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Mapping vegetation in a heterogeneous mountain rangeland using landsat data: an alternative method to define and classify land-cover units

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Abstract

Three major problems are faced when mapping natural vegetation with mid-resolution satellite images using conventional supervised classification techniques: defining the adequate hierarchical level for mapping; defining discrete land cover units discernible by the satellite; and selecting representative training sites. In order to solve these problems, we developed an approach based on the: (1) definition of ecologically meaningful units as mosaics or repetitive combinations of structural types, (2) utilization of spectral information (indirectly) to define the units, (3) exploration of two alternative methods to classify the units once they are defined: the traditional, Maximum Likelihood method, which was enhanced by analyzing objective ways of selecting the best training sites, and an alternative method using Discriminant Functions directly obtained from the statistical analysis of signatures. The study was carried out in a heterogeneous mountain rangeland in central Argentina using Landsat data and 251 field sampling sites. On the basis of our analysis combining terrain information (a matrix of 251 stands × 14 land cover attributes) and satellite data (a matrix of 251 stands × 8 bands), we defined 8 land cover units (mosaics of structural types) for mapping, emphasizing the structural types which had stronger effects on reflectance. The comparison through field validation of both methods for mapping units showed that classification based on Discriminant Functions produced better results than the traditional Maximum Likelihood method (accuracy of 86% vs. 78%).

Keywords: Conservation planning; Discriminant Functions; Heterogeneous areas; Land-cover mapping; Maximum Likelihood; Principal Component Analysis; Rangeland; Supervised classification; Vegetable mosaics

1. Introduction

Ecosystems dominated by natural and semi-natural vegetation occupy large portions of the Earth's surface, and provide important ecosystem services that should be preserved (Balvanera et al., 2001). Such areas are generally destined to domestic grazing, which has been viewed as an activity with potential to meeting both goals of sustainable production and conservation (Bloesch et al., 2002; Landsberg et al., 2003; Mohamed & Woldu, 2002). However, negative as well as positive effects of domestic grazing on biodiversity, primary productivity, and forage quality have been reported (Milchunas & Lauenroth, 1993; Oesterheld et al., 1999; Perevolotsky & Seligman, 1998; West, 1993). Thus, a careful management-planning and further monitoring of rangelands become of main importance, while accurate base-line maps are indispensable for these purposes.

Landsat TM satellite images are a good tool for mapping vegetation (Jensen, 1996), although conventional supervised classification techniques have some inherent problems, due to differences in type and scale of information acquired by humans and satellites (Cherrill et al., 1994; Keuchel et al., 2003; Wilkie & Finn, 1996). When the mapping area is complex and heterogeneous these problems are intensified, leading to mapping attempts of limited success (Budd, 1996). In rangeland ecosystems these difficulties are most likely to appear, because the influence of free ranging grazers combined to natural environmental gradients often create complex and heterogeneous vegetation patterns (Adler et al., 2001; McIntyre et al., 2003). Three main types of such difficulties are faced when attempting to map rangeland ecosystems.

In the first place, there are problems originated by the limited spatial resolution of the TM satellite images.

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The main goal of traditional vegetation mapping has been the identification of plant communities (repetitive combination of species), or structural types (repetitive combination of growth forms and other terrain attributes) (e.g. Clark et al., 2001; McGraw & Tueller, 1983; Tobler et al., 2003; Wellens et al., 2000; Zak & Cabido, 2002). However, when communities or structural types are arranged in the landscape as patches smaller than the pixel size (30×30 m for TM images), attempts to map them are hampered (Clark et al., 2001). Training sites of adequate size may be impossible to find and, if found, the results of a supervised classification using those sites is inaccurate, especially if mixed pixels represent an important portion of the area. Therefore, a more realistic approach for mapping this type of landscape is needed, such as the definition of informational units (land-cover classes based on terrain attributes) at a higher hierarchical level, i.e. as combinations (mosaics) of communities or structural types (Davis et al., 1994).

The second problem is also related to the definition of informational units for mapping. Once the adequate hierarchical level is decided, the problem of defining discrete units discernible by the satellite still remains. When the basic components of the units to be defined (e.g. species, growth forms, community types) vary gradually, and to some extent independently, in response to multiple environmental and disturbance factors, the limits of the informational units for mapping must be imposed arbitrarily by the researcher (Tanser & Palmer, 2000; Townsend, 2000; Wilkie & Finn, 1996), sometimes with the aid of multivariate classification techniques (Cingolani et al., 1998; Coker, 2000; Jongman, 1987; Zak & Cabido, 2002). However, the basic components of the terrain selected by the researcher as variables for performing the classification may not be detected by the satellite (Millington & Alexander, 2000). This may lead to the definition of informational units that are meaningful for the researcher but cannot be discriminated by the satellite sensor, so producing inconsistencies due to different underlying approaches (Cherrill et al., 1994) and leading to a time consuming trial and error process until a satisfactory map is obtained (Clark et al., 2001). This being so, a preliminary analysis of the association between brightness sensed by the satellite and the various land-cover components perceived by the researcher would enhance the definition of land-cover units for mapping purposes (Armitage et al., 2000).

The third problem is related to the selection of the best training sites. Sometimes, training sites of adequate size for the defined land-cover informational units are difficult to find or recognize in the field. In such cases, several small training sites must be used to create spectral signatures defining a single unit (Tobler et al., 2003; Wyatt, 2000). Depending on their characteristics, the various spectral signatures ought to be merged, maintained separately, or discarded as outliers, so leading again to a time-consuming trial and error process, until an acceptable set of signatures and an accurate final map are obtained. Even if large enough training sites for the different units could be obtained, the problem remains on how to select the most representative ones to perform the classification. Generally, the process is not straightforward, and an iterative and long procedure is the common rule to obtain acceptable results (Wilkie & Finn, 1996).

This paper addresses the way in which we have solved, using non-traditional approaches, these three types of problems obtaining an accurate map (based on Landsat imagery) of a heterogeneous mountain rangeland in central Argentina. Our approach was based on the following three points, each corresponding to one of the above-mentioned sets of problems: (1) definition of ecologically meaningful informational units as mosaics of different structural types; (2) consideration of brightness when defining informational units; (3) exploration of two alternative methods to perform the classification: the traditionally used Maximum Likelihood (ML) method, which was enhanced by analyzing objective ways of selecting the best training sites, and an alternative method using Discriminant Functions directly obtained from the statistical analysis of spectral signatures.

Considering these points, the objectives of this study were to: (1) define land-cover units useful for management purposes in the study area, based on structural attributes linked to the brightness data of Landsat ETM+ images, (2) explore objective methods for the selection of the best training sites, and perform a traditional supervised classification (ML) of the Landsat data, (3) perform an alternative method of classification taking maximum advantage of the spectral information of pixels in each of the spectral bands used, and (4) compare both classifications through field validation.

2. Material and methods

2.1. Study area

The study was carried out in the upper portion of the Córdoba mountains (1700–2800 m a.s.l., 31°34′ S, 64°50′ W; 124,700 ha, see Fig. 3), in central Argentina, comprising different landscape units, including valley bottoms and ravines, plateaus with different degree of dissection, rocky hilly uplands and steep escarpments (Cabido et al., 1987). Vegetation consists of a mosaic of tussock grasslands, grazing lawns, granite outcrops, *Polylepis australis* woodlands, and eroded areas with exposed rock surfaces (Cabido, 1985; Cabido & Acosta, 1985; Cingolani et al., 2003a; Funes & Cabido, 1995). Mean temperature of the coldest and warmest months are 5.0 and 11.4 °C, respectively, with no frost-free period. Mean annual precipitation is 840 mm, with most rainfall concentrated in the warmer months, between October and April (Cabido, 1985).

The main economic activity in the area is livestock rearing, which began early in the 17th century and completely replaced large native herbivores (*Lama guanicoe*, and probably *Rhea americana*) by the beginning of the 20th century (Díaz et al., 1994). Due to its intrinsic fragility and three centuries of domestic grazing and anthropogenic fires, this mountain range shows serious erosion problems and woodland degradation (Cabido & Acosta, 1985, 1986; Cingolani et al., 2003a; Renison et al., 2002; Renison et al., in press). These problems are especially alarming since the area constitutes a biogeographical island (Cabido et al., 1998) with 41 endemic plant and animal taxa (Cabido et al., 2003) and because rivers born there provide water to the lowlands.

In 1997 part of the rangeland (26,000 ha) was expropriated to create the Quebrada del Condorito National Park, while the private lands surrounding the Park were declared National and Provincial Water Reserves (12,000 and 117,000 ha, respectively). Domestic livestock was maintained in some areas of the National Park to prevent the excessive dominance of tussock grasslands at the expense of grazing lawns (Cingolani et al., 2003a; Díaz et al., 1994; Pucheta et al., 1998). However, livestock may prevent erosion control and long term regeneration of *Polylepis* woodlands, even at low stocking densities. Meanwhile, in the surrounding reserve areas, soil erosion and woodland degradation rates remain high. Due to these problems, informed management and monitoring plans for the area are indispensable.

2.2. Field and image sampling

To perform the field and image samplings, we followed steps 1 to 3 (Fig. 1) described below.

2.2.1. Step 1. Selection of stands for field sampling

We used a subset of a 1997 Landsat 5 TM image (Path/Row 229/082) of the first part of the growth season (14 November 1997) which comprised the study area and its surroundings (364,000 ha). Geo-referencing (to the Gauss Kruger projection, with Campo Inchauspe datum and the International 1909 ellipsoid) was carried out using 127 points taken from eight 1:50,000 topographic maps (Military Geographic Institute, 1963–1997) together with 103 points obtained in the field with a Garmin 12 GPS at sites easily identifiable in the image. A linear resampling with the nearest neighbor algorithm was performed, achieving a positional error of 1.42 pixels (40.5 m), with an output pixel size of

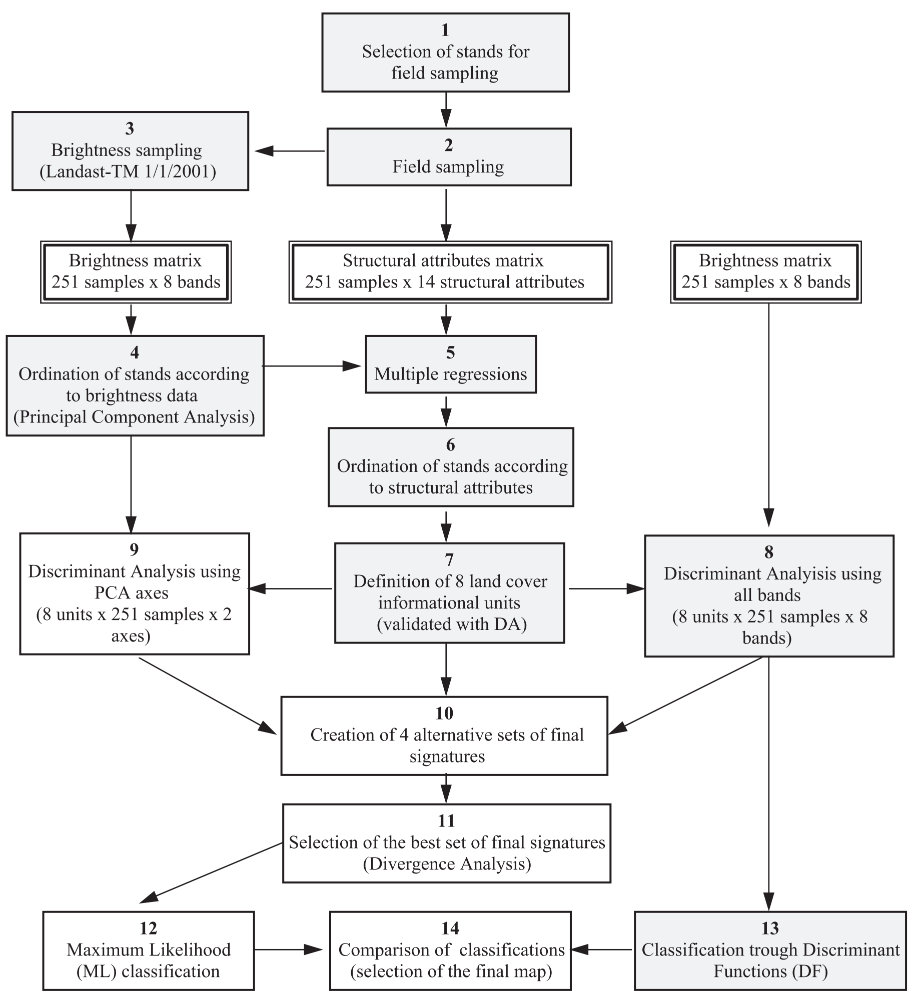

Fig. 1. Simplified outline of the procedure followed for the definition of land cover informational units, and the subsequent classification of the 2001 image using a traditional (Maximum Likelihood) and an alternative (using Discriminant Functions) method. In grey, the steps that leaded to the final map.

30×30 m. To stratify the field sampling according to spectral patterns we then performed an unsupervised classification with 10 classes (ERDAS, 1995). The number of classes was decided after visual examination of different band combinations. Among the resulting classes we selected 270 evenly distributed patches of at least 4×4 pixels (to cope with possible geo-location errors). For in-the-field geo-location of the selected sites, the coordinates of the central point of each patch were obtained from the classified image.

2.2.2. Step 2. Field sampling

From June 2000 to September 2002 we sampled terrain characteristics in 251 of the 270 selected stands (the remaining 19 stands were inaccessible or too close to human settlements and therefore discarded). Stands were defined as areas of 30 x 30 m (equivalent to the TM pixel), around the point located with the GPS. Based on previous studies, we recognized in the field 13 ecologically meaningful structural types (Table 1). As structural types were usually distributed in patches smaller than the stand size, we visually estimated the proportion of each structural type within the stands using categories ranging from 5% to 100% with 5% intervals. Additionally, we estimated the total percentage of bare rock (erosion plus natural), considering in a single measure the rock cover of all structural types within the stand. From these data we produced a "structural attributes matrix" of 251 stands $\times$ 14 structural attributes (13 structural types + total bare rock). Additionally, for each stand we recorded topographic position, slope, aspect, and altitude. We also recorded the abundance of cattle, sheep and horse dung depositions in a 30×1.8 m transect within each stand. The ratio between dung counts and the proportion of vegetation in the stand was used as an indicator of grazing pressure. For a characterization of erosion activity, we measured the length and average height of each active/inactive erosion edge (plant cover on their vertical surfaces < 50%/>50%, respectively) within the stand.

2.2.3. Step 3. Brightness sampling

To extract signatures for statistical analyses and land-cover mapping, we used a second sub-scene (geographically co-registered to the 1997 TM sub-scene) of an ETM + image

Table 1
Cover characteristics of plant communities and other features which form the basic structural types of the study area[a]

	Structural types	Dominant/subdominant species	Bare rock and soil (%)
A	*Polylepis* woodland/shrubland	*Polylepis australis*, as trees or shrubs, accompanied by the tree *Maytenus boaria* and the shrub *Berberis hieronymi*	0–10
B	Fern community	*Blechum penna-marina* dominates with high sociability forming a continuous cover	0–5
C	Shrubby tussock grassland	*Festuca*, *Deyeuxia* or *Poa* tussocks with shrubs (*Berberis hieronymi, Polylepis australis, Gaultheria poeppigii*, sometimes *Heterothalamus alienus*)	0–10
D	*Deyeuxia-Festuca* tussock grassland	Mainly *Deyeuxia hieronymi,* sometimes together with *Festuca tucumanica*, or the latter as the dominant	0–10
E	*Festuca* degraded tussock grassland	*Festuca tucumanica,* sometimes sharing dominance with *Stipa nidulans* or *Deyeuxia hieronymi*	15–50
F	*Poa* tussock grassland	*Poa stuckertii,* with *Alchemilla pinnata* and other short species in the intertussock space	0–5
G	*Eleocharis-Alchemilla* hydromorphic lawn	*Alchemilla pinnata* and *Eleocharis albibracteata*	0–1
H	*Alchemilla-Carex* lawn	*Alchemilla pinnata* and *Carex fuscula,* sometimes together with small tussocks of *Festuca tucumanica or Deyeuxia hieronymi*	0–15
I	*Sorghastrum-Alchemilla* degraded lawn	*Alchemilla pinnata*, *Carex fuscula*, *Mulenbergia peruviana* and *Sorghastrum pellitum*	15–50
J	*Muhlenbergia peruviana* lawn	*Muhlenbergia peruviana* and *Tagetes argentina*	1–20
K	Rock outcrop	Two types of rock outcrops were included in this unit: one dominated by *Berberis hieronymi* and *Satureja odora*, in larger outcrops, and the other dominated by *Heterothalamus alienus* and *Croton argentinus*	60–95
L	*Sorghastrum-Stipa* eroded stony grassland	*Sorghastrum pellitum* and *Stipa juncoides*	50–95
M	Erosion pavements of massive rock	Few individuals of *Stipa juncoides*, *Hypochaeris caespitosa*, *Plantago brasiliesnsis* var. *cordobensis* and *Noticastrum argenteum*	80–100

[a] Descriptions following Cabido (1985), Cabido and Acosta (1986), Cingolani et al. (2003a,b), Funes and Cabido (1995).

from the middle part of the growth season, acquired within the field sampling period (01 January 2001). Atmospheric corrections were found unnecessary since we used this single image for all further analyses and classifications (Song et al., 2001). Spectral signatures for 3×3 pixels surrounding each stand were produced for bands 1, 2, 3, 4, 5, 7 and 8, and for an additional NDVI band calculated as: (band4 − band3)/(band4 + band3). The mean brightness value of each band at each site was used to produce a data matrix of 251 stands × 8 bands ("brightness matrix").

2.3. Definition of land-cover informational units

To define land-cover informational units for mapping taking advantage of spectral information (objective 1), we first produced an ordination based on the land-cover attributes that best predict general patterns of reflectance (steps 4 to 6). Then, on the basis of that ordination, we classified land-cover informational units (step 7).

2.3.1. Step 4. Ordination of stands according to brightness data

The brightness matrix was subjected to a Principal Component Analysis (Afifi & Clark, 1984) to obtain two main axes that summarize brightness variation. In this way, each stand was positioned along the axes according to its spectral information.

2.3.2. Step 5. Multiple regressions

We analyzed which combination of terrain attributes best predicts the spectral characteristics of the stands. This was performed with two separate multiple regression analyses of the 14 structural attributes on each of the two PCA axes (from step 4). Significant predictor variables were selected using forward stepwise linear regression analyses. In this way, we obtained two multiple regression models (i.e. two linear combinations of structural attributes), one for each PCA axis.

2.3.3. Step 6. Ordination of stands according to structural attributes

From the two multiple regression models (step 5), we calculated the predicted scores along axes 1 and 2 for each stand, following one of the methodologies proposed by ter Braak (1988) for the analysis of two interdependent multivariate matrices. The two resulting new axes were plotted in a bidimensional space, so obtaining a new ordination plot based on terrain data. In this way, the contribution of each terrain attribute to the ordination is related to its importance for predicting reflectance.

2.3.4. Step 7. Definition of eight land-cover informational units

We used the new ordination axes (from step 6) as a basis for the classification of data into informational land cover units. The classification of stands was made by subdividing the continuous array of stands along the two predicted axes into 8 groups. The number of groups and their boundaries was decided on the basis of our knowledge of the ecology and characteristics of the study area, after a careful consideration of the ordination results. Since the classification was to some extent subjective, it was validated using Discriminant Analysis (DA, Afifi & Clark, 1984), with the eight groups as a priori groups, and the 14 structural attributes as variables.

2.4. Maximum likelihood classification

Once the informational land cover units were defined (steps 4 to 7), steps 8 to 12 (Fig. 1) were followed to explore objective methods for the selection of the best training sites, and to perform a ML classification of the ETM + sub-scene (objective 2). These steps included a statistical analyses leading to the creation, through different criteria, of alternative sets of eight final signatures, and the subsequent selection of the best set to perform the classification.

2.4.1. Step 8. Discriminant analysis using all bands

This analysis was performed using the 251 stands data set, with the eight informational land cover units as a priori groups, and the brightness values of each band (from step 3) as variables.

2.4.2. Step 9. Discriminant analysis using PCA axes

This analysis was performed using the 251 stands data set, with the eight informational land cover units as a priori groups, and PCA axes 1 and 2 (from step 4) as variables (i.e. only the main directions of variation in brightness data were here considered).

2.4.3. Step 10. Creation of four alternative sets of final signatures

(a) The first set was constructed without discarding the outliers, i.e. creating each final signature by merging all signatures of stands corresponding to the same informational land cover unit. (b) The second set was constructed by merging the signatures correctly predicted through the first DA (using all bands as variables, step 8), while the cases in which spectral data did not predict land-cover units correctly were discarded as outliers. (c) The third set was created using the correctly classified signatures through the second DA (using the two PCA axes as variables, step 9), discarding the remaining as outliers. (d) The observation of the spectral histograms and ellipses (ERDAS, 1995) of the signatures belonging to the previous three sets suggested that a combination of signatures from the second and third sets would improve separability. Thus, we decided to create a fourth set of eight signatures, which consisted in the combination of two signatures from the second and six signatures of the third set (a combination that showed higher visual separability than the other three sets).

2.4.4. Step 11. Selection of the best set of final signatures

For selecting the best set for classification, we performed a divergence analysis (ERDAS, 1995) for each of the four sets created, so obtaining separability values for all 28 pairs of signatures within each set (8 units combined by pairs = 28). For each set, we calculated the average minimum separability index as the mean of 8 values, one for each signature, so representing the divergence from its nearest neighbor. The set with the highest index was selected.

2.4.5. Step 12. Maximum likelihood classification

A ML classification, which constitutes the most widely used supervised classification method (Arbia et al., 1999), was performed based on the set of signatures selected in step 11.

2.5. Alternative method for classification

To fulfill the third objective of the study, we applied an alternative method of classification based on the classification functions derived from Discriminant Analysis.

2.5.1. Step 13. Classification through discriminant functions

For the alternative classification (hereafter "DF classification") of the ETM + sub-scene we used the Fisher's linear classification functions (Norušis, 1992) derived from the DA performed using all bands as variables (step 8). These functions consisted of eight linear combinations of variables (bands in our case), one for each group (land cover units in our case). To classify a sample (pixel in our case) according to these functions, each pixel was subjected to eight linear transformations, one for each function. Finally, the 8 final values for each pixel were compared, and the pixel was assigned to the class with the highest value.

2.6. Comparison of classifications obtained by both methods

To meet the fourth objective of the study we carried out the following field sampling and data analyses.

2.6.1. Step 14. Comparison of classifications

To perform the field validation of both classifications (obtained in steps 12 and 13), we selected 163 new stands evenly distributed throughout the study area in patches homogeneous (4×4 or more pixels belonging to the same class) in at least one of the classifications. The assessment of field samples was performed as described in step 2. Afterwards, field validation stands were classified into one of the 8 land-cover units previously defined, using Discriminant Analysis. To reduce unnecessary complexity in the accuracy analysis, 14 sampling stands intermediate between two classes (i.e. probability of belonging to a different class >35%, according to DA) were discarded. Of the remaining 149 field validation stands, 123 were in areas homogeneous enough for testing the accuracy of the ML classification, while 134 were adequate for testing the DF classification (108 were common to both classifications). Confusion matrices were constructed for both classifications. The Kappa statistic was calculated for each case, and the best classification was selected as the final map.

3. Results

3.1. Definition of land-cover informational units

The field sampling confirmed the high within-pixel heterogeneity of the area. Only 31 (12%) out of the 251 reference stands had a 95% or greater cover of a single structural type, while 96 (38%) had a 75% or greater cover of a single type.

The first two PCA axes (step 4) explained 77.5% and 14.1% of the variance in spectral data, respectively (a total of 91.6%). Axis 1 separated stands with high brightness in all bands (positive end) from stands with high NDVI values (negative end). Axis 2 separated stands with high brightness in band 4 (positive end) from stands with low brightness in the same band (negative end) (Fig. 2a and c). Linear combinations of structural attributes explained 86% of the variance in PCA Axis 1 (R^2 of the multiple regression = 0.865, $p < 0.0001$) and 62% of the variance in PCA Axis 2 ($R^2 = 0.622$, $p < 0.0001$). From the linear regression model (i.e. linear combination of the significant structural attributes) we obtained an ordination of stands according to terrain attributes (step 6, Fig. 2b). To illustrate how the structural variables contribute to predict reflectance variation, their correlation with the new (predicted) axes 1 and 2 was plotted in Fig. 2d. Variation of spectral and structural data along axis 1 indicate that total bare rock contributes strongly to increase general brightness, while woodlands (type A), *Poa* grasslands (type F) and *Alchemilla*-*Carex* lawns (type H) decrease general brightness and increase NDVI. Variation along axis 2 indicates that *Alchemilla*-*Carex* lawns (type H) contribute to increase brightness in band 4, while woodlands (type A) and outcrops (type K) absorb more light in this band (Fig. 2c and d).

According to their position along the predicted axes 1 and 2 we classified stands in eight groups (Fig. 2b), statistically validated through Discriminant Analysis ($p < 0.05$ for all canonical Discriminant Functions), which constituted the eight land cover units for mapping. Their mean proportion of structural types is shown in Table 2. The units were as follows.

3.1.1. Unit 1. Woodland

Dominated by *Polylepis* woodland or closed shrubland (structural type A), with low total rock cover. Generally occurred below 2000 m a.s.l on steep slopes in mid to low topographic positions, but was also found on flat sites in ravine bottoms or in gentle slopes. Erosion and grazing pressure were low.

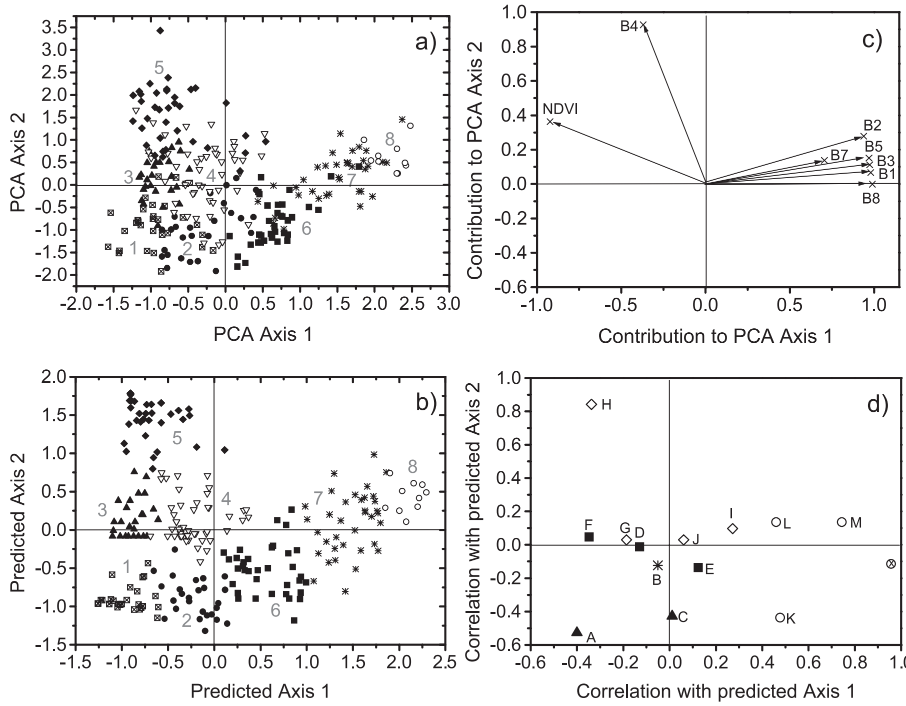

Fig. 2. (a) Location of sampling sites along the two main axis of PCA using bands as variables. (b) Location of sampling sites along the predicted axes according to structural attributes. For both figures, symbols and numbers represent the eight land cover units: ⊠ 1—Woodland; ● 2—Shrubby tussock grassland with outcrop and woodland; ▲ 3—Thick tussock grassland with hydromorphic lawn; ▽ 4—Thin tussock grassland; ◆ 5—Lawn; ■ 6—Outcrop with tussock grassland; ✻ 7—Outcrop with exposed rock; ○ 8—Rock pavement. (c) Contribution of bands to PCA axes. (d) Correlation of predicted PCA axes with total rock cover (⊗) and structural types (○ rock-dominated types, ■ tussock grasslands, ◇ lawns, ▲ woody types, ✻ fern dominated type), which were labelled with their identification letter (Table 1).

3.1.2. Unit 2. Shrubby tussock grassland with outcrop and woodland

Dominated by a combination of *Polylepis* woodland/shrubland (A), shrubby grassland (C) and rock outcrop (K). It was found in sites topographically similar to unit 1, at slightly higher altitudes and more exposed topographic positions with less steep slopes. Erosion was more active and grazing pressure higher. It could be totally or partially derived from unit 1 after burning followed by grazing, as suggested by fire evidences found on trunks of *Polylepis* individuals.

3.1.3. Unit 3. Thick tussock grassland with hydromorphic lawn

Generally located in low, flat and sometimes flooded positions. Some stands lack the hydromorphic lawn type (G), being mostly covered by *Poa* grassland (F). Proportion of active erosion edges was relatively high, but restricted to the margins of water courses. Grazing pressure was variable.

3.1.4. Unit 4. Thin tussock grassland

Dominated by *Deyeuxia*/*Festuca* tussocks (D). Generally found on gentle slopes and flat summits at all altitudes, although the dominant species shifted with altitude. Below 1900 m *Festuca* dominated at all topographic positions, being gradually replaced by *Deyeuxia* as altitude increased, up to 2300 m where this species dominated at all topographic positions. Erosion activity was low, and livestock pressure intermediate.

3.1.5. Unit 5. Lawn

Largely dominated by *Alchemilla-Carex* lawn (H), with some patches of other types. Rock pavement (M) was generally found at the bottom of concavities which get flooded in the rainy season. Located at sites with less than a 10% slope, usually at high altitudes. Erosion was more active, and grazing pressure more intense, than in tussock grasslands (units 3 and 4). Grazing prevents the succession of lawns towards tussock grasslands (Cingolani et al., 2003a; Pucheta et al., 1998).

3.1.6. Unit 6. Outcrop with tussock grassland

A mixture of natural outcrops (K), exceptionally reaching 120 m tall, and tussock grasslands (C, D, E), together with small patches of other types, including *Polylepis* woodlands or shrublands (A). Mainly located on mid and upper steep slopes. Erosion activity was intermediate, and grazing pressure low.

3.1.7. Unit 7. Outcrop with exposed rock

Dominated by rock (types K, L and M), with small vegetation patches. Found at similar topographic positions than unit 6, although at somewhat higher altitudes in more

Table 2
Percentage of each structural type (names are abbreviated) and total rock cover within each informational land cover unit defined

Structural type		Land cover unit[a]							
		1	2	3	4	5	6	7	8
A	*Polylepis* woodland	77	24	–	–	–	3	+	–
B	Fern community	4	3	–	–	–	2	+	+
C	Shrubby grassland	6	31	–	+	–	7	3	+
D	*Deyeuxia-Festuca* grassland	3	9	15	73	5	22	7	1
E	*Festuca* degraded grassland	1	2	–	2	–	10	2	3
F	*Poa* tussock grassland	2	6	52	4	5	2	+	–
G	Hydromorphic lawn	–	+	20	+	+	+	–	–
H	*Alchemilla-Carex* lawn	+	1	12	10	81	1	4	2
I	*Sorghastrum* degraded lawn	+	1	–	2	1	3	5	3
J	*Muhlenbergia* lawn	+	+	+	1	1	1	1	1
K	Rock outcrop	6	22	+	3	2	39	27	8
L	Eroded stony grassland	+	1	–	1	1	3	18	7
M	Erosion pavements	+	2	1	4	4	8	34	77
Total rock cover		6	23	1	8	6	49	74	91

+, < 0.5 %; –, absence.
[a] See description in text.

exposed and northerly sites. Activity of erosion and grazing pressure were high. This unit could be derived from unit 6, after erosion processes eliminated most vegetation.

3.1.8. Unit 8. Rock pavement

Its bare rock cover was higher than 80%, most of which was exposed due to erosion (L and M). Generally located in flat sites with high erosion activity. The grazing pressure on the few remaining vegetation patches was very intense.

3.2. Image classifications

Two discriminant analyses were involved in the process of signature creation for the ML classification. The first, performed with the eight land-cover units as a priori groups and the 8 bands as variables (step 8) was significant for most of its canonical axes (6 out of 7 axes, $p < 0.05$). This analysis showed that the combination of the 8 bands correctly predicted the land-cover unit for 83% of the stands. The second DA, performed with the eight land-cover units as a priori groups and the two main PCA axes as variables (step 9) was significant for its unique canonical axis ($p < 0.05$). This analysis showed that the combination of the two main PCA axes correctly predicted the land-cover unit in 69% of the stands.

The four alternative sets of spectral signatures (step 10) showed different average minimum separability indices (Table 3). The lowest index was obtained for the first set (constructed without discarding outliers), while the second and third sets (constructed by selecting signatures through DA) showed higher indices. As expected, the fourth set (a combination of signatures 1–6 taken from the third set and signatures 7 and 8 taken from the second set) had the highest separability index, and was hence used for the ML classification of the Landsat ETM + sub-scene (Fig. 3C).

The discriminant functions derived from the first DA (using all bands as variables, step 8) were used for performing the DF classification (Table 4, Fig. 3B and D) as they had higher predictive power than the discriminant functions using PCA axes (83% and 69%, respectively).

3.3. Field validation and comparison between classifications

Both classifications (ML and DF) showed a coincidence (i.e. identical patterns) of 71%. Of the 149 validation sites, 107 corresponded to homogeneous areas belonging to the same class in both classifications, 1 corresponded to homogeneous areas but belonging to different classes in each classification, while the 41 remaining sites consisted of homogeneous areas in one of the classifications and a mosaic-like pattern (i.e. few contiguous pixels belonging to the same class) in the other.

The ML classification showed lower accuracy values than the DF classification (78% and 86% respectively, Tables 5 and 6) and lower kappa indices (0.745 vs. 0.836). For the latter, the unit with the lowest producer's accuracy (sensu Congalton & Green, 1999) was the outcrop with tussock grassland (unit 6), which was sometimes classified as outcrop with exposed rock (unit 7) or as shrubby tussock grassland with outcrop and woodland (unit

Table 3
Divergence Index (DI) between each spectral signature and its nearest neighbour (NN), for the four final sets created by merging signatures according to various criteria

Final signature	First set[a]			Second set[b]			Third set[c]			Fourth set[d]		
	DI	NN	*n*	DI	NN	*n*	DI	NN	*n*	DI	NN	*n*
1	13	2	31	20	2	27	30	2	21	30	2	21
2	5	4	26	11	4	20	29	4	12	29	4	12
3	28	1	26	31	1	24	38	1	20	38	1	20
4	5	2	50	11	2	38	18	6	29	18	6	29
5	7	4	36	21	4	26	28	4	27	28	4	27
6	8	7	36	15	4	34	14	7	32	18	4	32
7	8	6	36	16	8	30	10	8	21	16	8	30
8	9	7	10	16	7	9	10	7	10	16	7	9
Average	10.4			17.6			22.1			24.1		

The number of signatures merged in each case is indicated in the column headed by *n*. The average minimum divergence index is indicated in the last row.
[a] Created by merging all the signatures.
[b] Created by merging the 208 (83%) properly classified signatures obtained through the DA described in step 8 (Fig. 1).
[c] Created by merging the 172 (69%) properly classified samples obtained through the DA described in step 9 (Fig. 1).
[d] Combination of the second and the third set.

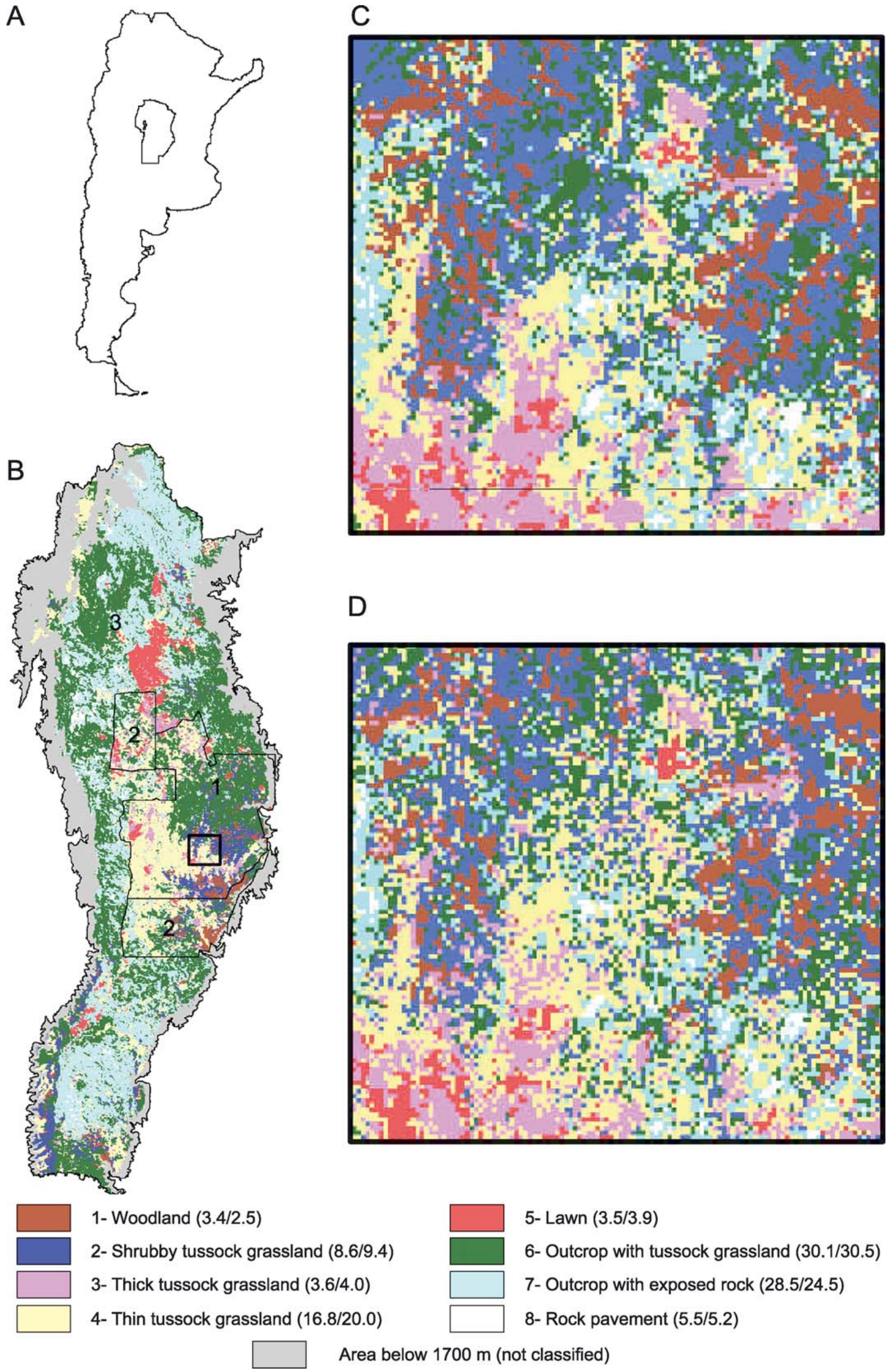

Fig. 3. (A) Location of the protected area under study in the Córdoba Province, Argentina. (B) Final map of the protected area, scale 1:774,684 subdivided according to their jurisdiction and land-tenure: (1) Quebrada del Condorito National Park, (2) Quebrada del Condorito National Reserve and (3) Pampa de Achala Provincial Water Reserve. (C) Detail of the ML classification (scale 1:45,190). (D) Detail of the DF classification (same area and scale than C). The legend indicates the land-cover units and total % of area occupied by each one in ML/DF classifications (between brackets).

Table 4
Classification functions obtained through DA, used for the alternative (DF) method of classification

Layer	Land cover unit							
	1	2	3	4	5	6	7	8
Band 1	25.96	25.12	24.30	24.71	24.37	25.47	26.15	25.22
Band 2	− 6.14	− 5.41	− 4.67	− 5.53	− 4.60	− 5.12	− 4.21	− 3.83
Band 3	− 0.98	− 2.03	− 1.53	− 1.56	− 2.44	− 2.85	− 2.53	− 0.70
Band 4	0.31	1.51	1.53	2.14	2.82	2.11	0.92	− 0.45
Band 5	− 0.98	− 1.11	− 1.03	− 0.79	− 1.09	− 1.33	− 1.21	− 1.66
Band 7[a]	12.32	12.48	12.53	12.65	12.65	12.54	12.14	11.90
Band 8[b]	− 5.51	− 5.54	− 5.99	− 6.35	− 6.01	− 5.22	− 4.94	− 4.17
NDVI	272.39	34.95	66.49	− 40.06	− 102.83	− 73.89	139.68	410.63
Constant	− 1540.75	− 1532.74	− 1545.61	− 1578.05	− 1600.61	− 1576.75	− 1621.34	− 1603.23

[a] Thermal.
[b] Equivalent to TM band 7.

2). The class with the lowest user's accuracy was the outcrop with exposed rock (unit 7), which in the terrain was sometimes outcrop with tussock grassland (unit 6) or rock pavement (unit 8). Meanwhile, the most accurately classified unit from the producer's standpoint was woodland (unit 1), always classified as such, while from the user's standpoint, the best classified class was thin tussock grassland (unit 4) (Table 6). The ML classification showed lower to similar accuracy values for all classes (Table 5).

4. Discussion

4.1. Land-cover patterns

The high within-pixel heterogeneity in our study area is the result of the interaction of disturbance factors (such as fire and grazing) with complex topographical and geomorphological patterns, which produce different communities and mosaic types (Cabido, 1985; Cabido & Acosta, 1986; Cabido et al., 1987; Cingolani et al., 2003a,b; Enrico et al., 2004; Funes & Cabido, 1995; Pucheta et al., 1998; Renison et al., 2002). *Polylepis* woodland occurs mainly on steep escarpments and deep ravines and valleys, conforming units 1 or 2. Grassland units (3, 4 and 5) occurred mainly on low to moderately dissected undulated plains with few outcrops. Rock dominated units (6, 7 and 8) are found in different types of landscapes, although they prevail in rocky and hilly uplands. From these general patterns, three main land-cover domains can be defined: the woodland domain (units 1 and 2), the grassland domain (3,4 and 5) and the rock domain (6, 7 and 8). The partial association of these groups with geomorphological units suggests that different geoforms have different resource availability patterns and susceptibility to disturbance, as was observed in other ecosystems (e.g. Anchorena & Cingolani, 2002; Bridge & Johnson, 2000; Collantes et al., 1999; McIntyre et al., 2003).

The association of the mapped units with disturbance and physical factors, and the spatial proximity and interactions among their components (structural types) highlight the ecological meaning of the units defined, giving insights about their adequate management (Cingolani & Falczuk, 2003). For example, the presence of a small amount of massive rock pavements in lawns (unit 5) indicate incipient

Table 5
Confusion matrix for ML classification

Spectral classes	Land cover units[a]								
	1	2	3	4	5	6	7	8	%
1	7	1							87.5
2		7				2			77.8
3			12	1	2				80.0
4			1	14	6	1			63.6
5			3	1	16				80.0
6						19	1		95.5
7						4	11	2	64.7
8							2	10	83.3
%	100.0	87.5	75.5	87.5	66.7	73.1	78.6	83.3	78.0

Land cover units 1 to 8 refer to stands classified according to terrain information, while spectral classes 1 to 8 refer to the classification of those stands according to spectral information.

[a] 1—Woodland, 2—Shrubby tussock grassland with outcrop and woodland, 3—Thick tussock grassland with hydromorphic lawn, 4—Thin tussock grassland, 5—Lawn, 6—Outcrop with tussock grassland, 7—Outcrop with exposed rock, 8—Rock pavement.

Table 6
Confusion matrix for DF classification

Spectral classes	Land cover units[a]								
	1	2	3	4	5	6	7	8	%
1	9	1							90.0
2		8				2			80.0
3			16	2	2				80.0
4				21	1				95.4
5			2	1	17				85.0
6						18	1		94.7
7						3	16	2	76.2
8							2	10	83.3
%	100.0	88.9	88.9	87.5	85.0	78.3	84.2	83.3	85.8

Land cover units 1 to 8 refer to stands classified according to terrain information, while spectral classes 1 to 8 refer to the classification of those stands according to spectral information.

[a] 1—Woodland, 2—Shrubby tussock grassland with outcrop and woodland, 3—Thick tussock grassland with hydromorphic lawn, 4—Thin tussock grassland, 5—Lawn, 6—Outcrop with tussock grassland, 7—Outcrop with exposed rock, 8—Rock pavement.

erosion processes, and suggest that this unit, at present under high grazing pressure, must be carefully managed to prevent a complete transformation into unit 8 (rock pavement). Other examples are units 2 and 6, where rock outcrops are combined with grasslands and/or woodlands. These units are extremely important for avian diversity (García et al., unpublished data), which is higher than in units where only one of those structural types dominate (e.g. unit 1 or 4). Additionally, grasslands (mainly structural type D) within units 2 and 6 are clearly different, in terms of livestock accessibility and utilization, than grasslands in less patchy units (3, 4 and 5), even when species composition is similar. These, as well as other examples (Cingolani & Falczuk, 2003; Renison et al., in press) show that units defined as mosaics not only solve an important technical problem, but also have an emergent ecological meaning, being therefore ideal for management purposes in markedly heterogeneous areas.

4.2. Advantages of the method

By defining land-cover units on the basis of terrain and spectral data relations, we arrived to an a priori trade-off between human criteria and satellite capabilities. The 14 variables of interest (13 structural types + total bare rock) were selected on the basis of ecological criteria, but it was their relation with spectral data what determined which of them were significant for defining the final map units. Thus, we avoided the trial and error process usually necessary when only one approach is considered (human criteria for traditional supervised classification and spectral data for unsupervised classification, Clark et al., 2001). Additionally, we increased the likelihood of obtaining an accurate map, often difficult for natural vegetation mapping using more traditional methods of defining units (Cherrill et al., 1994). A similar multivariate analysis for depicting the relation between reflectance and land-cover characteristics was performed by Armitage et al. (2000) as a prior step to satellite based vegetation mapping of semi-natural upland areas.

Once land-cover units were defined, the use of functions derived from Discriminant Analysis (DF classification) showed more accurate than ML classification. Discriminant Functions derived from Discriminant Analysis were widely used in other environmental sciences applications (e.g. Allen & Wilson, 1991; Anchorena & Cingolani, 2002), and were also used to discriminate classes in digital high resolution aerial photographs (Lobo et al., 1998). Our results suggest that they could also become a powerful tool for the classification of satellite data such as Landsat pixels. Additionally, this method is more direct and objective, because the classification functions optimize the available information about the discriminating capability of bands.

The use of fuzzy logic (Jensen, 1996; Millington & Alexander, 2000), or the modeling to generate quantitative and spatially explicit estimates of subpixel biophysical characteristics (Ju et al., 2003; Luoto et al., 2002; Millington & Alexander, 2000; Wyatt, 2000) could also be alternative approaches for dealing with heterogeneous areas with a high within-pixel variation. However, such methods are difficult to apply when vegetation is complex and highly variable (Townsend, 2000), while the outputs of such techniques are more difficult to interpret for most end-users, as compared to a single map summarizing most land-cover information (Millington & Alexander, 2000).

Our alternative (DF) classification showed a high accuracy, compared to other studies using various classification methodologies for Landsat data. For example, a classification of 15 purely natural land-cover units in a savanna rangeland in Tanzania (Tobler et al., 2003) using ML classification showed a similar accuracy (77%, kappa = 0.75) than our ML classification (78%, $k = 0.74$) but markedly lower than our DF classification (86%, $k = 0.84$). Clark et al. (2001), performed a ML classification of eight units for a sagebrush mountain rangeland in Idaho (four sagebrush types, two woodland types, and two types of cultivated lands) obtaining a similar (although slightly lower) accuracy than our DA classification (83.74%, $k = 0.814$), after using ancillary (altitude) data to correct misclassified pixels. Haapanen et al. (2004), classified three land cover types (forest, non-forest and water) in the Great Lake's region of the United States using a non-parametric estimation approach (k-Nearest Neighbor), obtaining an overall accuracy slightly higher than our DA classification (88%), but with a fairly lower kappa index (0.70). Keuchel et al. (2003) classified 10 natural and cultural vegetation units in Tenerife using three methods, including ML. Their best method (Support Vector Machines) produced a higher accuracy (93%, $k = 0.92$) than ours. However, this was also achieved by including ancillary (altitude) information, which greatly enhanced the classification of a vegetation cover distributed in belts. According to these and other examples analyzed (e.g. Lewis, 1998; Oetter et al., 2000; Tanser & Palmer, 2000) we understand that it is very difficult to obtain better accuracy and kappa index values than ours by only using single date Landsat spectral information.

4.3. Sources of error

Classification errors between domains (woodland, grassland and rock) were very low. The DF classification showed an error of 1.5% between domains, while the ML classification showed an error of 2.4%. Errors were due to confusion between units 6 and 2, which are relatively similar in their tussock cover and rock outcrops. Additionally, the ML classification confused unit 6 with 4, because both share a relatively high proportion of *Festuca*/*Deyeuxia* tussock grassland and a small proportion of rock (see Table 2).

Errors of classification within each domain account for most of the global error in both classifications, although the

DF classification method performed better. Greatest error was found within the rock domain, with unit 7 confused either with units 6 or 8. Variability in the type and shape of rock outcrops, age of the exposed rock (rocks exposed longer have darker, outcrop-like color), together with differences in lichen composition and cover on rock surfaces, are probable causes for the confusions. It is well known that soil and rock color strongly influence reflectance in sites with sparse vegetation (Post et al., 1994). Errors within the grassland domain could be due to high precipitation during the summer, which floods flat lawns during short periods, thus reflecting light like hydromorphic lawns. Additionally, some confusion among grassland units could be caused by the sub-dominance of *Poa stuckertii* in some *Deyeuxia* tussock grasslands, and vice-versa. An additional source of differences could be the uncoupling between satellite and validation field sampling (up to 2 years), since transformations among grassland types could be rapid after drastic changes in management, as was the case in some areas after the exclusion of cattle from the National Park (personal observation). Units of the woodland domain show little confusion. As shown by our results and other studies (Guyot, 1990; Haapanen et al., 2004; Huete et al., 1985; Zak & Cabido, 2002), both rock and woody cover have strong effects on reflectance. The opening of the woodland cover, exposing granite outcrops previously covered by the tree canopy, and the partial replacement of trees and shrubs by tussock grasses, converts unit 1 into unit 2, with the associated changes in spectral values, allowing the differentiation of both units. In none of the misclassified cases, validation stands were located in atypical topographic positions or expositions, indicating that topography is not a source of error in this map.

5. Conclusions

Our approach proved useful for mapping land-cover units in a heterogeneous area where an accurate map was needed but was impossible to obtain using traditional classification methodologies. The procedures used for definition and classification of land-cover units resulted in a map showing an accuracy of 87% ($k = 0.84$), where mosaics resulting from the interaction of natural and human factors are clearly recognized. The final map (Fig. 3B) was later entered as a thematic layer in a GIS (Cingolani et al., 2003b) presently used by the National Parks Administration for integrated conservation planning and monitoring of the whole protected area, and as a communication tool (Cabido et al., 2003; Cingolani & Falczuk, 2003). The wide acceptance and utilization of the map clearly indicate that the results here reported have been somehow critical for the future conservation of the area. Our approach (gray steps in Fig. 1) is therefore highly recommendable for areas where more traditional approaches are not possible or unsuccessful.

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