Modeling Bare Ground with Classification Trees in Northern Spain

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ABSTRACT
Bare ground abundance is an important rangeland health indicator and its detection is a fundamental part of range management. Remote sensing of bare ground may offer solutions for land managers but also presents challenges as modeling in semi-arid environments usually involves a high frequency of spectral mixing within pixels. Classification Tree Analysis (CTA) and maximum likelihood classifiers were used to model bare ground in the semi-arid steppes of the middle Ebro valley, Aragon, Spain using Satellite Pour l'Observation de la Terre 4 (SPOT 4) imagery and topographic data such as elevation, slope, aspect, and a morphometric characterization model. A total of 374 sample points of bare ground fraction from sixteen 500m transects were used in the classification and validation process. Overall accuracies were 85% (Kappa statistic = 0.70) and 57% (Kappa statistic = 0.13) from the CTA and maximum likelihood classifiers, respectively. While spectral attributes were essential in bare ground classification, the topographic and morphometric properties of the landscape were equally critical in this modeling effort. Although the specific layers best suited for each specific model will vary from region to region, this study provided an important insight on both bare ground modeling and the potential advantages of CTA.

KEYWORDS: Remote sensing, GIS, rangelands, Classification Tree Analysis, desertification

INTRODUCTION

Rangeland ecosystems cover approximately 40% of the earth's terrestrial surface (Huntsinger and Hopkinson 1996, Branson et al. 1981) and are typically dominated by grass and shrub communities. These vegetation communities exist because of the semi-arid or xeric nature of these sites. However, an effective hydrologic cycle (the capture, storage, and release of water) leads to healthy rangeland sites that produce green biomass (at least ephemerally) with minimal bare ground. The green biomass is effectively used by herbivores (e.g., livestock) which are an integral part of a functional rangeland ecosystem. When the hydrologic cycle is disturbed, rangelands desertify and as a result, exhibit increasing amounts of bare ground exposure. Chronic desertification shifts lead to a loss of ecosystem functionality, a reduction in biodiversity, and reduced livestock grazing capabilities (Daubenmire 1959, Schlesinger et al. 1990) with associated social and economic underpinnings (Savory 1999, Arnalds and Archer 2000, Griffin et al. 2001).

The degree of bare ground is a reliable indicator of rangeland health within otherwise similar regions (National Research Council 1994, Whitford et al. 1998, Pyke et al. 2002, O'Brien et al. 2003, Hunt et al. 2003, Booth and Tueller 2003). One of the consequences of sedenterization of livestock is the exceedingly high loss of plant cover and plant biomass. Although stocking rate can be relatively low, the way livestock use the landscape may have important consequences on triggering land degradation processes. Indeed, in spite of an average reduction of stocking rate in many areas of the world, recent increases in animal number per farm is leading to higher degradation around shelters (Alados et al. 2006).

Remote sensing provides a means to detect bare ground at various scales and continuous extents with multi-temporal capabilities (Booth and Tueller 2003, Palmer and Fortescue 2003, Washington-Allen et al. 2006). However, bare ground detection is challenging because of the high frequency of spectral mixing within pixels which is a function of image resolution relative to the size of the vegetation canopy and the distribution and arrangement of plants within a study area. Even when using the highest spatial resolution multispectral satellite imaging sensor (Quickbird 2.4-m pixels) pixels will nearly always be comprised of various fractions of shrub, grass, litter, and bare ground, etc. While high spatial resolution aerial imagery has been able to minimize or reduce mixed pixels (Booth and Cox 2008) it does not capture spectral reflectance data and is often fraught with georectification problems leading to numerous challenges and limitations as well (Moffet 2009).

Previous work in sagebrush-steppe rangelands suggests that bare ground can be reliably detected (overall accuracy = 87%) when bare ground is $\geq$ 50% (Gokhale and Weber 2006). Where bare ground is less common (< 25%) it becomes increasingly difficult to accurately model and classification accuracies are typically much lower.

This paper describes a study where classification tree analysis (CTA) and maximum likelihood classification were used to model bare ground fraction in northern Spain. CTA is a non-probabilistic, non-parametric statistical technique well-suited to modeling skewed, non-normal data and phenomena (Breiman et al. 1998; Friedl and Brodley 1997; Lawrence and Wright 2001; Miller and Franklin 2001). It is hypothesized that bare ground is non-normally distributed and for this reason, may be modeled more accurately with CTA relative to other supervised classification techniques. The CTA algorithms select useful spectral and ancillary data which optimally reduce divergence in a response variable (Lawrence and Wright 2001) such as bare ground exposure. CTA uses machine-learning to perform binary recursive splitting operations and ultimately yields a classification tree diagram that is used to produce a model of the response variable. Splitting algorithms common to CTA include entropy, gain ratio, and Gini. The entropy algorithm has a tendency to over-split, creating an unnecessarily complex tree (Zambon et al., 2006). The gain ratio algorithm addresses the over-splitting problem through normalization while the Gini algorithm partitions the most homogeneous clusters first using a measure of impurity while isolating the largest homogenous category from the remainder of the data (McKay and Campbell 1982; Zambon et al., 2006). As a result, classification trees developed using the Gini splitting algorithm are less complex and therefore more easily understood by the analyst. For these reasons, the Gini splitting algorithm was selected for use in this study.

A key advantage of CTA is its ability to use both spectral and non-spectral data selectively during the splitting and classification process. This allows for the use of topographic data which may be equally important in modeling bare ground. Such ancillary data can be used with other supervised classification techniques (Lillesand et al., 2008) but classifiers like maximum likelihood use all input data to arrive at a final classification. This is in contrast to the advantage of CTA noted above, which selectively applies input data in its classification process.

MATERIALS AND METHODS

Study Area

This study focuses upon the xeric-steppes of the middle Ebro valley, Aragon, Spain and is referred to as the Monegros study area (Figure 1). The dominant plant species in the area is Rosemary (*Rosmarinus officinalis*) with various gypsophile plant species over a gypsum substrate in the most xeric areas. Scattered remnants of the original Juniper woodland community (*Juniperus thurifera*) are also present. The study area covers over 300 000 ha (3 000 km^2) with the valley receiving the majority of its water from the Pyrenees Mountains, yet it is a dry area with low precipitation (< 0.30-m annually).

Grazing activity in the area consisted of various flocks of sheep grazed under a semi-extensive regimen. Specifically, livestock were led by a shepherd to graze the fallow fields and rangeland steppe continuously throughout the year. Flocks were moved daily from shelters to the surrounding grazing areas where they stayed from morning until evening. Supplementary food was provided during the driest season and for reproductive females. Livestock productivity in the area is low, with an estimated stocking rate of 0.2 head ha^{-1} yr^{-1} (Pueyo et al. 2008).

Satellite Imagery

Satellite Pour l'Observation de la Terre 4 (SPOT 4) collects data in 4 spectral bands from the visible (545 nm band center [green] and 645 nm band center [red]) through near-infrared (NIR) (840nm band center) and short-wave infrared (SWIR) (1665 nm band center) portions of the electromagnetic spectrum. These data are stored as raster imagery having a spatial resolution of 20-m x 20-m. One SPOT 4 image was acquired on May 11, 2007 for use in this study. The SPOT 4 data were processed to top-of-the-atmosphere reflectance using the Cos(t) image-based correction method (Chavez 1988) in Idrisi Andes software (Clark Labs, Worcester, MA). The imagery was then georectified (RMSE = 8.3 m) using 0.5-m x 0.5-m aerial photography and projected into Universal Transverse Mercator (zone 30N, European datum 1950) using a first order affine transformation and nearest neighbor resampling.

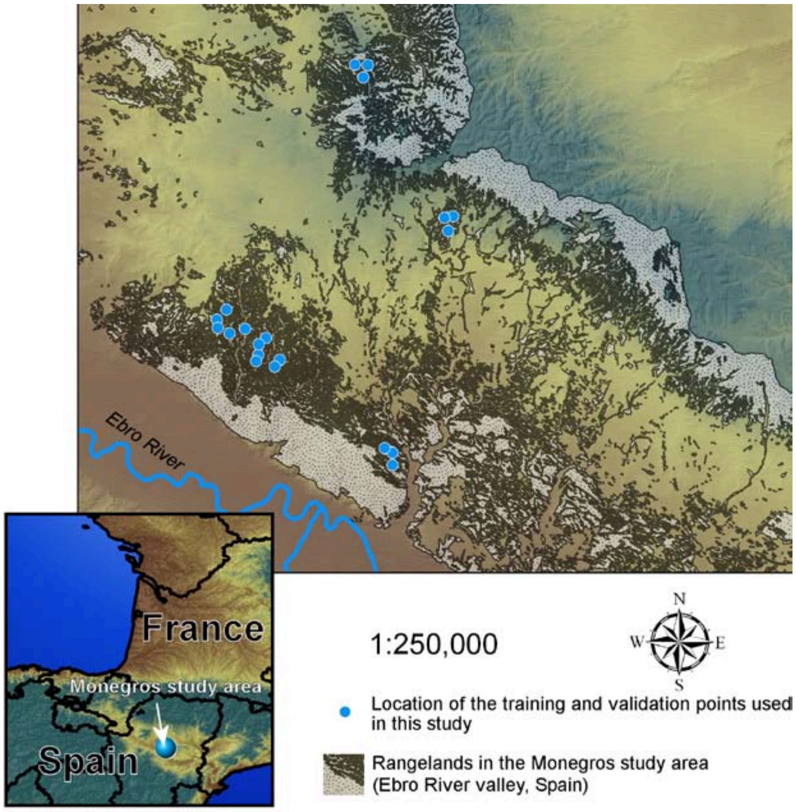

Figure 1. The Monegros study area in northern Spain. Note: due to scale, each individual sample point cannot be shown.

In addition to the atmospherically corrected SPOT 4 bands (1- 4), a normalized difference vegetation index (NDVI), moving standard deviation index (MSDI) (Tanser 1997, Tanser and Palmer 1999), principal components anlaysis (PCA) layers, and biomass estimates (Mirik et al. 2005) were also calculated within Idrisi Andes using SPOT reflectance data to develop a predictive model of bare ground for the Monegros study area.

The biomass layer is a simple ratio-type vegetation index where reflectance values from the short-wave infrared region (band) are divided by reflectance values from the green band. The resulting layer is an index and pixel values were not expressed in physical units. While Mirik et al. (2005) demonstrated a strong empirical relationship (R^2 = 0.87) between this index and actual standing crop biomass on rangelands, the relationship of the biomass index with actual above ground rangeland biomass at the Monegros study area was not performed as part of this study.

Topographic Data

A digital elevation model (20-m x 20-m pixels; RMSE = 7.42 [Pueyo 2005]) for the Monegros study area was acquired from the Confederación Hidrográfica Del Ebro (http://oph.chebro.es/ContenidoCartografico.htm). Slope (expressed in degrees) and aspect models were calculated in Idrisi Andes and a model of morphometric characterization (i.e., valley, ridge, pass, or flat) was developed using LandSerf software (Wood 1996). These topographic data (elevation, slope, aspect, and morphometry) were used to develop a predictive model of bare ground exposure.

Field Sampling

To estimate bare ground at the Monegros study area, sixteen 500-m transects were acquired between May 17 and May 24, 2004. The start location of each transect was recorded using GPS with eight transects located on north facing slopes and eight transects located on south facing slopes. Observations were made every 0.2m along each transect which described the cover type (plant species or bare ground) at that point (Gysel and Lyan 1980, Herrick et al. 2005). Percent bare ground was calculated for each 20-m segment of each transect and X- and Y-coordinates determined for the location of each segment. As each transect was oriented in an east-west direction the Y-coordinate remained constant along each transect line. The X-coordinate for each segment was determined by incrementing the beginning X-coordinate (+/- 10-m to shift the point to the center of the first line segment) by 20-m and repeating this process until the end of each transect was reached. Percent bare ground for each 20-m segment was subsequently represented as a point feature (n = 397) in all future analyses.

In May 2008, an additional 42 points were collected using GPS (+/- 0.3m @ 95% CI) which described bare ground only. Three bare ground classes were used: minimal (~ $\leq$ 10%), moderate (~ 10-50%), and high (~ $\geq$ 50%) with percent bare ground determined ocularly. All GPS locations were differentially corrected to minimize positioning error and improve coregistration among the data used in this study (Weber et al. 2008).

While two methods were used to collect field sample data these methods were considered complementary by the authors. Similarly, both McMahan et al. (2003) and Norton (2008) reported that these methods are applicable for ground truthing purposes especially where estimates are made at nadir and categorical cover classes are used to support image processing of remotely sensed data.

Data Preparation

All field sample locations (n = 439) were classified as either a 1) bare ground site (having $\geq$ 50% bare ground fraction [n = 129]), 2) non-bare ground site (having $\leq$ 10% bare ground [n = 65]), or 3) an intermediate site with 10-50% (n = 245) bare ground. Only bare ground and non-bare ground sample locations (n = 194) were used to develop the model as they effectively represented pure end-members. Sixty field sample locations were randomly selected using Hawth's tools in ESRI's ArcGIS and reserved as validation sites with 50% of the points selected from each class (bare ground and non-bare ground). The remaining locations were used as training sites (n = 134). The training and validation point shape files were imported into Idrisi Andes and rasterized using the same spatial parameters as the satellite imagery and topography layers described above (e.g., 20 x 20m pixels).

Image Processing and Accuracy Assessment

Spectral signatures for bare ground and non-bare ground training sites were extracted from all satellite imagery layers and examined for signature seperability. Most layers indicated some potential for separation between bare ground and non-bare ground sites save for PCA bands 2 and 3 which were subsequently removed from future analysis.

CTA was performed in Idrisi Andes using the Gini splitting algorithm (Zambon et al. 2006) with twelve input layers available for the classification process: green, red, near-infrared (NIR), and shortwave-infrared (SWIR) reflectance bands, NDVI and biomass band-ratios, MSDI band filter, PCA band one, and elevation, slope, aspect, and morphometry topography layers. Output included the resulting tree and a classified predictive model of bare ground with all pixels assigned one of two values; 1) bare ground site and 2) non-bare ground site. For comparison, a maximum likelihood classification was performed using spectral signatures from the same twelve input layers. Accuracy was assessed using a standard error matrix (Congalton 1991, Congalton and Green 2009) which reported user's accuracy, producer accuracy, overall accuracy, and the Kappa index of agreement statistic (Cohen 1960, Titus et al. 1984, Foody 1992, Monserud and Leemans 1992). Both error matrices were compared using Kappa and the variance of Kappa following Congalton and Green (2009) by calculating a pairwise Z-statistic (Equation 1).

$$Z_{\text{pairwise}} \quad \frac{|K_1 - K_2|}{\sqrt{\text{var}(K_1) + \text{var}(K_2)}} \tag{1}$$

Where K_1 and K_2 are the Kappa statistics for error matrices 1 and 2 and var(K_1) and var(K_2) are estimates of variance for matrices 1 and 2. The Z_{pairwise} critical value at the 95% confidence interval is 1.96.

RESULTS AND DISCUSSION

CTA classification yielded an overall accuracy of 85%, user's accuracy of 79%, and producer accuracy of 97% for the bare ground class (Table 1). The bare ground model had an overall Kappa of 0.70 and a Kappa Index of Agreement of 0.91 for the bare ground class alone. The Kappa scores indicate that the classification performed far better than a chance classification.

Table 1. CTA results for bare ground modeling in the Monegros study area in northern Spain

	Known validation sites			
Model results	Bare ground	Non-bare ground	Total	User accuracy
Bare ground	29	8	37	0.79
Non-bare ground	1	22	23	0.96
Total	30	30	60	
Producer's accuracy	0.97	0.74	Overall accuracy = 0.85	

Overall Kappa index of agreement = 0.70

Results of the maximum likelihood classification yielded an overall accuracy of 57%, user's accuracy of 54%, and producer accuracy of 83% for the bare ground class (Table 2). The Kappa score (0.13) indicates this classification performed only marginally better than a chance classification. While the same input layers, training sites, and validation sites were used for both classifications, CTA performed much better than the more traditional maximum likelihood classifier (Z_{pairwise} = 4.43; Z_{critical} = 1.96). The observed difference in performance is likely attributable to the way in which maximum likelihood functions with respect to the input layers the software is provided by the user. Maximum likelihood uses the spectral signature from all input layers to determine the output class of each pixel. As a result, some input layers may confuse the classifier and result in poor overall performance. This confusion is suggested in table 2 by the model over-committing pixels to the bare ground class.

Table 2. Maximum likelihood results for bare ground modeling in the Monegros study area in northern Spain

	Known validation sites			
Model results	Bare ground	Non-bare ground	Total	User accuracy
Bare ground	25	21	46	0.54
Non-bare ground	5	9	14	0.64
Total	30	30	60	
Producer's accuracy	0.83	0.30	Overall accuracy = 0.57	

Overall Kappa index of agreement = 0.13

In contrast, CTA can be given many input layers initially, but after running its splitting algorithm the final model may be based upon only a fraction of those layers. Subsequently, classification tree (Figure 2) can offer insight into the classification process by allowing the analyst to study what was identified as an indicator layer. In this instance, none of the raw imagery bands were selected for use in the classification with the exception of the SWIR band. In addition, the principal components layer was not used as well as the slope layer. The initial split chosen by the Gini algorithm was based upon elevation (~ 300m) where the elevation in the Monegros study area ranged from 137-805m ($\underline{x}$ = 354m). Within the lower elevation areas, moving standard deviation index (MSDI) was used but was not selected for use in the higher elevation areas. In the lower elevation areas, higher MSDI values were more indicative of a bare ground site than a non-bare ground site which agrees with Tanser and Palmer (1999) who reported that degraded or unstable areas exhibited higher MSDI values. SWIR reflectance was used to make two splits in the tree with the selected threshold values occurring at relatively low values (approximately 0.16 and 0.13, where the minimum value in the layer was 0.003 and the maximum value was 0.347) and below the mean (0.18). The biomass layer was also used by the Gini algorithm but was selected only within the low elevation branch of the tree. Here, low biomass values (< 6.2) were indicative of bare ground sites while all higher values higher were indicative of non-bare ground sites (x = 6.9).

Apart from the initial split which used the elevation layer, no topographic layers were used to arrive at a final classification for the lower elevation sites (38.8% of the Monegros study area). Instead, spectral information was used to finalize the classification of these areas. In contrast, the Gini algorithm used numerous topographic layers along with two spectral layers to classify the higher elevation areas (61.2% of the Monegros study area) including aspect (where westerly and northwesterly sites were more indicative of non-bare ground areas) and morphometry layers. One explanation for the increased number of variables used to classify bare ground above 300-m is the gradual increase in patch heterogeneity found in these areas. This is related to a higher proportion of residual forest and shrub land patches along the elevational gradient. The upper elevation areas were traditionally less used by local inhabitants as more favorable farming and grazing areas were found at lower elevations closer to the Ebro River. In most parts of the study area human activities such as timber harvesting, farming, and grazing, have been intensively developed for centuries (Pueyo and Alados, 2007). The result is these long-term anthropic disturbances has led to fragmented secondary communities which are very sensitive to aridity, and more directly related to past human activities than environmental factors (Pueyo and Alados, 2007).

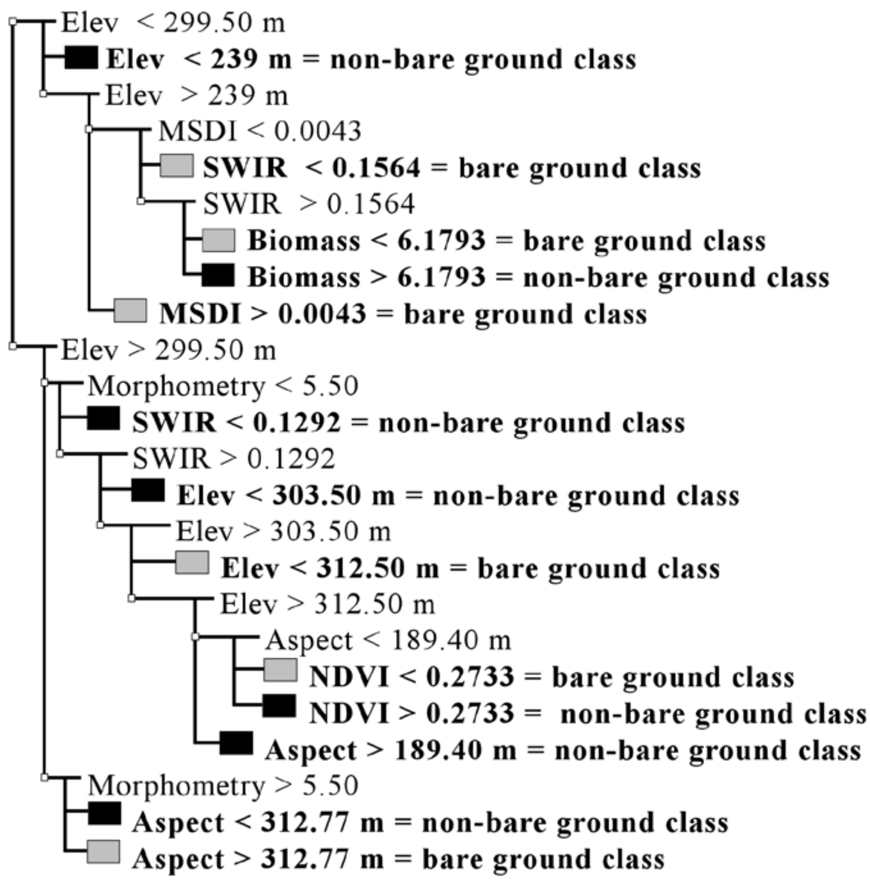

Figure 2. Classification tree produced for the bare ground model. Bold text is used to indicate where a final class decision was made: gray boxes = bare ground class and black boxes = non-bare ground class (bare ground sites were defined as having ≥50% bare ground).

The morphometry layer played an important role in the classification of higher elevation sites. Albeit a simple model, the morphometry layer described each pixel in the study area as either: valley (2 [23%]), pass (3 [3%]), ridge (4 [24%]), or flat (6 [5%]). During the classification, all values > 5.5 (i.e., flat areas) were differentiated from non-flat areas and then further split and classified using other layers. This corroborates well with field observations (Figure 3) where it was noted that the least amount of bare ground tended to be found in the flat areas between or at the foot of hills. These areas are sink sites and the result of where sediment and litter were exported from the hill top to the foot of the hill (Bilbro and Fryrear 1994; Belnap and Gillette 1998). As a result, soil fertility has increased, which favors the growth of a vegetation community dominated by rhizomatous grasses (Guerrero-Campo et al. 1999). In contrast the slopes have been more desiccated by wind (Aguiar and Sala, 1999) yielding more xeric conditions. In these higher elevation sites, NDVI and SWIR were the only spectral layers used with lower NDVI values (< 0.27) indicative of bare ground sites.

Figure 3. A photograph of the Monegros study area illustrating the effect of landscape morphometry on bare ground exposure. Very little bare ground exists in the flat areas (morphometry = 6) whereas much higher proportions of bare ground were found on the adjacent hilly sites. This phenomena was captured by the classification tree and used to improve the final model (cf. figure 2).

To further interpret the model, the 245 sample points previously removed from the classification process because they did not represent pure end-members (i.e., bare ground ranged from 10-50%), were cross-tabulated with the bare ground model. Similar in process to that described for the preparation of training and validation points, this shape file was rasterized for use in Idrisi Andes. As a result, 190 pixels were used in the cross-tabulation with 114 pixels (60%) falling into areas considered bare ground and 76 pixels (40%) falling into areas considered non-bare ground. Based upon field transect data, the mean bare ground at these sites was 31% suggesting that bare ground detection may be possible at levels below 50%. However, when additional CTA iterations were performed using training sites with bare ground ≥ 33%, classification accuracy decreased to 49% overall accuracy with a Kappa of only 0.03. This result suggests a bare ground detection threshold exists and a minimum of 50% bare ground is required to produce a model with reliable accuracies (i.e., > 75% overall accuracy; Goodchild et al., 1994).

CTA outperformed maximum likelihood (85% and 57% overall accuracy, respectively) in this study and produced classification accuracy results equivalent to those reported by Gokhale and Weber (2006) (87% overall accuracy). The previous study however, used Quickbird imagery (2.4-m pixels) while the present study accomplished comparable accuracies using 20-m pixels (SPOT 4). This provides a distinct advantage relative to both cost-effectiveness and the aerial extent covered by a single scene (~16.5-km x

16.5-km Quickbird; ~60-km x 60-km SPOT 4). These results suggest a need for additional research to learn more about the effect of spatial resolution on classification accuracy.

The results of this research indicate that CTA can be a valuable technique for the detection of bare ground in semi-arid rangelands where bare ground is $\geq$50%, especially when applied at landscape scales. Semi-arid ecosystems like the Monegros study area frequently exhibit plant cover <60 % (Aguiar and Sala, 1999) and the plant cover/bare ground fraction can change rapidly in response to disturbance. In these areas, detection of bare ground exceeding 50% can be beneficial to land managers as an early detection technique for land degradation and unsustainable use. While livestock grazing is common in the Monegros, stocking rate was considered relatively low (Pueyo 2005). However, the existing grazing management predisposes the areas near shelters to overuse as flocks frequent those pastures every day both before and after movement to/from the grazing areas. While daily movements of animals were typically < 3 km from shelters, the detection of bare ground in these areas is important for the management of critical water resources, which may otherwise trigger serious desertification processes.

CTA may have performed better than more traditional classifiers like maximum likelihood, because each branch and each leaf of the classification tree can use raster layers that may or may not have been used to finalize other branches or leaves of the same tree. This gives CTA the capability to fit a solution to each unique classification problem. In addition, while numerous input layers are available to the classifier, the classifier is not programmatically required to use each available layer. Rather, CTA will use only those layers offering optimal splitting. The user can then study the resulting tree to learn more about the landscape he/she is analyzing and in this way, CTA becomes a highly interactive human-machine learning system.

The results presented here do not imply that the best way to model bare ground is with those layers selected for this classification. Rather, one important result presented in this paper is the application of CTA for bare ground modeling and potentially other complex detection applications.

MANAGEMENT IMPLICATIONS

Where bare ground exceeds 50%, CTA appears to be a classification technique appropriate for modeling bare ground in semi-arid rangelands. The results presented in this paper are similar to those reported by Gokhale and Weber (2006) where Quickbird imagery and maximum likelihood classification was used for bare ground detection.

While spectral data were essential to this model, of equal importance were the topographic and morphometric characteristics of the landscape. This finding lends insight to both bare ground modeling and the potential capabilities of CTA. The results presented here should not be interpreted as the only way to model bare ground, but rather, CTA should be viewed as a powerful and flexible classification technique applicable to bare ground modeling with potential for application to other complex detection applications.

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