

## **Rangeland Health Modeling with Quickbird Imagery**

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### **ABSTRACT**

Rangeland health is very important for ranchers, farmers and land management agencies. It is also important to identify different rangeland health parameters and evaluate their impact on rangeland health. This study obtained various data describing rangeland health conditions in southeastern Idaho and prepared a rangeland health model using Quickbird multispectral satellite imagery. Five elements were chosen to evaluate rangeland health: presence of cheatgrass (*Bromus tectorum*), bare ground exposure, litter, percent shrub cover, and percent grass cover. A field survey collected information (percentage, dimensions etc.) for all the above parameters (n=424). These data was used to create 'training sites', which were then used to "teach the software" what each parameter "looks like" within the satellite imagery. IDRISI, a raster based software application, was used to perform various data analysis operations using individual bands and vegetation indices derived from the Quickbird imagery. Data redundancy was reduced using Principal Component Analysis (PCA). Spectral signature extraction was performed using the training sites and components created during the PCA process. Signatures were purified and then classified using maximum-likelihood. The purification process improved overall image classification accuracy by removing outliers and other non-typical training sites. Accuracy was determined by creating an error matrix and calculating the Kappa statistic for the each classification. All rangeland health parameter models as well as a slope and soil erodibility model were then combined in a multi-criteria evaluation to produce a rangeland health model. The rangeland health model was validated in 2005 and produced overall accuracies of 62-91% when a 15pt and 25pt error margin was applied, respectively.

*Keywords: rangeland health, multispectral imagery, Quickbird, Principal Component Analysis (PCA), maximum likelihood*

## **INTRODUCTION**

Rangelands occupy approximately 801 million acres in the continental United States. Healthy rangelands are important for wildlife, recreationists, ranchers, farmers, land management agencies, and many rural economies. Typically, definitions of rangeland health consist of several parameters describing evidence of soil erosion (rills, water flow patterns, gullies, and wind-scoured areas), bare ground exposure, litter amount and its movement, plant functional and structural groups, noxious and invasive plants, and soil resistance to erosion etc. (Pellant et. al 2000). Thus, rangeland health assessments are a function of several complex parameters. Indeed, rangeland health has been defined as the degree to which the integrity of the soil, vegetation, water and air as well as the ecological processes of the rangeland ecosystem are balanced and sustained (Pyke D. A. et al., 2002).

Water cycle, energy flow, and nutrient cycles are the three primary components of basic ecological processes. These processes support certain species of plants and animals within a normal range of variation. It is complicated and expensive to directly measure the site integrity and status of ecological processes due to the complexity of the processes and their interrelationships. Therefore biological and physical attributes are many times used as parameters of site integrity and functionality of the ecological processes and eventually, overall rangeland health (Pellant et. al 2000).

Various rangeland health parameters have been used in rangeland monitoring and resource inventories by land management agencies for a long time. These parameters are components of a system which are used to gauge soil or site stability, hydrologic function and the integrity of the biotic community for selected rangeland ecological sites. No single parameter of ecosystem health can address the complexity of ecological processes well. Therefore using a suite of key parameters has been suggested (Pellant et. al 2000).

Some studies have produced a number of parameters for assessing rangeland health. O'Brien (2003) and others studied rangeland health parameters (noxious weeds, ground cover, species composition and shrub cover) for evaluation of rangeland health. They also studied reliability and precision of the parameters (O'Brien et. al 2003).

This study deals with a similar suite of rangeland health parameters. GIS and remote sensing techniques were used to develop the model and perform an accuracy assessment. The result was a rangeland health index model based, initially upon bare ground exposure.

We developed the following working definition of rangeland health for this study: Healthy rangelands exhibit effective water cycles as indicated by minimal bare earth exposure and minimal evidence of soil erosion. In addition, the vegetation present will be a mixture of grasses, forbs, and shrubs that act synergistically to provide quality forage and habitat for wildlife and grazing animals. Litter will be present and biodegrading. Very little if any litter will be decomposing through oxidation.

## **OBJECTIVES**

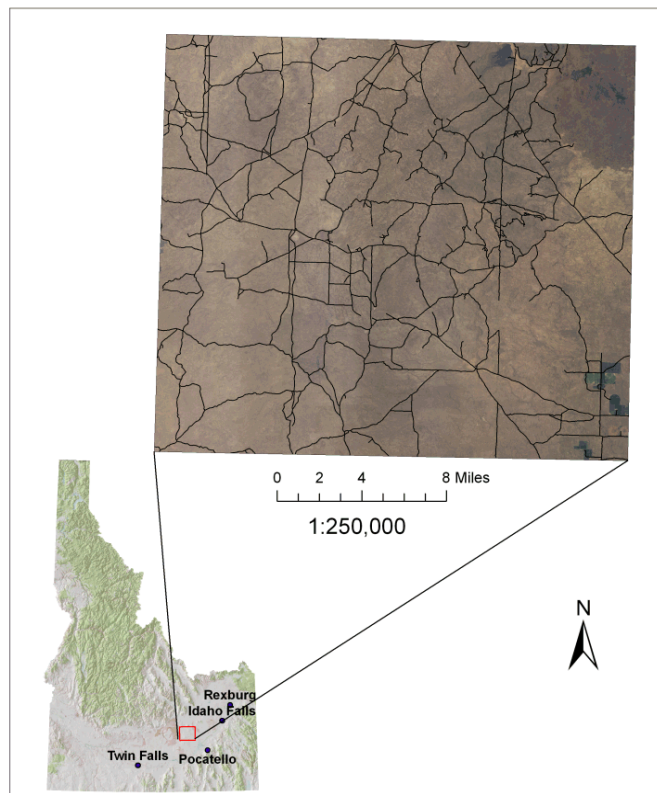
Several factors can influence rangeland health and may possess a complex connection among them. This study will identify the factors which can serve as rangeland health parameters. The primary objectives of the study are as follows:

- ❖ Obtain field data related to various rangeland health parameters for the study area.

- ❖ Develop a binary suitability model for each of the parameter using high resolution Quickbird satellite imagery and field data.
- ❖ Assess the accuracy of each suitability model.
- ❖ Develop a rangeland health model using all suitability models.

**THE STUDY AREA:**

The study area, known as the Big Desert, lies in southeastern Idaho, approximately 71 km northwest of Pocatello. The center of the study area is roughly located at 113° 4' 18.68" W and 43° 14' 27.88" N (figure 1) (Sander and Weber 2005). This area is managed by the Bureau of Land Management (BLM) and exhibits a large variety of native species as well as invasive species. The area is a sagebrush-steppe semi-desert which is bordered by geologically young lava formations to the south and west. Irrigated agricultural lands border the study area to its north, south and east. The area has a history of livestock grazing and wildfire occurrence (Weber and McMahan 2003).



**Figure 1. The Big Desert study area in southeastern Idaho.**

**METHODS**

Rangeland health is a function of several different (and complex) factors. Based upon our working definition of rangeland health, seven parameters were selected for the study. They are as follows:

1. Invasive plants (Cheatgrass or *Bromus tectorum*) are plants which are not part of the original local ecological system. These plants tend to grow in greater abundance for the particular rangeland system (Pellant et al 2000). For this study *Bromus tectorum* which is well known as cheatgrass, was identified as the primary invasive species in the study area. This plant is a problematic invasive species for Idaho's rangelands. It can germinate in spring or fall and is known to colonize areas quickly following a fire. During most of its life cycle, cheatgrass provides poor forage for livestock. In addition, it is considered a

fire promoter as its early senescence provides great quantities of fine fuel to carry late summer wildfires (Vavra et al., 1999).

2. Bare ground is defined as exposed mineral or organic soil which is susceptible to raindrop splash erosion. It represents the entire surface that is not covered by vegetation, litter, standing dead vegetation, gravel, rocks and visible biological crust (Pellant et al 2000). Bare ground does not contribute towards healthy rangelands. Therefore, bare ground is considered a key component in our assessment of rangelands health.

3. Grass cover plays a role in energy flow and nutrient cycling. Grasses comprise a group of species with the same root and/or shoot structure, and similar photosynthetic pathways. Thus they can be treated as a single functional or structural group (Pellant et al 2000).

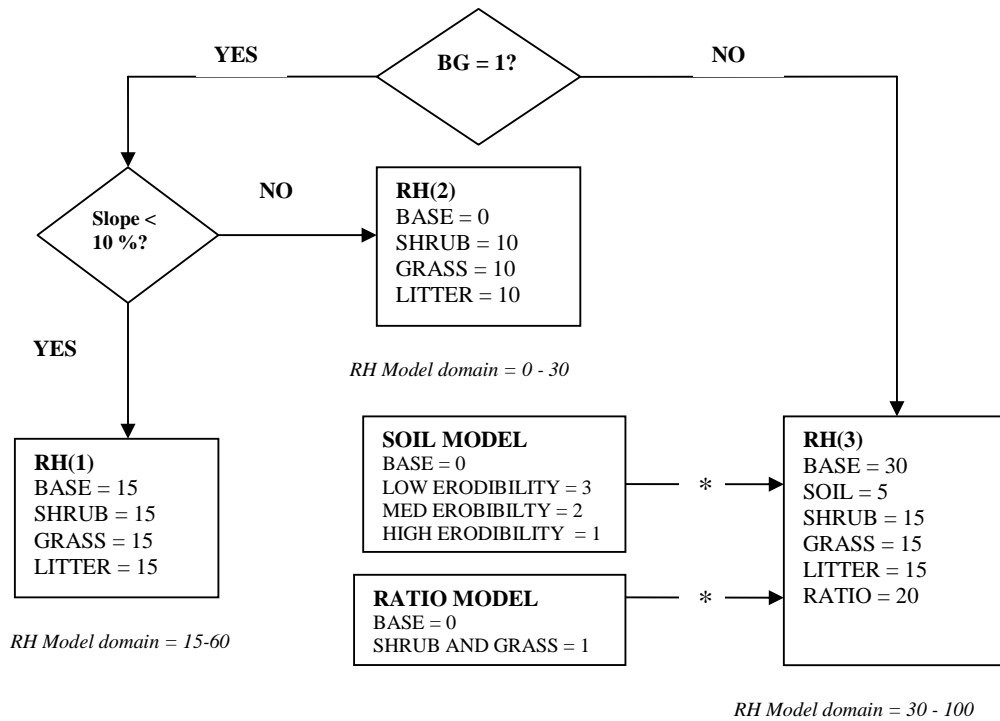
4. Shrub cover, similar to grasses, can also be treated as a functional or structural group. Percent shrub cover was assessed as part of the rangeland health model.

5. Litter cover was defined as any dead plant material which is in contact with the soil surface. Litter supplies essential organic material for onsite nutrient cycling. It dissipates the energy of raindrop splashes as well as overland flows thereby preventing soil erosion. (Pellant et al 2000).

6. Slope is an important factor influencing rangeland health. Higher slopes tend to result in higher runoff potential which can result in more erosion, especially if a steep slope area is coincident with bare ground. A slope of  $\geq 10\%$  would possess sufficient potential to damage rangelands especially where bare ground is present as well.

7. Erodibility is a function of bare ground, slope, and soil material. Soil cohesion is essential for healthy rangelands. Clayey soils exhibit less erodibility whereas silty soils tend to be more erodible where slope and bare ground are constant. Knowledge of these two factors was necessary to develop our rangeland health model. Therefore it was decided that both slope and soil erodibility models would be included in the final rangeland health model along with the first five parameter models described above.

It was understood that reliable bare ground detection was absolutely essential for rangeland health modeling and was treated as the main building block of our rangeland health model. The slope model was included in the model only where bare ground was present. Depending upon steepness of the slope ( $< 10\%$  or  $\geq 10\%$ ) shrub, grass, and litter were given appropriate weights (figure 2). In this part of the model, the rangeland health index (RH) would range from 0 to 60 (zero indicating very poor rangelands and 60 indicating moderately healthy rangelands). If bare ground was not present (indicating  $>50\%$  cover by litter or live plants) then factors such as soil erodibility, shrub and grass presence were considered. Soil erodibility was not including in the previous segment as it was determined that soil material type was insignificant under high bare ground exposure. These factors along with shrub, grass, and litter were similarly assigned appropriate weights. In this part of the model the RH index would vary from 30 to 100 (where the value 100 indicates very health rangelands). Figure 2 gives all assigned weights used in this study. This model is driven by the bare ground model. The maximum rangeland health index is 100 and the minimum is 0.



**Figure 2. A flowchart illustrating the conceptual approach for the rangeland health model developed in this study.**

All rangeland health parameter models except slope and soil erodibility were developed using supervised classification (an image processing technique). The soil erodibility model was readily available from the statewide soil database; STATSGO. The Slope model was developed using a digital elevation model (with 30x30m pixels) of the study area and the ‘Surface Analysis’ module of IDRISI software.

A total of 253 field samples were collected during 2003 for the first five models’ development and 171 samples were collected in 2004 for model validation. All sample points were randomly located across the study area. A Trimble GeoXT GPS receiver (+/-1m with a 95% CI) was used to record the location of each sample point. At each sample points, data describing percent cover of grasses and shrubs, dominant weed (cheatgrass, leafy spurge etc.) and shrub species, fuel load, sagebrush age, GAP vegetation classification, presence of microbial crust, litter type, and available forage was recorded. In addition, four photographs were taken at each point. Visual estimation was used to estimate percent bare ground, litter, shrub, and grass using the following categories: 1. None, 2. 1-5%, 3. 6-15%, 4. 16-25%, 5. 26-35%, 6. 36-50%, 7. 51-75%, 8. 76-95%, and 9. >95% (Sander and Weber 2005).

Quickbird satellite imagery was used for predictive modeling of cheatgrass, bare ground, litter, grass, and shrub presence. The imagery is comprised of four multispectral bands each using 2.4 x 2.4 meter pixels. The wavelengths sensed by each band were as follows:

- Blue: 450 to 520 nanometers
- Green: 520 to 600 nanometers
- Red: 630 to 690 nanometers
- Near-Infrared: 760 to 900 nanometers

ArcGIS and IDRISI software were used to 1) convert field samples into training sites (i.e., coded for cheatgrass presence/absence), 2) calculate various vegetation indices (e.g., normalized difference vegetation index), and 3) perform image processing and classification.

The individual rangeland health parameter models based upon satellite imagery were developed using the following sequence of steps.

- Create 'training-sites' using field sample points
- Create Vegetation Indices using processed Quickbird bands
- Principal Components Analysis
- Signature Extraction
- Classification - Maximum Likelihood
- Accuracy Assessment

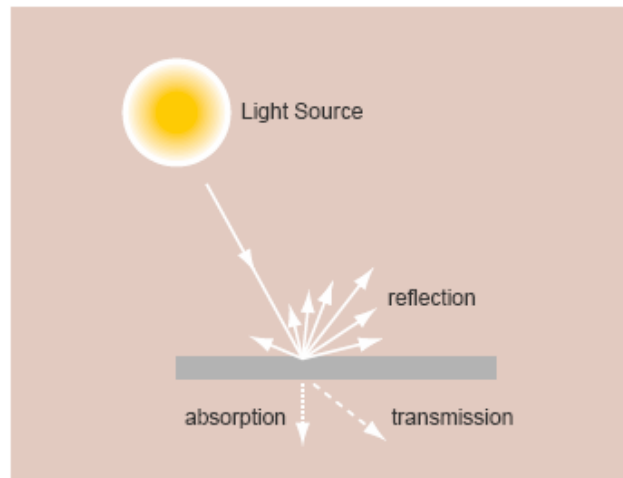
1. **Training sites** – Training sites were used to allow the image processing software to generate spectral signatures for the target of interest (i.e., cheatgrass). Each training site consists of a geographic location and sample attribute (e.g., 1=cheatgrass presence or 2=cheatgrass absence). To be considered a cheatgrass presence training site, the field sample had to contain  $\geq 16\%$  cheatgrass. To be considered a bare ground presence training site, the field sample has to contain  $\geq 50\%$  bare ground. The field sampling points (vector shapefiles) were converted into raster training sites (TIFF format) for use in IDRISI. Those pixels containing a training site were given a value (1 (presence) or 2 (absence)) where all other pixels (unknown) retained a value of zero.
2. **Vegetation Indices**- Various vegetation indices were calculated to better capture the vegetation characteristics of the study area and potentially improve our modeling results. These indices are relative measures of actively photosynthesizing vegetation present within each pixel (USWCL 2005). Different vegetation indices can be produced using different combinations/ratios of red and infrared bands and by including additional parameters such as slope and intercept of soil line and soil adjustment factors. Normalized Difference Vegetation Index (NDVI) is perhaps the most common, while the soil adjusted vegetation index (SAVI) also considers the reflectance of bare ground and its behavior in the red and near-infrared bands. Thus SAVI may offer a more accurate characterization of communities where bare ground is frequently encountered.
3. Eight vegetation indices were calculated for this study using the VEGINDEX module of IDRISI program. These indices were then evaluated for their relevance using Principal Components Analysis (PCA).
4. **Principal Components Analysis (PCA)** – In remote sensing PCA is used as a data reduction and noise removal technique. PCA produces a new set of images from a set of input images. The images of the new set are called components. The components are uncorrelated with each other and are ordered by the amount of variance described in the original input images (Eastman 2003).

The first two or three components from a PCA typically describe nearly all the variability contained in the input imagery. Subsequent components introduce

redundancy, outliers, and noise. Therefore these components can be eliminated from further processing without losing any important data.

We performed PCA using the four bands of Quickbird imagery along with eight vegetation indices. The PCA analysis produced a set of component images. Based on these results a subset of images (describing about 97% of total variance) was selected to be used for signature extraction.

5. **Signature Extraction-** Spectral signature is also known as spectral response pattern and the concept is very similar to the human concept of color. A spectral signature provides a description of the magnitude that light energy is reflected by the target in different regions of the electromagnetic spectrum. Thus it plays a key role in the interpretation of remotely sensed data. Figure 3 shows how light is reflected, absorbed, and transmitted from a particular object. The MAKESIG module of IDRISI was used to develop cheatgrass signatures from PCA component images.



**Figure 3. Light behavior of a surface (source: Eastman 2003, IDRISI Kilimanjaro Guide).**

6. **Maximum Likelihood Classification-** Maximum Likelihood Classification was used for image classification. This classification is a type of hard classifier. The hard classifier makes a definitive decision about the land cover class to which each pixel belongs (Eastman 2003).
7. The classification uses information present in the signature file to determine which class each pixel belongs to (i.e., cheatgrass presence or cheatgrass absence). Equal probability was assigned to each of the signature class. Therefore 50 percent probability was assigned to each class.
8. **Error Assessment-** This step is also known as validation. While there are different ways to judge the accuracy of a model, we chose to use a standard contingency table (or error matrix) and the Kappa statistic. An error matrix measures the agreement between ground truth data with the developed model.

The ERRMAT module was used for error assessment of the cheatgrass model. We calculated kappa (how much better or worse the classification performed

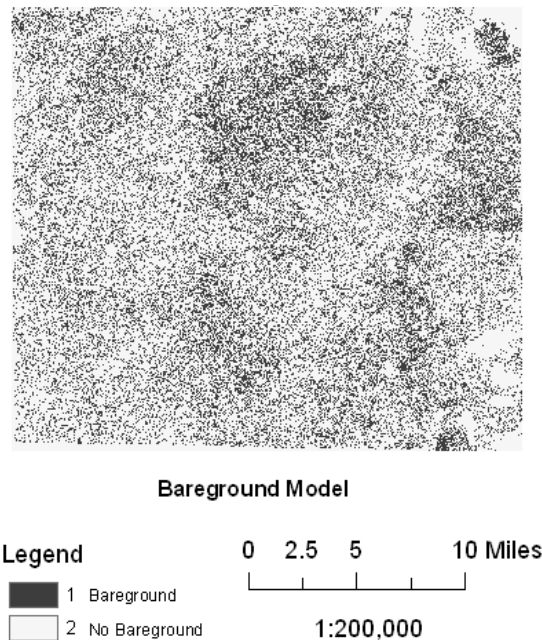
relative to a chance classification) (Titus et. al. 1984), overall, commission, and omission errors.

9. **Purification-** signature purification is sometimes necessary to achieve reliable results. The PURIFY module of IDRISI performs parametric and non-parametric purification. In parametric purification, the training pixel vector is retrieved from the images and the Mahalanobis distance to the mean of the class is calculated. The user is required to specify a typicality threshold which ranges from 0 to 1. A zero typicality threshold indicates that all the pixels will be kept in the data set while value 1 implies that nearly all pixels will be eliminated save for those equal to the mean. Based on the threshold, each pixel's typicality is evaluated (using Mahalanobis distance). A pixel with typicality value less than the threshold is dropped from the new data set (Eastman 2003). Signature purification was performed in the study and a new set of purified signatures was created and used for a second iteration maximum likelihood classification.

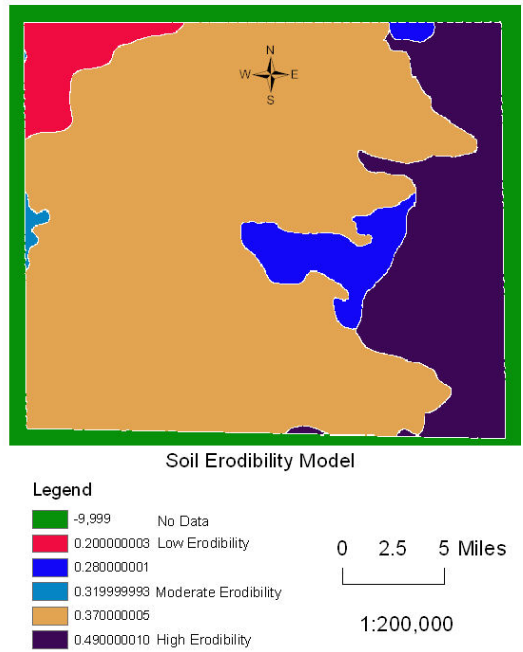
The purification-classification process was repeated iteratively to develop the most reliable model or until it was apparent that a reliable model was not possible. A reliable model was one having a user's accuracy of 75% or better.

## RESULTS AND DISCUSSION

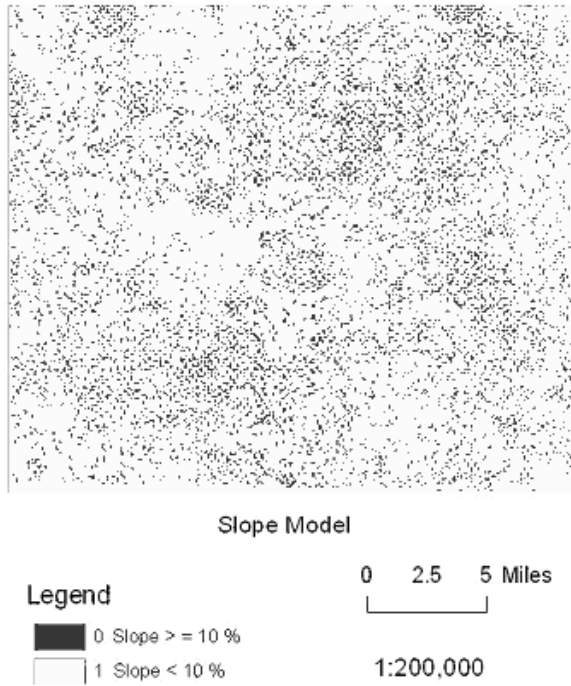
All models were produced following the methodology described above. Some models were improved through purification while others were not. This appears to be a function of training site variability and how much separability existed between target and non-target signatures (Richards 1993, Lillesand and Kiefer 2000). Figure 4 show the resulting bare ground model. Figures 5 and 6 show the resulting soil erodibility and slope models, respectively.



**Figure 4. The resulting binary model for bare ground. Dark pixels predict  $\geq 50\%$  bare ground exposure.**



**Figure 5. The resulting soil erodibility model for the Big Desert study area. The model was developed following RUSLE using STATSGO soils data.**



**Figure 6. The resulting binary slope model generated using SRTM DEM data. Dark pixels indicate steeper slopes whereas light pixels indicate gentle slopes.**

The results of model validation for bare ground, shrub, grass, litter and cheatgrass component models are given in tables 1-5.

Table 1 – Error Matrix for the bare ground model developed using purified signature

		Ground truth			
		Presence	Absence	Total	Commission
Model	Presence	28	4	32	0.12
	Absence	6	36	42	0.14
	Total	34	40	74	
	Omission	0.18	0.10		0.13

$$\text{Bare ground - Overall Kappa} = 0.7267$$

Table 2 – Error Matrix for the shrub model developed using purified signature

		Ground truth			
		Presence	Absence	Total	Commission
Model	Presence	10	3	13	0.23
	Absence	0	25	25	0.00
	Total	10	28	38	
	Omission	0.00	0.11		0.08

$$\text{Shrub - Overall Kappa} = 0.8143$$

Table 3 – Error Matrix for the grass model developed using un-purified signature

		Ground truth			
		Presence	Absence	Total	Commission
Model	Presence	18	54	72	0.75
	Absence	11	150	161	0.07
	Total	29	204	233	
	Omission	0.38	0.26		0.28

$$\text{Grass - Overall Kappa} = 0.2176$$

Table 4 – Error Matrix for the litter model developed using un-purified signature

		Ground truth			
		Presence	Absence	Total	Commission
Model	Presence	12	43	55	0.78
	Absence	2	176	178	0.01
	Total	14	219	233	
	Omission	0.14	0.20		0.19

$$\text{Litter - Overall Kappa} = 0.2787$$

Table 5 – Error Matrix for the cheatgrass model developed using un-purified signature

		Ground truth			
		Presence	Absence	Total	Commission
Model	Presence	18	55	73	0.75
	Absence	8	152	160	0.05
	Total	26	207	233	
	Omission	0.31	0.26		0.27

Cheatgrass - Overall Kappa = 0.2383

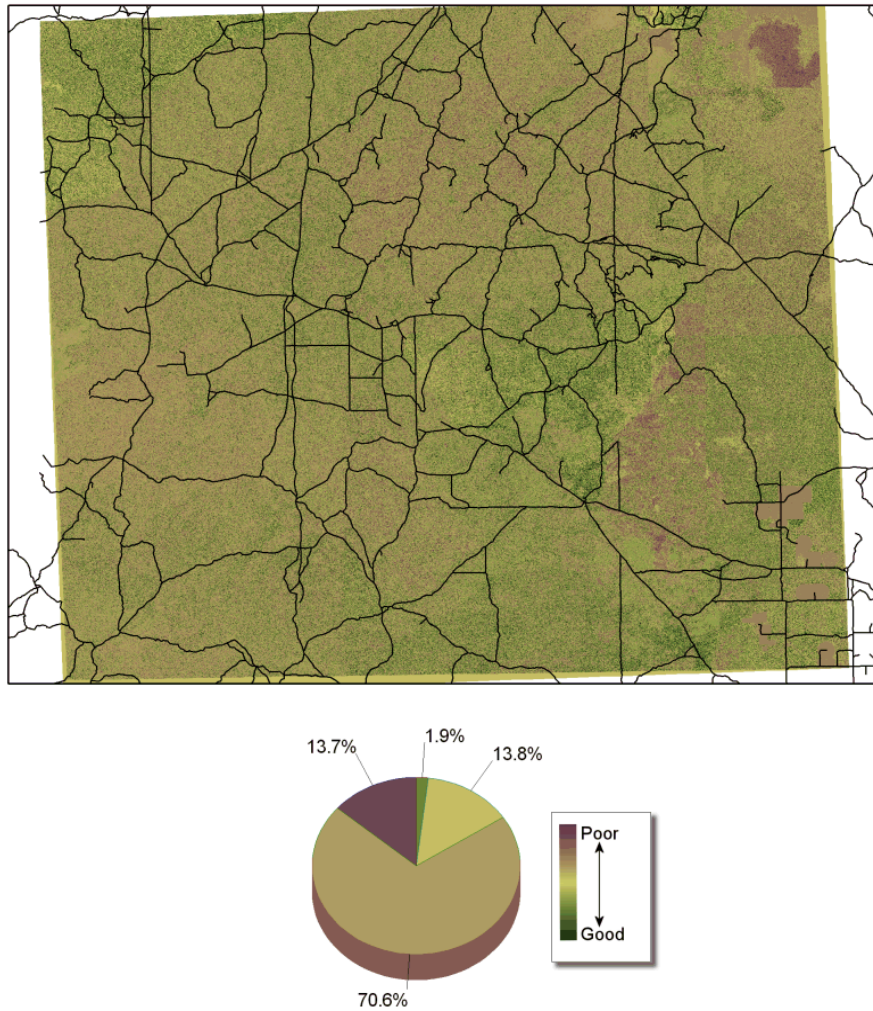
It is evident from tables 1 and 2 that the purification process worked well to improve the bare ground and shrub models. Although more than 60% of the training sites were lost during the signature purification process, the resulting models show higher overall accuracy and Kappa index (i.e. overall accuracy of 87% for the bare ground model and 92% for the shrub model with a Kappa index of agreement (KIA) of 0.7267 for the bare ground model and 0.8143 for the shrub model).

The purification process did not consistently improve either overall accuracy or Kappa indices for all models. Although purification did improve the overall accuracy of the grass, litter, and cheatgrass models (i.e. 72 %, 81% and 73 % respectively), the Kappa index for these models (KIA = 0.2176, 0.2787 and 0.2383 respectively) were very low indicating the classification was little better than a lucky random classification. Due to the patchy nature of grass, litter, and cheatgrass within the study area, purification was not advantageous. While very common, percent cheatgrass/grass cover ranged only up to 36% (with no training sites exceeded 36% cover). This means that even for cheatgrass/grass presence training sites, roughly two-thirds of each pixel was covered by non-target objects. We anticipated that by using imagery with high spatial resolution (i.e., Quickbird with 2.4x2.4m pixels) that the mixed-pixel affect would be minimized and allow for more reliable classification. Indeed, this is not the case. Further, using high-spatial resolution imagery introduced another difficulty in our processing; co-registration between imagery and training sites (Weber 2006).

Studying the cheatgrass and grass models and associated error matrices (tables 3 and 5) we see similarity in the results (i.e. overall accuracy of 72 % for grass and 73 % for cheatgrass and KIA = 0.2176 for grass and 0.2383 for cheatgrass). The obvious explanation is that cheatgrass and other grasses yield similar spectral signatures. This is an important observation, because it illustrates that even with relatively high radiometric resolution of Quickbird imagery (11bit), cheatgrass cannot be differentiated reliably from other grasses within the study area.

A primary source of error in all the models is poor co-registration (RMS = 5.20 m) between training sites locations and Quickbird imagery regardless of our attempts to eliminate this error using a ground control shapefile collected in the field. Still, the best RMS achieved was 5.20 m. When one considers the size of each pixel (2.40m) this implies a positional error of approximately two pixels. In other words, our cheatgrass training sites were likely shifted up to 2 pixels away from the actual pixel containing the target. This error propagated through the model and likely contributed to the very low accuracies in all models describing targets.

The seven individual parameter models provided the basic elements to produce a final rangeland health model. The parameter models were processed through the “Image Calculator” module of IDRISI software to produce a rangeland health model (Figure 7).



**Figure 7. The rangeland health model for the Big Desert study area.**

Similar to the individual parameter models, the rangeland health model was validated using rangeland health parameter values calculated from 189 field observations made during the summer of 2005. Note: for slope and soil erodibility parameters the modeled values were used since they could not be easily calculated in the field). Not surprisingly, no field observation values were exactly the same as modeled values. However, when reasonable confidence intervals were applied the rangeland health model showed much better corroboration with field observations (table 6).

Table 6. Validation of rangeland health model with 15 and 25pt error margins applied.

	Accuracy (+/- 15pts)	Accuracy (+/- 25pts)	n
RH1	75%	97%	68
RH3	55%	88%	121
Total	62%	91%	189

## **CONCLUSIONS**

Grass, cheatgrass, and litter cannot be modeled reliably (>75% overall accuracy) using Quickbird multispectral imagery. The overall accuracy of the grass and cheatgrass models never exceeded 73%. Purification did not improve accuracy for grass, litter, and cheatgrass models. We speculate that training sites dominated (>50%) by grass/cheatgrass/litter are required to achieve reliable results. This is probably true of all target/species differentiations except in those cases where the target has a distinctive spectral signature or texture. In addition, it appears that grass and cheatgrass produced nearly identical spectral signatures which resulted in similar overall accuracy and KIA.

The bare ground and shrub models produced very high overall accuracy (approximately 87% and 92% respectively). A distinct spectral signature may be the reason for such good classification results. The purification process was used and resulted in improved overall accuracy and KIA for these models. To further improve these models will require the use of imagery that is better co-registered with field data. This can only be accomplished using numerous ground-based control points which are visible within the imagery to eliminate co-registration error and the resulting loss of accuracy propagated by this error.

While not ideal for rangeland ecosystems, the RUSLE model was used in this study to estimate soil erodibility levels. Future versions of this model will attempt to make use of soil erodibility models designed for rangelands such as the rangeland hydrology and erosion model (Moffet et al 2006).

The rangeland health index model produced fairly reliable results. To accomplish this we did not attempt to differentiate annual invasive grasses from other types of grasses and thereby improved the model through generalization. Further research is required to fully examine the potential of high-spatial resolution imagery for rangeland management and the ability of remotely sensed imagery to reliably model rangeland health along with the parameters selected in this study.

## **MANAGEMENT IMPLICATIONS**

This model can be applied fairly easily to rangelands throughout the intermountain west. It should be understood however, that not all areas may have the potential to achieve a rangeland health index of 100. For this reason, the model and its results require careful interpretation by experienced range scientists who are familiar with the site being analyzed.

## **ACKNOWLEDGEMENTS**

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