COENOSES 6 (2): 61-70, 1991

THE PROPERTIES AND INTERPRETATION OF OBSERVATIONS IN VEGETATION STUDY

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Keywords: Characters, Hierarchy, Methods, Pattern, Space

Abstract. A review of the ordination and classification methods is done in the light of the interpretation of the results. The iterative process of sampling and data analysis at different hierarchical levels is suggested as a necessary exercise to understand vegetation patterns.

1. The Medium: its spaces and description

Vegetation is a complex system with states determined by all the interactions between living organisms (microscopic and macroscopic) and the chemical-physical environmental factors. Both are changing in time according to cyclic and/or non-cyclic trends, therefore the vegetation has to be seen under a dynamic system perspective. As suggested by Robert (1987a) vegetation and environmental dynamics can be modelled as trajectories in the space defined by the vegetation variables *(intrinsic)* and in the space defined by chemical-physical variables *(extrinsic)*. However, the system is unique and models should be developed within one space only. This space, which may be called *ecological space*, is defined by all the ecological factors. In this space every individual has its trajectory, so a population will have a set of trajectories, and a community existing in a specific area will have a set of the sets of trajectories of its populations. The community will endure in the site as long as the trajectories of its populations and the environmental components manage to stay within the hypervolume of its potential niche (Feoli, Ganis and Zerihun 1989).

One of the main aims of plant ecology is to describe and to model the ecological space. It is a latent space of which only some aspects are illuminated by our traditional, mechanistic Galilean approach to science. However we must be conscious of this and we should develop methods of sampling and data analysis which will be able to reveal more fully the properties of this space and will allow interpretations in a way consistent with the nature of this space. In doing this we follow an approach that was defined by Goodall (1970) as descriptive. The descriptive approach have a prominent role in being able to reach the level from which the planning of experiments and formulation of models may proceed. According to the descriptive approach vegetation is sampled and described as it appears in space and time. The observational unit is the relevé. This is a vector or a matrix with elements which are records of the state of the vegetation and environment within a given area. The aims for which relevés are taken may be many, however they can be categorized as concerned either with compositional comparisons of the vegetation in *space* and/or *time* on a floristic, structural, functional, biochemical, historical, geographic, evolutionary or reproductive basis, or with discovering spatial patterns and pattern connections inside or on the edges of community types.

2. Characters: states, types, measurement

A character to be useful must have two or more states. There are many characters that may be used to describe a vegetation stand. The choice depends on the aim for which vegetation is studied. Intrinsic and extrinsic characters are recognized at the level of individual organism, population, and community. For example, height is a character that we record for an individual. Nutrients, pH, etc. can be sampled near individuals or randomly through the community. Cover, biomass, density (the number of individuals per unit area) or frequency (occupancy rate or count) are characters recorded for a population. Diversity, stratification (spatial or functional), spatial heterogeneity, evapotranspiration, etc. are community level characteristic. There is a fundamental uniqueness to population and community characteristics. By this we can delineate populations and communities based on the recognition of equivalence. This is *typification*, a key process in the study of vegetation. The *type* is a key concept without which science would collapse.

The description of vegetation is accomplished by the measurement of its component organismal populations, individually or as a groups recognized according to their contribution to vegetation structure. Populations are normally typified as different species. The typification is mainly by conservative, reproductive characters which have little or no environment sensitivity. Adding weight to species as 'names' in a list is useful only if the interest is with the floristic aspects. If the aim is ecological, the vegetation description has to utilize environmentally sensitive characters, and the typification of plants have to be based on such characters.

A set of characters chosen and character states specified, similar combinations of character states is the basis of the typification of plants as *character set types* (*CST* Orlóci and Orlóci 1985). These may or may not coincide with species. As a matter of fact species may be grouped into *character set types* on the basis of a selected number of characters and numerical methods (Feoli and Scimone 1984, Lausi and Nimis 1986, Lausi *et al.* 1989). Weight can be given to the character set types in a relevé by estimation of the population quantities, such as cover, density, frequency, etc. (Orlóci and Kenkel 1985). Only recently (Orlóci and Orlóci 1985, Orlóci *et al.* 1986) has it been proposed that the relevé record should be comprised of a score matrix:

Character set type	Character State 1	2	... m	Weight in relevé j
1	x_{1j1}	x_{1j2}	x_{1jm}	x_{1j}
2	x_{2j1}	x_{2j2}	x_{2jm}	x_{2j}
.	.	.	.	.
p	x_{pj1}	x_{pj2}	x_{pjm}	x_{pj}

In a vector, such as the last column, the relevé elements describe only the weights of the *character set types*; this carries no information about relationships. In a score matrix, the relevé elements specify the character states in addition to the weights of the *character set types*; these carry information about *CST* relationships. The character states may be nested to form a hierarchy (Feoli 1984, Orlóci and Orlóci 1985, Orlóci and Kenkel 1985, Orlóci *et al.* 1986) or left as independent data dimensions. The latter is typical in the sequential schemes (e.g. Knight and Louks 1969, Werger and Sprangers 1982) whose limitations were attributed to overlapping taxa and inadvertant weighting (see Orlóci 1988a).

There are implications of these for the type of information that data analysis can reveal. Clearly when the relevé is a vector, the information which lies with the character states in imposing a unique order on the elements will not enter into the analysis and the relationships investigated are defined by the comparison of vectors. When the relevé is a score matrix, the relationships between the characters and character set types is implicit and comparisons of relevés will have a richer information base to be utilized (Orlóci 1988, 1990). For example, in the case of four binary characters, a relevé would be represented by the graph in Fig. 1. In this, the levels represent characters, the noda character states and the pathways, $++++$, $+++-$, $++-+$, etc., the *character set types*. The graph represents a multidimensional contingency table, since each nodum is a combination of character states to which corresponds a numerical value given by the sum of the values of the previous levels.

When the characters are ordered in some hierarchical way a graph is automatically established, however, not all the branches of the graph may be realized in a relevé. Each set of characters gives rise to a potential graph for each hierarchical order in which the characters may be arranged. Fig. 1 presents two score matrices and their graphs superimposed on the potential graph with origin in the hierarchical order A, B, C, D. This is a new way of conceiving relevés and the methodology of the analysis has been developed. Orlóci and Orlóci (1985) and Orlóci *et al.* (1986) propose to compare the score matrices according to the hierarchy chosen for the characters. In this case the order will matter (Orlòci 1991). However, the graph originating in a hierarchical order of the characters in the score matrices, can be conceived as a variable that counts the realized branches of the graphs. In this case for computing the similarity between score matrices the hierarchical order is not important. The simple Gower (1971) index or the more complex measure of Goodall (1964) can have utility. The data for the comparisons are arranged as in Table 1.

Also a set of relevés may be described by a score matrix and by a hierarchical graph summarizing the information of the separate score matrices and hierarchical graphs. In this case to each segment joining the noda in the possible hierarchical graph, a frequency value, absolute or relative, can be assigned.

The score matrix concept and the hierarchical analysis are relevant not only for the study of compositional variation of vegetation but also in studies directed to spatial pattern analysis where the spatial distribution of *character set types* would be of interest. An example of spatial pattern analysis of characters set types is given by Ganis (1985). When relevés are compared by spatial parameters of the character set types the last column of the score matrix shows the parameters. Further aspects of character-based vegetation analysis are discussed in Chapter 8.

3. Sample space and data structures

Sampling aspects are described in various monographs (Sampford 1962, Orlóci 1978, Greig-Smith 1984). But sampling is different in the study of the compositional variation of vegetation from that used to study spatial patterns. Also, the concept of space is different. In spatial pattern analysis the distribution of the elements occurs on the terrestrial surface; in the study of compositional variation it occurs in abstract spaces defined by the variables used for the description. Sampling optimality is also different if the aim is estimation and if it is to discover complex structures and structural connections (Orlóci and Patta-Pilar 1989, 1990). As a result of sampling and vegetation description, a data set is created. It is a matrix which contain row and column vectors. This matrix is a numeric or an alphanumeric description of the *sample*

	1	2	3	4
A	+	0	0	+
B	0	+	0	0
C	+	+	+	0
D	+	+	+	+
	7	9	10	2

j

	1	2	3	4	5
A	+	0	0	0	+
B	0	+	0	0	+
C	0	+	+	+	0
D	0	0	+	0	0
	5	6	10	4	2

k

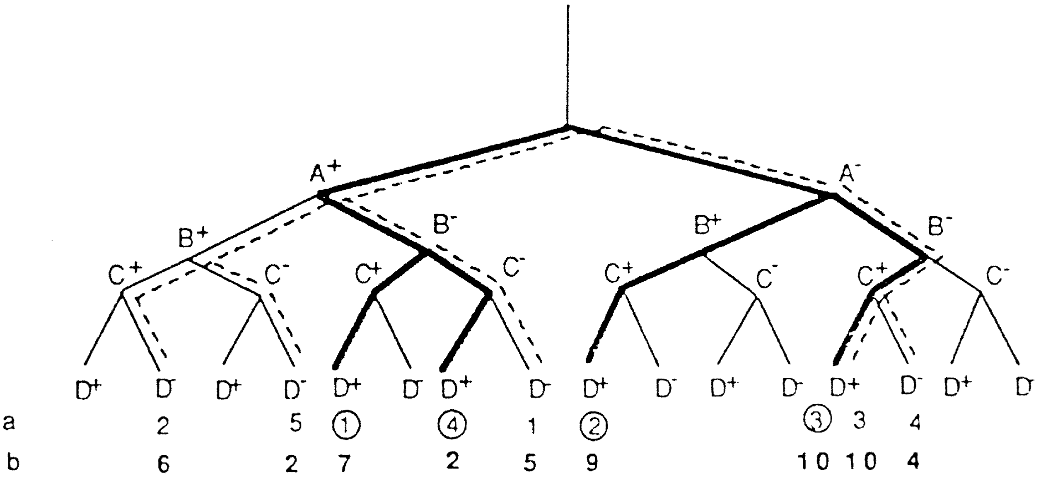

Fig. 1. Two hypothetical relevés *j* and *k* described by two score matrices and by the corresponding hierarchical graphs. A, B, C and D represent 4 binary characters. Relevé *j* has 4 character set types, while relevé *k* has 5 character set types. Bold solid line on the graph represents relevé *j* and dotted line relevé k. The numbers in *a* represent the character set types, and in *b* the abundance values.

space (Orlóci 1978). The sample space is just a subset of the *ecological space*. The sample space is multidimensional and the dimensionality is determined by the number of variables and by their relationships. If the variables are independent then the dimensionality of the space is equal to their number, but if the variables are correlated (positively or negatively) the data set is redundant and the space may be described by a lesser number of variables. There are methods which measure the redundancy of the variables (Orlóci 1978) and these methods facilitate an efficient selection. For continuous variables, the methods are based on sum of squares, multiple and partial correlations; for discrete variables (qualitative or ordered) the methods use the variables' contribution to the total information, mutual information or equivocation (see Orlóci 1978, Feoli, Lagonegro and Orlóci 1984).

One of the aims of data analysis is to reproduce efficiently the *sample space* by arrangement of points (spatial elements) according to a set of coordinate axes. The points may represent variables or relevés; the axes may be different constructs for which we use the general term of *'composite variables'*. They may be the original variables chosen because they are highly representative of other variables, as in the method of orthogonal functions (Orlóci 1978), but usually they are more or less complex combinations of the original variables. If the axes are the original *character set types* than the sample space may be defined at different hierarchical levels and this allows us to create a conceptual framework where convergence or divergence can be measured (Feoli, Orlóci and Scimone 1985, Orlóci *et al.* 1986, Orlóci and Orlóci 1981). The hierarchical order of characters will be important because it will influence the results. From Fig. 1 relevé *a* may find its position in four sample spaces defined respectively by the four hierarchical levels 1, 2, 3, 4. At level 1 the space is defined by 16 variables, at level 2 by 8 variables, at level 3 by 4, and at level 4 only by 2.

Depending on the manner of arrangement of the

Table 1. Transformation of score matrices to compare relevés. This takes into account both the quantities of the character set types as well as the qualitative aspect of the hierarchy. Part A represents the character set types, and part B the hierarchical relationship between the characters.

Part A

	Relevé		
Noda	**1**	**2**	
$D^+C^+B^+A^+$	0	0	
$D^-C^+B^+A^+$	0	6	
$D^+C^-B^+A^+$	0	0	
$D^-C^-B^+A^+$	0	2	
$D^+C^+B^-A^+$	7	0	
$D^-C^+B^-A^+$	0	0	
$D^+C^-B^-A^+$	2	0	
$D^-C^-B^-A^+$	0	5	
$D^+C^+B^+A^-$	9	0	
$D^-C^+B^+A^-$	0	0	A
$D^+C^-B^+A^-$	0	0	
$D^-C^-B^+A^-$	0	0	
$D^+C^+B^-A^-$	10	10	
$D^-C^+B^-A^-$	0	4	
$D^+C^-B^-A^-$	0	0	
$D^-C^-B^-A^-$	0	0	

Part B

	Relevé		
Noda	**1**	**2**	
$C^+B^+A^+$	0	1	
$C^-B^+A^+$	0	1	
$C^+B^-A^+$	1	0	
$C^-B^-A^+$	1	1	
$C^+B^+A^-$	1	0	B
$C^-B^+A^-$	0	0	
$C^+B^-A^-$	1	1	
$C^-B^-A^-$	0	0	
B^+A^+	0	1	
B^-A^+	1	1	
B^+A^-	1	1	
B^-A^-	1	1	
A^+	1	1	
A	1	1	

elements in the sample space, different types of data structures exist. The type will depend on the functional form of the responses of the character set types to the environmental factors and may be linear or curved (Orlóci 1978, Orlóci 1979).

4. Spatial parameters of the sample space

Spatial parameters in spatial pattern analysis are distances, areas, densities, fractals, etc. directly measurable on or over real surface elements. In sample space, the spatial parameters are abstractions and finding good spatial parameters is crucial. This is so because *sample spaces* are rendered operational by specifying the exact functional forms of the spatial parameters. Importantly, the measured relationships among the spatial elements determine the type of information that can be extracted from the data. In the metric conception of the sample space, where all the variables are continuous, the relationships between the elements are measured by metric functions such as *distances* or related *scalar products*. However, there are situations in community studies where the data derive from qualitative scores that cannot be ordered, only counted in frequency terms. In such cases and also in others that yield categorical data, divergences such as *mutual information* (Orlóci 1978, Feoli Lagonegro and Orlóci 1984), *probability* (Goodall 1964, 1966a, b, 1968, 1969, Goodall and Feoli 1988) and *topological indices* (Orlóci 1978) become attractive. When applied, the spatial parameters clarify structures on the sample through which trends and patterns can be detected. This clarification of structures is in fact the first transformation in data analysis and become operative through the *resemblance matrix*. The vectors of such a matrix may be used directly to represent the sample space, although this is rarely the case in their utilization. The resemblance values are the numbers, so they give rise to a quasi continuous space. This space is transformed by ordination methods and serve to define clusters of the spatial elements by clustering algorithms.

5. Extracting informazion from the sample space

The *sample space* described by the resemblance matrix is the information source to be laid open. Transformations are needed for this purpose which display spatial relationships between the elements in interpretable numerical and graphical terms. The relationships are represented by structures that are a hierarchical or a scatter type. The methods to obtain the transformations are many and need continuous reevaluation to keep abreast with technical and conceptual developments which have a synergetic relation with problem recognition and the type of questions investigators ask. Philosophical postering notwithstanding, a truly flexible view on problems under different perspectives and flexibility in combining and recombining information and methods, where sampling and data analysis become a part of the same iterative exercise (Wildi and Orlóci 1987, Orlóci 1988 a, b, Orlóci and Patta Pillar 1990), are the new dictates. To find consensus between different results is then another exercise necessitated by the flexible approach (Podani 1989).

The routines to obtain hierarchical graphs are included under *classification methods*, those for obtaining scattergrams under *ordination methods*. Hierarchical graphs are the tools on which to base hierarchical classifications. They can be obtained directly by hierarchical methods and iteratively by non-hierarchical method (e.g. Jancey 1966, Orlóci 1976, 1978). Hierarchical graphs, the dendrograms, do not give information of the sample space position of the elements, they just indicate that the elements are grouped in a certain way without necessarily revealing trends. Methods to test the sharpness of the groups at different hierarchical levels are available, such as discriminant analysis (Gittins 1984) and canonical contingency table analysis (Feoli and Orlóci 1979, 1985, Gittins 1981, Orlóci 1991a) and other methodologies such as information analysis (Orlóci 1978, Feoli, Lagonegro and Orlóci 1984, Orlóci 1991b) and the different permutation techniques (Biondini, Mielke and Redente 1988). Methods to perform tests on the composition of the groups are also available. These are based on Bayesian analysis (cf. Orlóci 1978), Goodall's probabilistic indices (Goodall 1968, Goodall and Feoli 1988).

Once a classification has been prepared a great deal of information is extracted from the data. Vegetation types and groups of correlated variables are defined. These explain vegetation heterogeneity in space, and/or vegetation changes in time. Other information quantities can be obtained by measuring classification predictability with respect to intrinsic and extrinsic variables (Orlóci 1978, Feoli 1983). If predictivity is measured with respect to intrinsic variables, the discriminant power of each is obtained; if measured with respect to extrinsic variables, it helps to discover correlation between the variables and the vegetation types.

Predictivity may be considered by taking the variables individually, but it is more informative if all variables are taken collectively as linear or non-linear combinations. Drawing extrinsic variables into the analysis may mean to recognize their synergetic relationship with the vegetation. For each combination it is always possible to measure the weight contributed by single variables either in terms of their specificity or redundancy. This can be done by standard methods (Orlóci 1987, 1988b, 1991), however, the classification itself can be used as a basis to produce composite extrinsic variables, in which each original variable has its weight, as suggested by Feoli and Zuccarello (1988) and used by Zerihun *et al.* (1989) and Banyikwa *et al.* (1990). The method is based on fuzzy set theory (Zadeh 1965, Zimmerman 1984, Bezdek 1987) and the composite variables are called *environmental fuzzy sets*. The application of fuzzy set theory gives great importance to vegetation classification. Vegetation types are not conceived only as a sole result of the classification process, but as constructs to be used in subsequent vegetation analyses besides the analysis of predictivity. Classification does not reveal trends in the sample space, but classifications can be used to produce scattergrams which have such an aim. The Feoli and Zuccarello (1986) method involves a simple multiplication of the centroids of vegetation types and the data matrix. The matrix multiplication produces *fuzzy sets* that can serve as ordination axes. Prior to multiplication the data may be transformed in different ways. If the data are mixed (alphanumeric) all the computations (centroids and matrix multiplication) are done by using the resemblance matrix. Fuzzy sets represent the degree of belonging of each relevé to a vegetation type. For each vegetation type there is a corresponding fuzzy set. For this reason when fuzzy sets are used as ordination axes, the latter are interpretable as the factor (composite variable) determinants controlling the corresponding vegetation types. Fuzzy sets may be obtained for relevés, intrinsic and extrinsic variables which may be superimposed in order to obtain a full representation of the sample space. Fuzzy sets may be determined in many other ways. Roberts (1986, 1989), Dale (1988) and Marsili-Libelli (1989) show examples with vegetation data.

Fuzzy sets may be used not only as ordination axes but also as data transformations prior to ordination by other methods. Zerihun, Feoli and Lisanework (1989) obtained a more efficient ordination by using environmental fuzzy sets than by using the original environmental variables. Patta-Pillar (1990) suggests to use fuzzy sets to reduce the indeterminacy in comparing relevés described by score matrices, and Boryslawski and Krusinska (1989) suggest to use the fuzzy linguistic concept to redescribe vegetation data.

Ordination methods belong to two categories. Some methods are aimed to reproduce the sample space as accurately as possible; the original functional form of the relationships between the variables may be ignored. The aim of other methods is to produce monotonous trends consistent with the functional form of the relationships between the variables (Orlóci 1980, Fewster and Orlóci 1983). In the first case, when the relationships between the variables are not respecting the underlying model of the ordination method, trends may appear in curved and twisted shapes. In the second case linear or monotonous trends should appear, if the method does what it was intended to do, but the information on the structure of the original sample space may be lost (Feoli and Feoli Chiapella 1980, Pielou 1982, Kenkel and Orlóci 1986).

Principal component analysis (PCA) is the most widely used method in the first category. It was introduced in vegetation ecology by Goodall (1954). The geometric properties of PCA were considered in an ecological context by Orlóci (1966, 1967) who first showed the duality of the R and Q techniques. PCA consists of an eigenanalysis procedure applied to a centered resemblance matrix which represents a metric space. The main property of the method is that if the original variables are on the ratio scale, PCA will not distort the sample space (Feoli and Feoli Chiapella 1980). If for example in the sample space the elements are disposed in a circle, PCA reproduces the circle; if they are disposed in a square, PCA gives back the squares. If users test PCA on simulated sample spaces of different shapes, they will always get the shapes back in full dimensions. This mathematical property of PCA is the so called 'arch effect'. But PCA is not creating it, it is just capturing it, when the relationships between the variables and the underlying factors are consistent with the coenocline model of Whittaker (1956, 1967). Orlóci (1978) shows how non-linear responses to factor influences lead to non-linear correlations between the response variables and how PCA reproduces successfully such non-linear relationships in curved trends. Relevés sampled along a long gradient are disposed in a PCA scattergram along a curved line, the so called horseshoe, indicative of the type of non-linearity of responses along the gradient. When viewed this way the 'arch effect' or 'horseshoe' is a revealing property of the sample space and it must not be disposed off as a mathematical artifact of PCA at the first opportunity. Two relevant properties are revealed by PCA for which it is worth performing: the type of data structure (linear or non-linear) and the complexity of the data structure in terms of its intrinsic dimensions (number of components necessary to reproduce it accurately). When PCA cannot be applied directly to the data matrix because the variables are not that type, it can be applied to a resemblance matrix using the vectors of similarity of the matrix as the new variables (Feoli Chiapella and Feoli 1977). If the relationship between the vectors is linear then the trends will be represented directly by the axes. If the relationship is non-linear (see Feoli 1984), trends or gradients have to be discovered along curved lines (Feoli and Feoli Chiapella 1980, Feoli and Zuccarello 1986). When the data structure is non-linear, the axes of PCA have reduced utility in revealing correlation between vegetation and environmental factors. Curved lines have to be unfolded which is not an impossible exercise. It can be done by polynomial regression (Phillips 1978), by angular seriation (Feoli and Feoli Chiappella 1980), by minimum spanning trees (Feoli, Lagonegro and Biondani 1981, Feoli and Ganis 1985, Lagonegro 1986, Kenkel and Orlóci 1986, Bradfield and Kenkel 1987), or simply by a visual rank seriation. However, the need for unfolding has been seen as the major drawback of PCA, and other methods of ordination have been suggested to obtain axes for correlations with the environment without taking into account functional relationships between the variables (intrinsic and/or extrinsic). The most pioneering was the polar ordination (PO) of Bray and Curtis (1957). In this method the endpoints (poles) of the axes are always two relevés (or species) selected according to some distance property in the sample space of the resemblance matrix. Roberts (1986) interprets this method in terms of fuzzy set theory and proposes the Bray and Curtis' formula to compute the anticommutative difference between fuzzy sets (Roberts 1987b). Because of the nature of the distance formula, PO gives a metric representation of the resemblance matrix and for this reason it is not free from the unfolding problem of PCA. A method that was presented as the next in the line of the 'best ordination methods' to reveal trends along axes is variously known as 'reciprocal ordering', 'reciprocal averaging' or 'correspondence analysis' (CA). Originally the method

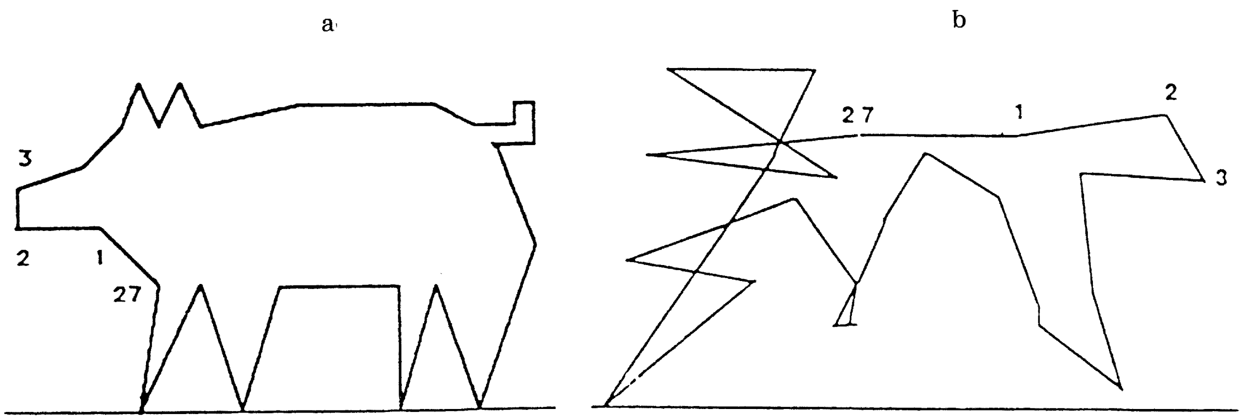

Fig. 2. Example of distortion (b) by DECORANA applied to a geometric figure (a) which is exactly reproduced by principal component analysis.

was developed for decomposing the total chi square of a contingency table (see Lancaster 1949, Williams 1952) and in this respect it has a clear statistical meaning with all the limitations implicit in the use of chi squared. However it started to be applied to any kind of numerical data after it was introduced in vegetation ecology (see Guinochet 1973). After the Hill (1973) presentation it was intensively used and especially strongly promoted in the U.S.A. Different from these applications, Feoli and Orlóci (1979), Orlóci 1991a) used the method in its original context, namely to test the sharpness of joint classifications and to get simultaneously an ordination of species groups and vegetation types. It was extended by lattice analysis to study vegetation dynamics (Orlóci 1981, Orlóci and Orlóci 1988) and species responses in gradient analysis (Feoli and Orlóci 1985, Yu and Orlóci 1989). Although the method is based on the same eigenanalysis solution as PCA, the difference lies in the fact that the resemblance matrix is computed based on double-adjusted data, expressed as deviations from expectation. In many cases this data transformation allows to get ordinations of simulated coenoclines in which the first and the last relevé of the sequence are at the extremes an axis. However the coenocline usually comes out as a curved line, a 'horseshoe'. To unfold this curve the method DECORANA was suggested (Hill 1979). Although Ter Braak (1985) insists that CA fits well the coenocline model, this is true only for short coenoclines. When the coenocline is extended to several half changes as Gaugh (1982) defined it, the curvature may become very severe owing to exactly the same causes as those which we already mentioned in connection with PCA, i.e. a consequence of the nonlinear correlation of the table's row entities (or column entities) which becomes increasingly more extreme as the coenocline length increases. This is clear from the papers of Fewster and Orlóci (1986) and Bradfield and Kenkel (1987). Adding to the nonlinearity problem in CA is the nonlinear scrambling related to the double adjustments to establish a new reference frame. As a matter of fact when CA or DECORANA are applied to a data set representing a fixed pattern such as the geometric figure in Fig. 2, this pattern will be severelly distorted. CA is properly applied to contingency tables where the cells represent joint frequencies of bivariate or multivariate Poisson distributions. For statistical interpretability the cells should have a good number of frequencies. These are unlikely in realistic vegetation studies. CA is a suitable method when used properly to compare types and to evaluate their predictivity with respect to intrinsic or extrinsic variables arranged in classes (Feoli 1983, Feoli and Orlóci 1985, Orlóci 1991b). When used improperly it is just another eigenvector method to analyze scalar products. CA allows simultaneous ordinations of relevés (or sets of relevés) and variables (or sets of variables) which is also available in PCA by the 'biplot' graphs (Gabriel 1971). Biplots give complete representation of the sample space and also information about the relationships between variables, and between variables and relevés. The smaller the angle included by the segments joining two points with the origin of the axes, the higher the relationships between the elements represented by the points.

A method which is not based on the eigenanalysis and which is strongly recommended for its flexibility (Kenkel and Orlóci 1986) is used by Bradfield and Kenkel (1987). This relies on the Kruskal (1964) method known as non-metric multidimensional scaling (NMDS), but uses modified distance measures (shortest path, chord, etc.) to define the external configuration. This method handles nonlinearities efficiently far beyond the capabilities of PCA or CA at comparable coenocline lengths (Kenkel and Orlóci 1986). This focus on the distance measure is consistent with method design by several workers (see Fewster and Orlóci 1983). Related methods were proposed by Ihm an Groenewoud (1975), by Johnson and Goodall (1979) and Goodall and Johnson (1982). Without a suitable external distance measure, NDMS will have little advantage over a PCA ordination or other Eigenordinations (Feoli 1983).

6. Further remarks and conclusions

Within the two categories of ordination each method is characterized by and will have performance characteristics dependent upon the resemblance measure. Eigenanalysis or NMDS applied to the same matrix often lead to similar results. The results are rarely the same, however, when different clustering algorithms are applied to the same resemblance matrix if the clusters are not sharp (Sneath and Sokal 1973, Lausi and Feoli 1977, Podani 1989). Different results can be obtained especially in the dendrogram structure. Generally, in agglomeration, the clusters at the first level of the hierarchy have the same membership, but they are fused in different ways at the higher hierarchical levels. The instability of the clustering results at higher levels is depending on the pattern of the space elements in the sample space. For more reliable structure evaluations, ordination and classification methods should be always applied jointly. The overimposition of classification results on ordination scattergrams, for instance by the technique of the ellipses of equal concentration (Lagonegro and Feoli 1985), generates a great deal of information about ordination and classification. Since centroids of the clusters are defined and distances between them are obtained on the basis of the distributional pattern of the relevés, the hierarchical relationships between the cluster become clear and more readily related to coenocline properties. Linear trends may be detected within clusters and a procedure such as that suggested by Wildi (1989 a, b) can be used to restructure the original data table according to the spatial pattern across the clusters and within the clusters. The non-linear structure of the sample space can be broken into many linear structures where predictions will be more easily measured and modelled (Wildi 1989 b).

Classification allows to define vegetation types, ordination permits definition of their mutual spatial position based on composition. Once the classification and ordination are completed, parameters such as niche hypervolume and niche overlap (Feoli, Ganis and Zerihun 1988, Ganis 1989, Yu and Orlóci 1990) of community and/or character set types, and parameters as autocorrelation (Feoli and Ganis 1986, Wildi 1990) for single or composite variables (intrinsic or extrinsic) may be easily calculated.

Many properties of the vegetation can be identified from a data set with methods giving interpretable results. Interpretability depends on the knowledge of the performances of the methods. The choice of the method is strictly related to the properties that are to be explored. A general searching for trends may lead to loose information on the general vegetation pattern under study. More explicit attempts of interpretation require specific tools for measuring correlation between intrinsic and extrinsic variables, i.e., to understand the ecological space. Computers allow us to explore many possibilities by many different methods and to use their results in a complementary way. Scores of data analytical techniques are candidates for such integrated uses satisfying different conceptualizations of problems and the vegetation processes.

The observations registered in a data sets can be used to obtain information different from what the data have been taken to reveal. This is an important point, considering the enormity of available data stashed away shelves in many institutions. Feoli (1984), Poldini (1989), show how a sample space can be transformed into another one using data bases in which the variables (species or character set types) have associated information on many phenomena related, for instance, to adaptation, competition, dynamics, chemistry, geographic distribution, impollination, etc., which were not of principle concern to those who collected the data.

The observations are carrying properties which are intrinsic and which have to be discovered by data analysis to understand vegetation structure and its environmental connections. Data analysis is not an exercise limited to the data matrix of observations, it interacts with knowledge about the vegetation and environment which may be coded and stored elsewhere. This leads to recognizing the importance of classifications and ordinations in their role as components in expert systems and vehicles of information transfer and generalizations. Classification leads to typification by associating properties with the sets. In these contexts typification is an exercise not only to produce vegetation types for developing a synsystematic scheme such as in Braun-Blanquet (1964), but it is a necessary exercise to inventory knowledge about the vegetation and to define typologies of spatial patterns and processes and to see connections. The process is iterative that stresses synergetic connections between sampling, data analysis, and the evolving knowledge of the investigator. This is a far advanced proposition over the simple minded unisample and unitechnique analytical environments of the not so distant past. The practice of an iterative approach to which Poore (1955, 1956) referred as 'successive approximation', would be greatly facilitated if a flexible and open computer system of storing, retrieving, and analyzing information is developed for vegetation science.

REFERENCES

Banyikwa, F., E. Feoli and V. Zuccarello. 1990. Fuzzy set ordination and classification of Serengeti short grasslands, Tanzania. Journal of Vegetation Science 1.

Bezdek, J.C. 1987. Some non-standard clustering algorithms. In: P. Legendre and L. Legendre (eds.) Developments in Numerical Ecology pp. 225-287. Springer, New York.

Biondini, M.E., P.W. Mielke and P.W. Redente. 1988. Permutation techniques based on euclidean analysis space: a new and powerful statistical method for ecological research. Coenoses 3: 155-174.

Boryslawski, Z.R. and E. Krusinska. 1989. Fuzzy linguistic concept in redescription of vegetation data. Coenoses 4: 169-173.

Braak, C.J.F. ter. 1985. Correspondence analysis of incidence and abundance data: properties in terms of a unimodal response model. Biometrics 41: 859-873.

Bradfield, G.E. and N.C. Kenkel. 1987. Nonlinear ordination using flexible shortest path adjustment of ecological distances. Ecology 68: 750-753.

Braun-Blanquet, J. 1964. Pflanzensoziologie. Grundzuge der vegetationkunde. 3 Aut. Springer, Wien, New York.

Bray, J.R. and J.J. Curtis. 1957. An ordination of upland forest communities of southern Wisconsin. Ecol. Monogr. 27: 325-349.

Dale, M.B. 1988. Some fuzzy approaches to phytosociology; ideals and instances. Folia Geob. et Phytotaxonomica 23: 239-274.

Feoli Chiapella, L. and E. Feoli. 1977. A numerical phytosociological study of the summits of the Majella massive. Vegetatio 34: 21-39.

Feoli, E. 1983. Predictive use of classification and ordination methods in plant community ecology. A summary with examples. In: C. Ferrari et al. (eds), Le Comunità Vegetali Come Indicatori Ambientali. Studi e Documentazioni 30: 83-108. Bologna.

Feoli, E. 1984. Some aspects of classification and ordination of vegetation data in perspective. Studia Geobotanica 4: 7-21.

Feoli, E and L. Feoli Chiapella. 1980. Evalutation of ordination methods through simulated coenoclines: some comments. Vegetatio 42: 35-41.

FEOLI, E. and P. GANIS. 1985. Comparison of floristic vegetation types by multiway contingency tables. Abstracta Botanica 9: 1-15.

FEOLI, E. and P. GANIS. 1986. Autocorrelation for measuring predictivity in community ecology: an example with structural and chorological data from mixed forest type of NE Italy. Coenoses 1: 53-56.

FEOLI, E., P. GANIS and W. ZERIHUN. 1988. Community niche, an effective concept to measure diversity of gradients and hyperspaces. Coenoses 3: 79-82.

FEOLI, E., M. LAGONEGRO and F. BIONDANI. 1981. Individuazione di cenoclini nell'analisi indiretta di gradienti. In: A. Moroni et al. (eds) Ecologia, pp. 207-211. Edizioni Zara, Parma.

FEOLI, E., M. LAGONEGRO and L. ORLÓCI. 1984. Information analysis of vegetation data. Dr. Junk, The Hague.

FEOLI, E. and L. ORLÓCI. 1979. Analysis of cencentration and detection of underlying factors in structured tables. Vegetatio 40: 49-54.

FEOLI, E. and L. ORLÓCI. 1985. Species dispersion profiles of anthropogenic grassland in the Italian Eastern Pre-Alps. Vegetatio 60: 113-118.

FEOLI, E., L. ORLÓCI and M. SCIMONE. 1985. Measuring structural convergence of vegetation types on the basis of floristic data. Abstracta Botanica 9: 17-32.

FEOLI, E. and M. SCIMONE. 1984. A quantitative view of textural analysis of vegetation and examples of application of some methods. Arch. Bot. Biogeogr. Ital. 60: 73-94.

FEOLI, E. and V. ZUCCARELLO. 1986. Ordination based on classification: yet another solution? Abstracta Botanica 10: 203-219.

FEOLI, E. and V. ZUCCARELLO. 1988. Syntaxonomy: a source of useful fuzzy sets for environmental analysis? Coenoses 3: 141-147.

FEWSTER, P.H. and L. ORLÓCI. 1983. On choosing a resemblance measure for non-linear predictive ordination. Vegetatio 54: 27-35.

GABRIEL, K.R. 1971. The biplot graphic display of matrices with application to principal component analysis. Biometrika 58: 453-467.

GANIS, P. 1985. Spatial autocorrelation analysis: computer program and examples of application with different data of grassland vegetation under natural reforestation process in the Karst near Trieste. Studia Geobotanica 5: 127-142.

GITTINS, R. 1985. Canonical analysis: a review with applications in ecology. Springer, New York.

GOODALL, D.W. 1954. Objective methods for the classification of vegetation. III. An essay in the use of factor analysis. Aust. J. Bot. 2: 304-324.

GOODALL, D.W. 1964. A probabilistic similarity index. Nature 203: 1098.

GOODALL, D.W. 1966a. A new similarity index based on probability. Biometrics 22: 883-907.

GOODALL, D.W. 1966b. Deviant index: a new tool for numerical taxonomy. Nature 210: 216.

GOODALL, D.W. 1968. Affinity between an individual and a cluster in numerical taxonomy. Biom. Prax. 2: 52-55.

GOODALL, D.W. 1969. A procedure for recognition of uncommon species combination in sets of vegetation samples. Vegetatio 18: 19-35.

GOODALL, D.W. 1970. Studying the effects of environmental factors in ecosystems. In: D.E. Reichle (ed.) Analysis of temperate forest ecosystems. Springer-Verlag. Berlin.

GOODALL, D.W. and E. FEOLI. 1988. Application of probabilistic methods in the analysis of phytosociological data. Coenoses 3: 1-10.

GOODALL, D.W. and R.W. JOHNSON. 1982. Non linear ordination in several dimensions. A maximum likelihood approach. Vegetatio 48: 197-208.

GOWER, J.C. 1971. A general coefficient of similarity and some of its properties. Biometrics 27: 857-871.

GREIG-SMITH, P. 1983. Quantitative plant ecology. 3rd ed. Blackwell, Oxford.

GUINOCHET, M. 1973. Phytosociologie. Masson, Paris.

HILL, M.O. 1973. Reciprocal averaging: an eigenvector method of ordination. J. Ecol. 61: 237-249.

HILL, M.O. 1979. DECORANA - a FORTRAN program for detrended correspondence analysis and reciprocal averaging. Ecology and Systematics, Cornell University, Ithaca, New York.

IHM, P. and VAN H. GROENWOOD. 1975. A multivariate ordering of vegetation based on Gaussian-type gradient response curves. J. Ecol. 63: 767-777.

JANCEY, R.C. 1966. Multidimensional group analysis. Aust. J. Bot. 14: 131-149.

JOHNSON, R.W. and D.W. GOODALL. 1979. A maximum likelihood approach to non linear ordination. Vegetatio 41: 133-142.

KENKEL, N.C. and L. ORLÓCI. 1986. Applying metric and nonmetric multidimensional scaling to ecological studies: some new results. Ecology 67: 919-928.

KNIGHT, D.H. and O.L. LOUKS. 1969. A quantitative analysis of Wisconsin forest vegetation on the basis of plant function and gross morphology. Ecology 50: 219-234.

KRUSKAL, J.B. 1964. Multimensional scaling by optimizing goodness of fit to a nonmetric hypothesis. Psychometrika 29: 1-27.

LAGONEGRO, M. 1986. Performances of a proximity index defined on a dendrogram table or a minimum spanning tree graph. GEAD-EQ. 4. University of Trieste.

LAGONEGRO, M. and E. FEOLI. 1985a. The use of ellipses of equal concentration to analyze ordination vegetation pattern. Studia Geobotanica 5: 143-165.

LANCASTER, H.O. 1949. The derivation and partition of chi square in certain discrete distributions. Biometrika 36: 117-129.

LAUSI, D. and E. FEOLI. 1979. Hierarchical classification of European salt marsh vegetation based on numerical methods. Vegetatio 39: 171-184.

LAUSI, D. and P.L. NIMIS. 1986. Leaf and canopy adaptations in a high elevation desert of Tenerife, Canary Islands. Vegetatio 68: 19-31.

LAUSI, D., P.L. NIMIS and M. TRETIACH. 1989. Adaptive leaf structures in a Myrica-Erica stand on Tenerife (Canary Islands). Vegetatio 79: 133-142.

MARSILI-LIBELLI, S. 1989. Fuzzi clustering of ecological data. Coenoses 4: 95-106.

ORLÓCI, L. 1966. Geometric models in ecology. I. The theory and application of some ordination methods. J. Ecol. 54: 193-215.

ORLÓCI, L. 1967. Data centering: a review and evaluation with reference to component analysis. Syst. Zool. 16: 208-212.

ORLÓCI, L. 1976. TRGRPS - An interactive algorithm for group recognition with an example from Spartinetea. Vegetatio 32: 117-120.

ORLÓCI, L. 1978. Multivariate analysis in vegetation research. 2nd ed. Dr. W. Junk, The Hague.

ORLÓCI, L. 1979. Non-linear data structures and their description. In: Orlóci L., C.R. Rao and W.M. Stiteler (eds.) Multivariate methods in ecological work, pp. 191-202. Int. Co-operative Publishing House, Fairland, Maryland.

ORLÓCI, L. 1980. An algorithm for predictive ordination. Vegetatio 42: 23-25.

ORLÓCI, L. 1981. Probing time series vegetation data for evidence of succession. Vegetatio 46: 31-35.

ORLÓCI, L. 1988a. Detecting vegetation patterns. ISI Atlas of Science, Plants and Animals, Vol. 1. pp. 173-177.

ORLÓCI, L. 1988b. Community organization: recent advances in numerical methods. Can. J. Bot. 66: 2626-2633.

ORLÓCI, L. 1990. Statistics in ecosystem survey. Abstracta Botanica 14: 31-49. (See Chapter 5).

ORLÓCI, L. 1991. On character-based plant community analysis: choice, arrangement, comparison. Coenoses 5: 000-000. (See Chapter 8).

ORLÓCI, L. 1991a. CONAPACK: Canonical Analysis of Classification Tables. Ecological Computations Series (ECS). Vol. 4. SPB Academic Publishing by, The Hague.

ORLÓCI, L. 1991b. Entropy and information. Ecological Computations Series (ECS). Vol. 3. SPB Academic Publishing by, The Hague.

ORLÓCI, L., E. FEOLI, D. LAUSI and P.L. NIMIS. 1986. Estimation fo character structure convergence (divergence) in plant communities: a nested hierarchical model. Coenoses 1: 11-20.

ORLÓCI, L. and N.C. KENKEL. 1985. Introduction to data analysis with applications from population and community ecology. International Co-operative. Publ. House, Fairland, Maryland.

ORLÓCI, L., N.C. KENKEL and P.H. FEWSTER. 1984. Probing simulated vegetation data for complex trends by linear and non-linear ordination methods. Abstracta Botanica 8: 163-172.

ORLÓCI, L. and M. ORLÓCI. 1985. Comparison of communities without the use of species: model and example. Annali di Botanica 43: 275-285.

ORLÓCI, L. and M. ORLÓCI. 1988. On recovery, Markov chains, and canonical analysis. Ecology 64: 1260-1265.

ORLÓCI, L. and V. PATTA PILAR. 1989. On sample size optimality in ecosystem survey. Biom. Praxim 29: 173-184.

ORLÓCI, L. and V. PATTA PILAR. 1990. Ecosystem surveys: when to stop sampling. Proceedings of the 1989 International Conference and Workshop on Global Monitoring and Assessment; Preparing for the 21st Century. Venice, Fondazione Cini.

PATTA PILAR, V. de. 1990. Fuzzy community components in community resemblance measures (This volume).

PHILLIPS, D.L. 1978. Polynomial ordination: field and computer simulation testing of a new method. Vegetatio 37: 21-39.

PIELOU, E.C. 1984. The interpretation of ecological data. A primer on classification and ordination. Wiley, New York.

PODANI, J. 1989. A method for generating consensus partitions and its application to community classification. Coenoses 4: 1-10.

POLDINI, L. 1989. La vegetazione del Carso Triestino e Goriziano. Edizioni Lint, Trieste.

POORE, M.E.D. 1955. The use of phytosociological methods in ecological investigations. J. Ecol. 43: 226-244, 245-269, 606-651.

POORE, M.E.D. 1956. The use of phytosociological methods in ecological investigation. J. Ecol. 44: 28-50.

ROBERTS, D.W. 1986. Ordination on the basis of fuzzy set theory. Vegetatio 66: 123-131.

ROBERTS, D.W. 1987a. A dynamical system perspective on vegetation theory. Vegetatio 69: 27-33.

ROBERTS, D.W. 1987b. An anticommutative difference operator for fuzzy sets and relations. Fuzzy Sets and Systems 21: 35-42.

ROBERTS, D.W. 1989a. Fuzzy system vegetation theory. Vegetatio.

ROBERTS, D.W. 1989b. Analysis of forest succession with fuzzy graph teory. Ecol. Modelling 45: 261-274.

SAMPFORD, M.R. 1962. An introduction to sampling theory. Oliver & Boyd. Edinburg.

SNEATH, P.H.A. and R.R. SOKAL. 1973. Numerical taxonomy. Freeman, San Francisco.

WERGER, M.J.A. and J.T.C. SPRANGERS. 1982. Comparison of floristic and structural classification of vegetation. Vegetatio 50: 175-183.

WILDI, O. 1989a. A new numerical solution to traditional phytosociological tabular classification. Vegetatio 81: 95-106.

WILDI, O. 1989b. Analysis of the disintegrating group and gradient structure in Swiss riparian forests. Vegetatio 83: 179-186.

WILDI, O. 1990. Sampling with multiple objectives and role of spatial autocorrelation. Coenoses 5: 51-60.

WILDI, O. and L. ORLÓCI. 1987. Flexible gradient analysis: a note on ideas and example. Coenoses 2: 61-65.

WILDI, O. and L. ORLÓCI. 1990. Numerical exploration of community patterns. SPB Academic Publishing, The Hague.

WHITTAKER, R.H. 1956. Vegetation of the Great Smoky Mountains. Ecol. Monogr. 26: 1-80.

WHITTAKER, R.H. 1967. Gradient analysis of vegetation. Biol. Rev. 42: 207-264.

ZADEH, L.A. 1965. Fuzzy sets. Information and Control. 8: 338-353.

ZERIHUN, W., E. FEOLI and N. LISANEWORK. 1989. Partitioning and elevation gradient of vegetation from southeastern Ethiopia by probabilistic methods. Vegetatio 81: 189-198.

ZIMMERMAN, H.J. 1984. Fuzzy Set Theory - and Its Applications. Kluwer-Nijhoff, Boston, Dordrecht.

YU, S.X. and L. ORLÓCI. 1989. Species disp ersion along soil gradients in Cryptocaria community, Dinghusan, South China. Coenoses 4: 39-45.

YU, S.X. and L. ORLÓCI. 1990. On niche overlap and its measurement. Coenoses 5: (In press).

WILLIAMS, E.J. 1952. Use of scores for the analysis of association in contingency tables. Biometrika 39: 274-289.

Manuscript received: June 1990