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Determining target detection limits and accuracy delineation using an incremental technique

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Abstract

Classification of terrestrial materials using remotely sensed imagery is becoming an increasingly popular method to assess natural systems. This study uses predictions derived from remotely sensed hyperspectral images to determine minimum target detection thresholds and to statistically constrain classification accuracies. Minimum detection thresholds are determined using an iterative regression breakpoint technique, and accuracy is delineated by quantifying the variance above the correlation breakpoint. Assessing confidence and determining detection limits generates a greater understanding of the classification process and adds significant utility to the classified product.
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1. Introduction

Analysis of remotely sensed imagery provides a mechanism to assess the status or distribution of terrestrial materials (Lillesand & Kiefer, 2000; Ustin et al., 2004). Many recent studies have utilized high-spatial and/or high-spectral resolution imagery to map the presence, absence, and percent canopy cover of specific spectral targets, such as vegetative species (e.g., Glenn et al., 2005; Mundt et al., 2005; Parker-Williams & Hunt, 2002, 2004; Underwood et al., 2003). Assessment of classification accuracy is a critical step in remote sensing analysis and interpretation (Stehman & Czaplewski, 1998). Typically, the classification accuracy is tabulated using an error matrix of predicted (classified) versus known (reference) occurrences of a target (Congalton, 1991). These tabulations produce estimates of producer's, user, and overall accuracy, and may also be used to calculate statistical measures of accuracy such as Kappa and Z-statistics (Congalton & Green, 1999; Foody, 2002, 2004).

Congalton and Green (1999) document the development of accuracy assessment techniques in three stages: (1) no assessment, (2) qualitative general assessments (non-site-specific), and (3) quantitative site-specific assessments generating measures of producer's, user, and overall accuracy. While these methods have great utility and widespread application, simple site-specific accuracy tabulation, and significance quantification do not fully describe classification accuracy (see following discussion), leaving room for interpretation or misrepresentation. This paper builds on previous methods by assessing target detection limits and defining statistical delineation on classification accuracy, thereby providing a method to make accuracy assessment more consistent and meaningful.

From previous work (Glenn et al., 2005; Mundt et al., 2005) and under the assumptions of linear mixing (e.g., Roberts et al., 1993), it is inferred that pixels containing a higher proportion of target material will generally classify correctly more often than pixels containing a lower proportion of target material (assuming uniform reflectance characteristics of all objects within each pixel). This study presents a new, empirically derived method to consistently and quantitatively define the range of potential accuracies from classification, thereby

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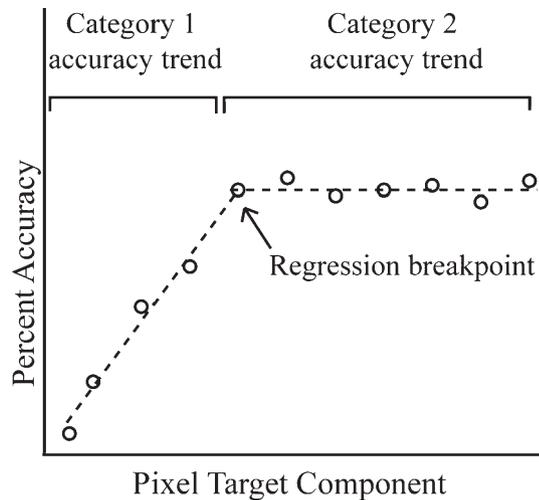E-mail address: jmundt@adaweb.net (J.T. Mundt).

Fig. 1. Empirical relationship illustrating idealized accuracy trends. The Y axis indicates accuracy and the X axis represents the proportion of a pixel occupied by the target (target component).

delineating the accuracy bounds and determining a minimum detection threshold. This quantification is derived through evaluation of the bivariate relationship between classification accuracy and nominal bins of percent target cover.

Incremental quantification of accuracy plots (herein referred to as incremental analysis) describes two characteristic accuracy trends (Fig. 1). The first exhibits increasing accuracy with an increasing proportion of the target component per pixel. This is termed a category 1 accuracy trend. The second trend is exhibited when targets have a higher percent cover with classification accuracies varying about a mean value (projected accuracy) and is defined as a category 2 accuracy trend. The transition between these two accuracy categories represents the limit of predictable detection, or the regression breakpoint. Above the breakpoint, the accuracy variance (category 2 variance) statistically delineates the expected range of category 2 accuracy.

This paper does not address all aspects of uncertainty in nominal data classification, but does note the important role subjective determination plays in understanding uncertainty (Longley et al., 2005). For example, the decision that a field site is representative of shrublands versus grasslands may be subjective, even when using consistent methods by a single observer. Furthermore, the fact that some proportion of a target must exist before its presence is recognized influences field data collection, model classification, and validation. As a result, an inherent error exists when modeling natural systems using crisp logic (Sauder et al., 2003), where each pixel is classified as either target type A, B, or Z. This paper addresses the propagation of these errors through the statistical derivation of accuracy delineation.

2. Study area and image acquisition

The demonstration area for this study is in Ada County, Idaho (Fig. 2), and classifications of hoary cress (*Lepidium*

draba) and rush skeletonweed (*Chondrilla juncea*), both noxious weeds in the State of Idaho, are used as classification targets. Hoary cress infestations in the study area range from isolated and small (less than 10 m^2) with low percent cover (<10%) to large (contiguous hectares) with high percent cover (~100%). As described by Mundt et al. (2005), hoary cress in Ada County is typified by two distinct growth regimes: mesic (containing slightly larger and higher percent cover infestations) and xeric (with smaller and lower percent cover infestations). Rush skeletonweed in Ada County is widely distributed with most areas typified by low percent cover, while other areas have abundant patchy high percent cover infestations. There are relatively few areas where rush skeletonweed is absent. It is dominantly found on sandy slopes with seasonal/ephemeral drainage patterns. The rush skeletonweed canopy is typically open, even at high stem density, and rarely obscures background (soil) reflectance.

Hoary cress and rush skeletonweed classifications were derived from HyMap hyperspectral imagery (HyVista, 2005). The HyMap sensor collects 126 contiguous spectral bands between ~ 350 nm and ~ 2500 nm, with spatial resolution of approximately 3.5 m. The hoary cress flight line (collected on May 21, 2003 while the plant was in full bloom) covered an area approximately 40 km^2 and dominantly included irrigated agricultural land, a riparian corridor, and adjacent xeric communities. Two images were collected to classify rush skeletonweed, the first on July 10, 2003 and the second on August 11, 2004. In neither of these images was the rush skeletonweed at peak bloom, which occurs in late August in the study area. The rush skeletonweed flight lines were located in the foothills surrounding Boise, Idaho, which are dominated by semiarid grass/shrub-steppe ecosystems with sandy soils. The 2003 and 2004 rush skeletonweed flight lines overlapped approximately 70%, and individually covered an area of approximately 30 km^2.
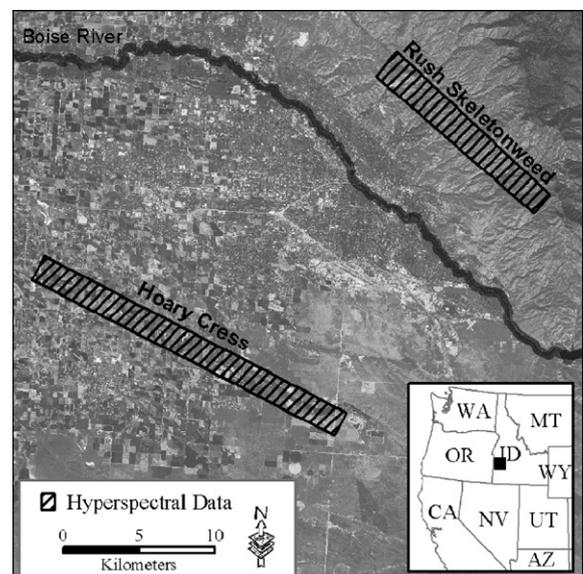

Fig. 2. Demonstration areas in Ada County, Idaho and the location of hyperspectral imagery flight lines for hoary cress and rush skeletonweed detection.

3. Field data collection

At each of the field areas, ground survey teams collected global positioning system (GPS) polygons (minimum 30 m^2) representing locations of weed presence (infestations) and absence. GPS data (collected using a Trimble GeoXT) were both real-time (WAAS) and post-process differentially corrected. Validation plots were selected using a modified stratified random sampling method (random locations filtered by logical improbability and accessibility), resulting in spatially distributed validation plots. There are many methods to sample vegetative cover in the field (Bråkenhielm & Qinghong, 1995), and this study utilized oblique visual methods to efficiently sample across a large study area. At each field plot, crews estimated percent cover either discretely (e.g., 37%) or by estimating 10% increments (e.g., 30–39% cover). For subsequent analysis, 10% increments were used as bin sizes. A total of 158 validation plots were collected for hoary cress (110 positive and 48 negative). Rush skeletonweed validation used 146 plots (103 positive and 43 negative) for the 2003 image and 119 plots (85 positive and 34 negative) for the 2004 image.

4. Image processing

In this study, image processing followed detailed methods presented by Glenn et al. (2005) and Mundt et al. (2005). Images were geometrically corrected and converted to units of apparent reflectance by the data vendor (corrections included a topographic adjustment based on USGS 10 m DEMs). Upon receipt, the images were tested for spectral consistency using field spectra collected using an analytical spectral device (ASD) full range spectrometer and tested for geometric accuracy using differentially corrected GPS ground control points. No modifications were made to either the geocorrection or the atmospheric correction of the images. All data sets were spectrally reduced using the minimum noise fraction transform (MNF; Green et al., 1988; Lee, 1980) to reduce data redundancy and increase target contrast. Classification training pixels were manually selected from the MNF images, and the spectral angle mapper (SAM; Kruse et al., 1993) classifier was utilized to generate all final presence/absence distribution maps.

It was determined that a 62 band visible–near infrared (452 nm–1307 nm) spectral subset optimized the separability of the rush skeletonweed training pixels from background vegetation (the 859 nm and 872 nm bands were removed due to sensor overlap). The rush skeletonweed classification utilized 60 of the 62 output MNF bands for classification; removing MNF bands 1 and 2 as they were dominated by topographic variance (elevation and slope). Iterative processing demonstrated no significant difference in classification output with further sub-setting the MNF spectral bands (such as using 80% cumulative variance as described below for hoary cress). A training set of 3 pixels, which was manually selected in the imagery from a known high percent cover infestation, served as classification input. The validation

Table 1
Matrix accuracies derived for hoary cress and rush skeletonweed in Ada County, Idaho

	Producer's accuracy (%)	User accuracy (%)	Overall accuracy (%)
2003 hoary cress	66	92	72
2003 rush skeletonweed	52	98	66
2004 rush skeletonweed	51	98	64

polygon corresponding to the training pixels was not used for accuracy assessment (the data sets were kept independent). Selections of the final presence/absence distributions of rush skeletonweed were selected using a threshold of 0.7 rad (in MNF space) for both years.

For hoary cress processing, the spectral separation between target and background was optimized when using the full spectral range of the imagery (bands at 1491 nm and 2492 nm were removed due to decreased signal to noise ratio). The hoary cress classification utilized the first 39 output MNF bands, which comprised 80% of the cumulative variance (confidently including all coherent variance while excluding noise dominated bands). A training set of 50 pixels, which were manually selected in the imagery from multiple known high percent cover infestations, served as classification input (independent selections and classifications were made for the mesic and xeric regimes; for more details, see Mundt et al., 2005). Due to the relatively large number of geographically distributed training pixels, it was assumed that much of the site-specific spectral information (local reflectance characteristics) was randomly minimized. As such, all validation polygons were used for accuracy assessment of hoary cress (158), including those used for classification training (~8). Selections of the final presence/absence distributions of hoary cress were selected using thresholds of 1 and 0.75 rad (in MNF space) for mesic and xeric hoary cress, respectively.

Following classification, all images were assessed for producer's, user, and overall accuracies. These accuracies (Table 1) are consistent with the final output of other target detection studies (e.g., Congalton, 1991; Glenn et al., 2005; Parker-Williams & Hunt, 2002). Despite the high user accuracies presented in Table 1, an analyst or land manager may determine the classifications suspect because of the generally low producer's accuracies. Further, though the rush skeletonweed classifications are roughly equivalent, one may consider the 2003 classification superior due to slightly higher producer's and overall accuracies.

A complimentary understanding of the classifications is obtained through incremental analysis of the accuracy. This technique adds significant utility to the output classifications. Because this study focused on targets with relatively high user accuracies, only producer's accuracy is discussed in this manuscript. It follows that parallel analyses of user accuracy may produce interesting and applicable results specific to other studies.

5. Incremental analysis methods

Incremental plots were analyzed using a three-step process: (1) regression breakpoint determination, (2) quantification of category 1 accuracy, and (3) quantification and delineation of category 2 accuracy. Accuracy breakpoints were determined using an iterative linear regression technique.

The coefficient of determination (R^2) between producer's accuracy and percent cover bin was calculated and subsequently used to test for the significance of R^2 (Davis, 1986). This test was repeated iteratively for the same data set, incrementally removing the lowest percent cover bin. For example, in a typical analysis, the first test considered all points, the second considered only points with greater than 9% cover, the third considered only points with greater than 19% cover, etc. When regression significance testing failed to reject the null hypothesis that the relationship was due to random chance (95% confidence, $P = 0.05$; Davis, 1986), the lowest percent cover increment included in the analysis was considered the limit of predictable detection (breakpoint). Below this breakpoint, there is a characteristic increase in classification accuracy with increase in percent target component, while above this breakpoint, there is no significant bivariate relationship (the classification accuracy is within a predictable range).

In this study, category 1 accuracy is represented by the R^2 value of all points below the breakpoint. Higher category 1 accuracy is indicative of a more characteristic accuracy behavior, while lower category 1 accuracy may indicate spectrally indeterminate or mixed targets, which are more difficult to differentiate from background. This is a logical response, for infestations with a larger target component in the same phenological stage will be spectrally similar to the training spectra (in this case, pixels from a high percent cover infestation), and will lie more closely in n-dimensional space than will pixels with a smaller target component.

Because the data within the category 2 accuracy range has no significant bivariate relationship, its characteristic is best represented by an average value, or projected accuracy. The bins defining this projected accuracy have individual deviation from the average value, and these deviations are used to generate a measure of the variance in the category 2 classification accuracy (in standard deviations, σ). Henceforth,

it can be said that the category 2 accuracy of a given classification is characterized by the projected accuracy value, the accuracy range is based on the standard deviation of the category 2 accuracy, and is constrained by the number of standard deviations defining the accuracy range (1σ, 2σ, 3σ, etc.). As such, it is possible to have two very similar classifications, yet one classification may have tighter delineation because the category 2 variance is smaller (i.e., tighter delineation indicates a more predictable classification).

6. Analysis—hoary cress

Incremental plots of hoary cress accuracy are illustrated in Fig. 3. Fig. 3A illustrates the R^2 value of all data points is 0.63, but reduces to 0.26 for canopy cover greater than 19%. While 0.26 is a relatively low R^2 value, significance testing rejects the hypothesis that this relationship is random (there is a significant relationship between the variables at 90% confidence). The bivariate relationship at percent covers greater than 29%, however, determined an R^2 value of 0.06, which failed to reject the hypothesis that the relationship may be due to random variability (95% confidence, t-stat $= 1.92$, t-critical $= 2.02$). Thus, this point ($>29\%$ cover) was determined to be the breakpoint between category 1 and category 2 accuracies, and 30% was estimated to be the minimum percent cover necessary for predictable detection of hoary cress.

Incremental analysis of the hoary cress accuracy (Fig. 3B) illustrates the two characteristic trends of accuracy behavior. The first characteristic trend is demonstrated by the low percent cover infestations ($<29\%$) having a strong bivariate relationship between infestation percent cover and classification accuracy ($R^2 = 0.99$). This strong relationship indicates that hoary cress is a spectrally distinct target. The second characteristic trend of this plot demonstrates accuracy variance about a projected accuracy for infestations with higher percent cover ($>29\%$). Because the bivariate relationship is statistically weak, the distribution of these six points is more appropriately described by an arithmetic mean, or projected accuracy, than by an increasing trend. This mean (83%) becomes the characteristic target detection accuracy for hoary cress (the expected accuracy at and above the regression breakpoint), and the standard deviation about the mean (13%)
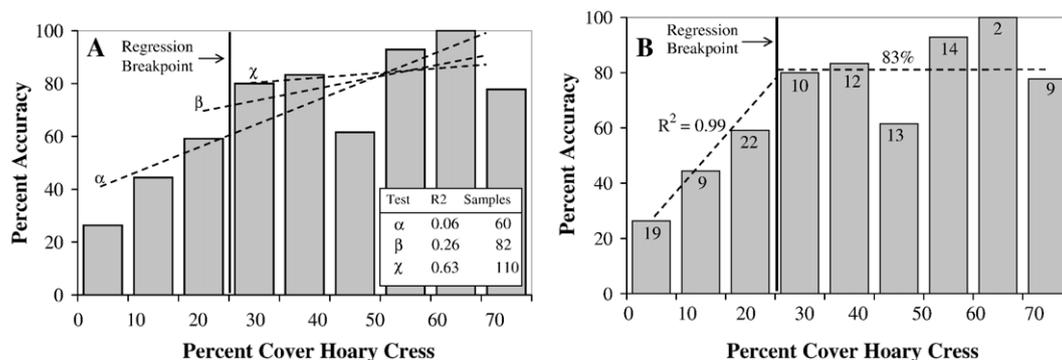

Fig. 3. (A) Regression testing to determine the regression breakpoint, in which significance testing of R^2 indicates predictable detection occurs at percent covers greater than 29%. (B) Incremental plot for hoary cress with a projected accuracy of 83%. Column labels indicate sample size in each bin.
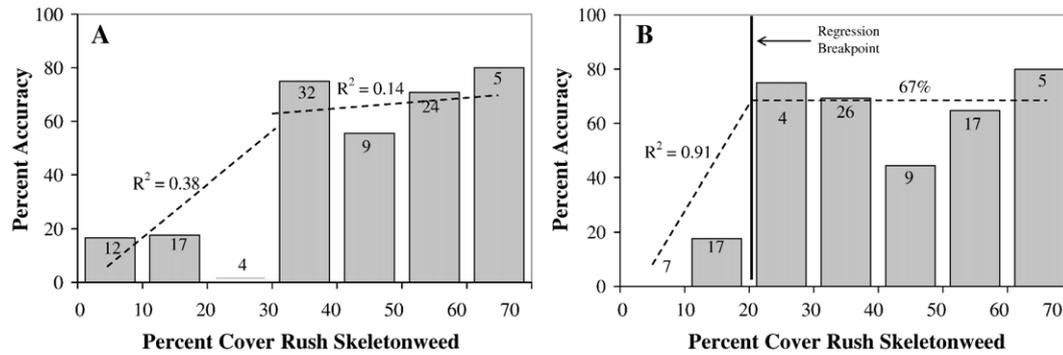
Fig. 4. Incremental plots for rush skeletonweed. The 2003 classification failed to return a regression breakpoint (A), while the 2004 classification returned a projected accuracy of 67% (B). Column labels indicate sample size in each bin.

describes a 1σ accuracy delineation. Thus, it can be said for hoary cress infestations with >29% cover that the classification accuracy is 83% with an accuracy range of ±13% and a 1σ accuracy delineation.

7. Analysis—rush skeletonweed

The characteristic trends of categorical accuracy are most clearly illustrated in the 2004 rush skeletonweed classification (Fig. 4). In both rush skeletonweed classifications, the category 1 accuracy is generally low, which is expected for an indeterminate target on bright background. It is notable that the 20–29% cover class had zero percent accuracy in 2003 and 75% accuracy in 2004. This is primarily attributed to the fact that there are only four samples in the 2003 cover class (bin), and it is hypothesized that increased sample size in 2004 may have resulted in more predictable accuracy behavior. Additionally, because the 2004 imagery was collected one month later than the 2003 imagery, the phenological state of rush skeletonweed may not have been the same between images. This, combined with potentially increased cover over one calendar year may have amplified the distinction between rush skeletonweed and senescent background vegetation, increasing the likelihood of detection.

Significance testing of the 2003 classification failed to determine a regression breakpoint. Fig. 4A illustrates the best potential analysis for breakpoint determination; however, the coefficient of determination (0.14) produced a *t*-statistic of 3.33 which exceeded the critical value of 2.00. As such, to 95% confidence, it can be stated that the accuracy variability above 30% cover is not random, but rather is characterized by an increasing trend (category 1 accuracy behavior). Because no regression breakpoint was determined, the projected accuracy, accuracy range delineation, and minimum detection thresholds cannot be quantified.

The 2004 classification did produce a regression breakpoint for canopy cover greater than 19%. Above this breakpoint, the coefficient of determination (0.01) failed to reject tests for randomness and, as a result, accuracy behavior is best described by a mean value (67%). The category 2 accuracy for rush skeletonweed ranges between 53% and 81% in 2004 (1σ range delineation of ±14%).

8. Discussion

Comparison of category 1 accuracies indicate that hoary cress may be more easily detected than rush skeletonweed at low percent cover. This is intuitive considering the white flowering head of hoary cress and the sparse, spectrally indeterminate nature of the rush skeletonweed. Category 2 accuracies (Table 2) illustrate that the hoary cress classification performed better than either rush skeletonweed classification. Further, this quantification illustrates the expected lower delineation on the hoary cress classification accuracy (minimum expected producer's accuracy) is 70% (1σ range), which for many applications is an acceptable level of accuracy.

While the error matrix approach did not demonstrate a significant difference between the 2003 and 2004 rush skeletonweed classifications, the incremental evaluation method demonstrates that the 2004 classification is superior. Because a regression breakpoint could not be determined, the lower detection limit, projected accuracy, and accuracy delineation could not be quantified for the 2003 classification. This has important repercussions when considering the overall quality of a classification, and how it may be used, and demonstrates a clear advantage of using the incremental analysis technique in addition to a standard error matrix.

The results of this study were empirically derived using data that were not collected specifically for this type of analysis, and as such, the numbers of samples per bin are inconsistent, and some bins have low numbers of samples (average of 12–15, but ranged between 2 and 32). This limitation may introduce a bias that potentially increases the category 2 accuracy range (lowers the σ delineation), and similarly may decrease the category 1

Table 2
Category 2 accuracy comparison for all targets

Target	Lower detection limit (% cover)	Mean accuracy (projected accuracy)	Accuracy delineation (1σ)	Accuracy range
Hoary cress	29	83%	± 13%	70–96%
Rush skeletonweed (2003)	N/A	N/A	N/A	N/A
Rush skeletonweed (2004)	19	67%	± 14%	53–81%

correlation. Typical remote sensing analysis calls for approximately 50 samples per class as an appropriate sample size (Congalton & Green, 1999), which may also be applicable to this technique. Future work may wish to use this approach to determine an appropriate sample size by optimizing sample size against the R^2 value for category 1 accuracy and the variance about the category 2 accuracy. Alternatively, future work may incorporate a simulation approach to increase sample size.

Another source of potential error is the 10% canopy cover bin size. Field estimations of percent cover can be biased with higher variance than the bin size and thus future studies may wish to evaluate the effect of bin size and field sampling protocols on the analysis output. Additionally, it has been hypothesized that field-sampling techniques generally positively bias field percent cover estimates when the vegetation is taller than 12 in. (e.g., Mundt, 2005). In this study, a positive field sampling bias would result in an increased (higher percent cover) breakpoint, thereby conservatively estimating classifier performance with negligible effects on the category 2 projected accuracy.

The regression breakpoint between category 1 and category 2 accuracy indicates the statistical cutoff between predictable and unpredictable target detection. This provides a quantitative measure of the limits of either the input data set (spatial/spectral resolution) or the classification algorithm. This knowledge benefits land managers through the determination of the limitations of remotely sensed classifications of invasive species. Additionally, the quantitative measure allows remote sensing analysts to determine where unique spectral differences become lost in background. This in turns assists in the development of new algorithms or approaches that are better able to differentiate low percent cover targets. While low percent cover targets are not reliably detected, this study demonstrates that they can be detected. As such, it is important to collect and validate low percent cover targets, because in some situations low producer's accuracy may be more desirable than no information at all.

To determine the breakpoint threshold, this study utilized a regression breakpoint technique at the 95% confidence interval. Determination of this breakpoint may have alternatively been achieved through other methods, such as the fitting of a polynomial curve to the scatter and derivation of the threshold through a modified variance modeling approach. However, a polynomial approach may have multiple solutions, and the use of a regression technique provides a simple approach to consistently derive a single solution. Future work may wish to explore the potential for using alternative methods to derive the breakpoint.

The central quantitative measure in this study is the mean accuracy of the category 2 trend or the projected accuracy. It should be noted that based on the category 1 to category 2 relationship, the projected accuracy will never be lower than the producer's accuracy generated in a standard confusion matrix. Thus, the producer's accuracy may be a general measure of accuracy, while the projected accuracy should be used as a measure of classification accuracy above a minimum detection threshold (regression breakpoint). It is assumed (due to spectral confusion) that there will always be some variance about the projected accuracy, and the projected accuracy will not reach 100%, regardless of how spectrally distinct the target is. In the case where producer's accuracy is 100%, the user accuracy should be critically evaluated, the classification should be explicitly validated to eliminate the potential for target occurrences missed by the classification, and proper distribution of target cover in the incremental analysis should be verified.

While this study focused its efforts upon vegetation, the methods presented herein are applicable to any object (target) observed using optical passive remote sensing techniques. As such, these methods have broad implications for accuracy assessment of any terrestrial target, vegetative or not. It is further notable that, while this study used SAM classifications, incremental analysis only requires the "best" classification as input, which could be derived from any combination of algorithms (e.g., spectral angle mapper, mixture tuned matched filtering, linear spectral unmixing, constrained energy minimization, receiver operating characteristic, etc.) and classification thresholds. While specific image processing details will affect model accuracy, the technique described here is independent of processing methodology, making use of the results derived from any classification. This study utilized this method to compare different data sets, but future work may wish to explore the effect of processing methods on accuracy using the same methodology.

9. Summary

Each of the three classifications in this study had relatively low Producer's accuracy based solely on a standard error matrix; however, incremental analysis determined the target detection limit, above which classification accuracy was more reliable. Further, classifications for canopy covers above the regression thresholds were delineated to an expected accuracy range. From this, the hoary cress classification was determined to be an adequate result, with a lower accuracy delineation, which still satisfied the needs of local land managers. Error matrix tabulations of the two rush skeletonweed classifications were very similar; however, incremental analysis demonstrated that the 2004 classification provides more useful information than the 2003 classification, even though the 2003 classification demonstrated slightly higher producer's and user accuracies in the standard error matrix. The 2004 classification provides a minimum detection threshold at an acceptable level (e.g., 67% accuracy for 20% cover).

While the techniques presented in this manuscript are useful to understand the limitations of a classification, every remote sensing study will likely not employ this methodology due to logistical complications of collecting large amounts of validation data. However, this technique does offer an opportunity to explore scalability of natural systems analysis. For example, since this technique has already been applied to hoary cress and rush skeletonweed in Ada County, land managers can make an informed weed management decision about the minimum detection limits and classification accuracy. Alternatively, this analysis could be repeated using high spatial resolution

multispectral sensors to compare output products to determine which sensor type best suits management needs.

For management applications, remote sensing classifications must commonly reach a minimum percent accuracy in order to be utilized. Previous studies have utilized the error matrix approach to define the accuracy of the project classification; however, this study indicates that these measures do not fully represent classification reliability. Evaluating only the error matrix, or worse, only the producer's, user, or overall accuracy, may lead to inappropriate and misleading conclusions. In order to determine the relative or absolute quality of a classification, statistical accuracy delineation based on percent canopy cover can, and should, be used.

Acknowledgements

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