. mismatches) that can be found in the HD removing each time that specific indicator.

In that case indicator 1 and 3 are the most influential ones. Removing in a first moment indicator 1 and secondly indicator 3 the HD assumes that two different shapes showing something a little bit different (Figures 4-40a and 4-40b):

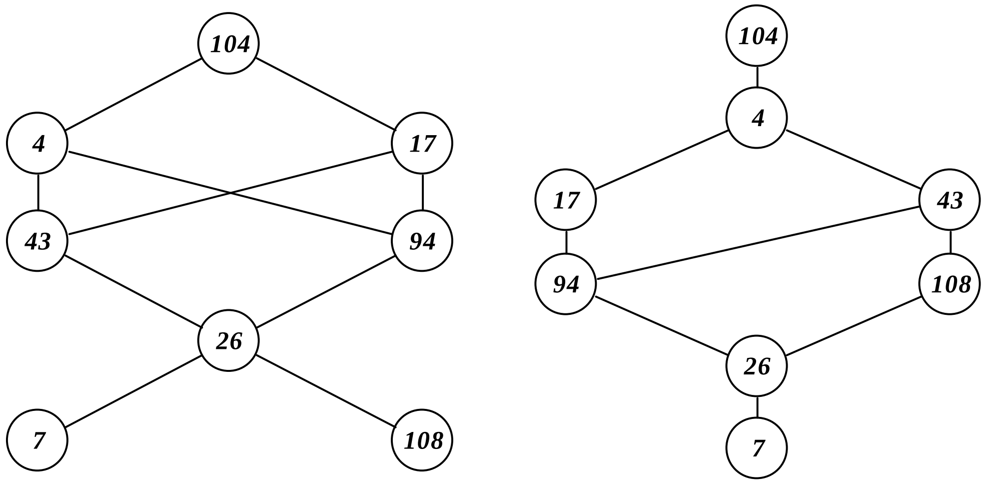


Figure 4-40a and 4-40b Hasse Diagrams obtained removing respectively the first and the third criterium.

Also, it is useful to compute all the possible linear extensions (maximum possible number is n! where n is the number of objects) in order to derive the probability matrix and generate the rank probability plot (based on the number of times that each object has a certain position in the linear extension). The probability plot is given (Figure 4-41):

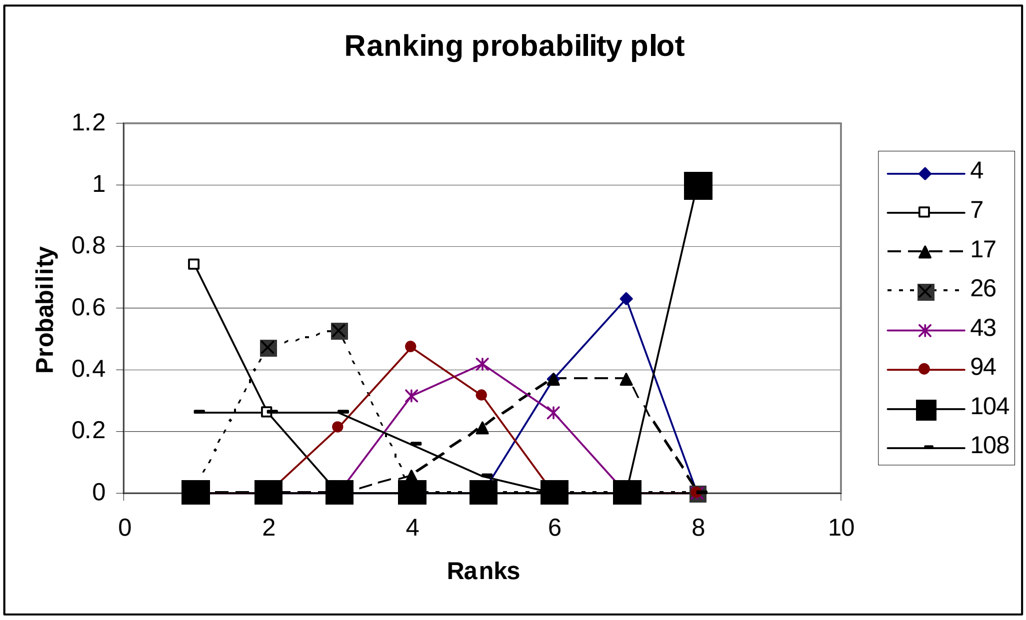


Figure 4-41 Rank Probability Plot of the 8 remained Communes due to the three further criteria.

Looking at this plot, it is clear that the most worthy Commune to be funded is number 104. Finally the LPOM average rank can be computed to give a linear ranking of the objects: According to this average rank the top 5 Communes are: 104 (AvRank = 8), 4 (6.6316), 17 (6.0526), 43 (4.9474) and 94 (4.1053).

4.3.3.3 Method "C": Salience and Primacy method

It is not uncommon for different kinds of considerations to enter into a prioritization context. Each consideration can have a constellation of indicators, and these constellations may be complementary or conflicting. In that case, like to explain method 2, over an administrative division of Communes is available a constellation of indicators that describes their ecological and demographical situation. Each Commune has a suite (constellation) of indicators for ecological value (9) and another for ecological sensitivity (9) derived by computing mean value weigthed on area of all the habitat belonging to the Commune. Additionally, each Commune has a constellation of indicators that speaks to Human Pressure (6) on the natural elements (i.e. habitats). One situation of interest is to determine Communes where there is high ecological value that also has high sensitivity in company with high human pressure. Such communes would be candidates for what might be called conservation crisis intervention through special funding programs. The data covers 108 Communes belonging to Study area "B", for which only what emerges analytically from the data is described.

One of the interesting aspects of this particular context is that ecological value and ecological sensitivity can be seen as having some complementary sense. However, human pressure generally tends to be the bane of the ecological aspects, and thus primarily conflicting with regard to indications. However, there can be situations were ecological elements are imbedded in zones that otherwise have high human pressure. Such imbedding can be as parks, preserves, sanctuaries, or local landscapes that have a topographic character that is more conducive to tourism than to industrial, commercial or residential development.

Ecological Value Indicators

Nine indicators of ecological value were provided, all of which were viewed as being positively indicative. For the present analysis, a decision has been made here to drop two of these due to preponderance of zeros. One of these concerned percent in protected areas, and the other concerned involvement in conservation areas. The remaining seven were place-ranked, with the first entry in the dataframe of place ranks being the identification number for the Commune. From this, a pairs() plot of the ranks was prepared as follows (Figure 4-42).

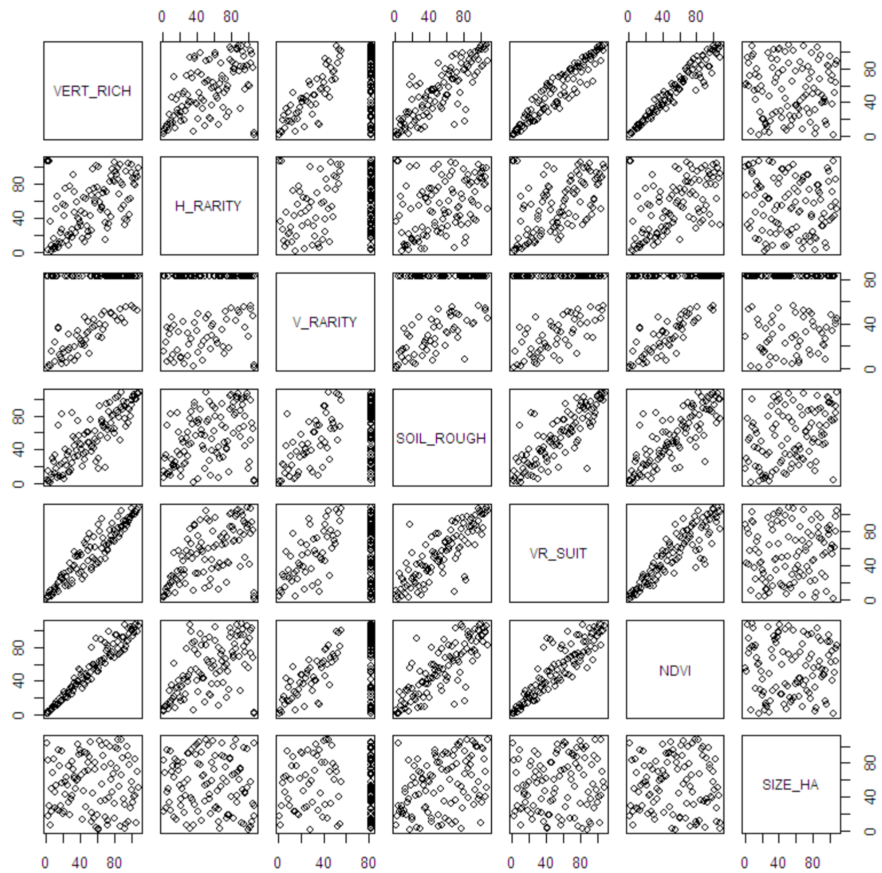


Figure 4-42 Pairs plot for seven place-ranked Ecological Value indicators.

It can be seen that several of indicators are strongly correlated, and Vertebrates rarity indicator will have a special influence by virtue of its partial stratifying effect.

The correlation matrix for the ranked Ecological Value data is (Table 4-45):

	Indicator	1.1	1.2	1.3	1.4	1.5	1.6	1.7
1.1	Vertebrates richness	1	0.533	0.456	0.840	0.938	0.964	-0.003
1.2	Rarity	0.533	1	0.247	0.372	0.543	0.520	-0.103
1.3	Vertebrates rarity	0.4563	0.247	1	0.446	0.270	0.471	-0.006
1.4	Soil roughness	0.840	0.372	0.446	1	0.833	0.820	0.380
1.5	Suitability for vertebrates at risk	0.938	0.543	0.270	0.833	1	0.899	0.102
1.6	NDVI	0.964	0.520	0.471	0.820	0.899	1	-0.016
1.7	Size (ha)	-0.003	-0.103	-0.006	0.380	0.102	-0.016	1

Table 4-45 Correlation matrix for the ranked Ecological Value data.

Indicator 1 is strongly correlated with indicators 5 and 6, and is also substantially correlated with indicator 4.

Ecological Sensitivity Indicators

There were again nine indicators provided for ecological sensitivity. Eight of these were seen as positively indicative, and one as counter-indicative. For present purposes, a decision was made here to drop one of the indicators due to a preponderance of zeros. The remaining positive indicators were then place-ranked, and the counter-indicator was given regular ranks – this latter being the second indicator. Pairs plots were then prepared as follows and depicted in Figure 4-43.

From Figure 4-43 it can be seen that the reorientation of indicator 2 did not make it consonant with the others, and that it is very strongly correlated with indicator 1 as shown in the correlation matrix for ranks that follows. Due to this contrary character of indicator 2 along with its informational redundancy to indicator 1 (Table 4-46), it has been decided here to drop it. Dropping of indicator 2 leaves seven indicators for Ecological Sensitivity.

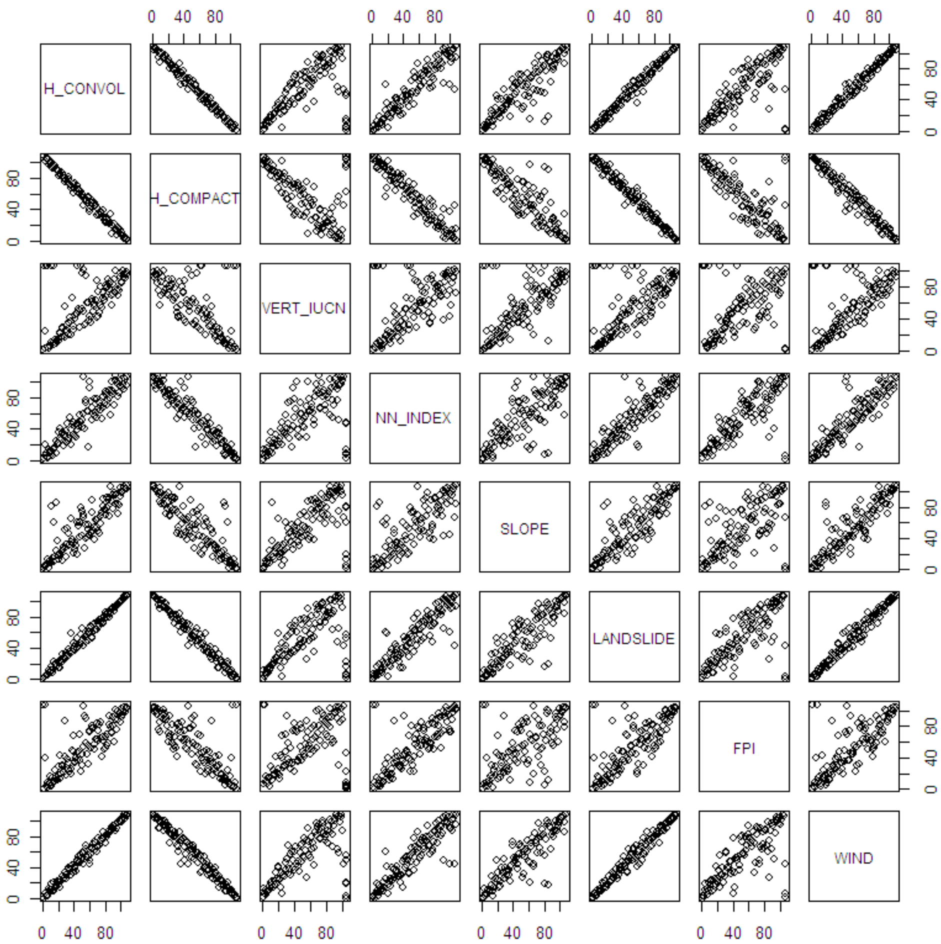


Figure 4-43 Pairs plot for place-ranked Ecological Sensitivity indicators, the second of which is not carried forward.

This is a like number to that for ecological value. The last indicator is strongly correlated with two of the other remaining indicators (Table 4-46).

	Indicator	2.1	2.2	2.3	2.4	2.5	2.6	2.7	2.8
2.1	Fractal Coefficient of perimeter	1	-0.993	0.631	0.923	0.871	0.989	0.771	0.990
2.2	Circularity Ratio of area	-0.993	1	-0.618	-0.946	-0.860	-0.985	-0.785	-0.977
2.3	Species of vertebrates at risk (IUCN)	0.631	-0.618	1	0.588	0.687	0.627	0.442	0.643
2.4	Nearest Neighbour Index	0.923	-0.946	0.588	1	0.778	0.906	0.787	0.901
2.5	Average slope	0.871	-0.859	0.687	0.778	1	0.862	0.624	0.884
2.6	Landslide index	0.989	-0.985	0.627	0.906	0.862	1	0.740	0.982
2.7	FPI	0.771	-0.785	0.442	0.787	0.624	0.740	1	0.752
2.8	Orientation compared to the main wind direction	0.990	-0.977	0.643	0.901	0.884	0.982	0.752	1

Table 4-46 Correlation matrix for the ranked Ecological Sensitivity data.

For purposes of salient scaling to be conducted, the substantial redundancy in both the ecological value and ecological sensitivity constellations of indicators does not entail impairment to the prioritization process. It should, however, be noted for whatever further work may be done in this context.

Human Pressure Indicators

Six indicators were provided for human pressure, with three being directly indicative and three being counter-indicative. Place-ranking was applied to the three direct indicators, and regular ranking was applied to the three counter-indicators. Thus, better-placed cases have lower rank numbers for all indicators. Pairs plots were produced as follows and appear in Figure 4-44.

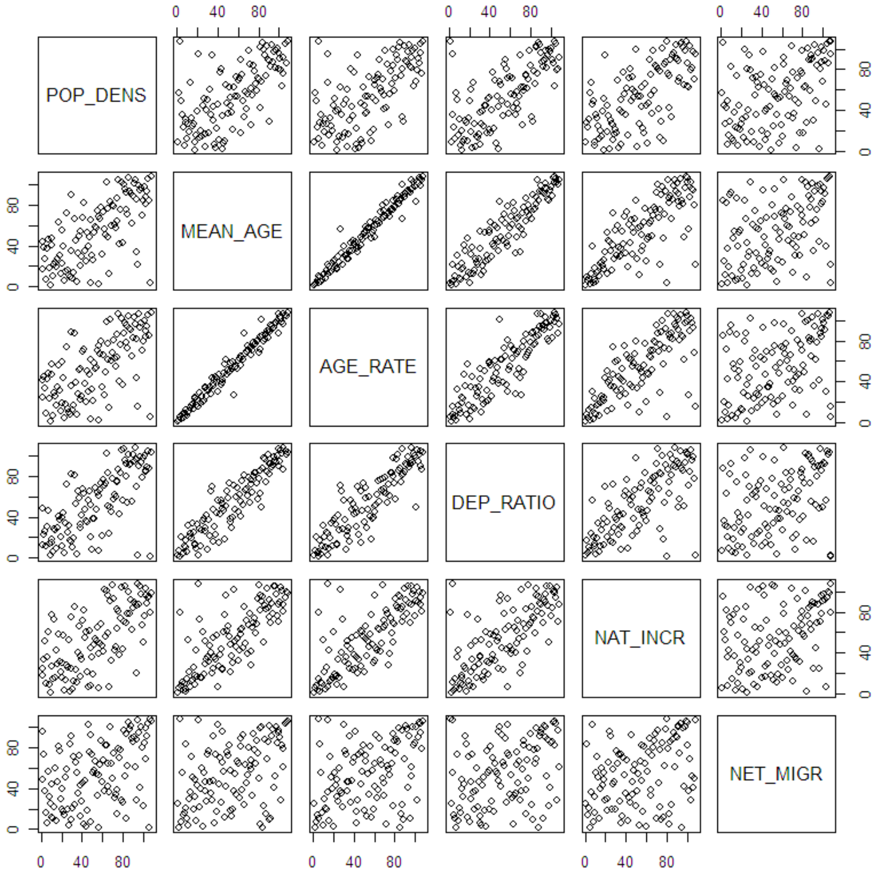


Figure 4-44 Pairs plot for Human Pressure indicators (low rank values reflect high Human Pressure).

Indicators 2 and 3 are very strongly correlated as seen in the following matrix (Table 4-47).

	Indicator	3.1	3.2	3.3	3.4	3.5	3.6
3.1	Population density	1	0.669	0.642	0.700	0.656	0.438
3.2	Mean age	0.669	1	0.982	0.922	0.781	0.407
3.3	Ageing rate	0.642	0.982	1	0.889	0.770	0.398
3.4	Dependency ratio	0.700	0.922	0.889	1	0.719	0.364
3.5	Natural increase	0.656	0.781	0.770	0.719	1	0.341
3.6	Net migration rate	0.438	0.407	0.398	0.364	0.341	1

Table 4-47 Correlation matrix for the ranked Human Pressure data.

Salient Scaling

Salient scaling is next conducted for each constellation separately using the Salient function derived from Salience Theory (see paragraph 3.1.3). The ten most salient cases (Communes) are listed for each as returned directly from the function. A dataframe of salient scale values arranged in case order is also prepared for use in cross-comparisons among the constellations (Table 4-48).

Salient EV			Salient ES			Salient HP		
Case	ID	Salient	Case	ID	Salient	Case	ID	Salient
[1]	108	36.00	[1]	26	10.00	[1]	4	29.00
[2]	7	42.00	[2]	43	13.00	[2]	39	30.00
[3]	19	52.00	[3]	94	14.00	[3]	104	31.00
[4]	101	53.02	[4]	40	15.00	[4]	108	35.00
[5]	18	54.00	[5]	58	15.02	[5]	43	43.01
[6]	11	60.00	[6]	18	18.01	[6]	17	48.00
[7]	33	61.02	[7]	33	19.01	[7]	51	51.00
[8]	105	62.02	[8]	41	27.07	[8]	20	51.03
[9]	9	64.02	[9]	17	29.08	[9]	8	52.00
[10]	6	69.00	[10]	19	30.05	[10]	94	53.00

Table 4-48 Salient scale values of the ten most salient Communes for each constellation of indicators(EV, ES and HP)

Perusal of the top-ten listings show that human pressure has one case in common with ecological value and three cases in common with ecological sensitivity. However, there is no case that appears in all three listings. Proceeding with cross-plots of case-ordered salient scores, Figure 4-45 shows human pressure in relation to ecological value with commune 108 being strongly salient in both respects.

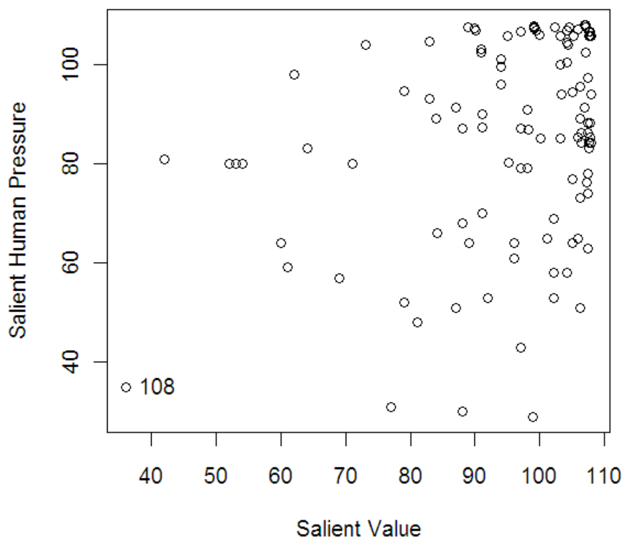


Figure 4-45 Salient scores of Human Pressure versus Ecological Value.

Plotting salient scores of human pressure and ecological sensitivity in Figure 4-46 highlights the three cases (43, 17 and 94) noted in the listings, along with case 33.

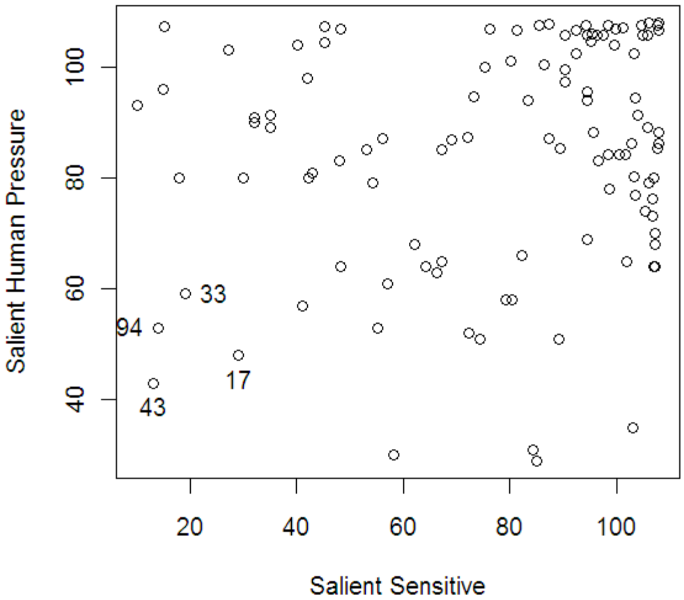


Figure 4-46 Salient scores of Human Pressure versus Ecological Sensitivity.

Salient scores for ecological value and ecological sensitivity are plotted together in Figure 4-47. This highlights 18, 19 and 33 which appeared in the top ten for both, along with 7 which appeared in the top ten only for ecological value. Notably, case 33 is also highlighted in the relation of human pressure to ecological sensitivity. Thus, case 33 has prominence in all three regards.

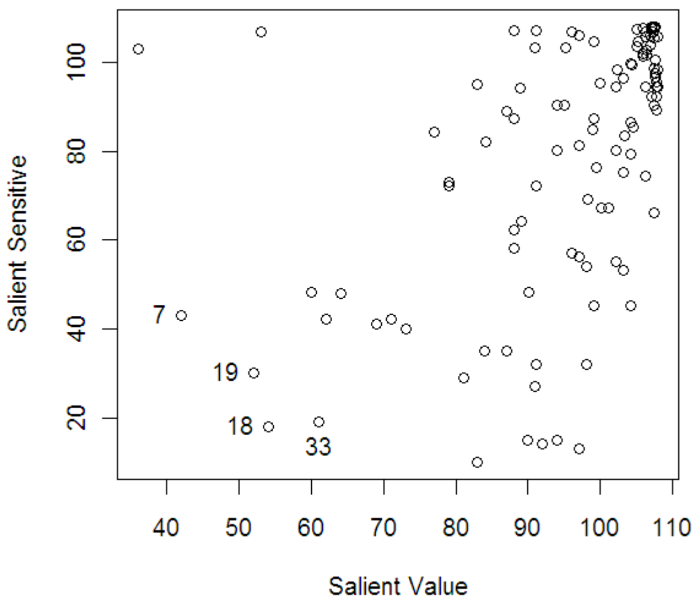


Figure 4-47 Salient scores of Ecological Sensitivity versus Ecological Value.

Pairs plots are frequently helpful in visualizing multiple interrelations. This can be obtained by binding together the three salient scorings and plotting as in Figure 4-48.

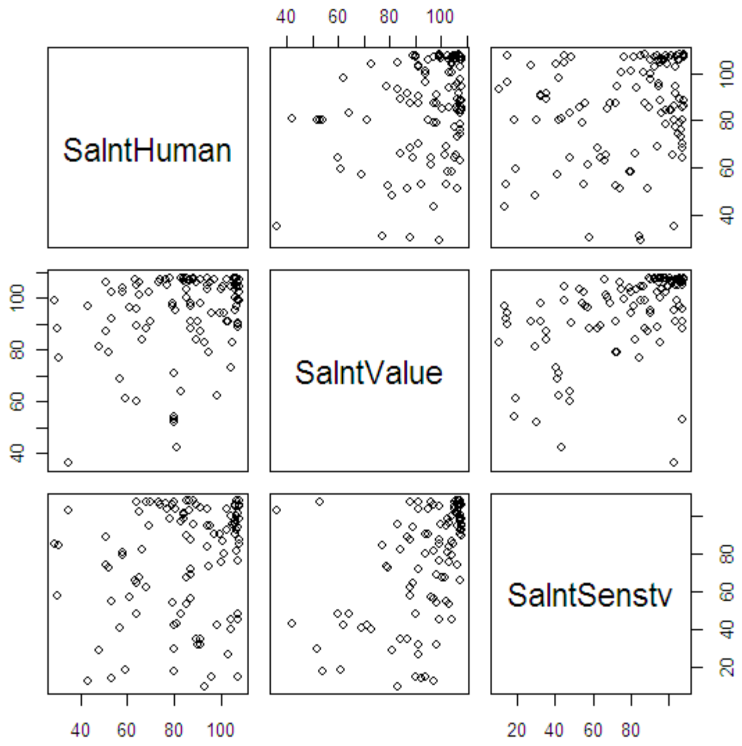


Figure 4-48 Pairs plot of salient scores for Human Pressure, Ecological Value and Ecological Sensitivity.

One further avenue for continuing the investigation is to bind together the ecological value indicators with the ecological sensitivity indicators for joint scoring on a salient scale (Table 4-49).

Human pressure can then be plotted against the joint salient scores for identifying the interesting elements as in Figure 4-49. This reinforces a focus on the commune identified as number 33. Commune 17 also appears from the top ten lists for both human pressure and ecological sensitivity.

Because of the overall oppositional nature between ecology and human pressure with human pressure tending to pose threats to ecology, it makes less sense to extract joint salient scaling for all three. One should never lose sight of sensibility in pursuing prioritization.

Salient EV-ES		
Case	IDs	Salnt
[1]	19	54
[2]	18	56
[3]	7	58
[4]	33	62
[5]	105	67
[6]	9	71
[7]	11	71
[8]	6	77
[9]	25	77
[10]	1	79

Table 4-49 Joint salient scores for Ecological parameters (EV and ES)

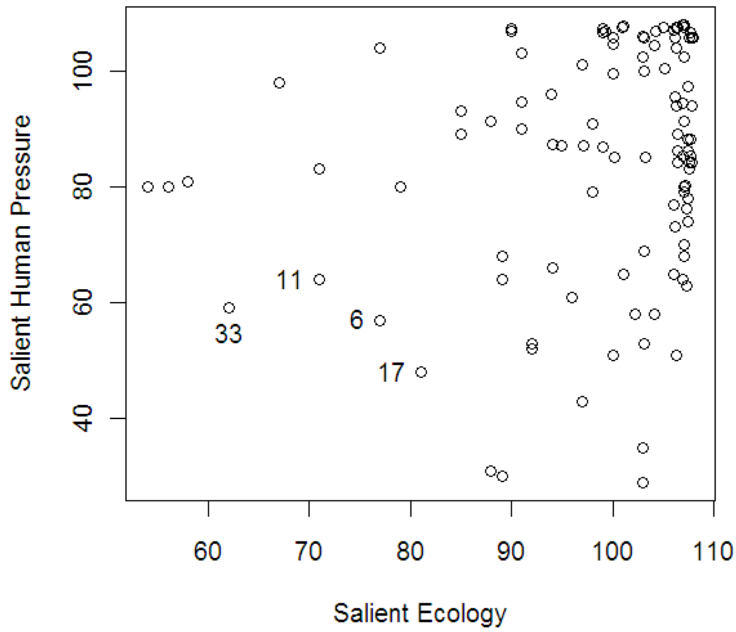


Figure 4-49 Plot of salient Human Pressure versus joint salience for ecology.

5 General conclusions

The progressive biodiversity loss is one of the evident and more dangerous aspects of the environmental crisis that regards all the world. It is usually coupled with the world population growth. Human needs correlated to this demographic growth must be balanced by a necessary environmental protection and especially by an attentive biodiversity conservation or management.

In Italy, in agreement with the Law 394/91 on Protected Areas, the conservation of each naturalistic unit must be located in the general territorial planning background. The planning and coordination of conservation actions and the valorisation of the naturalistic patrimony according to the collective needs is in fact assigned to the community and its representatives.

In the last decade, the majority of the Italian peripheral administrations, have collected and filed a large amount of ecological-environmental data and information regarding their own territory.

What is really important now is that environmental decision-makers of the different peripheral administrations decide to share databases and analysis methodologies with the common aim to preserve the biodiversity of the Country through appropriate forms of planning at the landscape scale.

It is really necessary that the environmental decision-maker is aware of these problems and has at his disposal not only updated databases but also methodological instruments to examine carefully each individual case so as to able to arrange, in advance, the necessary steps to withstand the foreseeable variations in the trends of human pressure on conservation zones.

The methodological contribution of this Thesis regards the integration of statistical methodologies in order to test and propose quantitative tools which can help the stakeholders in taking decisions that seem rational, transparent and effective.

More in detail the obtained results seems to be very interesting from different points of view (see Chapter 1):

1. **Habitat ranking methodologies comparisons**.

It has been developed and experimented a quantitative methodology which integrates the information deriving from sets of ecological indicators (i.e. Ecological Value and Ecological Sensitivity) in order to rank habitats and so to identify ecologically critical habitats worthy to be protected (called Hotspots of Ecological Attention). An important aspect of the proposed methodology concerns the necessary preliminary analysis of the indicators that convey the ecological information. In effect there is a diffuse tendency to collect a lot of indicators without asking if all are really necessary. In this Thesis all the set of indicators has been subjected to a Redundancy Analysis to clarify if the indicators are statistically orthogonal and therefore all necessary. This result has great consequences at economic management of biodiversity monitoring level. The monitoring costs of using two-three really necessary ecological indicators are, on average, much more smaller than those which utilize 10-15 indicators characterized by an high degree of redundancy.

The first method here used, the Ideal Vector one, has been compared with a Partial Order ranking method: This last, chosen at habitat level analysis, is called Salience method (i.e. Subordination and Dominance). It is to worthy to note that the common limit of many Partial Order softwares resides in the maximum total number of objects that can be compared. Salience is one of the few Partial Order methods with very high "count capacity".

Ideal Vector method is based on the aggregation of available indicators in one index (e.g. a multidimensional distance). The most frequent critic moved to this type of methods based on the aggregation concerns, first of all, the "loss of information" in the process of summarizing and secondly the presence of subjective considerations in giving weights to the original indicators when the index is to be composed. The risk is to generate an overall index which doesn't represent really "anything". From this point of view, the Ideal Vector has been built in order to reject these criticisms. In effect its procedure can be identified in two separated steps. In the first step Ideal Vector method generate an index which, broadly speaking, seems to "hide" the original indicators. But hiding doesn't mean necessarily loosing the information. In Ideal Vector index results are not simply scores to rank habitats but represents a measure which has a clear ecological meaning. It represents the multidimensional distance from the Ideal habitat (i.e. the habitat having the best performance in each indicator according to the considered ecological feature) for that given area. The second step of the Ideal Vector methodology regards the necessary identification of the habitats which are more interesting for their Ecological Value (E.V.) and/or their Ecological Sensitivity (E.S.). The necessary information regarding the original indicators is recovered performing a Multiple Discriminant Analysis among the quintiles (of Value or Sensitivity). Usually during this phase scientists concentrates on the First Discriminant Function to understand which are the most influencing indicators. This simplification can

produce sometimes a loss of information particularly if the First Discriminant Function explain less of the 90% - 95% of the total system variability.
The final identification of HSEAs is then obtained extracting habitats being in the best quintile (i.e. top 20% of habitats) for both ecological dimensions (EV and ES).
It is already worthy to note that Ideal Vector method is not only transparent and relatively easy to perform, but is also very flexible. This method gives the possibility to use different weights for eachone of the indicators.

Contrary to Ideal Vector methodology, Salience method does not aggregate the original indicators but accepted to loose, at the beginning, a certain fraction of information transforming the original data in ranks. This transformation entails the loss of the distance among the elements (i.e. habitats) to be ranked (contrary to the Ideal Vector methods which preserves distances among objects). This aspect involves a certain loss of information in the sense that two objects can be next in ranks but very far according to the original measurements, or vice versa. Salience method, utilizes two informative “views” (Subordination and Domination). Domination and Subordination are complementary constructs, but do not generally give the same results. Members of the same status level (in both “views”) are intrinsically incomparable due to the indicator conflicts (i.e. lack of consensus in indicators). As a consequence, neither the Domination view alone nor the Subordination view alone gives sufficient discrimination among the objects (i.e. the habitats). The plot obtained coupling the domination and subordination views can be analyzed to derive useful informations in habitat multidimensional position but the lack of consensus among the indicators will lead to salience sets which have low discriminatory power. Usually this lack increases with the number of indicators. Salience plot so obtained is very clear in the upper-left corner (i.e. objects with greater consensus on superiority and lower consensus in inferiority) and in lower-right one (i.e. the opposite tendency). The best habitats occupy the upper-left corner with high superiority and low inferiority, whereas the more inferior ones occupy the lower-right corner. Sets having complete consistency for the two view appear on the upper-left to lower-right diagonal. In the middle part of the plot the results are not so clear. Fortunately, for our purposes, we are interested in habitat that occupy the upper-left corner (i.e. having great consensus on superiority and low consensus in inferiority both for Ecological Value plot and Ecological Sensitivity plot) and so this result does not generate problems.

Salience method also needs a discriminant analysis to derive most influential indicators and in order to compare it with the results obtained using the Ideal Vector methodology. On contrary of Ideal Vector method, being the “Salience message” not clear in the central part of the plot, it is possible to compare only two or maximum 3 groups of habitats (habitats belonging to the upper-left corner, to the middle part and to the lower-right corner of the plot). We decided to utilize two groups of habitats: the best habitats (located in the upper left corners) and all the remaining ones. As consequence, the Discriminant Function explain the totality (100%) of the ranked information without any further loss.

Summarizing: while the Ideal Vector method looses a little part of the information conveyed by the original indicators, the Salience one accepted to sacrifice a part of it at the starting point transforming the original values in ranks. The preferential choice between these two methods probably resides in the spatial-ecological traits of the study area. Probably, the first method (Ideal Vector) can be preferentially used in environments characterized by high spatial heterogeneity. In effect, being great the distance among the natural units (i.e. habitats) inside these heterogeneous areas it is not advisable to transform original values of the indicators in corresponding ranks. This transformation looses too much information. On the contrary, the Salience method is probably to be preferred in ecological environments having a low degree of spatial heterogeneity (i.e. homogeneous ones) because, in that situations the original distance among the habitats is more or less equal and so a transformation in ranks doesn’t affect the distances themselves.

2. <u>**Coupling demographical data with ecological parameters on conserving habitat biodiversity in an administrative context.**</u>

Italy is one of the most densely populated countries in Europe (189.1 inhab/km^2) but also it is the european country having the highest values of biodiversity. It seems not only reasonable but necessary to introduce, in an explicit way, the demographic data in any policy of biodiversity conservation. It is already clear that the interesting information is contained not only in indicators of state (which convey the actual demographical situation) but also in indicators of demographical trend. In effect the demographical tendencies of the human pressure (represented clearly by the demographic indicators) are of great interest for the environmental policies involved in the territorial planning. What will happen in the future is the basic attention in evaluation studies and this previsional aspect and the consequent ecological monitoring and early warning is better accomplished by demography. The use of demographical data coupled with ecological ones for the direction of the environmental planning is not much spread in the scientific literature. One of the first examples is given in the Map of Italian Nature Project methodology.

In this Thesis it has been proposed and tested a methodology which, using a set of demographic indicators both of state and trend, coupled with ecological ones, has provided, two types of results: on one side it provides guidelines that helps the decision-makers in their choices for landscape management and biodiversity conservation, on the other hand it identifies and ranks the most ecologically worthy administrative partitions to receive funding from Central Environmental Decision-makers (i.e. National Ministry of the Environment).

In both cases the aim is to help the environmental decision-makers in their choices, but in two different ways. While the first procedure (i.e. giving guidelines) has only the aim of driving the stakeholders' choices without constraining too much their decisions' freedom, in the second attempt (i.e. providing a ranking of Communes having higher "ecological funding preference") it is suggested, in a clear and transparent way, which Communes are more worthy to be funded. It is worthy to note that there is an high probability that this same suggestion might be rejected by the Italian decision-makers because most of them wrongly feel this type of result as too binding their "political freedom".

In both cases it is required to move from a natural-ecological partition of the territory (the habitat) to an administrative one (the Commune). This logical need forces to face with practical problems in allocating habitats and their relative ecological information inside the Communes. There are mainly three problems of information conveyance on which it has tried to give solution in a rational way: (i) how to allocate habitats inside Communes; (ii) how to manage with Communes on the boundaries of the study areas; (iii) how to use the ecological information available at habitat level to the administrative one. According to the specific analysis implemented, it has been tried different reasonable technical solutions to these problems (see Chapter 4 – Results and Discussion).

For what concerns the first goal of this type of ecological-demographical analyses, it is worthy to underline that because of the current increasing human pressure on the Italian territory, it is not unusual that in many Italian regions some areas with high ecological value may experiment, in the near future, opposite destiny: some will undergo a strong increase in human pressure with unlikely evitable consequences on the landscape conservation and quality of life; others will risk complete abandonment of the territory and only a cautious policy will be able to avoid or mitigate the negative effects of the abandonment. Starting from this observation, possible management guidelines for conservation policies has been suggested according to the specific actual (and tendential) situation of each Commune. In this analysis the ecological parameters has been used directly at habitat level without summarizing them at a Commune level.

The main and most meaningful goal is to have focused the attention not only on that situations of high and increasing human pressure (due to overpopulation), but also and mainly the opposite one (i.e. depopulation) which generate abandon of the territory causing an increase in environmental risks (fires, landslides, etc.). In effect, it is evident how areas with high Ecological Value are usually placed in zones with low pressure, particularly if coupled with high Ecological Sensitivity. It seems clear that a habitat having high degree of sensitivity cannot be survived in a place historically characterized by an high level of Human Pressure. Consequently, habitats worthy to be protected with priority are mostly located in administrative partitions with low sensitivity in which a further negative demographic trend can cause more danger than the opposite trend (i.e. an increase of population density). So it is more important to focus on that situation suggesting alternative ways to face that type of problem.

Also the second way to proceed derives useful ranking results combining demographical explicit indicators (representing the actual Human Pressure and its future tendencies) with ecological parameters (Ecological Value and Ecological Sensitivity).

3. <u>Priority conservation areas and Ecological Network planning.</u>

In order to show how conservation strategies increase their results if a planned territorial structure is considered, an Ecological Network with some optimal characteristics has been proposed and tested. It seems extremely useful to place priority areas to be protected inside a well structured habitat network. This attempt should be done in any case, not only when the territory has “enough space” to design a network but also when there are few priority areas in an anthropized matrix or even in an urban context. Ecological Network planning is a crucial step in biodiversity conservation because even if it is composed by habitats, it must be managed at administrative level, usually involving more than one Commune. Currently exists a lot of helpful methodologies and related software in order to plan an E.N. The novel aspect of this Thesis concerns the effort to introduce essential but complex (being multidimensional) ecological concepts and metrics defined in the Map of Italian Nature Project (i.e. Ecological Value, Ecological Sensitivity and Ecological Attention) into one of the mostly well-known and used E.N. design techniques, the Systematic Conservation Planning (S.C.P.). The introduction of these essential multidimensional parameters: Ecological Value, Ecological Sensitivity, Ecological Attention and Ecological Fragility in S.C.P. technique has requested a calibration of the ecological parameters themselves in order to balance their entrance and their role with all the other parameters which commonly take part in defining and designing an E.N.. All these parameters tend to maximize the biodiversity and, at the same time, to minimize the “costs” of its protection. The obtained result is the balanced integration of these multidimensional ecological features in order to direct the E.N. planning in preserving characteristics having priority in biodiversity conservation issue.

Furthermore, another innovative aspect of the Thesis consists in introducing, after designing the E.N., a comparison between the so defined E.N. and demographic trend on the correspondent area. This allows the localization in the E.N. itself of the future possible management criticalities. The achieved goal is to provide, in advance, to the environmental-administrative decision makers involved in the E.N. the necessary knowledge (i.e. early warning) in order to favour a better management of it.

Last of all, in this type of analyses, the human pressure (always represented by demographic indicators) can operate at two levels: or, in advance, in the phase of the design of the network, playing directly a strategic role in the sites’ selection (i.e. designing a Network which tried to move away from areas with high pressure) or after introducing it downstream of E.N. planning (i.e. identifying its management criticalities). the second perspective has been chosen to favour the “ecological point of view” and in this way it has been recovered useful information for the environmental decision-makers involved in its management.

The administrative decisions concerning the environment must, more and more often, balance the necessity of the socio-economical growth with the exigencies of the ecological conservation and therefore with the quality of life the protection of high levels of social development with the environmental quality. The understanding of the relations between demographical situation and ecological indicators permits, not only in designing Ecological Network, to individuate in advance (early warning) the most suitable ecological-environmental intervention policies.

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