Plant Ecology **158:** 153–169, 2002.

A spatially constrained ecological classification: rationale, methodology and implementation

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Received 13 July 1999; accepted in revised form 26 April 2000

Key words: Ecological classification, Ecological weights, Geostatistics, Landscape structure and patterning, Scales, Spatial weights, Spatial variation

Abstract

The theory, methodology and implementation for an ecological and spatially constrained classification are presented. Ecological and spatial relationships among several landscape variables are analyzed in order to define a new approach for a landscape classification. Using ecological and geostatistical analyses, several ecological and spatial weights are derived to recreate landscape pattern and structure in a classification model. An ecological and spatial constrained classification is obtained such that it describes the forms of scale and spatial variation of several ecological variables. As an example, several ecological factors are identified applying multivariate analysis methods on a collection of variables (remotely sensed measures of vegetation activity and water balance variables) to define ecological weights. Posteriorly, by analyzing the forms of spatial variation and scales through semivariogram analysis, several necessary spatial weights are derived to spatially constrain the classification. Ecological and spatial information derived from previous analysis is used as GIS mapping tools (i.e, constrained rules) to recreate patterns of regional ecosystems. The approach is successfully implemented for the analysis of tropical forest ecosystems in Mexico.

Introduction

The process of identifying large homogeneous zones, highly similar in landscape characteristics, is the one of the main goals of an ecological landscape classification. The stratification of the landscape into conceptually homogeneous zones (or landscape units) has been a premise for helping to deal with landscape complexity (i.e., heterogeneity) in decision-making and planning (Barnes et al. 1982; Host et al. 1996; Mora 1994; Moss 1983; Schlueter 1987). Classification into ecologically homogeneous units (e.g., ecoregions) has been an important task for some time, both with manual approaches (Bailey 1996; Gallant et al. 1989) and more recently, automated approaches (Hargrove and Hoffman 1999; Mora and Iverson 1997).

When a landscape is ecologically classified, an underlying spatial structure is identified, and the landscape heterogeneity, which interacts regionally at different scale domains, is stratified according to the variability of ecological processes. Because ecological processes have recurrent patterns in space and time, the spatio-temporal dimensionality of landscape variables can be reduced to several ecological relationships that are formalized in a classification scheme, and later on, used as mapping rules (Mora 1994). A landscape classification then becomes a simplified description of the underlying processes that create landscape heterogeneity, and the landscape structure that is identified with the ecological analysis is imposed throughout the classification process.

Landscape classifications stem from the analysis of landscape structure and landscape heterogeneity at different scales. However, landscape structure (i.e., the spatial arrangement of the objects), is not self-evident from landscape heterogeneity. In order to obtain an adequate description of the landscape heterogeneity, at least two structural landscape components have to be considered within a classification process, i.e., the *landscape composition* and the *landscape pattern*. Landscape composition refers to those features associated with the presence and amount of patchiness of a particular type within a landscape (e.g. the amount of forest patches vs. grassland patches in a landscape mosaic). Landscape pattern refers to the features associated with the spatial distribution of those patches (e.g., contiguous vs. fragmented mosaics). Clearly, the identification of both components, landscape composition and pattern, depends not only at which scale (landscape context) the patches are identified, but also on which criteria are used for the definition of the patches.

Landscape ecologists have analyzed the composition and pattern of landscapes based on the identification of patches (as structural landscape units) in many different ways. Landscape patches can be defined in relation to ecological processes that sustain an ecosystem (e.g., patterns of vegetation productivity and climate), the functional response of organisms to the habitat (e.g., "reproductive patches", "food resource patches"), population trends (e.g., "sink" and "sources" patches), or simply *a priori* by automated (remotely sensed) methods.

Whatever the method and criteria used, the representation of a spatial landscape structure, particularly the arrangement of patches in geographical space, results not only from the way in which patterns are identified, but also from the methods of analysis. The application of numerous multivariate classification techniques, such as cluster analysis or discriminant analysis can result in quite diverse representations of pattern when applied to spatial data, depending largely upon the amount of spatial autocorrelation present. Autocorrelation is a statistical property of ecological variables observed across geographic space, mostly observed as patchiness and gradients (Legendre 1993). Therefore, spatial information, especially that related to location and context, should play a major role defining the way in which the relationships among ecological variables are established, and consequently, in the way in which patches are identified.

Recently, new quantitative approaches are being developed for the characterization and mapping of ecosystems at different scales (Hargrove and Hoffman 1999; Host et al. 1996). However, spatial information is still not widely considered in a landscape structure analysis, and rarely is used for classification purposes. Furthermore, patches identified by automated methods do not use their context or location to define "clusters" in the resulting "classified" landscapes.

One way to integrate spatial information in a classification process is by using spatial constraints or spatial weights (Lefkovitch 1980; Legendre 1987; Oliver and Webster 1989b). When building a classification, spatial constraints are necessary to impose a structure in the patterns identified with spatial data, and also to define homogeneous zones when the patterns of interest are mapped. In fact, the main purpose of a constrained clustering (or classification) is to delimit homogeneous regions on a multivariate surface forming blocks (or "patches") that are adjacent in space or time (Legendre 1987).

Spatially constrained classification methods that use cluster analyses in defining homogeneous zones have been widely used in the soil analysis literature. Oliver and Webster (1989a, 1989b) have offered the rationale for the application of constrained cluster analysis, and have developed a geostatistical approach. As "space" has been identified as an important variable to explain the variation of response variables in ecological studies, several techniques that "constrain" environmental ordinations are now used in ecology to evaluate the simultaneous contribution of both environmental and spatial variables (Borcard et al. 1992; Okland and Odd 1994).

Throughout this paper, we present the rationale and methodology to develop a spatially constrained, ecological classification that could be implemented in landscape ecological studies. First, the theory behind this approach is presented. Later on, the approach is illustrated with its application a particular data set. The method is applied to a regionally "small" area in Mexico, where the distribution of rainforest ecosystem types has been identified and mapped using multi-temporal satellite imagery and ancillary ecological information (Mora and Iverson 1997). In this applied part of the paper, we test the usefulness of the approach in defining more homogeneous zones when patterns of ecological variation and landscape units are mapped with spatial and ecological constraints. Finally, the usefulness of the approach is evaluated by comparing the resulting rainforest landscape structure with the structure previously obtained via traditional classification techniques.

Developing an approach for a spatially constrained landscape classification

Several steps are necessary to develop a spatially constrained ecological classification (Figure 1). This approach is based on the integration of ecological information gathered via remotely sensed methods and implemented into a GIS, and subsequently analyzed with geostatistical methods. The implementation of this methodology requires three main methodological phases: (1) exploratory data analysis, (2) the definition of ecological and spatial constraints, and (3) a classification procedure.

During the first phase, exploratory data analysis defines the body of the classification by identifying landscape ecological variables that can be used as mapping elements. Several landscape variables are integrated as ecological components or factors that are obtained from linear or non-linear combinations of landscape attributes of interest. Secondly, geostatistical tools analyze their respective forms of spatial variation and scale, which are subsequently used as ecological and spatial constraints for the classification. In order to define these constraints, a similarity matrix of ecological variables (attributes) is weighted by the importance of ecological factors (amount of variance explained) from which the classification is built. Later on, a dissimilarity matrix among objects (patches) is also weighted by the spatial location and scale parameters derived from semivariograms. The similarity-dissimilarity matrices are transformed into measures of spatial arrangement via principal coordinate analysis in the final phase, and finally the principal coordinates are classified with cluster analysis to define the final classification scheme.

Phase 1: Exploratory data analysis

Identification of mapping elements: Definition of ecological factors

Landscape attributes are generally highly spatial autocorrelated and, for that reason, are indicative of similar landscape processes. Spatial autocorrelation in ecological variables is functional in ecological analysis because it often reveals complex interactions between a target-set of ecological variables (e.g., species, plant type distributions) and the environment (Legendre 1993). Spatial autocorrelation (e.g., things more similar when close together) is the basis for geographical patchiness and the identification of ecological classes.

The spatial interaction of several environmental variables defines ecological gradients on which natural communities can be distributed. When target variables respond to forms of variation in environmental datasets, pattern analysis can be analyzed with ordination techniques. Ordination is the collective term for multivariate techniques that arrange sites along axes on the basis of data on species composition (ter Braak 1987c). The core of ordination analysis is to identify "combinations" of variables on which species, vegetation types, and other ecological variables respond to ecological gradients (ter Braak 1987b). Then, combinations of landscape attributes (vegetation, climate, terrain, and soils) can be used as surrogates of certain ecological processes (e.g., primary productivity) that are summarized in a few variables or components. Such variables can be derived assuming linear or non-linear relationships among variables, depending upon the methods used for analysis (Anand and Orloci 1996; Okland 1996; Orloci 1988; Palmer 1993; ter Braak 1987a, 1987b, 1987c; ter Braak and Prentice 1988).

One of the methods used for detecting ecological gradients as combinations of variables or "components" is Principal Component Analysis (PCA). PCA is an ordination technique that involves eigenanalysis of the correlation matrix or the covariance matrix of several environmental or space (i.e., principal coordinate analysis) variables (Gower 1967, 1987). In some cases PCA is appropriate for the analysis of samples in environmental space because it is likely for most environmental variables to be monotonically related to underlying factors, and to each other. Also, PCA allows the use of variables that are not measured in the same units (e.g. elevation, concentration of nutrients, temperature, pH) (Shi 1993).

Although PCA is often useful for the ordination analysis of samples in species space, it is also restricted for the "horseshoe effect", e.g. a distortion in ordination diagrams (Palmer 1993). The definition of ecological gradients by applying Detrended Correspondence Analysis (DCA) and Canonical Correspondence Analysis (CCA) can also result in the definition of ecological gradients (Hill and Gauch 1980; Jackson and Summers 1991; Palmer 1993). CCA is particularly appropriate when the main objective is to describe the community variation with respect to a particular set of measured environmental variables (McCune 1997).

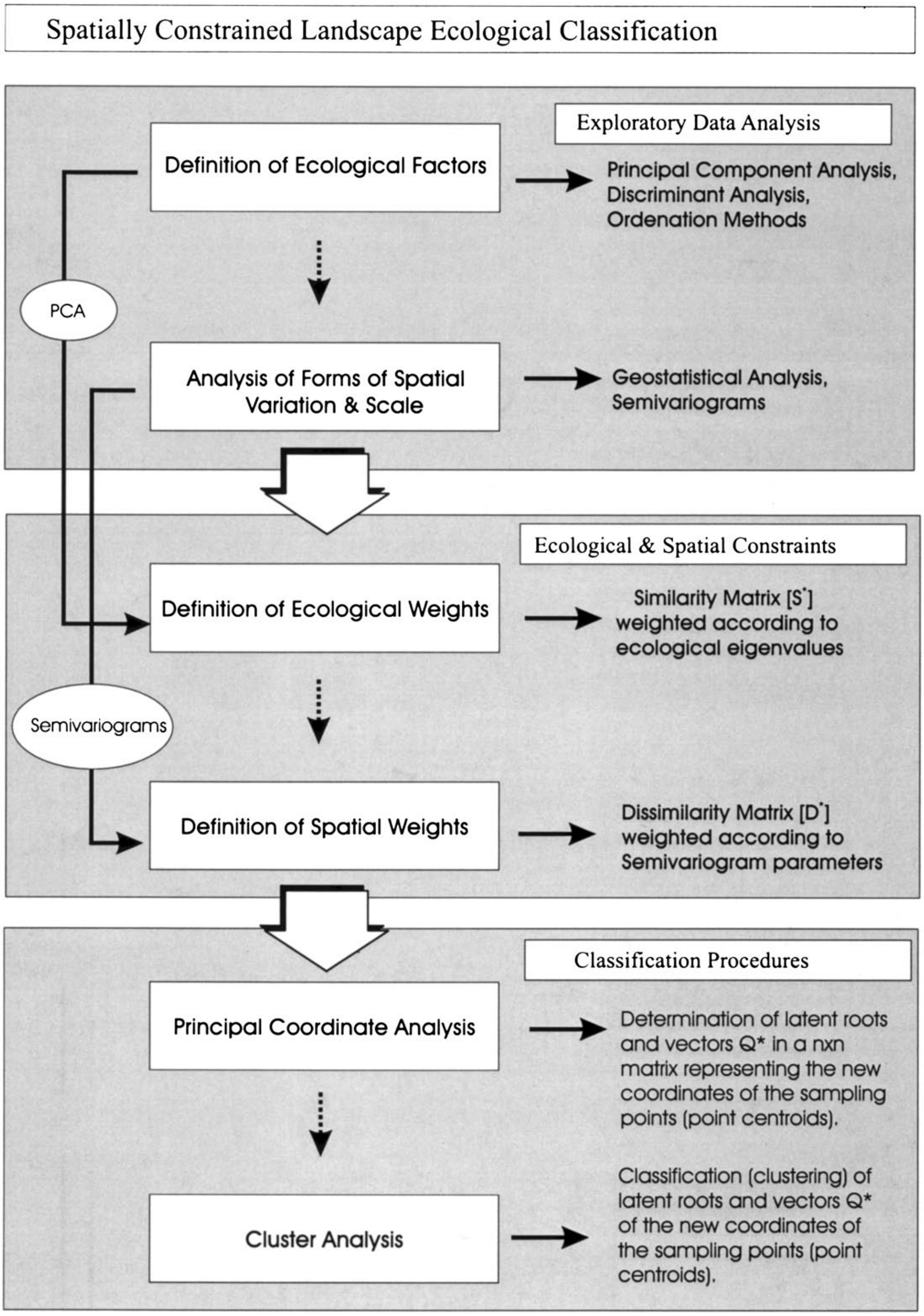

Figure 1. A methodological approach for implementing a spatially constrained ecological landscape classification.

In this paper, variations of vegetation activity, combined with variations in climate, water balance and terrain can be reduced to a few, but meaningful ecological factors by applying multivariate PCA, but can be flexible to integrate other ordination techniques such as DCA and CCA.

Within a classification, certain combinations of landscape attributes can be more important than other combinations, simply because they convey more information about the ecological characteristics of the landscape. A classification scheme describing landscape heterogeneity can be derived primarily on factors that explain most of the variability in landscape variables. Several multivariate methods that are useful to obtain ecological factors (as a combination of individual variables) are also helpful in deciding their relative importance. Multivariate methods based on eigenanalysis (e.g., principal component analysis, canonical discriminant analysis, and canonical correspondence analysis) generally produce combinations of variables, which contain more information than the original variables (Jongman et al. 1987; Mora and Iverson 1997; ter Braak and Prentice 1988). The "factors" (or combinations) obtained are interpreted based on their information content, and the amount of variance they convey from the original variables. Eigenvalues permit the evaluation of each newly obtained factor, ranking their importance according to the amount of variance explained. Later on, ecological weights based on eigenvalues can be applied to a classification by using the information derived from multivariate methods. Similar efforts that measure the relative contribution of sets of explanatory variables by using eigenvalues are found in constrained and partial ordinations (Borcard et al. 1992).

Forms of spatial variation and scales

Because several ecological processes take place simultaneously over a particular area, landscape attributes often co-vary spatially in the landscape, and operate at similar scales. Due to spatial autocorrelation effects, the analysis of ecological factors for classification purposes should include a description of their forms of spatial variability and an evaluation of their scale domains. The analysis of the forms of spatial variation among landscape variables is the second step of analysis in deriving a constrained ecological classification.

Forms of spatial variation in continuous landscape variables can be modeled with geostatistics. Semivariograms have been used extensively to describe and interpolate the spatial variation of landscape variables (McBratney and Webster 1986). Semivariogram models include parameters that not only describe the forms of spatial variation in ecological variables, but also identify the scale domain at which certain factors (or landscape attributes) operate when several observations are made. Generally, the grain and extent at which ecological processes occur, delineate their "scale domain" (Turner 1989; Wiens 1989) and these, in turn, determine ecological levels within a hierarchy (Kotliar and Wiens 1990). Semivariogram parameters can be linked to elements of scale and landscape heterogeneity by offering a quantitative measure of the scale domain at which ecological factors operate.

In a semivariogram model, autocorrelation can be used to quantify the magnitude of similarity in the spatial variation of the factors considered, and defines the spatial scale of the variation. Autocorrelation can be seen as the minimum spatial variation of an ecological variable, and for that reason, can be associated with the "*grain*", or minimal resolution. Additionally, the semivariogram parameter called "*range*" indicates the distance at which the variation is no longer autocorrelated, e.g., the limit of spatial dependence. The range is similar to the scale concept of "*extent*". Consequently, the scale at which ecological factors produce their effects can be evaluated quantitatively by semivariogram parameters. For a spatially constrained classification, semivariogram parameters can be also used as spatial weights to constrain a landscape classification (Oliver and Webster 1989a, 1989b).

Phase 2: Definition of ecological and spatial constraints

Ecological constraints are used in order to make the classification process dependent upon certain (i.e., the most important) factors under consideration. Basically, ecological constraints place more weight on those variables that convey more information about the landscape process of interest. Frequently, landscape categories defining a landscape structure have diffuse boundaries and are difficult to delineate. Spatial weights make possible that "classes" or patches can be identified as a function of spatial properties in addition to ecological criteria. Spatially "constrained" means that a classification is obtained by the effect of spatial proximity in the response of landscape variables or processes.

For the definition of ecological weights it is necessary to obtain a matrix of similarities **S*** among landscape attributes, in which factors that convey more information about the ecological processes of interest will have more weight in the final clustering. On the S* matrix, each element represents a similarity coefficient $\mathbf{s_{ij}}$ (Gower 1971) obtained as:

$$s_{ij} = [\Sigma(1 - |z_{ik} - z_{jk}|/r_k)W_{ijk}]/[\Sigma w_{ijk}] \qquad (1)$$

where: $\mathbf{s_{ij}}$ = similarities between objects, $\mathbf{r_k}$ = range of attribute variable k, $|\mathbf{z_{ik}} - \mathbf{z_{jk}}|$ = absolute value of the difference between object i^{th} and object j^{th} for attribute k, $\mathbf{W_{ijk}}$ = weight for variable k $\mathbf{\Sigma w_{ijk}}$ = sum of all variable weights

Posteriorly, the statistical ranges for ecological components have to be calculated, and each ecological factor is weighted according to its variance explained in the multivariate method used (e.g., PCA, DCA or CCA) by using the eigenvalues in the $\mathbf{W_{ijk}}$ and $\mathbf{\Sigma w_{ijk}}$ terms for equation [1].

Spatial constraints make use of the spatial information derived from the geostatistical analysis by integrating the scales and forms of spatial variation of the ecological factors, and are applied to a dissimilarity matrix **D***. The **D*** dissimilarity matrix is calculated from a similarity matrix **S***. First, dissimilarity [**d**] elements are calculated as:

$$d = [2(1 - s_{ij})] \qquad (2)$$

and the dissimilarities are weighted geostatistically according with the semivariogram parameters of the ecological factor of interest. The weighted **[d*]** dissimilarities can be obtained by using (Oliver and Webster 1989a):

$$d^*_{ij} = d_{ij}C/C_o + C\{1 - \exp(-u_{ij}/a)\} + d_{ij}C/C_o + C \qquad (3)$$

where: u_{ij} = physical distances between landscape patches, a = range (maximum distance over which variation is spatially correlated), C = difference between the total and nugget variance, C_o = nugget variance.

Phase 3: Principal coordinate analysis and classification

Spatially modified similarities (dissimilarities) can be grouped together by several multivariate classification (cluster) techniques. Hierarchical agglomerative methods (e.g., cluster analysis) can be applied directly to the matrix of dissimilarities when hierarchical relationships are suspected among landscape elements. Oliver and Webster (1989a, 1989b) recommended the use of non-hierarchical agglomerative methods for elements that are not hierarchically structured. In this case, **D*** can be transformed to principal coordinate variates that represent linear combinations of localities (Gower 1966, 1967). Then, hierarchical or non-hierarchical cluster algorithms can be applied to these new variates.

An example using rainforest patches in Mexico

Deriving interrelationships in the landscape: Definition of ecological factors

A geoecological landscape dataset for Mexico (Mora 1994) was used to test the spatially constrained methodology proposed in this paper. The data consisted of landscape attributes that describe vegetation activity, water balance, and terrain (Table 1). Measures of vegetation activity were derived from satellite data by using multitemporal vegetation index imagery, which are associated with vegetation productivity and seasonality (Mora and Iverson 1997). Water balance variables were modeled with GIS, and elevation was obtained from digital elevation models. All information was implemented in a cartographic ARC/INFO GIS raster model with an 8 km spatial resolution.

From this information, an ecological classification has been previously obtained for the landscape of Mexico without applying spatial constraints (Mora 1994). This ecological classification system stratified the landscape at two ecological scales, identifying 6 ecoregions and 40 ecosystem types distributed among 1743 landscape patches. For illustration purposes, 105 patches associated with the rainforest ecoregion (“selvas”) were used for the constrained classification analysis presented here.

The rainforest ecoregion contained five types of “selvas”, mostly distributed in the Yucatan peninsula and the border with Guatemala. These types were differentiated in terms of their productivity, seasonal

Table 1. Landscape ecological data set used for a spatially constrained classification.

Vegetation:	Indexes derived from multitemporal AVHRR imagery
VP	Vegetation Productivity Index
VS	Vegetation Seasonality Index
MinPA	Minimum Photosynthetic Activity
MaxPA	Maximum Photosynthetic Activity
PLP	Photosynthetic Level at Peak of Growing Season
PLO	Photosynthetic Level at Onset of Growing Season
Water Balance:	Modeled variables with GIS
APE	Adjusted Potential Evapotranspiration (mm/year)
AE	Actual Evapotranspiration (mm/year)
WD	Deficit of Water (mm/year)
P	Precipitation (mm/year)
SM	Soil Moisture (mm/year)
WS	Surplus of Water (mm/year)
ELEV	Mean Elevation above Sea Level

variation and vegetation response to water balance (Mora 1998). Regions (or patches) for each class were identified using GIS overlaying procedures, and every landscape element (or patch) was used as a sample to describe the spatial rainforest heterogeneity. Several GIS functions permitted us to characterize each rainforest patch with the ecological information, and zonal statistics (mean values) of each landscape attribute were obtained for each landscape patch in order to use them in the subsequent numerical analysis.

Exploratory data analysis showed that several original ecological variables characterizing each "selva" patch were highly correlated. Particularly, there were significant correlation between actual evapotranspiration with precipitation ($r = 0.87$, $p < 0.005$) and soil moisture ($r = 0.82$, $p < 0.005$); vegetation productivity with maximum photosynthetic activity ($r = 0.80$, $p < 0.005$) and minimum photosynthetic activity ($r = 0.79$, $p < 0.005$); and between elevation and potential evapotranspiration ($r = -0.78$, $p < 0.005$).

Principal component analysis [PCA] was used to reduce the dimensionality of landscape attributes and to identify components of variation in the ecological data set by obtaining ecologically meaningful factors or components. A scree test on the obtained PCA eigenvalues indicated that 4 components accounted for almost 88% of the total variance in the untransformed ecological variables (Table 2). The first principal component explained more than 51% of the total variance in the entire data set. The second component explained $\sim 17\%$, and the third and fourth component explained $\sim 14\%$ and $\sim 6\%$ of the total variance respectively. Since the remaining components had more unexplained than explained variance (eigenvalues < 1), these were not used during subsequent analyses. A varimax orthogonal rotated solution was applied to obtain the scores for four principal components.

Table 2. Principal component analysis results for the geoecological dataset of 1743 patches in the Mexican landscape. Four principal components were used to constrain ecologically the final classification.

Factor	Eigenvalue	% Exp.	Cum. %
1	6.668436	51.29566	51.30
2	2.253472	17.3344	68.63
3	1.763812	13.56778	82.20
4	0.747967	5.75359	87.95

The simple structure criterion in PCA was used as an aid for ecological interpretation of the components (Figure 2). Simple structure showed that the first principal component (PC1) could be interpreted as a vegetation activity component. PC1 was mostly associated to annual vegetation productivity (VP) (measured indirectly through integrated NDVI values), and minimum and maximum photosynthetic activity levels (MinPA, MaxPA), which scored high in their respective loadings. The second principal component (PC2) showed a strong and inverse relationship between elevation (ELEV) and adjusted potential evapotranspiration (ADPE). The PC2 indicates that

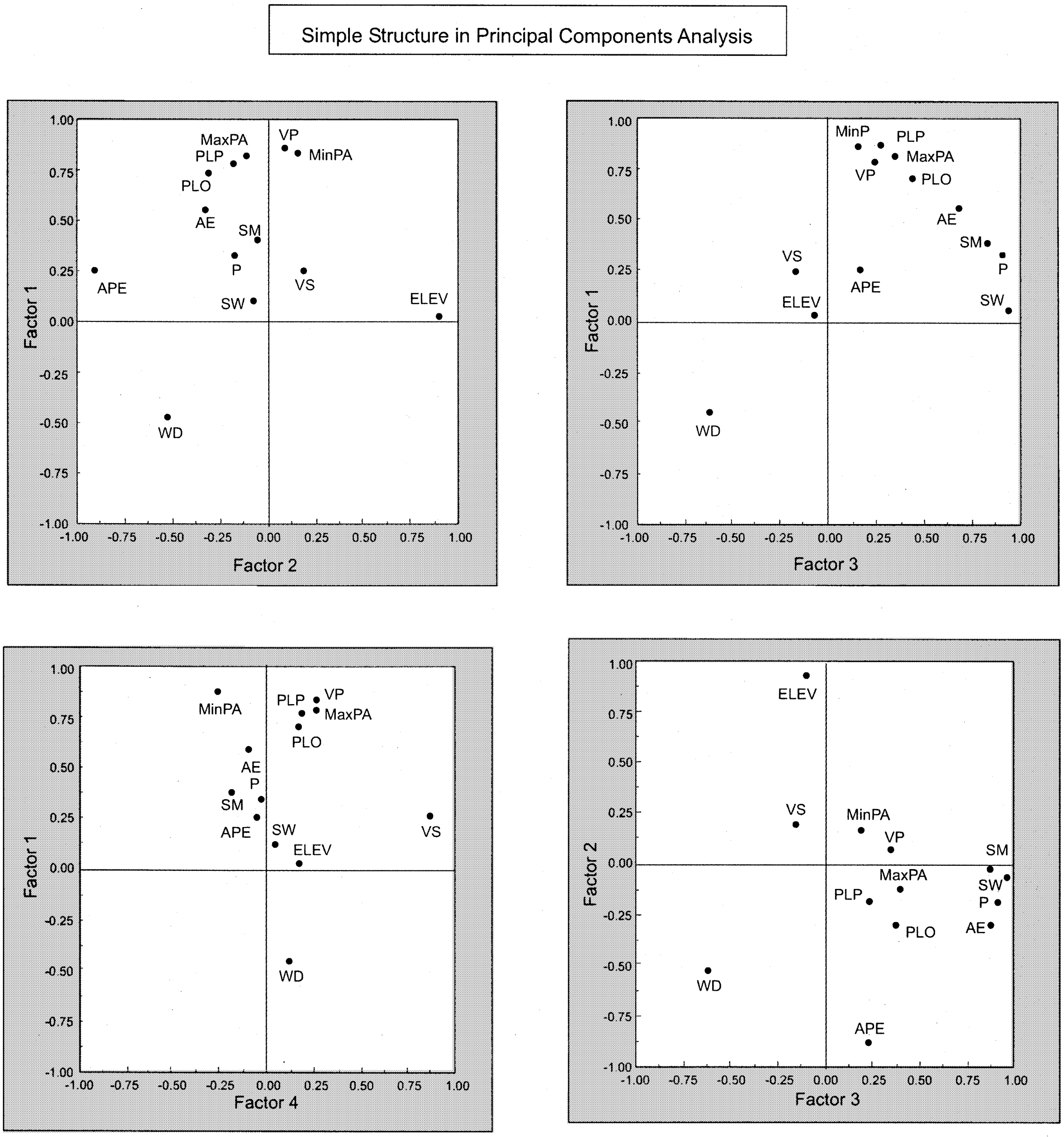

Figure 2. Simple structure for principal component scores of the ecological components derived from the geoecological data set.

high potential evapotranspiration rates occur at lower elevations, and/or lower potential evapotranspiration rates at higher elevations. The third principal component (PC3) was interpreted as a major humidity gradient component, integrating the effects of water surplus (WS), precipitation (P) and soil moisture (SM). Finally, the last obtained principal component (PC4), was almost exclusively associated with vegetation seasonality (VS). The four principal components were thus designed as: Vegetation productivity, ADPE/ELEV, humidity gradient, and vegetation seasonality in the subsequent analysis.

Analyzing forms of variation and scale in ecological factors

The spatial variation of each of these ecological factors was analyzed through semivariogram models, and their respective surfaces were krigged using GIS. Two kriging models, spherical and exponential, were used to model the spatial variation of ecological com-

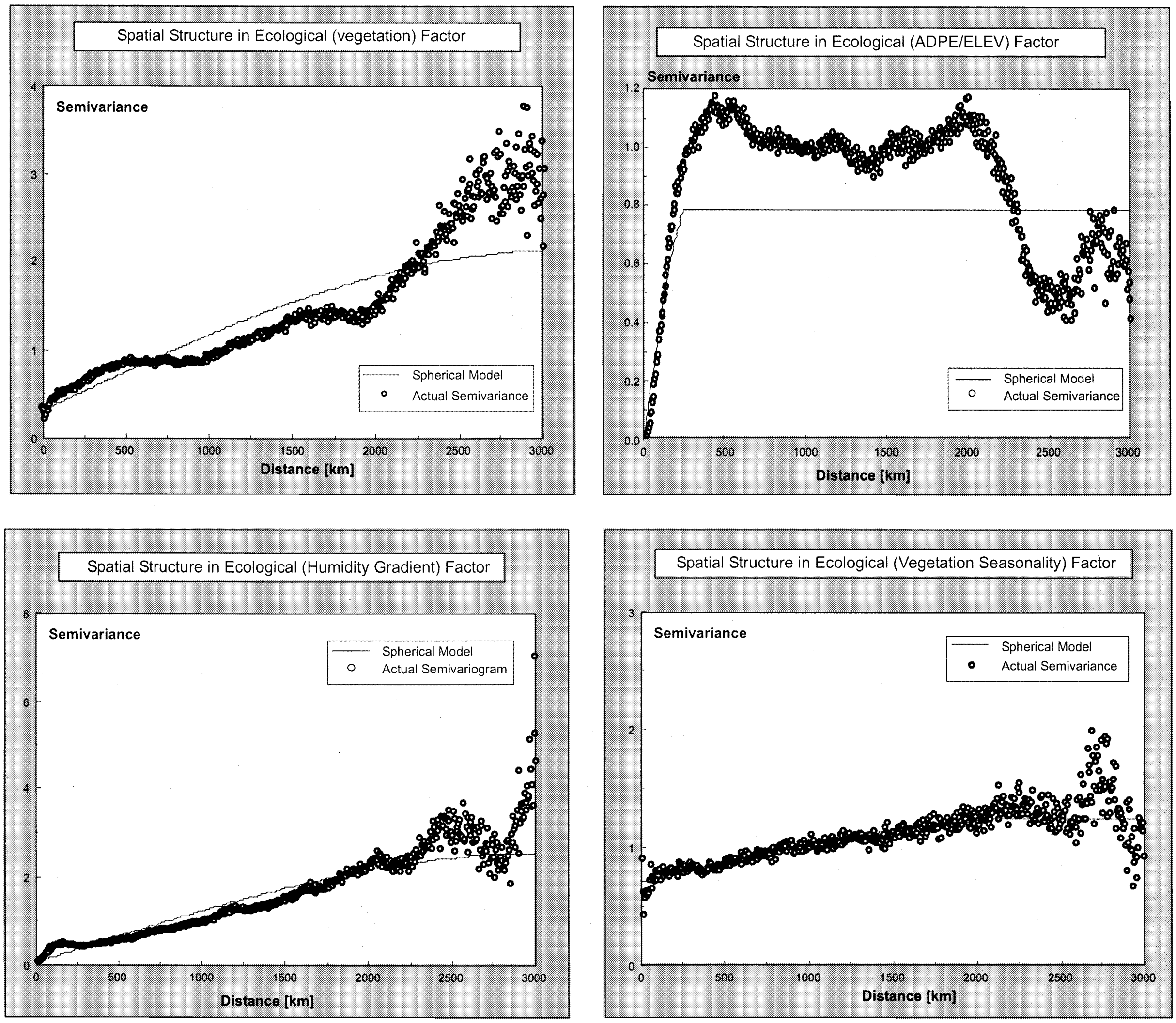

Figure 3. Spatial variation modeled with spherical semivariogram models for the ecological components.

ponents (Oliver and Webster 1986, 1990). Their respective semivariograms were estimated with the ARC/INFO GIS software (Environmental Systems Research Institute 1995).

The spherical models, as compared to the exponential models, resulted in better fits to the actual semivariance and were used to represent the spatial variation of each of the four ecological components (Figure 3). The parameters of the spherical model for the first ecological factor (vegetation productivity) were used to constrain the classification geostatistically. The semivariogram parameters for all the factors obtained with the spherical model in this analysis are shown in Table 3.

Ecologically constrained dissimilarities

In order to ecologically constrain the classification, the matrix of ecological similarities **S*** is first obtained according to equation **{1}** as illustrated in the following example. Let's assume that the classification for selvas is going to be constrained by two factors (vegetation productivity and ADPE/ELEV). Let's also assume hypothetical values for vegetation productivity (factor 1) in patches 1 and 2 being equal to 45 and 50; and 50 and 65 for ADPE/ELEV (factor 2) respectively. The similarities between patches 1 and 2 are calculated from the absolute difference between the mean attribute value (e.g., the mean vegetation productivity and ADPE/ELEV). So, $|\mathbf{z}_{11} - \mathbf{z}_{21}| = \mathbf{5}$ and $|\mathbf{z}_{12} - \mathbf{z}_{22}| = \mathbf{15}$ for these two patches and these

Table 3. Semivariogram parameters that describe the spatial variation of the ecological components used for the classification. Ecological factors were obtained by applying PCA on individual variables described in Table 1.

Ecological Factor	Nugget Variance [Co]	Range [C]	Autocorrelation parameter [a]	sill
Vegetation productivity	0.318	1.806	3055000	2.124
ADPE-Elevation	0.000	0.791	275421	0.791
Humidity gradient	0.052	2.507	3055000	2.559
Vegetation seasonality	0.710	0.536	2371089	1.247

two attributes. The $\mathbf{W_{ijk}}$ value for vegetation productivity is **0.513**, and **0.173** for ADPE/ELEV according to the eigenvalues and their explanatory power, as obtained previously by applying PCA (Table 2). The sum of these two factors determines the $\mathbf{\Sigma w_{ijk} = 0.686}$ value. Values for the ranges in the attributes for all factors considered are necessary for defining the $\mathbf{r_k}$ term, so statistical ranges for each ecological component are calculated, let's assume values of 30 and 47, respectively. Then, the multivariate similarity coefficient for these two patches will be:

$$S_{12} = [1 - (5/30)*0.5129] + [1 - (15/47)*0.1733]/0.686 = 2.709$$

An analysis for the totality of landscape patches in Mexico (1743) imposes serious restrictions in the constrained cluster analysis methodology. The dimension for the transposed matrix of similarity and physical distance (1743×1743) is very difficult to manage for numerical analysis. For that reason, rainforest ecosystem landscape patches were selected as an example for the following analysis. According to a previously obtained classification scheme, 105 patches of 5 ecosystem rainforest ecosystems were identified. To spatially constrain the ecological classification of these patches, a similarity **S*** matrix (with 105×105 dimension) was obtained. Four ecological factors and their eigenvalues were used for deriving the ecologically constrained similarities.

Spatially constrained dissimilarities

Similarities were then transformed to a **D*** dissimilarity matrix with the correspondent **d*** elements by using equations **{2}** and **{3}**. Following the previous example, the equation **{2}** gives as a result **d** = – 3.41. Let's assume a physical distance value of 50 between the two patches so equation **{3}** becomes:

$$d^*_{12} = -3.41*1.806/0.318 + 1.806\{1 - \exp(-50/3055000)\} + -3.41*1.806/0.318 + 1.806 = -36.93,$$

using the numerical values from the semivariogram parameters of the vegetation factor presented in Table 3.

For comparison purposes an additional unweighted dissimilarity matrix was transformed to their respective principal coordinates, and dynamically clustered with a k-means' method to provide an unconstrained classification of reference (below). This classification of reference evaluates the improvement of the constrained classification.

Principal coordinate analysis

The distances in the **D*** dissimilarity matrix represent "ecological distances" among objects (samples) weighted by semivariogram functions, but they are still referred to "ecological" principal axes. Some of these ecological distances may not exist in a real (physical plane) because the resulting matrix may have negative roots (Gower 1967). In order to constrain the classification spatially, actual physical distances should be used to express the dissimilarities **D*** in a physical plane.

In order to do this, the physical distances among centroids of the 105 landscape patches were calculated with the POINTDISTANCE command in ARC/INFO. Then, the dissimilarity **D*** matrix with elements **d*** was transformed into principal coordinate analysis (Gower 1966), where latent roots and vectors **Q*** were determined and arranged as columns in a *nxn* matrix representing the new coordinates of the sampling points (point centroids). This was accomplished by applying principal component analysis over the **D*** matrix. Then, all distances in **Q*** meet the sufficient and necessary conditions for real coordinates (Gower 1967). Principal coordinate analysis on unweighted and weighted dissimilarities resulted in 6 principal coordinates that capture 94% and 96% of the variance from the complete set of unweighted and weighted dissimilarities, respectively.

Final classification process: cluster analysis

A k-means clustering method requesting 5 final clusters was applied to the principal coordinates of both, spatially weighted and unweighted dissimilarity matrices. A non-hierarchical cluster algorithm was used. The cluster groups for the rainforest landscape patches, displayed as 95% (two standard deviations) ellipses in the plane of the first two ecological factors, are shown in Figure 4. The cases (patches) corresponding to each cluster were identified and spatially mapped to compare their distribution (Figure 5). Unweighted (unconstrained) and spatially weighted (constrained) classifications were directly compared with the actual distribution of all five *selva* ecosystem types (Table 4). Kappa coefficients and Tau statistics (Zhenkui and Redmond 1995) were used to evaluate the similarity between the two obtained classification (Table 5).

Both unconstrained and constrained classifications identified 4 of the five previously identified rainforest classes. Cluster 1 (unweighted) and clusters 3 and 5 (weighted) were associated 57% and 54% (average of cluster 3 and 5) with the *hyperwet perennial selva* patches, respectively. Cluster 2 (unweighted) and cluster 4 (weighted) were 42% and 45% associated with the *submountainous perennial selva*. Cluster 3 (unweighted) and cluster 2 (weighted) were 83% and 82% associated with the *highest productive perennial selva* patches; and finally, cluster 5 (unweighted) and cluster 1 (weighted) were 71% and 69% associated with the *subperennial selva* patches. None of the two methods was able to clearly (> 50%) identify patches of the *less productive subperennial selva*.

A direct comparison of the map obtained with the multitemporal analysis of GVI images and the one obtained with the spatially constrained classification was performed based on *Kappa* and *Tau* statistics. The overall percentage of agreement between the two maps is ~65% with the *less productive subperennial selva*, the *hyperwet perennial selva* and the *submountainous perennial selva* being the classes less accurately represented by the spatially constrained classification (see producer's accuracy values, Table 5). However, the classification resulted in ~54% fewer

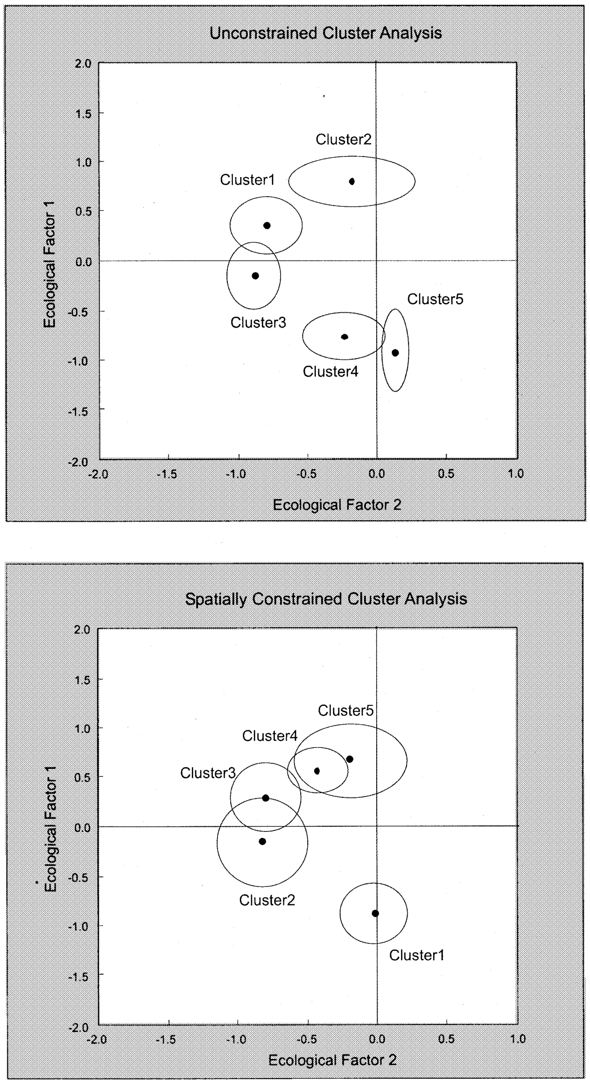

Figure 4. Rainforest landscape patches groups, displayed as 95% (two standard deviations) ellipses in the plane of the first two ecological factors.

errors than would be expected by a random allocation of classes (*Tau* $p < 0.001$). The coefficient of agreement (*kappa*) is considered "good" according to the scale presented by Monserud and Leemans (1992).

A similar analysis between the ecologically constrained and the spatially constrained classifications revealed that no significant differences existed between the two classifications (*kappa* = 0.930, $p < 0.001$; *Tau* = 0.941, $p < 0.001$). However, there were significant differences in the spatial patterns depicted for the two maps that can be directly attributable to

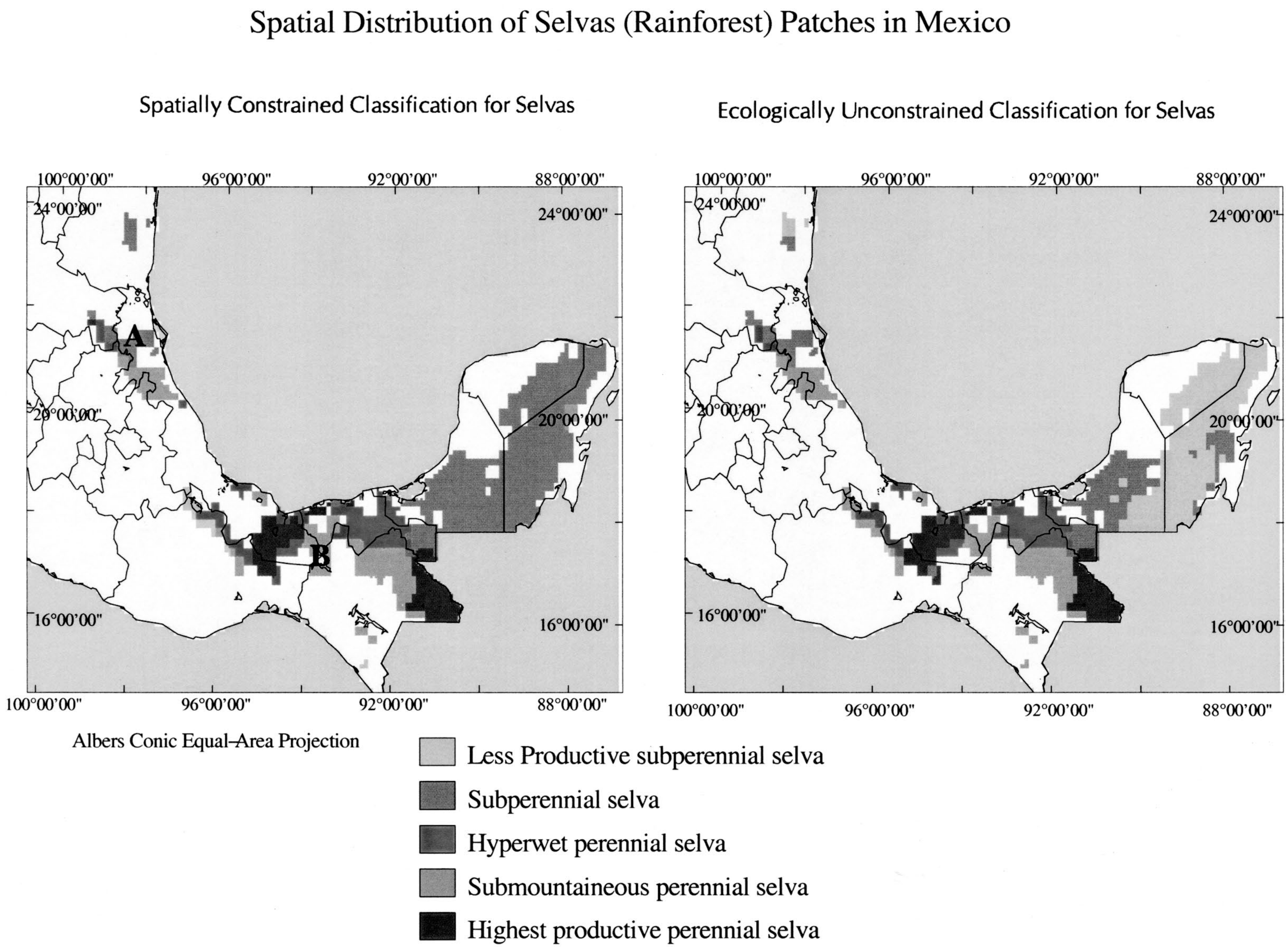

Figure 5. Geographic distribution of *Selvas* according with the spatially constrained and unconstrained ecological classifications.

Table 4. Percentage of cases (patches) identified by the two methods, and associated with the ecological classification.

Spatially Unconstrained Classification	Cluster number:				
	1	2	3	4	5
Less productive subperennial selva	30.73%	28.68%	3.28%	21.12%	
Subperennial selva			3.79%	62.15%	71.23%
Hyperwet perennial selva	57.14%	23.77%	2.46%		0.45%
Submountainous perennial selva		42.12%	1.64%	1.42%	
Highest productive perennial selva	11.41%	1.78%	83.08%	12.73%	26.89%

Spatially Constrained Classification	Cluster number:				
	1	2	3	4	5
Less productive subperennial selva	8.17%	3.36%	29.97%	24.32%	46.04%
Subperennial selva	69.05%	5.15%	1.14%		
Hyperwet perennial selva		2.52%	52.90%	20.35%	53.96%
Submountainous perennial selva		3.89%		45.07%	
Highest productive perennial selva	20.69%	81.81%	13.61%	6.36%	

Table 5. Accuracy assessment for the spatially constrained classification of *Selvas* evaluated with *Kappa* and *Tau* statistics.

	1	2	3	4	5	User's Acc
Less productive subperennial selva	64	312	315	306	32	6.22%
Subperennial selva	0	2637	12	0	49	97.74%
Hyperwet perennial selva	75	0	556	256	24	61.03%
Submountainous perennial selva	0	0	0	567	37	93.87%
Highest productive perennial selva	0	790	143	80	778	43.44%
Producer's accuracy	46.04%	70.53%	54.19%	46.90%	84.57%	
kappa =	0.534					
Tau =	0.539					
Overall Accuracy =	0.654					

the spatial constraints. These differences are evaluated in the next section.

Classification evaluation

Multi-temporal vegetation patterns have been analyzed and used previously for classifying the Mexican landscape, showing that different levels of vegetation productivity and seasonality of particular land-cover types can be related to water balance variables such as soil moisture and actual evapotranspiration to define landscape units (Mora and Iverson 1998). All these variables were used to derive an ecological classification where vegetation response is common to different combinations of environmental variables, and can be used to stratify landscape heterogeneity. The mechanisms that produce a particular ecosystem water balance involve vegetation activity (photosynthetic activity and biomass production) in relation to variations in available water (evapotranspiration) and climate (amount of precipitation). For that reason, it is reasonable to assume that regional environmental factors control the distribution of vegetation types at the landscape scale, rather than intracommunity relationships, and these vegetation types can be delineated when ecological gradients are identified as linear combinations of landscape variables.

However, spatial location is also a considerably important factor in explaining ecological gradients as linear relationships among environmental variables. When applying partial correlation analysis to test for the contribution of environmental and spatial variation in vegetation activity, more than 40% of the regional variation of primary productivity is explained by spatial variables (Mora and Iverson 1998). It is clear that a spatial constraint is necessary to identify and to delineate homogeneous regions.

Principal component analysis (PCA) seemed particularly suitable for this analysis due to the number of significant linear relationships among environmental variables. However, DCA, CCA or other ordination technique that provides a measure of the importance of the ecological factors (e.g., eigenvalues) could be also used to ecologically constrain the classification. This is particularly valid when the proportion of variance explained by environmental factors is greater than that explained by spatial variables. In any case, an ordination with variance partitioning may be the best method of choice (Borcard et al. (1992); Okland (1996, 1999); Okland and Odd 1999).

The linear combination of variables obtained with PCA indicates that four different ecological factors, identified on the basis of vegetation activity, annual water balance variations, and elevation could be used to ecologically constrain the classification. Of these, vegetation productivity is more important (to define ecological regions) than water balance variables and terrain in this case. Furthermore, the spatial variability in these ecological gradients can be identified and used to map the patterns of ecological variation of rainforest ecosystems.

The spatial pattern analysis of ecological gradients is important because patterns of ecological variation are discordant in spatial scales as shown with the semivariogram analysis. There is a clear differentiation among all ecological factors according to their scale characteristics (Figure 6). Vegetation activity and the water gradient have a scale domain ranging in thousands of kilometers (both are no longer spatially autocorrelated after ~3050 km). The seasonal vegetation factor operates at intermediate scales (the range is ~2370 km). Abiotic ecological processes, such as those described by the ecological factor 2 (ADPE-ELEV), are small scale ecological processes, because the distance at which it is no longer autocorrelated is much shorter (~275 km).

From the previous results, it was clear that there are at least three types of scales operating for the ecological processes under consideration. Large-scale ecological processes, like the interrelationship between water balance and vegetation activity, translate their effects over a landscape scale at ranges of thousands of kilometers. Similarly, vegetation seasonality operates at intermediate ranges of scale, but still in the thousands of kilometers. On the other hand, local gradients of distribution (elevation ranges), or small-scale processes, are associated with the decrease of potential evapotranspiration as elevation increases. This pattern occurs "locally" over hundreds of kilometers. Large-scale variation is typical for ecological factors that integrate vegetation activity and small-scale variations are typical of local processes such as the relationship between elevation and potential evapotranspiration.

In terms of ecological regionalization, the identification of ecological patches is constrained to the maximum range of spatial variation defined for by ecological factors, i.e., no greater than scale of variation for vegetation productivity and water balance (~3,500 km) and no less than the scale of variation than ADPE-Elevation (~500 km). Certainly the analysis of scales of variation in ecologically and spatially constrained classifications opens the possibility to evaluate quantitatively the potential distribution of vegetation types according with the (geographic) scales of variation of ecological gradients. This may have an important impact in bio-geographical research to explain the present distribution of vegetation and their modification by climate change.

In terms of classification results, landscape rainforest patches were identified differently by applying constrained and unconstrained cluster analyses. The results obtained suggested differences among all the previously identified rainforest classes. Neither of the two methods was able to clearly identify the *less productive subperennial selva* as an independent type of rainforest, indicating that this class is neither ecologically nor geographically different from the others. Unconstrained cluster analysis was unable to differentiate this type from the others, while constrained clustering indicates that this type is highly similar (in both attributes and spatial distribution) with the *hyperwet perennial selva* type (Table 5).

The unconstrained classification does not offer better results identifying the different rainforest types than the previous classification scheme (Mora 1994). The unconstrained method identified the *highly productive perennial group* (cluster 3), the *hyperwet perennial group* (cluster 1) and the *submountainous group* (cluster 2) (Table 5). Clusters 4 and 5 are highly related to the *subperennial group*, dividing the *subperennial* rainforest patches of the Yucatan peninsula into two groups. Basically, unconstrained cluster analysis identifies the four groups based only on ecological characteristics.

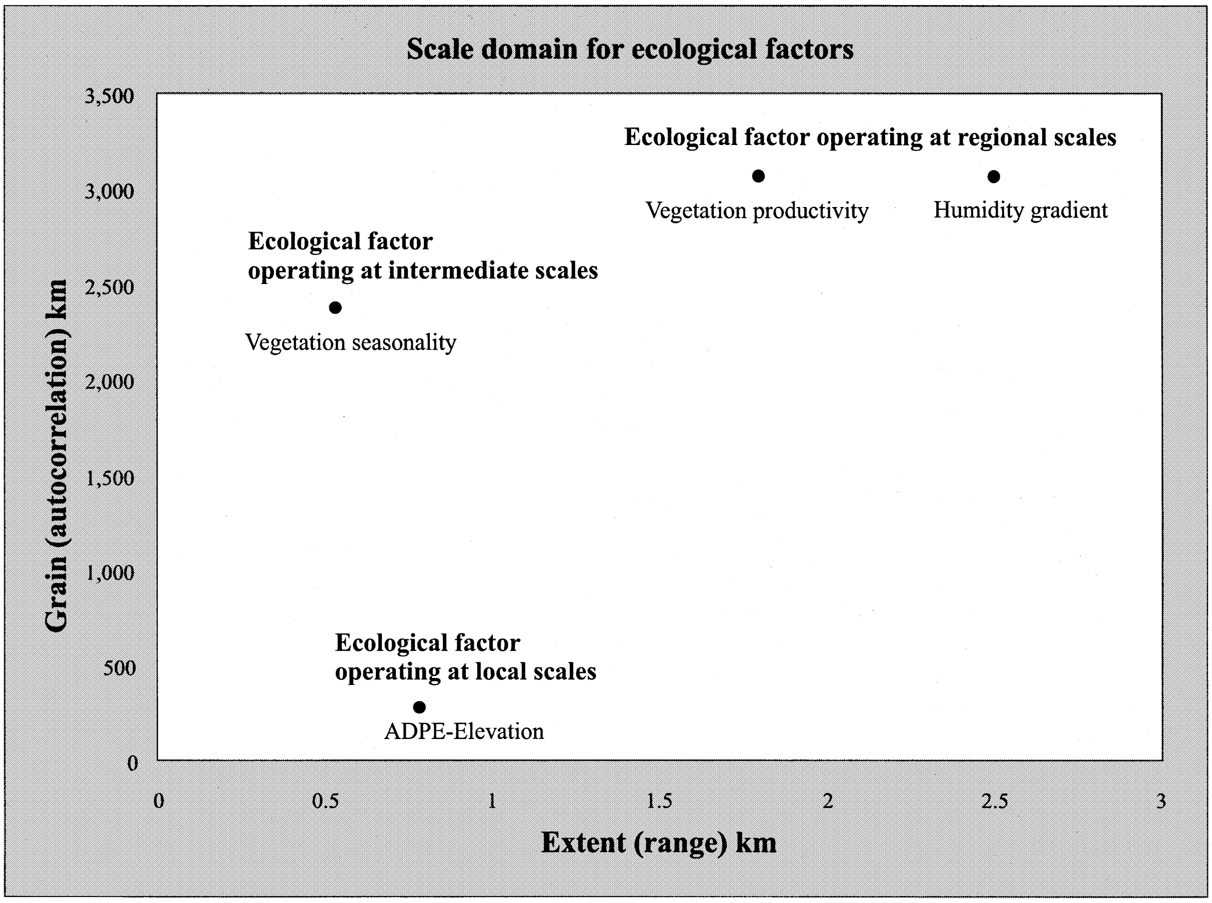

Figure 6. Scale domains for ecological landscape variables. The scale is defined by the position of each ecological factor in a feature space plot determined by the grain (measured as the autocorrelation) and the extent (measured as the range) values determined by semivariogram analysis.

On the other hand, the spatially constrained classification not only identified four ecologically different groups, but divided also the *hyperwet perennial selva* type in two groups, according to their geographic distribution (Table 5). One occurred in the northern part of the Mexican State of Veracruz (denoted as "**A**" in Figure 5), and the other ecologically similar type occurred in the states of Oaxaca and Tabasco ("**B**", Figure 5). Clearly these two groups could be classified in different categories if the location of patches were considered in the final classification scheme.

Spatially constrained cluster analysis also offers a new feature in the spatial representation of the classification. Clearly, ecological groups identified with this approach are more geographically homogeneous than those identified in the previous classification. This homogeneity is the direct result of the spatial location of patches, and the spatial co-variation of ecological factors in the definition of the resulting landscape structure.

The addition of spatial constraints to the information conveyed within the ecological factors integrates their intrinsic scale of variation before clustering, and is a key element for the definition of the landscape structure in the distribution of the rainforest. From the set of vegetation, water balance and elevation variables, new interrelated ecological components can be derived and their patterns of distribution can be evaluated with semivariogram analysis. This information can provide a sound basis for spatially constrained classifications.

With this example, it is clear that the spatial analysis of the variation in ecological attributes resulted in more information that can be used to define the landscape structure. Similar forms of spatial variation, using different ecological variables, can be detected with PCA (and/or other ordinations techniques) scales and forms of spatial variation can be captured by semivariograms; and similar patterns can be identified with a spatially constrained classification. Consequently, landscape ecological classifications can integrate information about the forms of co-variation in ecological variables (using principal component analysis when linear relationships are predominant, and DCA when non-linear relationships are dominant), and their spatial structure and scales of variation (using semivariograms and principal coordinate analysis).

Implications for future research

The results suggested that a spatially constrained, landscape ecological classification can be implemented with the methodology described here. In addition, the classification approach identified homogeneous landscapes based on the spatial patterns of landscape ecological variables.

An analysis of the landscape structure within large regions can start by identifying landscape heterogeneity at one scale, and continue by making an additional analysis of ecological information at different scales. For example, vegetation productivity patterns can be analyzed by looking at the modification of large-scale effects such as climate, and then by looking at small scale effects such as soil characteristics and landform (e.g., slope and aspect), or by using more integrative factors such as the integrated moisture index (Iverson et al. 1997). Combinations of site productivity (measured, for example, as height of trees) can be combined with forms of variation of soil nutrients (nitrogen and phosphorus) and topography (integrated moisture index) to create new ecological components. Their ranges of spatial autocorrelation (scale) can be determined and used to constrain the classification in different ways. In the above example, the first ecological factor was used in order to constrain the final classification, but a different landscape structure could be obtained if other factors (such as terrain and vegetation seasonality) are used to constrain the classification. This suggests that a nested approach can be developed to identify landscape structure at different scales, by using the forms of spatial variation of different ecological factors.

With the application of constrained classifications, a new set of possibilities is opened for landscape analysis. Ecological and spatially constrained classifications can therefore used more often by landscape ecologists in defining not only groups of ecological patches, but also their patterns of distribution.

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