

Final Report for Idaho State University (ISU) Landscape Data Fusion and Assessment: Improved Feature Extraction using Multivariate Stacking

A project of the Pacific Northwest Regional Collaboratory (PNWRC)

Background

Idaho State University (ISU) is one of six institutions (Pacific Northwest National Laboratory (PNNL), Idaho National Engineering and Environmental Laboratory (INEEL), ISU, Oregon State University, University of Idaho, and University of Washington) participating in the Pacific Northwest Regional Collaboratory (PNWRC). The mission of the PNWRC is to facilitate the integration of geospatial technologies and data to serve the needs of resource managers and decision-makers across the Pacific Northwest. Of the several PNWRC projects, ISU has participated in 2003-2004 in developing a multitemporal stacking tool for the detection of cheatgrass in southern Idaho. The project goals were to research and experiment with the concept of temporal stacking of Landsat imagery for better detection of cheatgrass; and to apply linear unmixing (or equivalent classification algorithms) to help identify cheatgrass cover. Once these goals were accomplished, we began preliminary technology transfer from a remote sensing environment (e.g. ENVI) to a geographic information system (GIS) environment (e.g. ArcGIS dlls) for ease-of-use by a broad audience. The majority of our work concentrated on a field area in southeastern Idaho, Bureau of Land Management's Big Desert Allotment. A secondary analysis was performed in southwestern Idaho in the Birds of Prey Area. ISU partnered with PNNL and INEEL on this project; PNNL developed a Bayesian linear unmixing model (BLUM); while INEEL developed a model with the use of MODIS satellite imagery to identify ideal times to acquire the multitemporal imagery based on cheatgrass phenology.

This report provides information on our work from August 2003 – March 2004 and includes information on:

- Personnel and Students Involved
- Original project proposal
- Background Literature Review
- Temporal Stacking for the Big Desert Area
- Temporal Stacking for the Birds of Prey Area
- Developed Products
- Meetings
- Conferences/Outreach
- Reporting
- References

Personnel Involved

- Ed House (PI): ISU representative on PNWRC Executive Panel
- Nancy Glenn (Co-PI): ISU-PNWRC contact; supervision of remote sensing and temporal stacking activities; interaction with end-users
- Keith Weber (Co-PI): Proposal development, student supervision; interaction with end-users
- Thomas Windholz (Co-PI): Supervision of programming and students, webpage development; interaction with end-users

Students Involved

- Walt Bulawa (ISU Geotechnology Certificate Major)
 - Literature review and coordination with PNNL
 - Development of integral components for temporal stacking (e.g. image stacking, LSU, endmember extraction) in ArcGIS
 - Webpage development; relational database design
- Ben McMahan (M.S. Anthropology Student)
 - Development of temporal stacking design in ENVI for the Big Desert
 - Development of validation techniques
 - Coordinate data sharing between PNNL, INEEL, and ISU
- Nagendra Singh (M.S. Geosciences Student)
 - Nagendra joined the project during the last month with the goal of working on the project during Year 2 and developing an M.S. thesis based on the temporal stacking concept

Background Literature Review

A thorough literature review was performed on the themes of temporal stacking, data cubes, sub-pixel endmember extraction, and remote sensing of cheatgrass. Literature was gathered from journals and articles at ISU, Utah State University, and PNNL. **Table 1** lists the most pertinent journals for this project. The journal articles indicated that, on the whole, temporal stacking was useful for extracting vegetation information from multispectral images however, very little research has focused on remote sensing of cheatgrass (and other invasive species).

Table 1

| Title | Journal | Subject matter | Temporal Stacking? | Sub-Pixel Endmember Determination? | Multispectral |
|--|--|---|---------------------------|---|----------------------|
| Separation of Soil-Plant Spectral Mixtures by Factor Analysis | Remote Sensing of Environment 19: 237-251 (1986) | Uses Factor Analysis to decompose the elements of pixel cells. | | X | X |
| Vegetation in Deserts: I. A Regional Measure of Abundance from Multispectral Images | Remote Sens. Environ 31:1-26 (1990) | Introduces SMA to determine estimates of quantities of endmembers in a region. | | X | X |
| Assessing the relationship between spectral vegetation indices and shrub cover in the Jordana Basin, New Mexico | Int. J. Remote Sensing 14:3395-3416 (1993) | Compares several "greenness SVIs" and "brightness SVIs" | | | X |
| Improved forest classification in the northern lake states using multitemporal Landsat imagery | Photogrammetric Engineering & Remote Sensing 61:1129-1143 (1995) | Successive masking and layering techniques of images taken at different times of the year were used to successfully identify and distinguish different forest-cover species | X | | X |
| Optimization of Endmembers for Spectral Mixture Analysis | Remote Sens. Environ 59:472-489 (1997) | Presents a Modified SMA where the endmembers are derived mathematically from the image data subject to user defined constraints | | X | X |
| Detecting fire and grazing patterns in tallgrass prairie using spectral mixture analysis | Ecological Applications 7:493-511 (1997) | Used Linear SMA on AVIRIS data to determine endmember measures of burn/grazing effects. | | X | X |

Table 1 cont.

| Title | Journal | Subject matter | Temporal Stacking? | Sub-Pixel Endmember Determination? | Multispectral |
|---|--|--|---------------------------|---|----------------------|
| A comparison of single date and multitemporal satellite image classifications in a semi-arid grassland | Journal of Arid Environments 49:401-411 (2001) | Found that single-date image classifications were more accurate than multi-date classification. | X | | X |
| Mapping of boreal vegetation of a temperate mountain in China by multitemporal Landsat TM imagery | Int. J. Remote Sensing 23:3385-3405 (2002) | Used various band ratios to classify ground cover; found significant accuracy improvement (from 70% to 80%) when using data from both Oct/Jul when compared to single scene determination. Further improvement (4%) when incorporating DEM. | X | | X |
| Multidate adaptive unmixing and its application to analysis of ecosystem transitions along a climatic gradient | Remote Sens. Environ 82:5-20 (2002) | A method was presented which provides differentiation between physiognomic types at a subpixel level. The methodology is based on the phenomenology of seasonal growth patterns of the different vegetation formations and both temporal and spatial adjustments to the application of the multispectral unmixing technique. | X | X | X |
| Remote Sensing Progress Report, SERDP, Yakima Washington | N/A | Spectral unmixing algorithms were used to classify knapweed and cheatgrass. Temporal variation was used to assess remediation efforts. | | X | X |

Table 1 cont.

| Title | Journal | Subject matter | Temporal Stacking? | Sub-Pixel Endmember Determination? | Multispectral |
|--|---|---|---------------------------|---|----------------------|
| National park vegetation mapping using multitemporal Landsat 7 data and a decision tree classifier | Remote Sensing of Environment 85: 316-327 (2003) | Evaluated the performance of a commercially available decision tree classifier C5.0 for land cover classification using Landsat ETM+ data. Using data from both Sept and Jan scenes reduced error by about one half over each scene taken individually. | X | | X |
| Subpixel classification of Alder trees using multitemporal Landsat Thematic Mapper imagery | Photogrammetric Engineering & Remote Sensing 68:77-82 (2002) | Used a linear unmixing method with ground-truth data to determine endmember composition. | | X | X |
| Mapping Percent-Cover of the Invasive Species Bromus Tectorum over a Large Portion of Nevada from Satellite Imagery | US Fish and Wildlife Service Report, Nevada State Office, Reno, by the Nevada Natural Heritage Program, Carson City | Used multispectral data using NDVI for cheatgrass detection - unique validation techniques | X | | X |

Temporal Stacking: Big Desert

The following sections provide details on:

- Endmember and Pure Pixel Derivation
- Scene Selection / Band Selection
- LSU vs. MTMF model outputs
- NDVI Mask
- Categorical Field Data vs. LSU Outputs

Endmember and Pure Pixel Derivation

We used field data collected during May and June 2002 (n (number of sample data) = 370) as training data for the multitemporal image stacking classification project. These data were collected at GPS waypoint locations specific to previous land cover change models generated as part of the INEEL Land Cover Change project

(http://giscenter.isu.edu/research/techpg/lcc/vegchange_web.htm). At each waypoint we estimated the approximate percent cover of the dominant vegetation types (sagebrush/shrub, all grass and forb species, cheatgrass, litter/duff, and bare ground) using semi-continuous ordinal categories:

| <u>Category</u> | <u>Approximate Percent Cover</u> |
|-----------------|----------------------------------|
| 0 | 0% |
| 1 | 1-5% |
| 2 | 6-15% |
| 3 | 16-25% |
| 4 | 26-35% |
| 5 | 36-50% |
| 6 | 50-75% |
| 7 | 76-95% |
| 8 | 96-100% |

In order to better characterize the landscape with the field data measurements, and in a manner similar to the way large spatial resolution multispectral satellite platforms image the landscape (e.g. Landsat, SPOT, etc.), we made our vegetation estimations in a circle with a radius of ~20 meters around the waypoint. Our measurements took into account the sparse nature of some vegetation types and the bare ground and/or litter and duff that were visible through gaps in the vegetation. *Note: Cheatgrass was included in estimations of grass percent cover.*

Endmembers for each class were determined by selecting points that had high categorical values of the given class, and low values for other potentially conflicting classes:

| | |
|-------------------------|--|
| <i>Grass:</i> | <i>Grass > 4 and Cheatgrass < 2 (n=12) (green)</i> |
| <i>Cheatgrass:</i> | <i>Cheatgrass > 3 (n=7) (red)</i> |
| <i>Shrub/Sagebrush:</i> | <i>Shrub > 4 and Cheatgrass < 2 (n=9) (blue)</i> |
| <i>Bare Ground:</i> | <i>Bare Ground > 6 and Cheatgrass < 2 (n=5) (yellow)</i> |

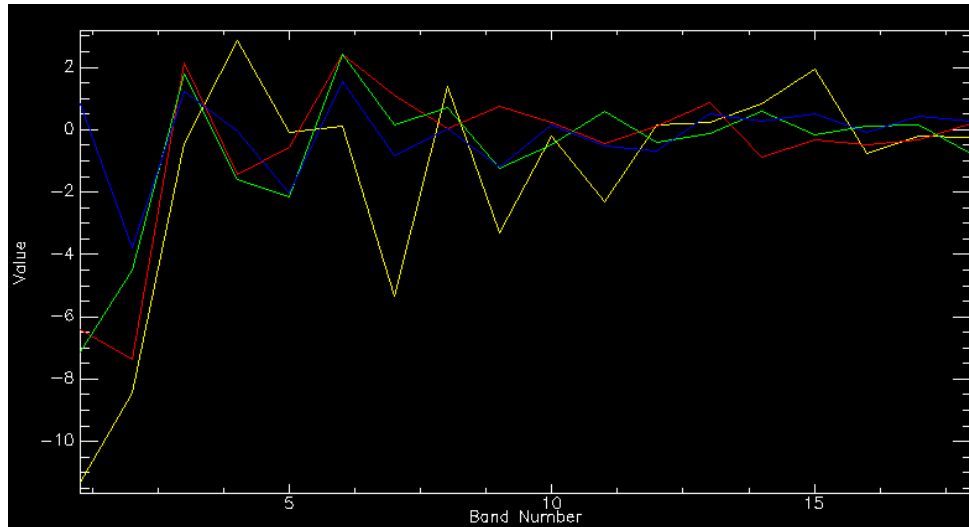


Figure 1: Endmember spectral plot of Grass, Cheatgrass, Shrub, and Bare Ground using MNF transformed data from 3 Landsat scenes (April 23, May 25, and June 26, 2002)

Given the relative homogeneity of the spectral values for the four main vegetation types that were included in the model, it has proven difficult to accurately predict a given class or its relative proportion. Since the field data were not collected with pure endmember identification in mind, we treated the given classes (identified by the attribute query discussed above) as relatively pure endmembers, or the highest proportion of a given class found in the study area (e.g. > 35% grass is a 'pure' grass endmember). This recognizes that in a given rangeland setting, because of the sparse nature of sagebrush-steppe vegetation types, grass cover is not often found in proportions greater than ~50%. These conditions will vary depending on the relative canopy cover provided by the vegetation in question, e.g. sagebrush-steppe ecosystems typically have a lower canopy cover than a deciduous forest.

In all following plots

White = 0% Cheatgrass

Cyan = 1-5% Cheatgrass

Yellow = 6-15% Cheatgrass

Orange = 16-25% Cheatgrass

Red = >25% Cheatgrass ←CHEATGRASS ENDMEMBER

X-axis = Landsat bands 1- 6

Y-axis = Average DN (image digital number)

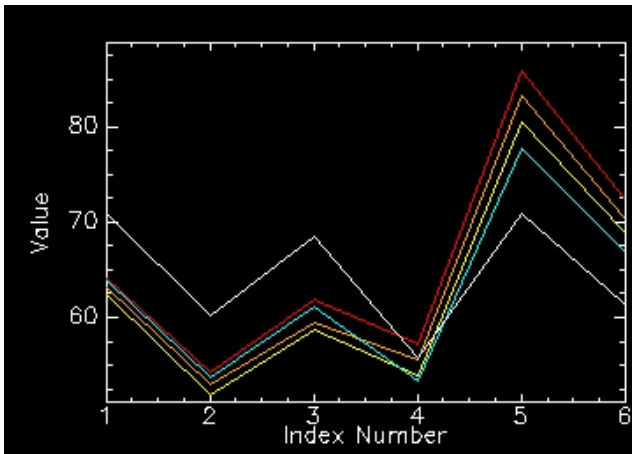


Figure 2A: April 07, 2002

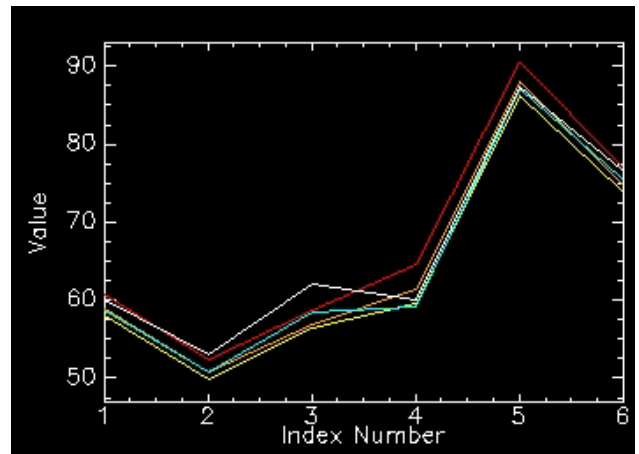


Figure 2B: April 23, 2002

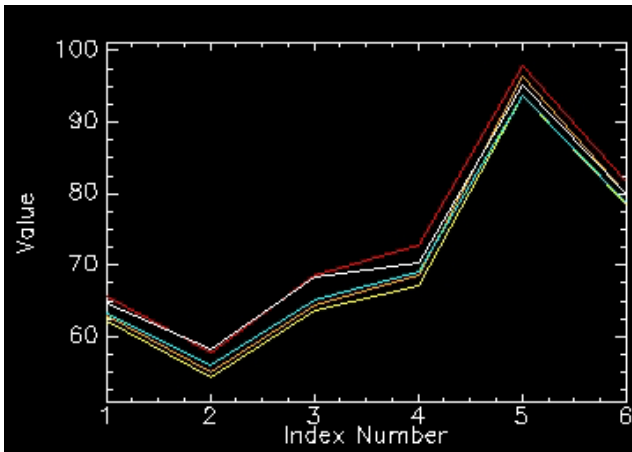


Figure 2C: May 25, 2002

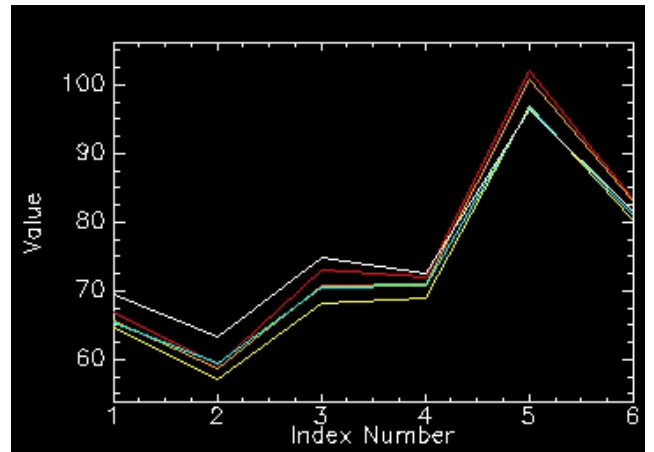


Figure 2D: June 26, 2002

Scene Selection / Band Selection – Prior to MNF Processing

We analyzed data comparing NDVI values of the four endmember classes at their various categorical percent covers to determine the optimal image dates for identifying cheatgrass in stacked multitemporal imagery. Late spring and early summer dates proved optimal, as they were most likely to identify phenological differences between native grass species (typically perennial grasses) and invasive species such as cheatgrass (a winter annual). Additionally, growing degree days will also affect phenology, and somewhere between 80 and 120 growing degree days are required for cheatgrass to begin its green up (Klepper, 2004). We analyzed weather station data from four stations on and near the Big Desert Allotment to determine when this threshold (>80 GDD) was reached, which was typically the first or second week of April. Given the limited availability of cloud-free imagery, the results of the NDVI analysis, and the phenological calculations, four scenes of Landsat ETM7+ were chosen. April 7, 2002; April 23, 2002; May 25 2002, and June 26, 2002.

In order to eliminate redundancy and reduce processing times we explored the possibility of using a subset of the 24 available bands. We tested the 24-band image cube to determine if any of the individual bands or dates could be eliminated. While there is considerable redundancy in the data (Table 2), a data reduction via principal component (and/or minimum noise fraction) analysis will address this redundancy more appropriately. The 1st April scene (April 7, 2002) had snow in higher elevations and cloud contamination that would affect accuracy. Preliminary analyses of our models showed that the first April scene had the lowest individual accuracy of the four scenes (Figure 3), and that analyses on data cubes that excluded the April 7 scene could increase prediction accuracy (Figure 4). Both of these figures helped us pick the best date combination based on model performance. Even though the R² value of the May and June cube was the highest, the difference was minimal, so we focused on the cube that would have the broadest potential range of phenology. Subsequent models used an 18-band image cube consisting of three scenes: April 23, May 25, and June 26, 2002.

Table 2: Correlation Matrix of Four Scenes of Landsat ETM7

| Correlation Matrix | | | | | | | | | | | | | | | | | | | | | | | | | |
|--------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|--|
| Band | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | |
| 1 | 1.000 | | | | | | | | | | | | | | | | | | | | | | | | |
| 2 | 0.971 | 1.000 | | | | | | | | | | | | | | | | | | | | | | | |
| 3 | 0.941 | 0.988 | 1.000 | | | | | | | | | | | | | | | | | | | | | | |
| 4 | 0.850 | 0.934 | 0.967 | 1.000 | | | | | | | | | | | | | | | | | | | | | |
| 5 | 0.626 | 0.753 | 0.819 | 0.918 | 1.000 | | | | | | | | | | | | | | | | | | | | |
| 6 | 0.629 | 0.755 | 0.821 | 0.911 | 0.994 | 1.000 | | | | | | | | | | | | | | | | | | | |
| 7 | 0.755 | 0.835 | 0.864 | 0.874 | 0.801 | 0.803 | 1.000 | | | | | | | | | | | | | | | | | | |
| 8 | 0.760 | 0.854 | 0.891 | 0.913 | 0.855 | 0.860 | 0.985 | 1.000 | | | | | | | | | | | | | | | | | |
| 9 | 0.760 | 0.858 | 0.901 | 0.926 | 0.877 | 0.884 | 0.970 | 0.992 | 1.000 | | | | | | | | | | | | | | | | |
| 10 | 0.723 | 0.836 | 0.887 | 0.956 | 0.941 | 0.936 | 0.919 | 0.956 | 0.965 | 1.000 | | | | | | | | | | | | | | | |
| 11 | 0.646 | 0.769 | 0.833 | 0.917 | 0.970 | 0.970 | 0.829 | 0.882 | 0.906 | 0.956 | 1.000 | | | | | | | | | | | | | | |
| 12 | 0.644 | 0.766 | 0.830 | 0.900 | 0.957 | 0.967 | 0.826 | 0.882 | 0.910 | 0.940 | 0.990 | 1.000 | | | | | | | | | | | | | |
| 13 | 0.660 | 0.774 | 0.829 | 0.887 | 0.908 | 0.915 | 0.838 | 0.885 | 0.904 | 0.917 | 0.922 | 0.927 | 1.000 | | | | | | | | | | | | |
| 14 | 0.681 | 0.797 | 0.854 | 0.911 | 0.923 | 0.930 | 0.854 | 0.905 | 0.925 | 0.940 | 0.938 | 0.942 | 0.989 | 1.000 | | | | | | | | | | | |
| 15 | 0.673 | 0.791 | 0.849 | 0.909 | 0.925 | 0.933 | 0.841 | 0.894 | 0.918 | 0.938 | 0.940 | 0.944 | 0.986 | 0.994 | 1.000 | | | | | | | | | | |
| 16 | 0.694 | 0.810 | 0.868 | 0.937 | 0.939 | 0.938 | 0.856 | 0.906 | 0.927 | 0.966 | 0.949 | 0.940 | 0.940 | 0.966 | 0.960 | 1.000 | | | | | | | | | |
| 17 | 0.642 | 0.760 | 0.821 | 0.903 | 0.949 | 0.947 | 0.811 | 0.860 | 0.881 | 0.933 | 0.960 | 0.950 | 0.950 | 0.958 | 0.966 | 0.951 | 1.000 | | | | | | | | |
| 18 | 0.617 | 0.734 | 0.795 | 0.871 | 0.929 | 0.935 | 0.785 | 0.837 | 0.860 | 0.905 | 0.942 | 0.943 | 0.948 | 0.951 | 0.964 | 0.918 | 0.989 | 1.000 | | | | | | | |
| 19 | 0.596 | 0.707 | 0.761 | 0.833 | 0.868 | 0.869 | 0.747 | 0.795 | 0.811 | 0.858 | 0.876 | 0.869 | 0.899 | 0.896 | 0.905 | 0.845 | 0.903 | 0.913 | 1.000 | | | | | | |
| 20 | 0.632 | 0.746 | 0.802 | 0.871 | 0.896 | 0.899 | 0.786 | 0.838 | 0.855 | 0.898 | 0.907 | 0.901 | 0.924 | 0.928 | 0.936 | 0.889 | 0.928 | 0.932 | 0.990 | 1.000 | | | | | |
| 21 | 0.599 | 0.709 | 0.765 | 0.839 | 0.875 | 0.877 | 0.744 | 0.795 | 0.813 | 0.867 | 0.883 | 0.877 | 0.896 | 0.897 | 0.911 | 0.853 | 0.912 | 0.923 | 0.990 | 0.992 | 1.000 | | | | |
| 22 | 0.692 | 0.807 | 0.864 | 0.925 | 0.914 | 0.914 | 0.858 | 0.907 | 0.928 | 0.950 | 0.926 | 0.922 | 0.897 | 0.929 | 0.921 | 0.971 | 0.904 | 0.867 | 0.784 | 0.839 | 0.787 | 1.000 | | | |
| 23 | 0.594 | 0.708 | 0.767 | 0.858 | 0.915 | 0.910 | 0.750 | 0.799 | 0.816 | 0.890 | 0.921 | 0.904 | 0.890 | 0.894 | 0.909 | 0.877 | 0.951 | 0.950 | 0.958 | 0.966 | 0.972 | 0.823 | 1.000 | | |
| 24 | 0.540 | 0.649 | 0.705 | 0.791 | 0.863 | 0.865 | 0.685 | 0.736 | 0.754 | 0.825 | 0.869 | 0.862 | 0.853 | 0.849 | 0.870 | 0.807 | 0.908 | 0.927 | 0.959 | 0.956 | 0.976 | 0.736 | 0.984 | 1.000 | |

April 7: Bands 1-6
 April 23: Bands 7-12
 May 25: Bands 13-18
 June 26: Bands 19-24

Figure 3: Single Month Comparison: X axis = % Cover Cheat; Y axis = Mean Model Value

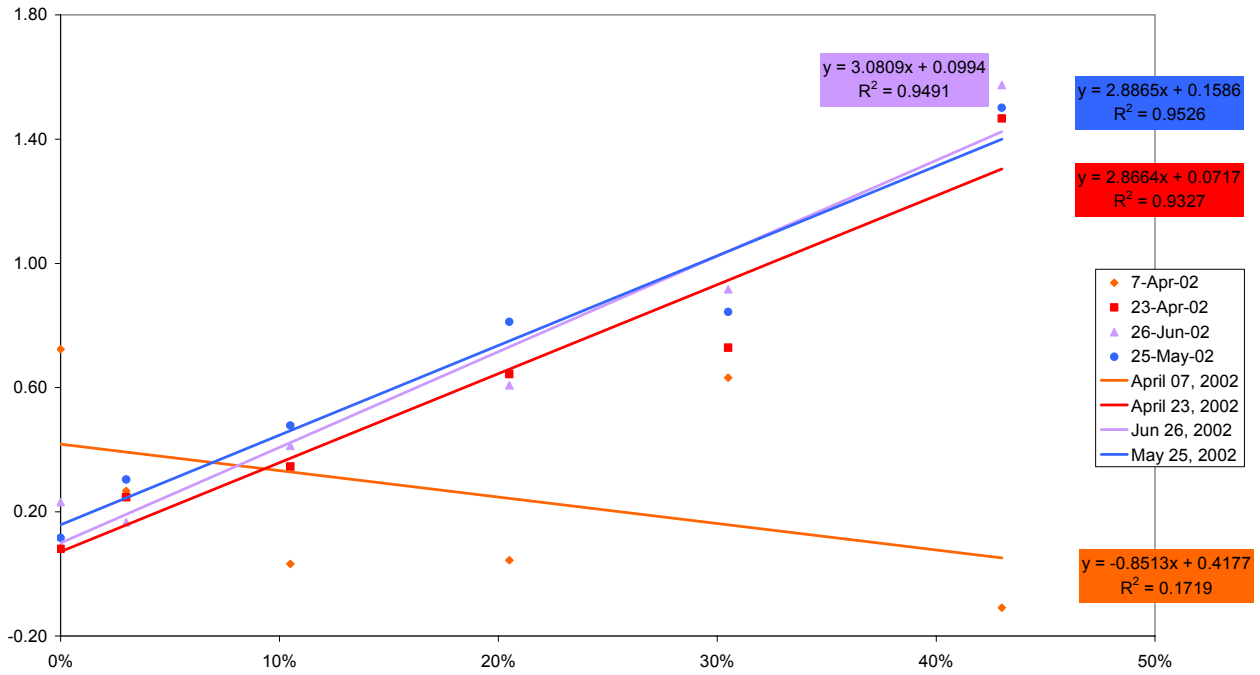
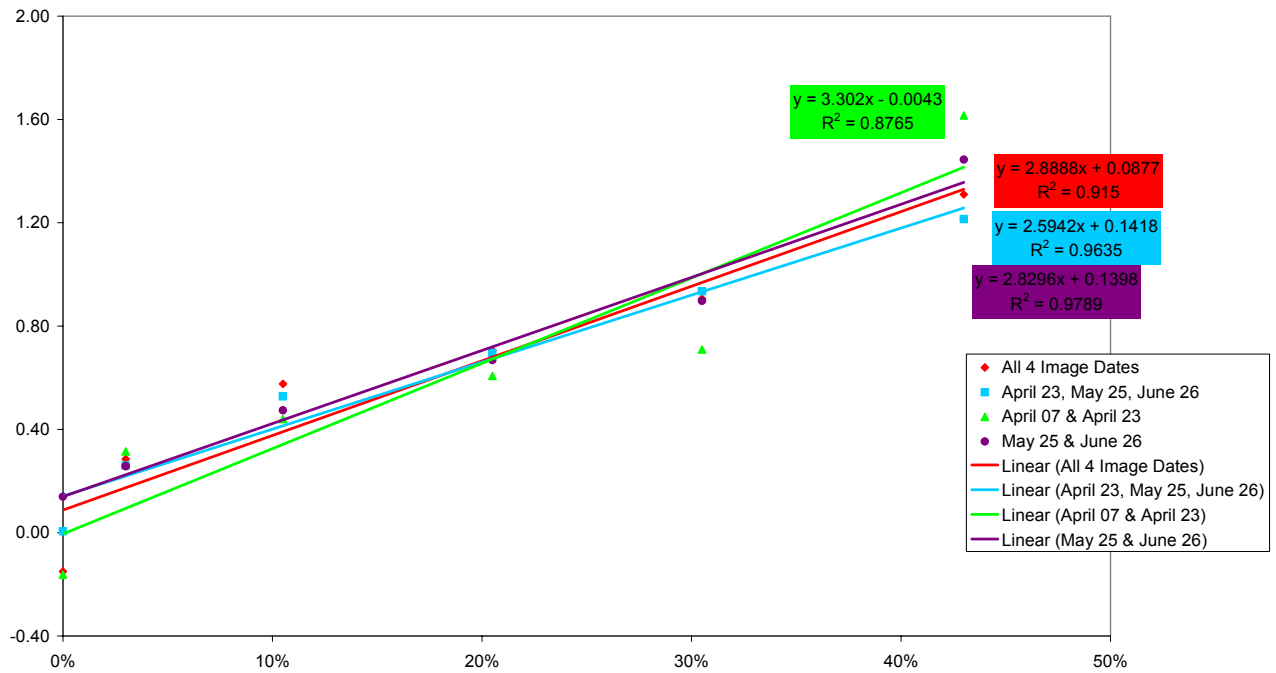


Figure 4: Data Cube Comparison: X axis = % Cover Cheat; Y axis = Mean Model Value



Band Selection / Scene Selection – Following MNF Processing

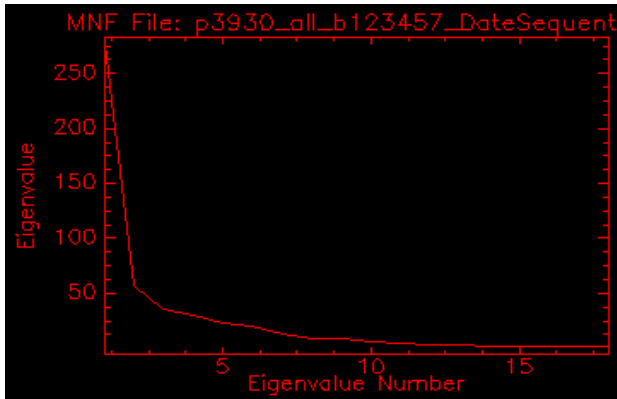


Figure 5: Screen Plot of MNF Eigenvalues

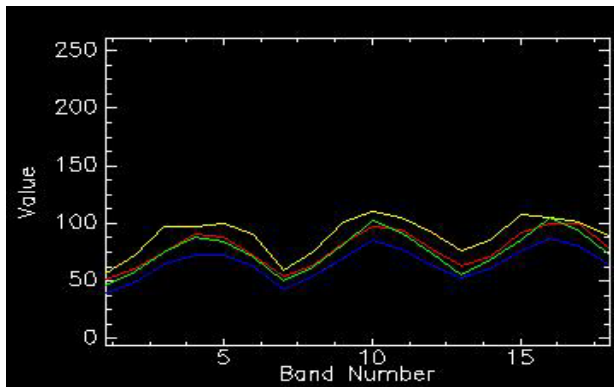


Figure 6: Endmember Means Plot of Raw Imagery
X-axis is MNF band number; Y-axis is DN value

We used Minimum Noise Fraction (MNF) principal component forward rotation in order to reduce data dimensionality and multi-collinearity.

Approximately 7 principal components would be required to capture 95% of the variability in the 18-band data cube (Figure 5). We could eliminate data redundancy by using only the first 7 components, but small variations in spectral response may be the subtle distinction that characterizes cheatgrass. Because of this, all 18 MNF rotated bands were used in subsequent analyses.

In addition to the reduction of data dimensionality, the MNF rotation also decorrelated the data. As shown in Table 1, the raw imagery is highly correlated, and initial results of classifications vs percent cover on single scenes showed strong correlation between dates (Figures 3 & 4). The means of the endmembers for the raw data (Figure 6) demonstrate how the patterns of spectral response were quite similar over the 18 bands. The MNF rotation altered these patterns of spectral response, and served to separate (spectrally) the four main endmember classes we modeled (Figure 7). Even in the later components of the MNF data, there is still separation between cheatgrass (red) and other vegetation types – thus all 18 MNF transformed bands were used.

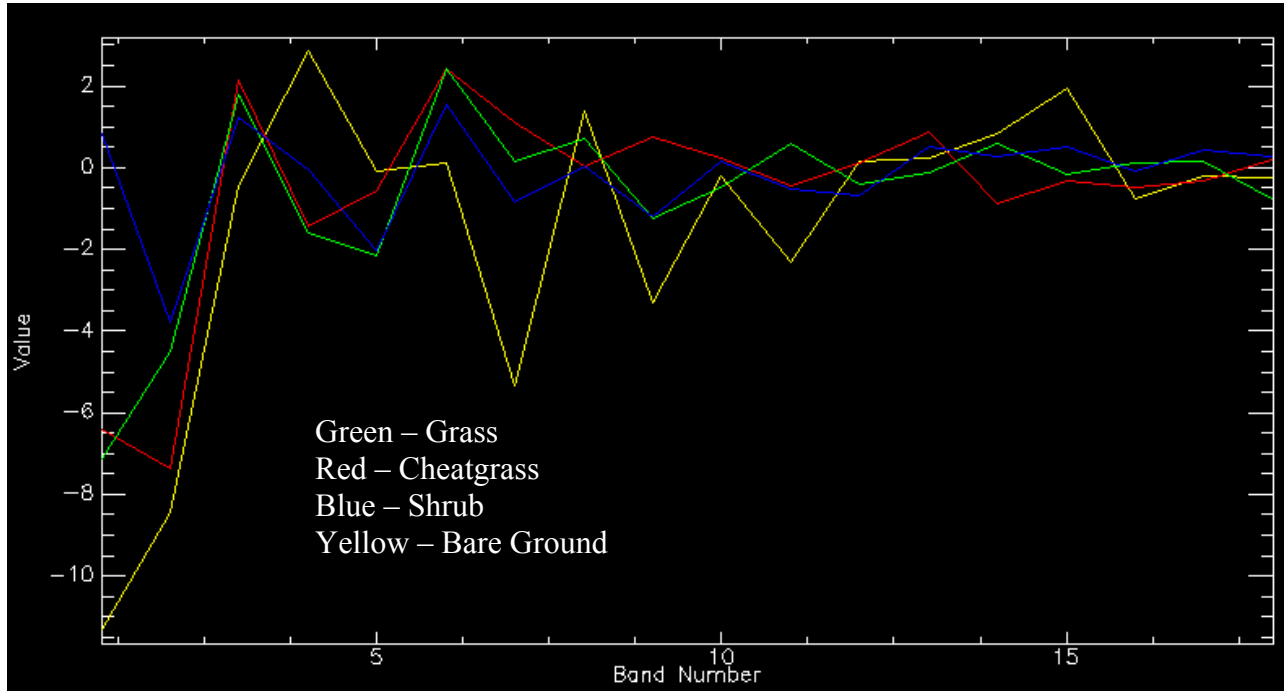
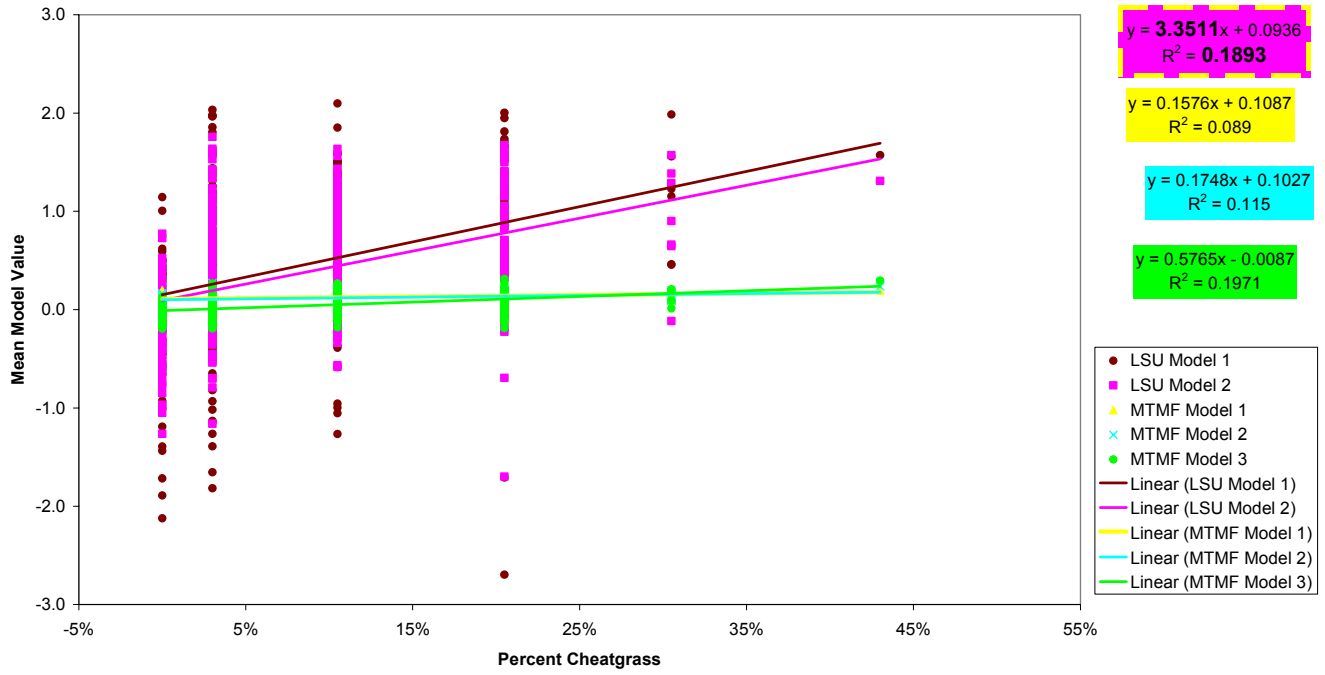


Figure 7: Endmember Means Plot of MNF Transformed Imagery; MNF Component (X-axis) vs. Mean MNF value for each endmember (Y-axis)

LSU vs. MTMF model outputs

Both Linear Spectral Unmixing (LSU) and Mixture Tuned Matched Filtering (MTMF) have been used to analyze multispectral and hyperspectral imagery. While MTMF has worked well in identifying other invasive plant species (Mundt 2003), it seems to have limited accuracy when more than one vegetation type is being modeled. Conversely, LSU seems to perform better when it has distinct choices to analyze. We wanted to determine which image-processing algorithm would be more appropriate for cheatgrass. We tested preliminary LSU and MTMF models using our 2002 field data under the assumption that a ‘good’ model would be one that had both increasing categorical percent cover of cheatgrass *and* increasing model value for cheatgrass (a positive slope) (Figures 8 and 4). Figure 8 tests between early preliminary models (LSU and MTMF) to determine which methodology (LSU vs. MTMF) would better characterize the region given the available data. Figure 4 compares different model performance for all image dates, 3 image dates (April 27, May 25, and June 26), and two sets of 2 image dates (April 07 and April 23; May 25 and June 26). Models with negative or zero slopes are intuitively poor performers, as this indicates either negative or no correlation between predicted model values and measured cheatgrass values. The MTMF models had slopes ranging from slightly negative to ~ 0.5 , indicating there was little or no correspondence between changes in the model value and changes in the actual percent cover. The LSU models demonstrated slopes ranging between 2.5 and 3.0, indicating a strong positive relationship between predicted model value of cheatgrass and actual cheatgrass categorical percent cover. Thus, we used LSU as the classification algorithm.

Figure 8: Preliminary Model Comparison
X axis = Percent Cheatgrass; Y axis = Mean Model Value



NDVI Mask

ENVI has an option to allow the user to mask classifications using a binary image derived from a query or reclassification of another image. For the purposes of this study, we were interested in identifying cheatgrass within the sagebrush-steppe ecosystem on the Snake River Plain, a vegetated but relatively dry region in SE Idaho. An NDVI mask allowed us to mask out regions that had a much higher NDVI value (e.g. agriculture) as well as regions that had lower NDVI values (e.g. lava, concrete, etc.). We masked out all NDVI values less than zero and greater than 0.45.

NDVI Mask

| | |
|-------------------|-----|
| Values $-1 - 0$ | : 0 |
| Values $0 - 0.45$ | : 1 |
| Values $0.45 - 1$ | : 0 |

This mask identified regions that are characterized by irrigated agriculture, bare lava areas, and open water (Figure 9). However, when we tested the classification results using the NDVI mask vs. no mask, the results were identical. The mask simply prevented a model prediction at masked locations; it did not change the results of unmasked regions. Subsequent analyses were performed on unmasked imagery.

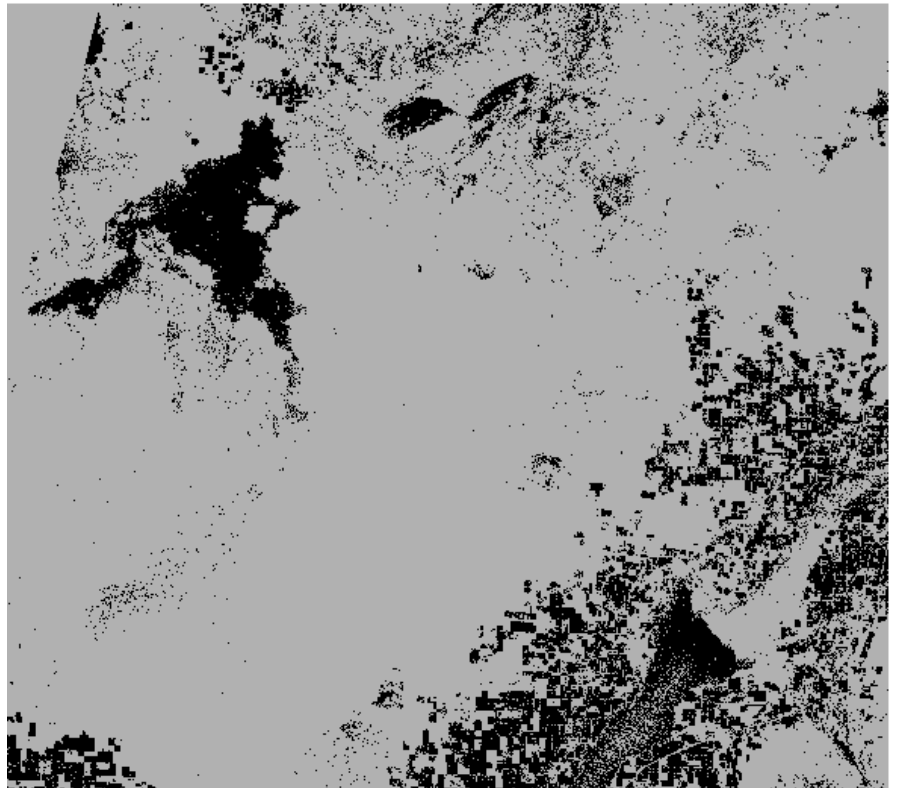


Figure 9: NDVI Mask

Categorical Field Data vs. LSU Outputs

The LSU model output range of values is (ideally) between 0 and 1, with 0 being 0% of endmember agreement, and 1 being 100% endmember agreement. The values are continuous, posing some difficulty in comparing the continuous model value with a categorically derived (but semi-continuous) field measurement value. Because of this discontinuity, there are multiple values for each field data category. It is useful to consider each one of these values a single measurement, and taking the average of all these measurements gives us a reasonable estimation of the mean. If models are performing adequately, that is they are predicting genuine cheatgrass locations, we should see an increase in the mean model values at the increasing field percent cover values. Negative or zero slopes indicate changes in model value have little or no correspondence to changes in measured percent cover. Separate documents demonstrate the variability in model performance among various stacking combinations (different image dates). The LSU model outputs often exceeded the ideal range of 0 to 1. Thus, we created a reclassified image to convert the continuous LSU outputs to categorical outputs to compare to categorical field measurements.

| LSU Value Level | Predicted Cheatgrass |
|-----------------|----------------------|
| -0.4 – 0.1 | Low |
| 0.1 – 0.6 | Medium |
| 0.6 – 1.1 | High |

For cheatgrass, 0% cover was considered to be low, 1-15% cover - medium, and 16-35% cover - high. This allowed us to build error matrices testing the low/medium/high field categories against the low/medium/high LSU model categories. Field percent cover cheatgrass is on the Y (vertical) axis, with categorical model values on the X (horizontal) axis.

| | | LSU Model Category | | |
|----------|--------|--------------------|--------|------|
| | | Low | Medium | High |
| Percent | Low | 9 | 27 | 7 |
| Cover | Medium | 15 | 44 | 7 |
| Category | High | 2 | 11 | 8 |

The overall accuracy of the **Big Desert** area error matrix was 47% or 61 points out of 130 (using **2002** data points as validation points) Kappa = 0.05

| | | LSU Model Category | | |
|----------|--------|--------------------|--------|------|
| | | Low | Medium | High |
| Percent | Low | 20 | 44 | 1 |
| Cover | Medium | 32 | 97 | 14 |
| Category | High | 4 | 30 | 11 |

The overall accuracy of the **Big Desert** area error matrix was 50.4% or 128 points out of 253 (using **2003** Big Desert points as validation points) Kappa = 0.09

| | | LSU Model Category | | |
|----------|--------|--------------------|--------|------|
| | | Low | Medium | High |
| Percent | Low | 42 | 76 | 11 |
| Cover | Medium | 25 | 109 | 39 |
| Category | High | 2 | 37 | 30 |

The overall accuracy for the **whole** area we analyzed was 49.9% or 181 points out of 370 (using **2002** data points for validation) Kappa = 0.17

$$K = \frac{N \sum_{i=1}^k n_{ii} - \sum_{i=1}^k n_{i.} n_{.i}}{N^2 - \sum_{i=1}^k n_{i.} n_{.i}}$$

Cheatgrass Maps

Figure 10: Cheatgrass Map for Whole Region

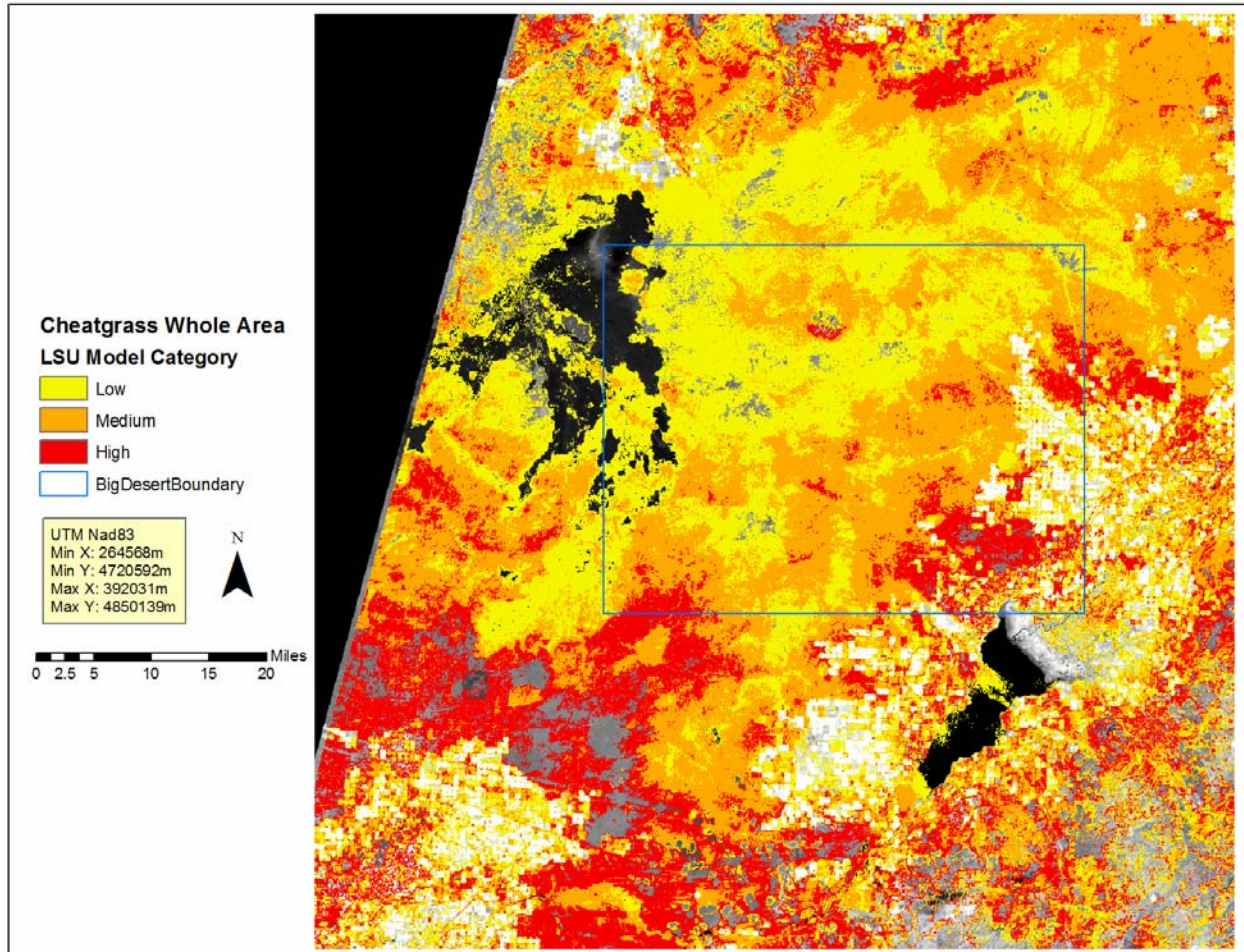
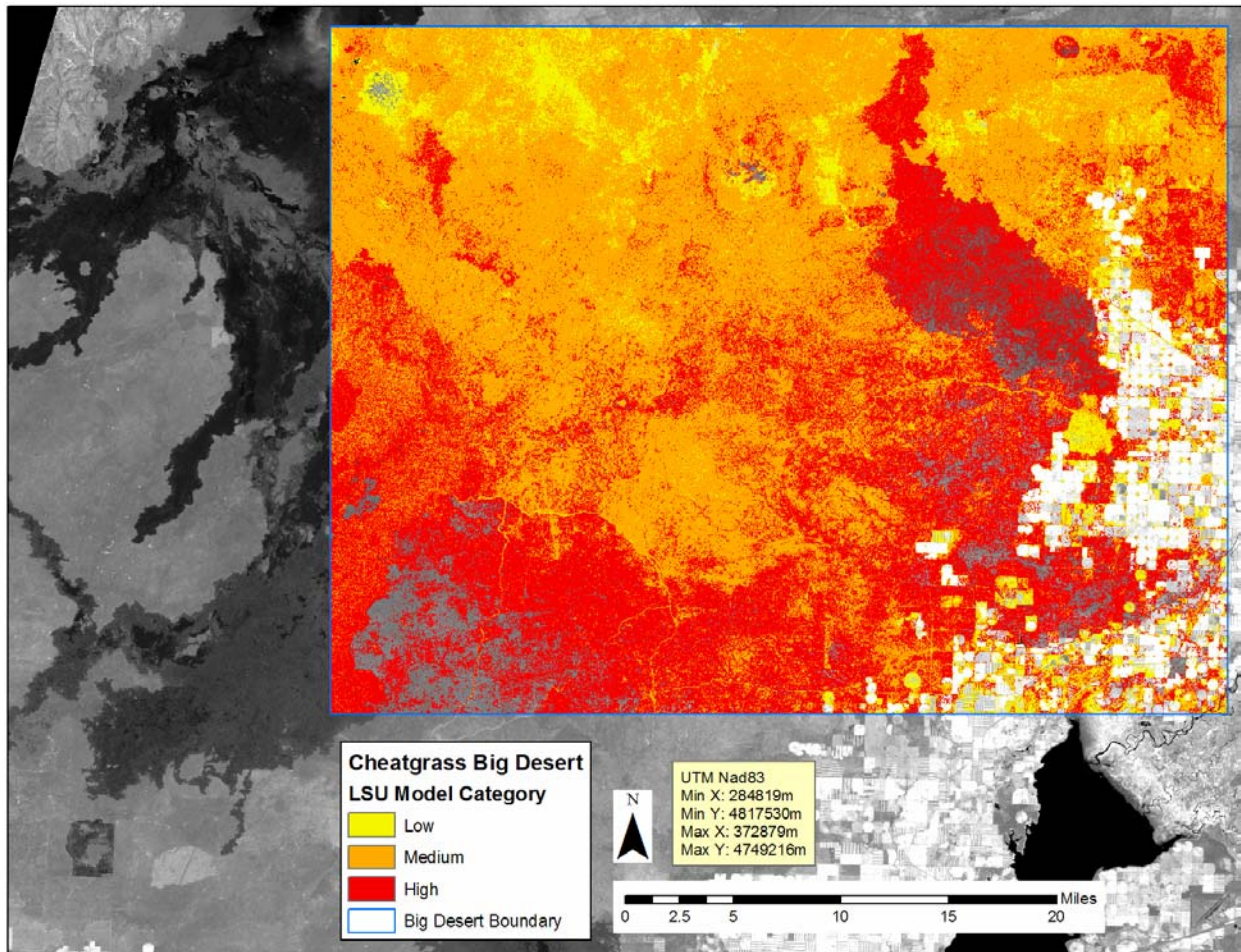


Figure 11: Cheatgrass Map for Big Desert Region



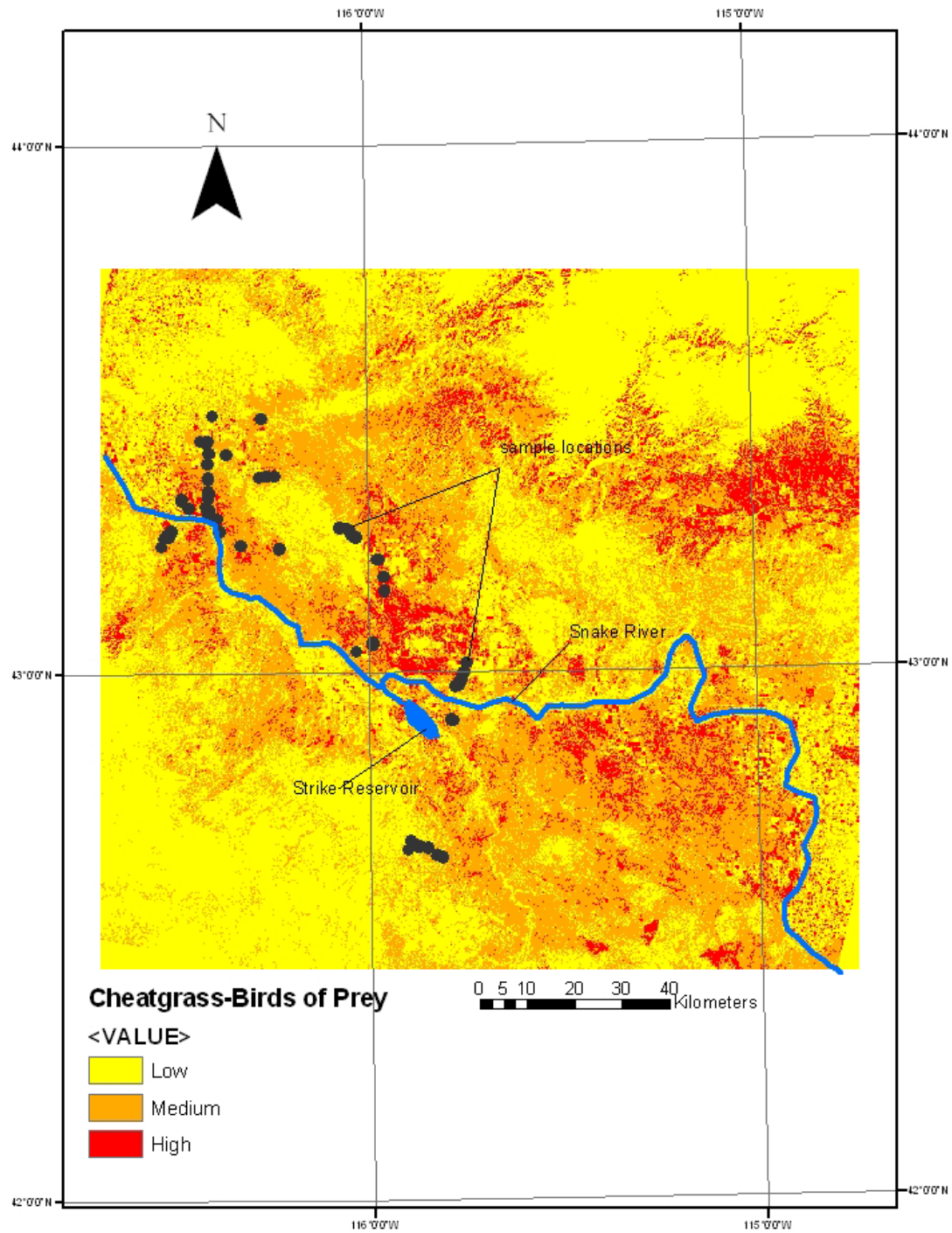
Temporal Stacking: Birds of Prey

A preliminary study utilizing similar methodology from the Big Desert Region was performed for the Birds of Prey area in Southwestern Idaho. Landsat dates of April 08, May 26, and August 06, 2003, were used in this study. Three endmembers were used in the LSU classification, including cheatgrass, sagebrush, and bare soil. The LSU-derived cheatgrass output was then categorized into cheatgrass categories of low, medium, and high, similar to the Big Desert data. Validation data was used for an error matrix with an overall accuracy of approximately 50%.

| LSU Value Level | Predicted Cheatgrass Category |
|------------------------|--------------------------------------|
| -0.4 – 0.1 | Low |
| 0.1 – 0.6 | Medium |
| 0.6 – 1.1 | High |

| | | LSU MODEL CATEGORY | | |
|-------------------------------|----------|---------------------------|--------|------|
| | | Low | Medium | High |
| Percent Cover Category | Low | 0 | 5 | 1 |
| | Medium | 6 | 19 | 4 |
| | High | 5 | 17 | 12 |
| Overall | Accuracy | 31/69 = | 49% | |

Figure 12: Birds of Prey Cheatgrass Map



Developed products

- Programming: Three programs were developed as part of a technology road map towards Improved Feature Extraction using Multivariate Stacking in ArcGIS. A description of each program and the .dlls can be found at http://giscenter.isu.edu/research/techpg/PNWRC_cheatgrass/Cheatgrass.html
- Cheatgrass Maps: Two final cheatgrass classification maps (with values ranging from low, medium to high) are included in this document (Figures 10 and 11). Note that the maps need to be further validated in Spring/Summer 2004.
- Website: ISU developed their own web-page for our end-users and reporting. This page links to the main PNWRC webpage (www.pnwrc.org)
http://giscenter.isu.edu/research/techpg/PNWRC_cheatgrass/Cheatgrass.html

Meetings with end-users

A formal meeting with end-users occurred on October 10, 2003, in Idaho Falls. We discussed the purpose of the project, goals, and solicited feedback during this meeting. Since then, we've had continued correspondence (informal in-person meetings, via email, and telephone) with the end-users to acquire additional feedback (especially on historical/change detection needs). One result of interaction with the end-users is the development of proposals and additional funding beyond the PNWRC

- Dr. Steve Seefeldt (an ISU-PNWRC end-user) and ISU GIS Training and Research Center are developing a proposal focusing on remote sensing of rangeland health.

Conferences/Outreach

ISU participated in a variety of outreach events and conferences. These include:

- Raytheon Site Visit (October 24, 2003)
- Idaho State Department of Agriculture Weed Mapping Workshop (October 2003)
- ISPRS Workshop (November 2003)
- Society of Range Management Meeting (January 2004)
- 84th American Meteorological Society Annual Meeting (January 2004)
- Idaho Weed Conference (February 2004)
- Governor's Invasive Species Summit (February 2004)

Reporting

ISU spent considerable time in the following reporting activities:

- Initial proposal development and refinement
- Roadmap and development of components (.dlls) in consideration of future roadmap directions
- Monthly Raytheon reports for product development, user outreach, product dissemination, and self-evaluation metrics
- User-matrix for "land" application for Raytheon
- One-page summaries for Raytheon
- Contributed to PNWRC final report to Raytheon

References

Klepper, B., 2004, Growing-degree days and development of the wheat plant, USDA, Agricultural Research Service, Columbia Plateau Conservation Research Center, Available URL (accessed March 2004): www.panhandle.unl.edu/personnel/lyon/gdd.pdf.

Mundt, J., 2003, Detection of leafy spurge (*Euphorbia Esula*) in Swan Valley, Idaho, using hyperspectral remote sensing with limited training data, M.S. Thesis, Department of Geosciences, Idaho State University, Pocatello, Idaho.