Detection Thresholds for Rare, Spectrally Unique Targets within Semiarid Rangelands

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ABSTRACT
Many factors influence classification accuracy and this study assessed detection thresholds for various sub-pixel targets using Quickbird multispectral imagery. Six iterations of maximum-likelihood classification were used to determine classification accuracy for 100 spectrally unique targets randomly placed over a semiarid rangeland site. Error matrices were calculated using independent validation sites and producer's, user's, and overall accuracy, Kappa Index of Agreement, and transformed divergence were analyzed to compare the performance of each classification and determine detection thresholds. Results indicate a strong relationship between target size and classification accuracy ($R^2 = 0.94$) as well as an increasingly prominent role played by training site selection as target size decreased. Strong spectral separability and good classification accuracies were achieved for targets >25% cover. Sub-pixel targets <25% in size were not detectable. This study highlights the effect of target size upon classification accuracy and has direct implications for invasive plant research and rare target detection.

KEYWORDS: sub-pixel classification, Quickbird, cover threshold, accuracy assessment

INTRODUCTION

Much has been written about the effects of various input parameters and processing decisions on classification accuracy. Researchers have investigated and described the 1) selection of appropriate classification algorithms (Foody and Arora, 1997), 2) effects of orthorectification (Cheng et al., 2003; Robertson, 2003; Toutin and Chenier, 2004; Wijnant and Steenberghen, 2004; Parcharidis *et al.*, 2005), 3) effect of mis-registration between image layers (Townshend *et al.*, 1992; Dai and Khorram, 1998; Stow, 1999; Roy, 2000; Verbyla and Boles, 2000; Wang and Ellis, 2005), 4) influence of spectral resolution (Mehner *et al.*, 2004), 5) effects of co-registration between training sites and imagery (Weber, 2006; Weber *et al.*, 2008), 6) influence of atmospheric anomalies and correction processes (Lillesand and Kiefer, 2000), and 7) effects of training site purity relative to minimum ground cover threshold (Mundt *et al.*, 2006). The result of these and other efforts has allowed geospatial scientists to construct a fairly complete error budget and, thereby, better understand and interpret image classification results. The latter topic is the focus of this paper with emphasis upon the detection threshold of sub-pixel targets.

In semiarid environments, the ability to detect sub-pixel targets is critical because landscape features such as sagebrush, shrubs, invasive weeds, and bare soil are frequently encountered in relatively small patches (i.e., 1-4 m^2). Past research investigating detection limitations in remote sensing have frequently focused upon invasive plants and have reported detection thresholds from 10% cover (Parker-Williams and Hunt, 2002) to 40% cover (Glenn *et al.*, 2005; Weber *et al.*, 2006) for leafy spurge (*Euphorbia esula* L.), 30% cover for hoary cress (*Cardaria draba*) (Mundt *et al.*, 2006), and 20% cover for Rush skeletonweed (*Chondrilla juncea*) (Mundt *et al.*, 2006). In all cases, detection thresholds in these studies were determined using hyperspectral imagery with high spatial resolutions (e.g. 5 m).

The purpose of this research was to experimentally address the following questions related to the reliable detection (i.e. $\geq$ 75% overall accuracy; Goodchild *et al.*, 1994) of spectrally unique, patchy, and rare targets within semiarid rangeland ecosystems: 1) what is the detection threshold (100%, 50%, 25%, 5%, and 1% of a pixel) that can be achieved using high spatial resolution multispectral imagery? and 2) what is the impact of target size and site selection on sub-pixel target detection and classification accuracy? To address the former objective various measures of classification accuracy and spectral separability were used including transformed divergence, error matrices, and the Kappa Index of Agreement (KIA). The latter objective (2) was addressed by exploring the variability of the above measures following six iterations of each classification trial and by examining the relationship between KIA and target size using linear regression analysis.

METHODS

Study Area

The experiment was performed in sagebrush-steppe rangelands of southeast Idaho approximately 30 km south of Pocatello, Idaho, at the O'Neal Ecological Reserve. This 50 ha site contains sagebrush-steppe upland areas located on lava benches. The Reserve receives <38 cm of precipitation annually (primarily in the winter) and is relatively flat, with a mean elevation of approximately 1,400 m (1,401-1,430 m). The dominant plant species is big sagebrush (*Artemisia tridentata*) with various native and non-native grasses, including Indian rice grass (*Oryzopsis hymenoides*) and needle-and-thread (*Stipa comata*) present throughout the Reserve.

Field Data

Throughout the study area, 20 target locations were randomly generated for each of five target sizes (n=100) (Table 1). Bright blue tarps were placed at each of these locations using the following set of criteria established for final placement in the field: 1) no part of the tarp was placed beneath vegetation, 2) tall vegetation (>1 m) that could cast a shadow on a portion of the tarp during image acquisition was not located near the tarps (+/-2 m), and 3) tarps were installed flat and horizontal to avoid deformation and changes in their apparent size within the imagery (Fig. 1). All blue tarps were secured into the ground using four to eight, 25 cm spikes approximately one month prior to the acquisition of remotely sensed imagery. The location of the tarps was recorded by occupying each site until 120 positions were acquired with a Trimble GeoXH GPS receiver. The averaged positions were post-process differentially corrected using data from five base stations each within 80 km of the Reserve. Resulting horizontal positional accuracy was +/- 0.3 m (95% confidence interval [CI]). An equal number of non-target points (n=20) typical of the semiarid rangelands found at the Reserve (i.e., sites dominated by big sagebrush) were randomly located throughout the study area and used as non-target training sites for all analyses and classifications. This was done to eliminate variability and bias due to disproportionate sample sizes. None of these points fell within 10 meters of a target site.

Table 1. Percent target size and actual target size of the five classes used in this study (note: Quickbird multispectral imagery has a spatial resolution of 2.40 x 2.40 m).

Target class (%)	Actual size (m)
100	2.40 x 2.40
50	1.70 x 1.70
25	1.20 x 1.20
5	0.55 x 0.55
1	0.24 x 0.24

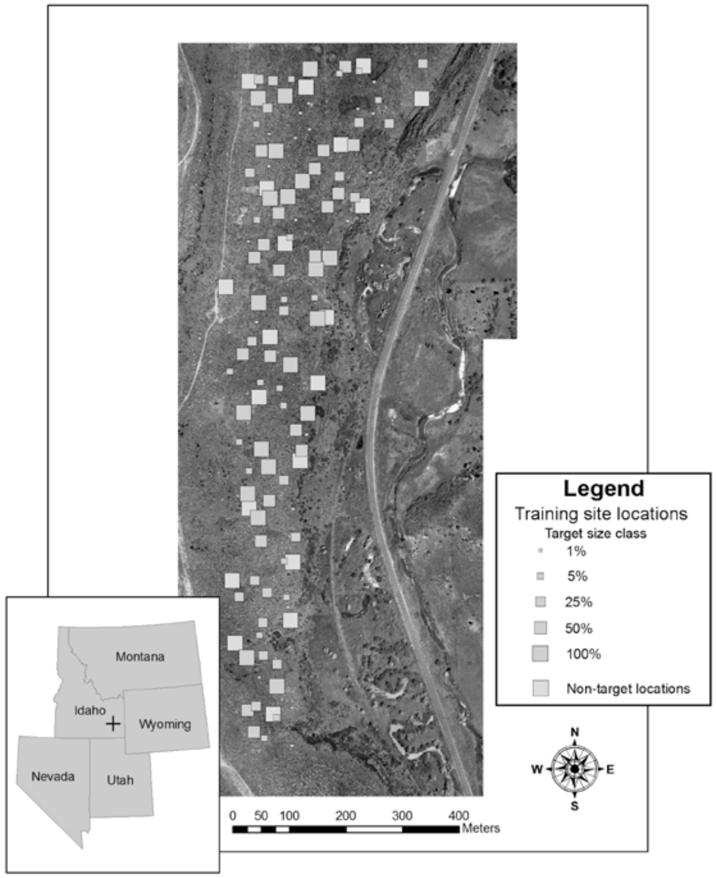

Figure 1. Map of study area with location of tarps (target sites) and location of non-target sites (note: the size of the training sites is not drawn to scale).

To better understand the results of subsequent classification, the spectral properties of the blue tarps targets were compared to the spectral properties of the common rangeland elements found at non-target sites using an Analytical Spectral Device (ASD) FieldSpecPro hand-held field spectroradiometer. Measurements were made during a sunny day (without clouds) at +/- 1 hour of solar noon prior to image acquisition. For each target, between 15 and 25 spectral recordings were taken. Spectral comparison included blue tarps, bare soil, basalt, low sagebrush (*Artemisia arbuscula*), and big sagebrush (*Artemisia tridentata*).

Imagery

Standard Quickbird imagery (July 6, 2009) was delivered by DigitalGlobe Corporation and projected into Idaho Transverse Mercator (NAD83) using nearest neighbor resampling to match the reference system of all other GIS data used in this study. The imagery was corrected for atmospheric effects using Chavez' Cos(t) model in Idrisi Taiga's ATMOSC module (Chavez, 1996). To improve georegistration of the imagery and co-registration between the imagery and ground truth locations (Weber *et al.*, 2008) within the relatively small, flat study area, five permanent ground control platforms were used. Each platform was 2.4 m x 2.4 m in size and stood 1.2 m above the ground. During satellite image acquisition periods, highly reflective silver tarps were tightly secured to the platforms. The location of the platform’s corners were recorded and processed in the same fashion as noted above. All five ground control platforms were used to georectify the Quickbird imagery using first order, affine transformation and nearest neighbor resampling (RMSE=0.678).

Analysis

To determine how small a target can be detected using high spatial resolution Quickbird multispectral imagery a series of supervised presence/absence classifications were performed. To accomplish this, a geodatabase feature class containing 100 points representing the location of the blue tarp sites was created. This blue tarp feature class was randomly resampled without replacement to select 50% of the points in each target size class (n=5 target size classes). This process was repeated six times (Table 1) to achieve a better estimation of classification accuracy (Weber and Langille, 2007). A single resampling event was used to randomly select 50% of the non-target training sites (n=10). The remaining non-target sites were used as independent validation sites.

Bootstrap resampling was used in this study (Good 2006) and for each target class 10 points were randomly selected while the remaining 10 points were reserved for validation. Ten non-target points were randomly selected and these same points were used in every classification trial while the remaining 10 non-target points were used in all validations. To eliminate between-trial variability in the non-target class iterative resampling of non-target sites was not performed.

The result of each resampling iteration produced two datasets for use in the classification process. The first dataset contained 20 training sites (10 blue tarp training site points per size class and 10 non-target training site points) and the second contained 20 validation sites (10 blue tarp points per size class and 10 non-target points). Each individual dataset was saved as a shapefile (n=30; 6 iterations of 5 size classes) and used to extract spectral signatures from Quickbird imagery (bands 1-4) at the locations of the training sitess using Idrisi's MAKESIG module. Spectral signature extraction is a required step for maximum likelihood classification and the resulting signature files statistically describe the spectral characteristics (minimum, maximum, mean, variance, and covariance) of those pixels identified as a target (i.e., the pixel contains a blue tarp) or non-target site (i.e., the pixel was a typical sagebrush-steppe rangeland site).

Spectral signatures were evaluated using the SEPSIG module of Idrisi which calculated a transformed divergence score (Richards and Jia, 2006). This score was used to indicate the separability of target and non-target sites for each spectral signature file (n=30). Using a constant value of 2000, spectral endmembers with separability values exceeding 1600 were considered good candidates for successful differentiation during the classification process. Regardless of the separability score, all maximum likelihood trials were completed (n=30).

A series of maximum likelihood classifications (Richards and Jia, 2006) were performed using Idrisi (MAXLIKE) and validated using the ERRMAT module, which calculates both a standard error matrix (Congalton and Green, 2009) and KIA (Cohen, 1960; Titus *et al.*, 1984; Foody, 1992; Monserud and Leemans, 1992). A cumulative error matrix (CEM) was developed by calculating the sum of each individual error matrix within each target size class. To determine the statistical difference among classification results, the CEM for a given target class was compared with the CEM of all other target size classes using variance of KIA by calculating a pairwise Z-statistic following Congalton and Green (2009) (Equation 1).

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

Where K_1 and K_2 are the KIA's 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

Detection threshold

Transformed divergence separability scores of the spectral signature files for the 100% and 50% target classes (*n*=6 signature files/target class) exceeded the threshold value of 1600 ($\bar{x}$ = 1998.8 and 1991.4 for the 100% and 50% classes, respectively), indicating the spectral signatures of those targets were statistically differentiable from the signatures of non-target sites. This result compares well with results from spectroradiometer analysis indicating the blue tarps were spectrally unique and separable from the adjacent matrix of features (Fig. 2). Four of six (67%) signature files for the 25% target class had transformed divergence scores in excess of 1600 ($\bar{x}$ = 1657.8), suggesting that under most instances targets with 25% cover were differentiable from non-target sites. Since the same non-target sites were used in all cases throughout this study, no effect can be inferred related to sub-sampling non-target sites. Rather, the observed difference in separability must be due to the specific combination of target training sites selected and the ground conditions within the remainder of the pixel not covered by the blue-tarp target. Only one of six signature files for both the 5% and 1% target cover classes had transformed divergence scores exceeding 1600 ($\bar{x}$ = 1172.0 and 1242.3 for the 5% and 1% classes, respectively) suggesting that a reliable classification at these cover levels was highly unlikely.

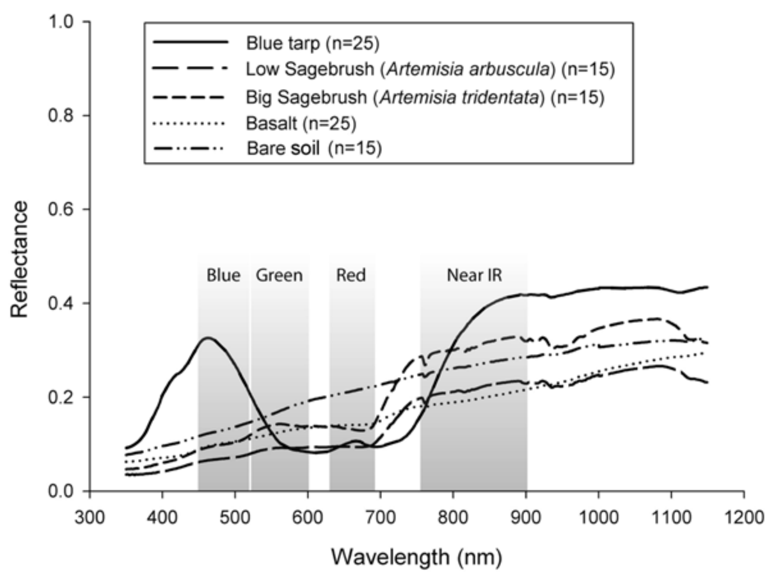

Figure 2. A comparison of spectral signatures from common rangeland targets and the artificial blue tarps used in this study. Signatures were acquired with a spectroradiometer and the mean signatures of n (15-25) spectra are shown. Quickbird image bands are shown in grey for reference.

Following six iterations of maximum likelihood classifications, mean producer's accuracy for the 100% blue tarp target class was 75%, mean user's accuracy was 92%, and mean overall accuracy was 84% (Table 2). While all measures of accuracy were reduced for the 50% target class ($\bar{x}$ overall accuracy =

70%) and even further reduced for the 25% target class ($\bar{x}$ overall accuracy = 69%), the user's accuracy exceeded 80% in all cases (*n*=6 classifications/target class). In contrast, the 5% and 1% target classes performed poorly with mean overall accuracies of 60% and 55%, respectively. In addition, both producer's and user's accuracies for the 5% and 1% target classes were $\leq$ 65% in all cases corroborating well with the results of separability testing reported above.

Table 2. Resulting measures of accuracy and standard error (SE) for each blue tarp target class following six iterations of maximum likelihood classification

	Accuracy (%)		
Target class (%)	**Producer's**	**User**	**Overall**
100	0.75 (SE = 0.05)	0.92 (SE = 0.03)	0.84 (SE = 0.02)
50	0.50 (SE = 0.08)	0.83 (SE = 0.08)	0.70 (SE = 0.05)
25	0.45 (SE = 0.03)	0.87 (SE = 0.05)	0.69 (SE = 0.02)
5	0.45 (SE = 0.11)	0.64 (SE = 0.09)	0.60 (SE = 0.04)
1	0.22 (SE = 0.08)	0.65 (SE = 0.15)	0.55 (SE = 0.07)

Target Size and Site Selection

Resulting mean KIA statistics reported a similar trend (Fig. 3) of decreasing agreement with decreasing target size (R^2 = 0.94) but also indicated that only the 100% target class resulted in substantial agreement (0.68) between known/modeled blue tarp target locations (Landis and Koch, 1977). Following Landis and Koch (1977) a fair level of agreement was found for the 50% and 25% target classes (0.40 and 0.38, respectively) while the mean KIA for the 5% and 1% target classes (0.20 and 0.10, respectively) were considered slight and similar to that expected from a chance (random) classification.

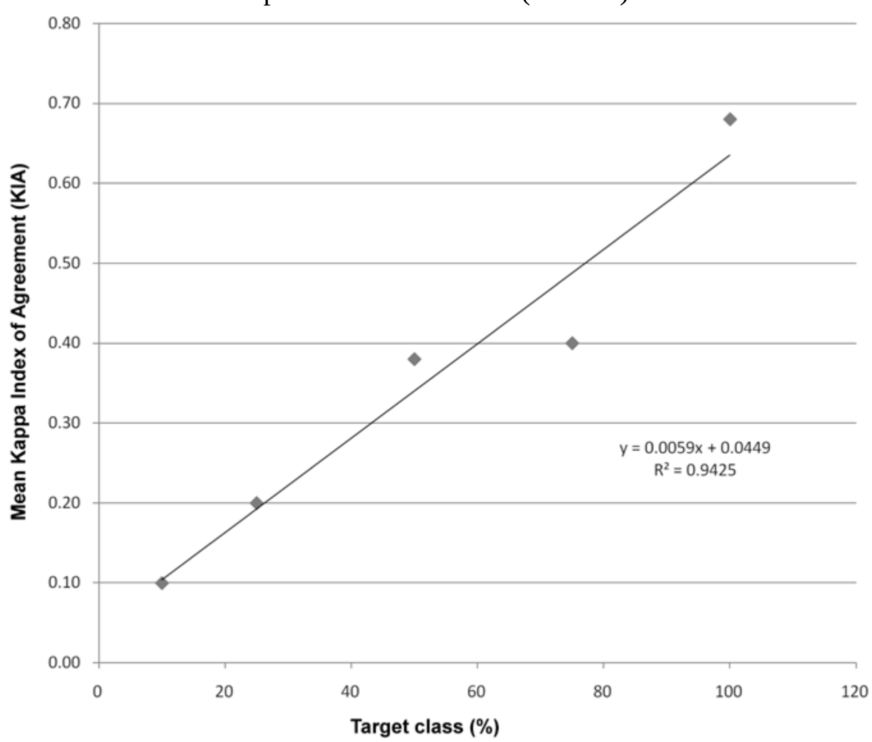

Figure 3. Mean KIA followed a strong negative trend with target class size. The line of best fit resulted in a coefficient of determination of 0.94

A pairwise Z-statistic was calculated to compare resulting error matrices between target classes (Table 3). These results indicate the 100% target class performed significantly better than all other target classes ($z > 1.96$). This may be attributable to the fact that the 100% target class had the potential to occupy full pixels homogenously while all other target classes represented sub-pixel, heterogeneous classes. While the size of the blue tarps used for the 100% target class were equal to that of a Quickbird pixel, it is unlikely that each tarp was positioned to perfectly fit the extent of a pixel as acquired by the sensor. Consequently, it is more likely that individual training sites contained <100% cover by a blue tarp. This same problem is encountered regularly in all field studies and the results reported here are considered applicable and valid. Indeed, target detection thresholds should be stated in terms of the size of the *in situ* target with full understanding that many training sites will be subdivided during image acquisition by the sensor.

Table 3. Pairwise z-statistic results comparing variance of Kappa from cumulative error matrices of each target class. Comparisons with z-scores > 1.96 represented significantly different classification results.

		Target Class (%)				
		100	**50**	**25**	**5**	**1**
Target Class (%)	**100**	--	2.84	3.16	4.56	7.46
	50		--	0.20	1.81	3.54
	25			--	1.67	3.47
	5				--	1.08
	1					--

The pairwise comparison between the 50% and 25% sub-pixel target classes showed no difference ($z = 0.20$) indicating these classifications performed similarly. The comparison between the 50% and 5% target classes had a z-score of 1.81 while the z-score comparing error matrices for the 25% and 5% target classes also showed no difference ($z = 1.63$). While the resulting classification accuracies reported in this study demonstrate the reliable detection of the 50% and even 25% target classes, the results of pairwise comparisons indicate that none of these classifications performed statistically different relative to one another.

Nearly all pairwise comparisons with the 1% target class were statistically significant (different) save for the comparison with the 5% target class ($z = 1.08$). In these cases, the overwhelming majority of each training site pixel was occupied by non-target features and classification results were similar to that expected by a chance (random) classification. It is not surprising then, that pairwise comparisons with the 1% target class showed statistical differences ($z > 1.96$) as effectively no trace of the blue tarp's spectra may have been present and classification results followed a random distribution. The 5% target class performed similar to the 1% target class for many of the same reasons, resulting in pairwise comparisons that showed no difference. These results serve to emphasize the observation suggested by the results of separability testing; targets covering < 25% of a pixel were unlikely to achieve reliable classification results under the conditions of this study.

Goodchild et al. (1994) suggested 75% overall accuracy be used as a benchmark of classification reliability and hence, detection. Under these guidelines, only the 100% target class achieved a reliable classification. However, the 50% and 25% target classes achieved a mean user's accuracy of >80%, albeit with producer's accuracies of only 50% and 45%, respectively ($\bar{x}$ KIA = 0.40 and 0.38, respectively). These results suggest that while the 50% and 25% target classes were spectrally differentiable, other classification methods (e.g., linear spectral unmixing or classification and regression tree) may be required to achieve accurate classification results with multispectral sensors. A detailed study of the resulting error matrices indicates there was confusion between target and non-target classes. This may be reduced however, by including simple band ratio layers (e.g., NDVI, MSAVI2), data reduction layers (e.g., principal components analysis image layers), or by excluding individual image bands where the greatest spectral similarity existed (e.g., the green and red bands in this study [Fig. 2]).

This study was performed using Quickbird satellite imagery (2.4 mpp) as this sensor's spatial and spectral characteristics best facilitated the need to accurately locate rare and spectrally unique, sub-pixel targets. In semiarid environments, this ability is critical because landscape features such as sagebrush, shrubs, patches of invasive weeds, and patches of bare soil are frequently encountered at the same spatial order (i.e., 1-4m). We believe these results may be applicable to other multispectral sensors regardless of the instrument's spatial resolution with 25% cover suggested as the detection threshold of these systems. However more research is required before such statements can be unequivocally made. To substantially improve the ability to detect small targets (i.e., < 0.25) the use of hyperspectral imagery may be required (Parker-Williams and Hunt, 2002; Glenn *et al.*, 2005) and/or techniques other than maximum likelihood to improve sub-pixel detection.

Assessment of Error and Bias

All efforts were made to design and execute an experiment that would rigorously and empirically test the detection capabilities of multispectral imagery relative to rare and spectrally unique targets in semiarid ecosystems. The results reported here may vary somewhat if repeated in other ecosystems but the ability to significantly reduce sub-pixel detection with multispectral sensors is not anticipated. In many ways, the results observed in this study may represent a best-case scenario as all targets were spectrally unique and both physically homogeneous (i.e., laid flat upon the earth with no neighboring shadow), and spectrally homogeneous (i.e., $\bar{x}$ standard deviation = 0.0001 for target spectra).

One potential error in this study relates to the exact placement of each target relative to the location and "edge" of each pixel acquired by the Quickbird sensor. It is possible, and indeed likely, that some of the targets were captured across pixels instead of within a single pixel as was assumed throughout the image analysis process. In these cases, target size was effectively reduced and the training site corrupted. For example, if a 50% blue tarp target site was captured across two pixels, the training site (located in the center of the target) might represent a 25% target spectrally as only a portion of reflectance from that tarp affected the training site pixel. This problem was most likely to have occurred with the larger target classes ($\geq$50%) and was less probable with smaller target classes (5% and 1%). This unavoidable error is not attributable to the experimental nature of this study but is common to all remote sensing studies and especially problematic with any study focusing upon patchy and rare target detection (e.g., the early detection of invasive weed infestations).

The number of samples used in this study presents another concern. To emulate the presence of rare targets, 100 blue tarps were prepared for this experiment, with 20 created for each target class. Of these 20, 10 were randomly selected to be used for training sites while the remaining 10 were used for independent validation in each trial, thus the sample size for each classification trial was 10. However, this bootstrap resampling technique was repeated six times to better capture the variability within the training site samples (Weber and Langille 2007). While this remains a potential bias of this study, it should be understood that the spectral variance of the blue tarp targets was very low ($\bar{x}$ std. dev. = 0.0001; $\bar{x}$ reflectance 0.07, 0.10, 0.06, and 0.26 for the blue, green, red, and NIR bands respectively) and the majority of variance was explained within the existing sample size. In addition, if the sample size were insufficient for this particular experiment, one would expect to see accuracy and KIA values that varied greatly between trials. This was not observed however, and indeed the standard error for all measures of classification accuracy were small for target classes $\geq$25% (Table 2).

CONCLUSIONS

This study sought to experimentally determine the detection capabilities of multispectral imagery and was not designed to develop and test new algorithms for sub-pixel classification. For this reason, the authors used a common classification technique (maximum likelihood) and only basic (atmospherically corrected) image bands (i.e., blue, green, red, and near infra-red). To address the objectives of this study, six iterations of maximum-likelihood classification were used to determine classification accuracy for 100 spectrally unique targets randomly placed over a semiarid rangeland site. Error matrices were calculated using independent validation sites and producer's accuracy, user's accuracy, overall accuracy, KIA, and transformed divergence were analyzed to compare the performance of each classification and determine detection thresholds. The results of this study suggest training site selection (both initial site selection in the field and the selection of sites during resampling operations in the laboratory) has significant effect on classification accuracy. This effect became more pronounced as target size decreased, as the standard deviation of overall accuracy increased from 0.06 (100% target class) to 0.16 (1% target class).

This study demonstrated 1) the applicability of transformed divergence separability scores as an indicator of potential classification success, 2) an empirical relationship (R^2 = 0.94) between target size and classification accuracy, and 3) the limitation of multispectral imagery for sub-pixel target detection. Regarding the latter, it appears the detection threshold of spectrally unique targets is approximately 25% cover within semiarid rangelands. This has direct implication for invasive plant research and rare target detection as targets such as leafy spurge or purple loosestrife may be undetectable until an infestation covers 25% or more of a pixel. If the results and relationships demonstrated in this study transfer directly to other multispectral sensors and furthermore, if Landsat imagery (30 x 30 m pixels) were used, then weed infestations would need to be 225 m^2 in area before the infestation would be detectable. This is problematic as land managers rely upon early detection for effective control and eradication of weeds.

While the classification results reported in this study for both the 50% and 25% target classes were not ideal (overall accuracy was <75%), the user's accuracy was satisfactory (>80%). To substantially improve the ability to detect proportionally small targets (< 0.25 pixel) the use of hyperspectral imagery may be required and/or techniques other than maximum likelihood (e.g., linear spectral unmixing or classification and regression trees) to improve sub-pixel detection.

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