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A classificatory approach integrating fuzzy set theory and permutation techniques for land cover analysis: a case study on a degrading area of the Rift Valley (Ethiopia)

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Abstract: We suggest a classificatory approach for land cover analysis that integrates fuzzy set theory with permutation techniques. It represents a non parametric alternative and/or a complement of traditional multivariate statistics when data are scarce, missing, burdened with high degree of uncertainty and originated from different sources and/or times. According to this approach, the Operational Geographic Units (OGUs) in which landscape is subdivided and sampled are classified with hierarchical clustering methods. The clusters of a classification which are significantly sharp are used to define fuzzy sets. In this way, the original data scores are transformed by degrees of belonging. We introduce the concepts of endogenous and exogenous fuzzy sets and we suggest to apply the Mantel test between the similarity matrices of these fuzzy sets to test the predictivity of internal variables with respect to external variables. The approach is applied to OGUs corresponding to the smallest administrative units (kebeles) of the Ethiopian Rift Valley, a degrading area with high risk of further degradation. We found that: 1) there is a high correlation between geo-physical features of the landscape (geology, rainfall and elevation) and some indicators of the human pressure such as land use/cover, land management for livestock breeding and human, household and livestock densities, 2) there is a high correlation between land degradation, measured with relative loss of Normalized Difference Vegetation Index (NDVI) and the human pressure. However, the correlation is higher when the human pressure is considered in the geo-physical context of the landscape. The approach can be easily applied to produce maps useful for planning purposes thanks to geographical information system (GIS) technology that is becoming available at low cost even to small administrative units of developing countries.

Abbreviations: CoCla–Correspondence between Classifications, CoSiM–Correlation between Similarity Matrices, DEM–Digital Elevation Model, LU–Lanscape Unit, NDVI–Normalized Difference Vegetation Index, OGU–Operational Geographic Unit, ShECla–Sharpness of Exogenous classifications, USLE–Universal Soil Loss Equation

Introduction

In developing countries, the high rate of population growth often induce environmental degradation. Therefore there is a strong need to conduct studies to enhance understanding of degradation processes with methodologies of data integration that can be used to the level of problem solving. Today this is more feasible than in the past as a result of merging geographical and ecological disciplines by the help of geographical information system (GIS) technology which is becoming available even to small administrative units in developing countries at a relatively low cost (Opdum et al. 2002).

In this paper, a classificatory approach, primarily used in plant community analysis (e.g., Pausas and Feoli 1996), is suggested to evaluate trends of land degradation using data from a degrading area in the Central Rift Valley of Ethiopia. The approach offers a sound alternative to canonical correlation and partial correlation analysis in community analysis and landscape ecology (e.g., Feoli et al. 2002a,b) where the assumptions of traditional statistics are not met by the data. This often happens when data are either scarce, missing, burdened with high degree of uncertainty or acquired from different sources and/or at different times. The approach is based on fuzzy set theory (Zimmerman 1996) following the method introduced in vegetation science by Feoli and Zuccarello (1986, 1988) and on the application of permutation techniques (Mantel 1967, Mantel and Valand 1970, Biondini et al. 1991, Pillar and Orlóci 1996, Manly 1997, Anderson and Legendre 1999, Pesarin 1999, Pillar 1999, Kong and Nicolae 2000, Peres-Neto and Olden 2001, Fortin et al. 2002, Anderson and ter Braak 2003). With this approach we used degrees of belonging to sets (fuzzy sets), consequently the interest is shifted from the "actual" measurements of the variables to the relationships between variables, sets of variables and objects and sets of objects. This approach does not remove vagueness, imprecision and the related uncertainty but simply considers them as part of the analysis since they are "included" in the degrees of belonging of the fuzzy sets.

The approach is applied to answer the following two specific questions:

- Is the pattern of human pressure of the area significantly influenced by the geo-physical features of landscape such as elevation, climate and geology?
- Is the pattern of vegetation mass significantly affected by human pressure?

We have measured the human pressure by a set of variables corresponding to land use/land cover, land management for grazing by livestock (hereafter mentioned for brevity as livestock management) and human, household and livestock densities. To estimate the vegetation mass we used NDVI (Normalized Difference Vegetation Index) that is widely recognized as a very sensitive indicator of land degradation (Dregne 1983, Tucker et al. 1983, Box et al. 1989, Price 1992, Davenport and Nicholson 1993, De Jong 1994, Hill et al. 1994, Lacaze 1996, Myneni and Asrar 1994, Pickup and Chewings 1996, Gamon et al. 1995, Hill and Peter 1996, Thornes 1996, Duncan 1997, Hurcom and Harrison 1998, Lyon et al. 1998, Peńuelas and Filella 1998, Purevdorj et al. 1998, Azzali and Menenti 2000). Furthermore, NDVI is easily obtained for different periods with images that can be downloaded free of charge from internet. However, knowing the problems of the application of this index (Gamon et al. 1995), we have used its values in a relative context that would avoid at least the problems related to direct comparison of NDVIs among different times.

The approach

The approach relies on the following ideas:

a) The similarity between n objects based on a selected set of characters (C); beside being a function of the "fundamental nature" of the objects (origin, evolution, functions), is also a function of the combined effects that a set (E) of internal and/or external factors (that generally have to be identified), has to the states of the selected characters (C). It follows that if two objects are similar for C they should be similar also for E. C is usually the set of dependent variables while E is the set of independent or the explanatory ones. Both sets of variables are chosen from those considered relevant for understanding the system under study. The idea may be formulated in more general terms without involving causality, namely if there is a significant overall "link" between two sets of variables C and E, the pattern of similarity between the n objects described by matrix $\mathbf{X}(C)$ should be similar to the pattern of similarity between the n objects described by the matrix $\mathbf{X}(E)$.

b) A similarity (dissimilarity) matrix $\mathbf{S}(n \times n)$ of n objects is a fuzzy set matrix in which the measures of similarity are degrees of belonging of the objects to the sets represented by the objects themselves (Zhao 1986). This is a consequence of the traditional set theory for which any object defines at least one set: the set represented by itself.

c) $\mathbf{S}(n \times n)$ can be rearranged according to any hierarchical classification in order to produce a $\mathbf{S}(n \times k)$ condensed similarity matrix, with $k < n$, in which the values are degrees of belonging of the objects to the sets produced by the classification (Feoli and Zuccarello 1986, 1988). The degrees of belonging can be calculated according to one of the following criteria: 1) the maximal similarity with one of the objects in each of the k classes (max); 2) the minimal similarity with one of the objects in each of the k classes (min); and 3) the average similarity with the objects of the k classes (mean). The three criteria are analogous to the criteria of assigning objects to classes by single (max-max), complete (max-min) and average (max-mean) linkage clustering methods (Feoli et al. 2006) and may be applied considering all the objects of the clusters or only some of them (e.g., those called "medoids", Kaufman and Rousseeuw 1990).

d) The definition of fuzzy sets should be based on significantly sharp classifications. The sharpness can be calculated and tested in several ways using both parametric (e.g., discriminant analysis, Pausas and Feoli 1996) and permutation techniques (e.g., Biondini et al. 1991, Pillar and Orlóci 1996, Manly 1997, Legendre and Legendre 1998, Tobisch and Standovar 2005). Carranza et al. (1998) and Feoli et al. (2006) discussed the matter from a vegetation science context and suggested to measure the sharpness of the clusters by their separation in the space defined by the eigenvectors of the corresponding similarity matrix. This may be easily calculated by the ratio:

$$D(\lambda) = -\frac{\sum p_i \ln p_i}{\ln k} \quad \text{where} \quad p_i = \frac{\lambda_i}{\sum \lambda_i}$$

with $i = 1, \ldots, k$ and λ_i the i-th eigenvalue of the matrix $\mathbf{S_F}(k \times k)$, that is obtained by grouping the rows and the columns of the corresponding matrix $\mathbf{S}(n \times n)$. This suggestion follows the idea that in case of a perfect classification, $\mathbf{S_F}(k \times k)$ should be diagonal (scores only on the diagonal elements) and the scores should be 1 when the objects belong to the k classes with a degree equal to 1 (perfect belonging, crisp classification). It follows that the closer $D(\lambda)$ to 1 the sharper is the classification.

e) The correlation between C and E can be measured with one of the following criteria: 1) CoSiM: "Correlation between Similarity Matrices" $\mathbf{S}(C)$ and $\mathbf{S}(E)$, 2) ShECla: "Sharpness of Exogenous classifications", 3) CoCla: "Correspondence between Classifications".

The first criterion CoSiM is direct, since it is based on the correlation coefficient between $\mathbf{S}(C)$ and $\mathbf{S}(E)$. In other words the correlation coefficient is computed between the $n(n\text{-}1)/2$ similarities (dissimilarities) of the two similarity matrices. The correlation must be tested with a permutation technique as suggested by Mantel (1967) and Mantel and Valand (1970), since the similarities in the matrices are not independent. The second and third criteria are indirect. ShECla is based on the sharpness of the k classes obtained with $\mathbf{S}(C)$ but described with $\mathbf{S}(E)$ (or vice-versa). In this way, when a classification (with k classes) obtained with the set of variables C is imposed to a similarity matrix obtained with

the set of variables E, we produce an "exogenous" description of the k classes obtained with C. This criterion is analogous to that of analysis of variance (simple or multiple). If the within/between k clusters similarity matrix obtained with $\mathbf{S}(E)$ is diagonal, the sharpness is perfect and the correlation between C and E is maximal. CoCla is based on the comparison of the classifications obtained with $\mathbf{S}(C)$ with the classifications obtained with $\mathbf{S}(E)$ using contingency table analysis. In this case both classifications are endogenous. If a resulting contingency table is a diagonal matrix the correlation between C and E is maximal. The same criteria may be used to compare different similarity functions and clustering algorithms applied to the same set of data, namely to C or to E. This can be useful to reduce the number of classifications to be analysed.

In the present paper, besides using CoSiM in traditional way, we propose to compare the matrices of similarity of endogenous and exogenous fuzzy sets ($\mathbf{S}_F(k \times k)$) and to test their correlation with Mantel test. To obtain the endogenous fuzzy sets $\mathbf{F}(C)$ and the exogenous fuzzy sets $\mathbf{F}(E)$ the steps are the following:

1) Get a number t of similarity matrices $(n \times n)$, $\mathbf{S}_1(C)$, $\mathbf{S}_2(C)$, ..., $\mathbf{S}_t(C)$ with different similarity functions using the matrix $\mathbf{X}(C)$. Many similarity functions can be suitable for this purpose (Podani 2000) and if considered necessary, the significance of similarities between objects can be tested using the method suggested by Pillar (1996);

2) Compare the t $\mathbf{S}(C)$ matrices with Mantel test and select some (s) among those that are uncorrelated. In this way, the t matrices are reduced to $s < t$;

3) Apply clustering methods to each of the s similarity matrices and define the "optimal" classification on the basis of distinctiveness or sharpness of the k respective clusters computed as suggested in d);

4) Calculate the degrees of belonging of the k fuzzy sets $\mathbf{F}(C)$ corresponding to the clusters of the "optimal" classification according to one or all the mentioned criteria (max-max, max-min and max-mean);

5) Get a number z of different similarity matrices $(n \times \nu)$ $\mathbf{S}_1(E)$, $\mathbf{S}_2(E)$, ..., $\mathbf{S}_z(E)$ with different similarity functions using the matrix $\mathbf{X}(E)$ and select those $(w < z)$ most dissimilar according to step 2;

6) Rearrange the similarity matrices according to the classification obtained in step 3) and define the degrees of belonging of the exogenous fuzzy sets according to one of the criteria in step 4);

7) Choose the exogenous fuzzy sets on the basis of their distinctiveness measured with the same methods used for getting the endogenous fuzzy sets (step 3);

8) Calculate the degrees of belonging of the n objects to the k fuzzy sets $\mathbf{F}(E)$ according to one of the criteria in step 3).

The overall correlation between the set of variables in $\mathbf{X}(C)$ and the set in $\mathbf{X}(E)$ is calculated by measuring the correlation between the matrix of similarity $\mathbf{S}_F(C)$ of the k endogenous fuzzy sets in $\mathbf{F}(C)$, and the matrix of similarity $\mathbf{S}_F(E)$ of the k exogenous fuzzy sets in $\mathbf{F}(E)$. Correlation between different sets of variables can also be obtained comparing different matrices $\mathbf{S}_F(E)$. In this case the correlation would be conditioned by the classification based on C. With Mantel test it is possible to test also the partial correlation between two sets of variables by removing the effects of a third one as suggested by Anderson and Legendre (1999) and discussed further by Legendre (2000).

Application of the approach

Data

Data were collected within SUNRISE project (Sustainable Use of Natural Resources in Rural Systems of Eastern Africa Drylands - Ethiopia, Kenya, Tanzania - Strategies for Environmental Rehabilitation, INCO Project No. ERBIC 18CT970139), funded by European Commission from 1997 to 2001. The objects of the study (operational geographic units, OGUs, Feoli and Zuccarello 1996) are the Kebeles, the smallest administrative units for which some socio-economic data are available. They have been established during an intensive villagization program imposed with the Agrarian reform of 1975, however their boundaries were frequently subject to changes. A sample of 32 kebeles, belonging to three different districts (Weredas), is considered. They are supposed to represent the rural landscape of the Rift valley. Kebeles such as Abomsa, Ziway, Adami-Tulu and Bulbula, being completely urbanized (towns), were used only to evaluate their influence on the other kebeles.

A GIS was constructed with the software of public domain ILWIS using the following maps:

1. Boundaries of kebeles and of the main towns digitized on 1:50,000 topographic maps purchased from the Central Statistical Office of Ethiopia.

2. Topographic maps (1:50,000 scale) from which contour lines (at 20 m intervals), rivers, streams, lakes, roads and towns have been digitized in separate layers.

3. Digital Elevation Model (DEM) created from the 20 m contour lines map.

4. Slope and aspect maps obtained from DEM.

5. Precipitation Map derived from kriging the climatic data available for the main towns (Ziway, Langano, Metehara, Mojo, Debrezeit)

6. Geological map at 1:50,000 scale (Dainelli et al. 2000)

7. Land use/land cover Map (Sagri 1998), derived from Landsat TM images of 1994 classified using supervised method (based on field surveys and aerial photo interpretation). Only physiognomic-structural types of the vegetation were considered: grasslands, open grasslands, saline grasslands, hydrophytic vegetation and open woodland (*Acacia* trees with poor and rich grassland layers), scrub vegetation

(shrubs and trees with poor and rich grassland layers) and broad leaved woodland with very dense *Acacia* trees and under canopy vegetation. A comparison between the images of 1989 and 1994 does not show sensitive changes in land cover in the study areas.

8. Map of livestock management practices.

9. Maps of human population and members of households (male or female) and livestock densities derived from the Ethiopian Central Statistical Authority census of 1998. All these are considered as socio-economic variables.

10. Soil erosion map obtained by integrating into the modified Universal Soil Loss Equation (USLE) of Wischmeier and Smith (1978) and Hurni (1985, 1990) land use-land cover map, land management map, precipitation map, slope length and slope gradient (from DEM).

11. NDVI maps (Normalized Difference Vegetation Index) calculated from TM-Landsat images belonging to 1989 and 1994 both from the end of the rainy season (November and December).

With the use of GIS's crossing functions, the following set of data matrices describing the kebeles was obtained:

- **El.-rain-geology**: matrix of the average elevation, average rainfall and percentage of geological features
- **Land use/land cover**: matrix of the percentages of land use/ land cover.
- **Livestock management**: matrix of the percentages of land management type for livestock.
- **Socio-economy**: matrix with the densities of socio-economic variables.
- **EROSION**: matrix of the percentages of land in seven classes of soil erosion.
- **NDVI**: matrix of Normalized Difference Vegetation Index of the two years.

To remove the effects of possible different meteorological regimes, and thus the major problem associated with the use of NDVI when comparing he values of different periods (e.g., Gamon et al. 1995), we have standardised the scores within each year (1989 and 1994) and we have calculated the differences between the standardized values. These express the relative changes of NDVI among the kebeles. The positive differences indicate that in the six years the values got a positive trend with respect to the average value of the year while the negative difference indicate the contrary, however the values do not indicate increase or decrease of the real NDVI values.

Methods

To answer the first question: "Is the pattern of human pressure of the area significantly influenced by the geophysical features of landscape such as elevation, climate and geology?" we merged the matrices **Land use/cover**, **Livestock management** and **Socio-economy** into one matrix **Land-soc** and used the Mantel test between the similarity matrix of **Land-soc** and the similarity matrix of **El.-rain-geology**.

To answer the second question: "Is the pattern of vegetation mass significantly influenced by human pressure?" we applied the Mantel test between the similarity matrix obtained with **NDVI** and the similarity matrices of **Land use/cover**, **Livestock management**, **Socio-economy**, **Land-soc**, **El.- rain- geology** and the matrix **TOT** obtained by merging the last two and **EROSION**. To identify the areas most influenced by the human pressure we have mapped the relative changes of NDVI from 1989 to 1994 and tested if there is a correspondence between the pattern of the values and the pattern of landscape features. To identify this pattern we have classified the kebeles using matrix **TOT** with different similarity functions and methods of hierarchical classification. We used hierarchical classifications because we did not have *a priori* idea on the possible number of classes of kebeles. We have chosen among about 100 classifications, obtained at different hierarchical levels of dendrograms, the one that gave the sharpest classification according to $D(\lambda)$. The classification was tested for significance also using the method proposed by Pillar and Orlóci (1996) with the eigenvectors of the similarity matrix as input data. On the basis of this classification we obtained the endogenous fuzzy sets for objects and variables following the method of Feoli and Zuccarello (1986, 1988). Using this method we obtained degrees of belonging of objects and variables to classes of a given classification and degrees of belonging of objects to the sets defined by the variables (fuzzy sets objects-variables) conditioned by the classification. The exogenous fuzzy sets were calculated with matrix **NDVI** using the similarity function giving the sharpest classification.

To test how much the classification based on **TOT** is predictive with respect to **NDVI** we applied: CoSiM, "Correlation between Similarity Matrices" using Mantel test between the similarity matrix of endogenous fuzzy sets and the similarity matrix of exogenous fuzzy sets. To be consistent we have calculated the similarity between the fuzzy sets with the same function giving the sharpest classification; ShECla, "Sharpness of Exogenous classifications" with the permutation technique proposed by Pillar and Orlóci (1996), and CoCla, "Correspondence between Classifications" using contingency tables obtained considering the distribution of NDVI values above and below the average values of 1989 and 1994 for all the clusters and for the single clusters against the others.

We have also considered the contingency tables given by the distribution of the differences between the standardized values of the two years above and below the average value and we have tested the chi square of the contingency tables with the randomisation technique suggested by Estabrook and Estabrook (1989).

We used the SYNTAX program (Podani 1994) to perform the classifications and MATEDIT (Burba et al. 1992;

Table 1. Results of Mantel test applied between different similarity matrices in order to answer the question 1 (see text).

Matrix 1	Matrix 2	r	p
El.-rain-geology	Land-soc	0.43	<0.001
El.-rain-geology	Land use/cover	0.30	0.00
El.-rain-geology	livestock management	0.09	0.03
El.-rain-geology	Socio-economy	0.14	0.04
Land use/ cover	Socio-economy	0.20	0.02
Land use/ cover	Livestock management	0.03	0.27
Livestock management	Socio-economy	0.03	0.31
TOT	El.-rain-geology	0.70	<0.001
TOT	Land-soc	0.60	<0.001
TOT	Land use/cover	0.59	<0.001
TOT	Socio-economy	0.25	0.01
TOT	Livestock management	0.13	0.01

Table 2. Results of Mantel test simple and partial, applied between different similarity matrices in order to answer question 2 (see text).

Matrix 1	Matrix 2	r	p
El.-rain-geology	NDVI	0.35	<0.0001
El.-rain-geology	NDVI/Land-soc	0.19	0.023
Land-soc	NDVI	0.41	0.000
Land-soc	NDVI/ El.-rain-geology	0.32	0.002
Land use/cover	NDVI	0.28	0.026
Land use/cover	NDVI/ El.-rain-geology	0.32	0.002
Livestock management	NDVI	0.16	0.030
Socio-economy	NDVI	0.11	0.180
TOT	NDVI	0.52	<0.0001

Burba et al. 2008, submitted) to prepare the data for SYNTAX, and calculate the sharpness of the classifications, the significance of the sharpness according to the method of Pillar and Orlóci (1996), the degrees of belonging of fuzzy sets and the significance of chi square. We used the *zt* software written by Bonnet and Van de Peer (2002) available in public domain for the Mantel test.

Results

The results of Mantel tests between the single matrices El.- rain- geology, Land use/cover, Livestock management, Socio-economy and TOT, used to answer the first question are shown in Table 1. We have not considered EROSION because the erosion is calculated using almost all the variables in Land-soc and El.- rain- geology. From this analysis it looks that all the single matrices significantly contribute to the overall similarity pattern but in different degrees. Table 1 shows also that there is a significant correlation between the geo-physical features of the landscape and the spatial pattern of human pressure (represented by land use/cover, livestock management and human and livestock density). However, land use/cover is significantly correlated with human and livestock density, but not with livestock management, and this is not significantly correlated with human and livestock density. This means that the same land use/cover pattern may have different livestock management system and that land use/cover pattern is independent from human and livestock densities (Socio-economy).

The results of the application of Mantel test used to answer the second question are shown in Table 2. **NDVI** is strongly correlated with **Land-soc**, **Land use/cover** and **Livestock management**, and also, as it can be obviously expected, with geo-physical features (**El.- rain- geology**). However, the correlation between **land use/cover** and **NDVI** improves when the effects of **El.- rain- geology** is removed. This means that the influence of land use/cover over NDVI is higher than that of geo-physical features. The same does not happen when we consider the correlation between **Land-soc** and **NDVI** by removing the effects of geo-physical features (**El.-rain-geology**). This suggests that the human and livestock densities do not necessarily produce loss of vegetation mass when considered independently from landscape features. In fact, the correlation of NDVI with the variables of human pressure increases as the number of variables increases, e.g.: $r = 0.28$, $p = 0.026$ with **Land use/cover**; $r = 0.41$, $p = 0.0002$ with **Land-soc** (that includes also livestock management and human and livestock densities), and becomes maximal with **TOT**: $r = 0.52$, $p = 0.00001$. This proves that the effects of human pressure on the process of land degradation can be explained better when considered within the geo-physical context of the landscape.

The sharpest classification of kebeles based on TOT was obtained using similarity ratio as the resemblance measure and hierarchical clustering using average linkage within merged groups (Podani 2000) as clustering method. Based on the TOT we have identified an optimal classification of 5 clusters of kebeles, with a sharpness highly significant as

tested using the metehod of Pillar and Orlóci (1996) (Qt = 1.40 Qw = 0.12, Qb = 1.28, p = 0.00001).

The fuzzy partitions for OGUs and variables based on this classification are given respectively in Appendix 1 while Appendix 2 presents the average values, the standard deviation and the degrees of belonging of the variables in the 5 clusters. Figure 1 shows the position of the clusters, the high correspondence between the spatial pattern of clusters and the spatial pattern of the NDVI changes.

The results of the application of Mantel test to the similarity matrices of endogenous (**TOT**) and exogenous fuzzy sets (**NDVI**) proves that the classification into 5 clusters is significantly predictive with respect to **NDVI** with r = 0.55 and p = 0.025. The significance is also proved by using the method given by Pillar and Orlóci (1996) for measuring the sharpness of the classification in terms of NDVI (Qt = 62, Qw = 25, Qb = 37, p= 0.0001), and by the chi-squared of the contingency table produced to compare the classification with the one based on changes in NDVI and then tested by the Estabrook and Estabrook 's method (χ^2 = 23 and p = 002).

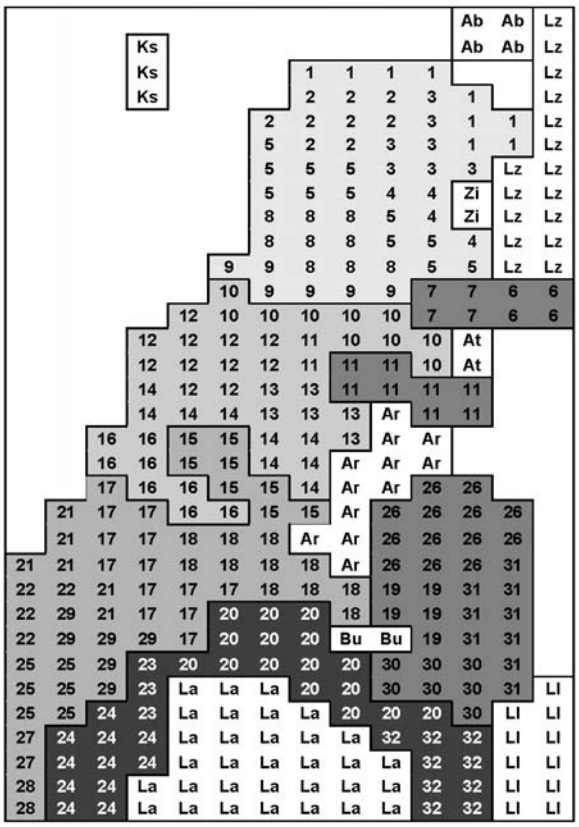

Figure 1. A raster representation of the study area with the localization of the 5 clusters defined by the classificatory process and recognizable by the following colors: cluster 1 = ■, cluster 2 = ■, cluster 3 = ■, cluster 4 = ■, cluster 5 = ■ (for names of the kebele's code see Appendix 1). Codes of towns: Ab = Abjata, At = Adami Tulu, Bu = Bubula, Ks = Koshe, Zi = Ziway. Codes of lakes: Lz= Lake Ziway, Ll= Lake Longano, La= Lake Abiyata; Ar = Abernosa Ranch.

Accordingly, Kebeles 1, 2, 3, 4, 5, 8, 9 belonging to cluster 1 (all the kebeles of the cluster!), kebeles 10 and 12 belonging to cluster 2, and almost all the kebeles of cluster 4 (6, 7,19, 26, 30) show relative loss of NDVI; kebeles 25 and 28 of cluster 3, kebeles 7 and 11 of cluster 4 and kebele 20 of cluster 5 show a stable situation while kebeles 13, 14, 16 of cluster 2, almost all the kebeles of cluster 3 (15, 17, 18, 21, 22, 27, 29) and kebele 31 of cluster 4 show a relative gain of NDVI.

Table 3 shows the differences in NDVI from the two years grouped by clusters. The most degraded kebele is Oda Anshara (kebele 19) belonging to cluster 4, close to the city of Bulbula. The most healthy kebele is Kormi Bujae (kebele 16) belonging to cluster 2. Considering the general NDVI average values, cluster 1 and cluster 4 had the highest loss of NDVI from 1989 to 1994.

Table 4 presents the results of the contingency table analysis based on chi square and the randomisation technique of the distribution of NDVI values above and below the averages of 1989, 1994 considering all the clusters and the individual clusters. The overall difference between the NDVI values among clusters was not significant in 1989, only cluster 5 shows values significantly below the average value of the year, while the overall difference becomes significant in 1994 where cluster 3 shows a value significantly above the average. Cluster 5 shows values under the average also in 1994. Considering the distribution of the NDVI differences, cluster 1 and 4 show loss of vegetation mass significantly above the average value. This proves that these clusters include kebeles that are under a process of evident land degradation.

As already emphasized, the increment or decrement of NDVI does not correspond to an actual absolute increment or decrement of vegetation mass, but it relates to the average situation in 1989 where no significant NDVI differences between the clusters 1, 2, 3 and 4 occurred. Cluster 5 showed lower values of NDVI also in 1989 since it represents a peculiar coastal situation of Lake Abijata with large sandy and humid areas without dense vegetation cover.

Using the information of Appendices 1-2 and Table 3, the clusters of kebeles can be described briefly as follows:

Cluster 1 includes 7 kebeles (1, 2, 3, 4, 5, 8, 9) located at a relatively high altitude of 1713±48 m. The total area is about 222 km^2. The average precipitation is over 700 mm/year. This cluster is characterized by old terraced deposits of Lake Ziway (clay, reworked pumice and shellbeds, colluvial-alluvial gravel, sand, silt and pyroclastic and clay, diatomeite, shell beds and reworked pumice). It shows the lowest percentage of cultivated areas, the lowest density of cows, bulls, calves and horses and mules. There is however, a high density of sheep and goats. The human population density is relatively high, just below the maximum density found in cluster 4. There are many roads crossing the kebeles and connecting Abosa, Ziway and Koshe. This cluster has the highest percent cover of bare soil, rock outcrop and a relatively high

Table 3. Deviations of NDVI from the mean value of the year.

Kebele ID		NDVI		
	cluster	1994	1989	difference
1	1	1.48	2.03	-0.55
2	1	-0.65	-0.30	-0.35
3	1	-0.92	0.01	-0.93
4	1	-1.72	-0.90	-0.82
5	1	-0.96	-0.60	-0.36
8	1	-0.36	0.39	-0.75
9	1	-0.09	0.88	-0.97
average		-0.46	0.22	-0.68
10	2	-0.03	0.64	-0.67
12	2	1.01	1.48	-0.47
13	2	0.94	0.16	0.78
14	2	1.11	0.11	1.00
16	2	1.25	-0.10	1.35
average		0.86	0.46	0.40
15	3	0.86	-0.30	1.16
17	3	0.41	-0.80	1.21
18	3	-0.19	-0.40	0.21
21	3	1.00	-0.30	1.30
22	3	0.87	0.67	0.20
25	3	0.49	0.54	-0.05
27	3	0.74	0.57	0.17
28	3	0.54	0.50	0.04
29	3	0.11	-0.20	0.31
average		0.54	0.03	0.51
6	4	0.86	1.30	-0.44
7	4	-0.38	-0.30	-0.08
11	4	0.34	0.25	0.09
19	4	-0.59	0.68	-1.27
26	4	0.62	1.46	-0.84
30	4	-0.38	-0.20	-0.18
31	4	0.63	0.35	0.28
average		0.16	0.51	-0.35
20	5	-2.11	-2.10	-0.01
23	5	-1.19	-1.30	0.11
24	5	-2.35	-2.50	0.15
32	5	-1.27	-1.70	0.43
average		-1.73	-1.90	0.17

cover of open grassland (about 10%), and a relatively high rate of soil erosion (11-20 t/ha/year is most common). The average NDVI of this cluster was relatively high in 1989, but showed a significantly reduction in 1994 (the highest reduction among the clusters). The influence of Ziway, the largest town of the study area with a population of about 20,000 people, appears to account for the high human population density and the rapid degradation of the vegetation. This degradation should be mainly due to cutting wood for charcoal and the grazing pressure exerted by sheep and goats and the high livestock population of the town.

Cluster 2 includes 5 kebeles, (10, 12, 13, 14, 16) located at an average altitude of 1728±30 m. The total area is about 122 km^2. The interpolated rainfall exceeds an average of 700 mm/year as in cluster 1. The cluster is characterized by colluvial-alluvial gravel, sand, silt and pyroclastic and clay, diatomite, sand, shell beds and reworked pumice. The cultivated area of land reaches 53%, but the human as well as the livestock population density is low. Goats are the unique exception in this cluster having an average population density of 64.52/km^2 with more than 97/km^2 in Andola Chabi and Karakata Waransa. This cluster has the highest percent cover of woodland and open woodland, and shows the highest NDVI of the study area and the lowest average relative decrement of NDVI from 1989 to 1994. This may be due to the fact that this cluster is far from the main road connecting the North and South of the Rift valley. The presence of the Habernosa cattle ranch has influenced the livestock population of the adjacent kebeles of cluster 2 by the spill over effect of the benefits in the ranch such as the veterinary attention, improved bred of animals and water supply. The proximity of the kebeles of this cluster to the ranch seems to have influenced the percent cover of the woodland as well.

Cluster 3 consists of 9 kebeles (15, 17, 18, 21, 22, 25, 27, 28, 29) located at an average altitude of 1645±28 m. The total area is about 220 km^2. The interpolated precipitation reaches an average of 785 mm/year (the highest precipitation in the study area). Geological features are mainly rift floor ignimbrites (peralkaline rhyolitic ignimbrites, poorly welded ignimbrites and pumice fall), shore sand and reworked pumice of poorly preserved strandlines, and basaltic lava flows and scoria cones. Soils derived from basaltic rocks are known for their fertility. The potentially higher fertility of the soil in Cluster 3 appears to have influenced the high percent cover of croplands. This cluster has the highest average percentage of cultivated area (66.60%) and grassland (11.53%). The population density is relatively low (the third among the clusters), may be because of high distance from the city centres and the main roads (Figure 1). It is clear that the livelihood of the people depends on agriculture as shown by the high percent cover of cultivated area, the high density of poultry, the high density of goats (both being the second among the clusters). The decrement of NDVI from 1989 to 1994 is the lowest suggesting that cultivation does not necessarily produce so drastic reduction of NDVI as it happens by cutting wood for charcoal (e.g., in cluster 1 and 4).

Cluster 4 consists of 7 kebeles (6, 7, 11, 19, 26, 30, 31) located between the three lakes (Ziway, Langano and Abjata) at an average altitude of 1651±22 m. The total area is about 160 km^2. The interpolated average precipitation reaches 660 mm/year, which is the lowest among the clusters. It is characterized by the highest percent of lacustrine deposits, clay, marls, diatomite, sand, shell beds and reworked pyroclastics and Alutu-Bericcio rhyolitic lava flow (mainly in Bochiso kebele). Human and livestock population is the highest among the clusters. This is certainly due to the main road connecting Addis Ababa with the South which runs through this cluster and the fact that the towns of Bulbula (about 1500 inhabitants) and Adami Tulu (about 5000 inhabitants) are adjacent to this cluster along the main road. The vegetation types characterizing this cluster are open grassland and open woodland. Despite the presence of high cover of open grassland, erosion is very limited because the terrain is flat. Owing to the low rainfall, this cluster has the highest percentage of pasture during the rainy season. The NDVI, which on the average was the highest in 1989 notwithstanding the low rainfall, shows a very high relative decrement in 1994 (the second highest reduction after cluster 1), presumably because of extensive cutting of wood for charcoal production and because of a situation of relatively low rainfall that does not facilitate vegetation mass recovery.

Table 4. Analysis of the chi-squared differences of NDVI within the same year and between years (NDVI changes) in contingency tables obtained considering all the clusters simultaneously (all clusters) and the single clusters against the others (cluster *i*).

	Type of contingency table	Chi- squared	p	Notes
NDVI 89	all clusters	6.10	0.194	
NDVI 94	all clusters	16.04	0.001	
NDVI change	all clusters	20.6	0	
NDVI 89	cluster 1	0.06	0.8	
NDVI 89	cluster 2	2.64	0.123	
NDVI 89	cluster 3	0.03	0.879	
NDVI 89	cluster 4	0.38	0.535	
NDVI 89	cluster 5	4.04	0.03	Below the average
NDVI 94	cluster 1	3.82	0.059	
NDVI 94	cluster 2	2.61	0.123	
NDVI 94	cluster 3	8.87	<0.001	Above the average
NDVI 94	cluster 4	1.2	0.29	
NDVI 94	cluster 5	4.04	0.03	Below the average
NDVI change	cluster 1	8.47	0.003	Above the average loss
NDVI change	cluster 2	1.30	0.27	
NDVI change	cluster 3	9.06	0.003	Below the average loss
NDVI change	cluster 4	4.21	0.04	Above the average loss
NDVI change	cluster 5	0.005	0.94	

Table 5. Example of within/between similarity matrices obtained with program MATEDIT (see text). **a:** Within/between clusters similarity ratio, **b:** Similarity between fuzzy sets of Table 3 with similarity ratio.

a	1	2	3	4	5
1	**0.497**	0.408	0.372	0.356	0.259
2	0.408	**0.574**	0.439	0.362	0.193
3	0.372	0.439	**0.589**	0.398	0.301
4	0.356	0.362	0.398	**0.515**	0.268
5	0.259	0.193	0.301	0.268	**0.474**
B/W	0.700	0.610	0.630	0.670	0.530

b	1	2	3	4	5
1	1.000	0.539	0.351	0.447	0.076
2	0.539	1.000	0.576	0.449	0.003
3	0.351	0.576	1.000	0.489	0.102
4	0.447	0.449	0.489	1.000	0.087
5	0.076	0.003	0.102	0.087	1.000

Cluster 5 consists of 4 kebeles (20, 23, 24, 32) all adjacent to the north eastern shore of Lake Abijata and Langano at an average altitude of 1595±4 m (the lowest of the area). The total area is about 140 km^2. The interpolated average precipitation is 682 mm/year. This cluster has the highest percentage of bare soils (28%), the lowest percentage of total vegetation cover and therefore the lowest values in NDVI which has not changed significantly between the two years. The dominant geological feature is shore sand and reworked pumice of poorly preserved strandlines which makes the soil relatively porous and poor, high percent of Wonji Butajera basaltic flows and scoria cones and rift floor ignimbrites in Hara Kado. This may be the reason for the relatively high percentage of cultivated area of land (54%) with respect to the lowest human density. The density of horses in this cluster is the highest probably due to the open terrain and the grazing area available along the lakeshore .

Discussion

The history of human interaction with natural resources leading to degradation in the Ethiopian Rift valley is relatively new (Zerihun and Mesfin 1990) as compared to the Northern parts of the country (Fatovich 1997). In northern Ethiopia, the interaction of the human population with natural resources for a long period of time has led to depletion of the vegetation cover, impoverishment of biodiversity and high rate soil erosion (McDougall et al. 1975, Virgo and Munro 1977, Egziabher et al. 1998). In the Rift Valley, the rate of environmental degradation caused by more intensive resource utilization in a relatively shorter period of time is rivalling that of the northern part mainly in the depletion of vegetation cover and erosion of biological diversity. Human activities in the area have resulted in open canopy vegetation which is floristically poor and physiognomically uniform (Feoli and Zerihun 2000). Only few sites were set aside with

the aim of environmental protection (Zerihun and Mesfin 1990).

The rapid development of towns along the main roads in the Rift Valley, which connects the northern and central parts with the southern parts of the country, has created external demands on the resources of the rural system. The regional administration and the people are conscious about the ongoing degradation process but the range of options available to them is quite limited and relatively inflexible.

The access to GIS technology and simple analytical procedures of available information may help stakeholders to better control the situation and to plan interventions where most needed. The classificatory approach we are suggesting is easy to understand and to be applied with limited effort for data acquisition. The data that can be obtained from remote sensing images of public domain and from the official Census are adequate to characterize the environmental situation of a given landscape at a given time. The approach clearly shows where the process of degradation is more active and why. It offers the possibility to group the kebeles according to their similarity based on their landscape features and socio-economic variables and to rank them according to the ongoing process of land degradation within and between each group. The advantage of using a classificatory approach based on fuzzy set theory and permutation techniques is evident. Appendices 1 and 2 give a measure of the continuity of spatial variation among the OGUs notwithstanding the fact that they have been classified in classes which are significantly sharp. The relative high difference between cluster 5 and the others appears very clearly in the fuzzy partition tables (e.g., Appendices 1-2).

The approach offers tables which are easy to inspect (e.g., Table 5) in which similarity between and within cluster are presented to show the pattern of cluster similarity in the landscape. In our case, it is clear that the similarity between adjacent clusters is higher than those which are apart (e.g., the similarity between cluster 1 and the others gradually decreases as the distance increases). This becomes even clearer when considering the similarity between fuzzy sets. However, the ratio between/within similarity is relatively high (more than 50%) for all the clusters. As consequence, the fuzziness of the fuzzy partition is high. It is clear that cluster 5 is the most dissimilar from the others. It represents a peculiar coastal environment in which human impact is not very high probably due to the low fertility of the soil. Cluster 3 is the one with the highest within similarity, cluster 5 with the lowest, probably due to the fact that lake Abijata appears to be highly affected by El Niño events. The frequent expansion and recession of the water level of the lake and the extraction of the water for the "Soda Ash Factory" has left large areas with heterogeneous land cover mainly devoid of vegetation especially at its north-western shore where we find the most peculiar kebeles of this cluster (Adansho Barnola and Adansho).

The approach proves clearly that human pressure must be considered in the geo-physical context of the landscape since the same land management can produce different impacts on the environment in which it is put into operation. The fact that the spatially contagious distribution of the changes of NDVI corresponds very well to the distribution of clusters of kebeles (Fig. 1) is a strong evidence that factors influencing the human pressure have a clear zonation in the area. Elevation, climate, geology, and proximity to the lakes influence the pattern of human settlements and therefore the intensity of resource utilization. The significant correlation between geological and socio-economic data suggests that geology has a strong influence on the settlement through its effect on soil physical and chemical properties such as nutrient status and moisture retention capacity (Zerihun and Mesfin 1990). The indirect effect of geology on land cover/land use is expressed through the preferential human settlement pattern, which also influences the human and livestock density and the pressure on natural resources. The approach clearly shows that the kebeles that are undergoing the strongest process of degradation are those hosting the most important roads of communications and are closer to the towns.

In general, the percent area of land not cultivated ranges between 35 and 63%. The presence of uncultivated land in some of the kebeles suggests that there is still some room to initiate efforts for rehabilitation of the vegetation. The approach proves that the variables related to human and livestock densities are those most affecting land degradation (correlation between C and the **Land-soc** variables) therefore control over human and livestock density which are indicators of land degradation and adjustments on land use based on the policy environment could be considered mandatory strategy for rehabilitation.

Conclusions

The approach offers logical and powerful tools to detect and understand landscape patterns. However, it requires recognizing the following facts in order to be properly and profitably used:

- The landscape units (LUs) in which the landscape is subdivided and sampled can only have the meaning of operational geographic units (OGUs) for two opposite reasons, one is the high number of different kinds of LUs we can reasonably define (see Feoli and Zuccarello 1996), while the other is the constraint related to the fact that some relevant data are accessible only for some kinds of OGUs. For example, in our case socio-economic data are available in aggregated form only for administrative units (kebeles). This limitation may result in heterogeneity within the OGUs that can lead to the weakness of the correlation between the variables;

- The scale of the analysis is defined by the choice of OGUs, however with the use of GIS technology it is always possible to generate new OGUs and move from smaller scales to bigger scales and vice-versa (Longley et al. 2001);

- Given *n* OGUs the number of possible classifications may be so high that their enumeration would be practically impossible as was stressed by Podani and Feoli (1991) and recently by Miklós et al. (2005). This is not only because we can use different sets of variables, but also because even if we fix a set of them, they can be transformed and weighted in several ways and also because there are many clustering (or table rearrangement) methods that can be applied (Podani 2000). Since it is almost impossible to find the "absolute" optimal classification (if there is any!), it follows that classification should be seen not as the final aim of a research, but mainly a process extracting information from data, to learn from data and to organize information and knowledge;

- Permutation techniques can be useful to limit the number of possible classifications by testing the similarity between the matrices obtained with different similarity functions. From among the significantly similar similarity matrices we can choose only one. In this study similarity ratio gave the sharpest classification, but this would not mean that it is the best similarity function in all the circumstances. Other similarity functions used in this study also gave significantly sharp classifications, e.g., Gower's, Goodall's and Yager's indices. We chosen the classification based on similarity ratio because it produced slightly more significant sharpness than the others, and because the Mantel test showed that the correlation between the mentioned similarity functions was significantly high. It should, however, be clear that the differences between the significant probability levels could not be significant, in other words choosing one classification among those significantly sharp is always a subjective choice.

- Fuzzy sets have only operational meaning even if they correspond to a significant sharp classification. Their degrees of belonging show the uncertainty of the objects and/or variables to belong to the classes of a given classification. This is very useful because fuzzy sets offer the opportunity to challenge the emerging pattern of that classification against patterns emerging from other "reasonable" classifications.

- The conclusions we put forward are relevant and can be extrapolated only within the context of the data used for the study or within similar data contexts.

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Appendix 1

Fuzzy partition of the kebeles in the 5 clusters with the highest sharpness.

Appendix 2

Average values, the standard deviation and the degrees of belonging of the variables in the 5 clusters.

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