LOW-ALTITUDE AVIRIS DATA FOR MAPPING LAND COVER IN YELLOWSTONE NATIONAL PARK: USE OF ISODATA CLUSTERING TECHNIQUES

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1. INTRODUCTION

Northeast Yellowstone National Park (YNP) has a diversity of forest, range, and wetland cover types. Several remote sensing studies have recently been done in this area, including the NASA Earth Observations Commercial Applications Program (EOCAP) hyperspectral project conducted by Yellowstone Ecosystems Studies (YES) on the use of hyperspectral imaging for assessing riparian and in-stream habitats. In 1999, YES and NASA's Commercial Remote Sensing Program Office began collaborative study of this area, assessing the potential of synergistic use of hyperspectral, synthetic aperture radar (SAR), and multiband thermal data for mapping forest, range, and wetland land cover. Since the beginning, a quality "reference" land cover map has been desired as a tool for developing and validating other land cover maps produced during the project. This paper recounts an effort to produce such a reference land cover map using low-altitude AVIRIS data and unsupervised classification techniques.

The main objective of this study is to assess ISODATA classification for mapping land cover in Northeast YNP using select bands of low-altitude AVIRIS data. A secondary, more long-term objective is to assess the potential for improving ISODATA-based classification of land cover through use of principal components analysis and minimum noise fraction (MNF) techniques. This paper will primarily report on work regarding the primary research objective.

This study focuses on an AVIRIS cube acquired on July 23, 1999, by the confluence of Soda Butte Creek with the Lamar River (Figure 1). Range and wetland habitats dominate the image with forested habitats being a comparatively minor component of the scene. The scene generally tracks from southwest to northeast. Most of the scene is valley bottom with some lower side slopes occurring on the western portion. Elevations within the AVIRIS scene range from approximately 1998 to 2165 meters above sea level, based on U.S. Geological Survey (USGS) 30-meter digital elevation model (DEM) data. Despain (1991) and the National Park Service (NPS) (2000) provide additional description of the study area.

2. RESEARCH RATIONALE

Although undersampled in the along-track direction, the 1999 low-altitude AVIRIS data was employed for this study because of its well-known overall high spectral quality, its ability to be georeferenced, and its sufficiently large areal extent. The unsupervised classification approach was selected over the supervised method because of the great diversity and complexity of land cover types within the study area. During this project, several YES research collaborators assessed various supervised classification methods for mapping targeted cover types in the area. These studies produced impressive maps of specific riparian and in-stream habitats (Crabtree et al., in press) but apparently did not yield wall-to-wall land cover maps. The latter can be constructed with the ISODATA unsupervised classification routine now resident in most commercial-off-the-shelf software packages. In essence, the acronym ISODATA means the Iterative Self-Organizing Data Analysis Technique Algorithm. It is often used for processing multispectral image data into effective land cover maps. ISODATA has worked well for mapping land cover from broad-band multispectral data sets, which tend to include 3 to 15 bands and spectral coverage in the visible, near infrared (NIR), and short-wave infrared (SWIR) regions. Therefore, ISODATA should also be effective for classifying land cover from narrow-band hyperspectral imagery with 15 bands or less in comparable regions of the electromagnetic spectrum.

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A literature review revealed a lack of publications discussing the effect of total number of input hyperspectral bands on ISODATA classification success. Sensor, application, and scene characteristics can individually or collectively affect the optimum number of bands needed for ISODATA classification success. The review did show some studies that successfully employed AVIRIS band subsets for effective land cover classification. For example, Martin et al. (1998) reported that 11 bands of AVIRIS data were effective for supervised classification of forest cover types within the Harvard Experimental Forest. Fuentes et al. (2000) produced boreal forest habitat maps that showed improvement over Landsat-based mapping. Fuentes used a subset of AVIRIS bands, data stacks of band ratios, and other indices, plus maximum likelihood supervised classification.

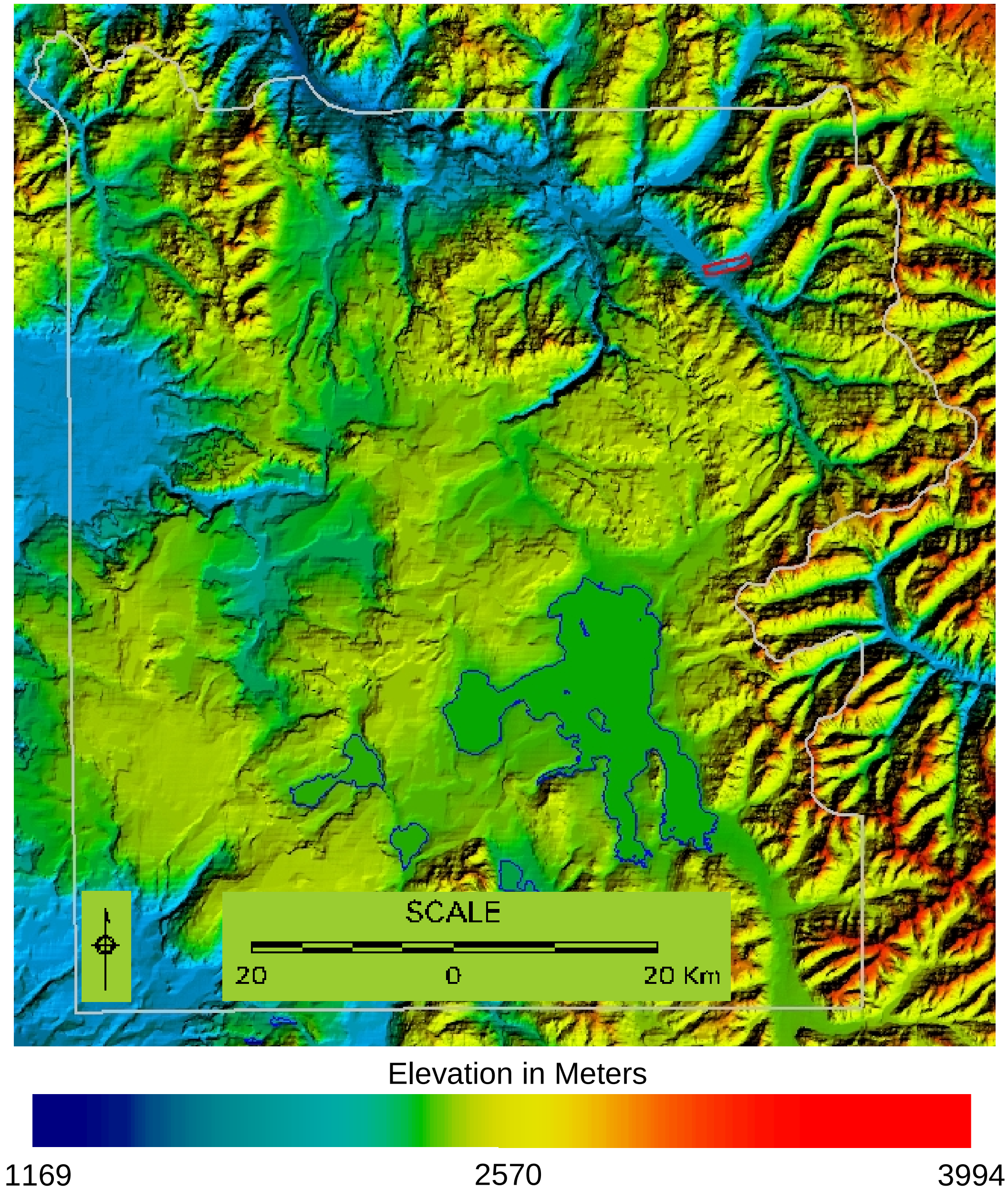

Figure 1. Location of study area within Yellowstone National Park. The graphic shows a hillshaded 90-meter DEM from the USGS with the AVIRIS scene boundary outlined in red.

The number of bands clearly affects the amount of time needed to perform ISODATA classifications. Based on first-hand experience, the amount of time needed to run an ISODATA classification on a whole AVIRIS cube is substantially greater than for the time needed to classify 10-15 bands. An initial classification of the entire low-altitude AVIRIS cube used in the Yellowstone study took about 20 times longer to compute than did classification of the same image with only 11 subset bands (7 hours as opposed to 20 minutes). The input data volume for the 11-band data set contains 78 megabytes, while the full AVIRIS cube includes 1600 megabytes. These classifications employed an SGI Onyx2 workstation with four CPU's and five Gigabytes of RAM.

One clear advantage of ISODATA is that it can be used in a supervised manner to generate spectral signatures, which can later be subject to a supervised classifier, such as the maximum likelihood routine. In addition, ISODATA can be used in the classification refinement process known as cluster busting to effectively reclassify "confused" cluster classes (Jensen, 1996). Such reclassification runs using all of the AVIRIS bands would be extremely time consuming and would generate excessively large volumes of intermediate raw data files. It would be quite advantageous if an accurate, detailed land cover classification could be computed with ISODATA clustering on a relatively modest subset of representative bands.

3. DATA ACQUISITION

The related NASA EOCAP hyperspectral project with YES enabled acquisition of and access to a wealth of remote sensing data, much of which was also acquired in 1999 (Table 1). These data sets included Probe-1 hyperspectral data at various resolutions, ATLAS multispectral data with multiple thermal bands, very high resolution color infrared (CIR) aerial photography scanned at 0.5 meters, plus synthetic aperture radar imagery collected by the AIRSAR and STAR-3*i* sensors. In addition, the study also employed several geographic information system (GIS) compatible field surveys and thematic maps generated by the USGS, the NPS, and others (Table 2).

Table 1. Remote sensing data available for study.

Remote Sensing Data Type	Date Acquired	Spatial Resolution
AVIRIS Hyperspectral data	7/23/99	1.6 by 4.8m
ATLAS Multispectral/Thermal data	8/17/99	2.5m
Zeiss CIR Aerial Photo data	8/17/99	scanned at 0.5m
Positive Systems Multispectral data	early 10/99	0.5m
USGS DOQQ data	mid 1990s	1m
Probe-1 Hyperspectral data	summer 1999	1 to 8m
STAR-3*i* X-Band SAR data	fall 1999	2.5m
AIRSAR data	5/28/99	10m
Landsat ETM+ data	7/13/99	30m

Table 2. Field reference data.

Reference Data	GIS Format	Source
Analytical Spectral Devices spectra	point	NASA/YES
Field checks and photos	point	NASA/YES
40x40m vegetation plots	polygon	YES
DEM data - 10 to 30m	raster	USGS, EarthWatch
Digital line graph data	polygon	USGS
Digital raster graphic data – multiple scales	raster	USGS
National wetlands inventory	polygon	U.S. Fish and Wildlife Service National Wetlands Inventory
Habitat map	raster	NPS
Vegetation map	raster	NPS
Fire intensity - 1988 wildfire	raster	NPS

4. METHODS

ATREM and EFFORT software were used to compute ground reflectance from the AVIRIS data. Afterwards, an additive offset was applied to eliminate negative reflectance values in waters and shadows. The AVIRIS data was later georeferenced with software developed by Analytical Imaging Geophysics and subsequently co-registered to USGS digital orthophoto quarter quadrangles (DOQQ's) using 80 ground control points and a second-order polynomial transformation. Output imagery contained an across-track resolution of 1.6 meters, an along-track resolution of 4.8 meters, and an overall root mean square error fit of 2.70. This unusual resolution is due to along-track undersampling (i.e., skip) from the plane's not flying high enough to permit sampling at the same resolution as in the cross track. Future collects should not have this problem as the AVIRIS data can now be collected at sufficiently high altitudes to avoid along-track skip.

Prior to classification, the author conducted a literature review to identify spectral bands or regions important for classification of vegetation, soil, and water conditions. Relevant publications include Ahern (1988), Guyot et al. (1992), Penuelas et al. (1994), Clark et al. (1995), Goetz and Boardman (1995), Carter et al. (1998), Kokaly et al. (1998), Martin et al. (1998), Sampson et al. (2001), Adams et al. (1999), Zarco-Tejada et al. (1999), Fuentes et al. (2000), Jensen (2000), Mohammed et al. (2000), and Thenkabail et al. (2000). This review led to the selection of 11 bands for classification, including six bands in the visible, three bands in the NIR, one in the "Landsat" short wave infrared-1 (SWIR-1), and one in the "Landsat" SWIR-2 region (Table 3). Selection included representative bands indicative of healthy, stressed, and dead vegetation. Bands sensitive to vegetation health and biomass help to promote detection of several grassland types growing along a topographic moisture gradient. Selection also consisted of blue and green bands for aiding separation of forest types as well as for mapping water. In addition, selection included one SWIR-1 band for adding information on soil and vegetation moisture and one SWIR-2 band for enhancing detection of vegetation moisture, dead forest, woody debris, exposed soil, rock, mineral deposits, and alluvial surfaces. Band selection avoided bands with known significant atmospheric influence.

The 11 selected bands were subset from the path-oriented yet georeferenced output. Classification analyses required at least some initial georeferencing because the non-georeferenced data could not be effectively related to field surveys. In particular, classification products could not be most effectively assessed without visual comparison to the ground reference data. The use of the path-oriented raw data and the band reduction collectively also enabled significant reductions in data volume and expedited classification run times.

Table 3. Bands selected for ISODATA classification.

AVIRIS Band	Band Center	Spectral Region	Characteristic Sensitivities Per Selected Band
13	488.37	Blue	soil, water, and vegetation
17	527.67	Green	vegetation - chlorophyll reflectance – in left side slope
20	557.14	Green	vegetation - "green peak" for chlorophyll reflectance
23	586.61	Yellow	vegetation – reflectance of chlorotic foliage
27	625.90	Orange	vegetation – reflectance - early phase necrotic foliage
37	692.33	Red	vegetation – right side of red "chlorophyll absorption well"
42	740.03	Red/NIR	vegetation - band located in far red portion of "red edge"
51	825.93	NIR Plateau	vegetation condition, soil moisture, and water body detection
70	1012.21	NIR Plateau	vegetation condition, soil moisture, and water body detection
137	1654.04	SWIR-1	clouds, snow, soil moisture, and vegetation moisture
194	2211.8	SWIR-2	mineral, rock type, and vegetation moisture

Classifications were performed with ERDAS IMAGINE software as follows: ISODATA was used to generate an initial classification of 30 cluster classes using settings of 50 iterations, 99% convergence, means initialization along the first PC axis, automatic scaling, and sampling every pixel. The 30-class output was compared to assorted reference data (e.g., aerial photographs and field survey data) and then recoded into 9 broad classes.

For the most part, at least some visually apparent confusion occurred in each broad class of the regrouped initial classification. Consequently, cluster-busting techniques were applied to reduce misclassification. In doing so, masking was performed to isolate raw data for each broad class. These raw data sets were then reclassified with ISODATA clustering. The settings for these follow-up "runs" were identical to the initial classification, except with respect to the number of classes. For each raw data mask, the number of classes was set to twice the apparent number of distinct spectral tones evident on representative RGB color composite displays. This reclassification process worked well for most situations but did not usually separate targeted classes that were locally common yet regionally rare. To break out the latter, area of interest (AOI) polygons were screen delineated and later used to guide ISODATA clustering within AOI's. In paved highway, AOI's had to be defined around the category of interest as well as the category with which it was confused. Running ISODATA on both confused features enabled spectrally similar but distinct signatures to be identified. In the reclassification process, "keeper" cluster classes refer to those not needing cluster busting. Such classes contain minimal apparent confusion between spectrally similar land cover types.

Reclassification led to several secondary classifications being output as classification imagery and signature files. All of the "keeper" secondary classification signatures were appended into one master signature file. The master signature file and the original 11-channel subset were then subject to the maximum likelihood classifier to produce a classification image containing 147 cluster classes. The latter represented 33 specific land cover categories falling under 13 general classes: 1) wet herbaceous cover, 2) moist to seasonally wet herbaceous cover, 3) moderately moist grassland without and with sage, 4) dry sage habitats without and with dry grassland, 5) dry grassland without sage, 6) very dry grassland on exposed sites, 7) coniferous forest – alive and dead, 8) deciduous forest and shrubs, 9) woody debris, 10) bare rocks and coarse soil, 11) bare alluvial deposits, 12) water, and 13) shadowed non-forested areas.

The 147-class image was regrouped to 33 classes that were subsequently filtered using IMAGINE's ELIMINATE routine and a 9-pixel elimination threshold (Figure 2). Areal extent for each of 33 categories in the "final" classification was summarized (Table 4). The final classification was then evaluated qualitatively through comparison with large-scale CIR aerial photographs and field survey data. The latter includes field-annotated hardcopies of the aerial photography as well as Global Positioning System referenced field photographs. Time scheduling did not permit for results of a quantitative accuracy assessment to be presented at the workshop.

5. PRELIMINARY ANALYSIS OF FINAL CLASSIFICATION

This classification includes not only distinct land cover types but also variants (i.e., subclasses) in some cases. In doing so, the classification scheme includes ecological and/or spectral subclasses to aid qualitative and quantitative accuracy assessment, plus the editing of class descriptions.

Rangeland cover types dominate the scene, collectively composing about 67 % of the total mapped area. The final map clearly shows the main herbaceous plant and sage communities occurring along the topographic moisture gradient readily seen in the field. In general, the classification separates extremely dry grassland, dry grassland, moist grassland, moderately moist grassland, and moist to seasonally wet herb-dominated grassland as well as sage/grasslands growing in moderately moist to dry sites (Figure 2 and Figure 3).

Wetland habitats commonly occur in some parts of the scene. The classification identifies several types of herb-dominated wetlands, including sedge-dominated communities and mixed grass/forbs with Canada thistle, an exotic species. The latter is a land cover condition of interest to the NPS for its program to combat invasive plant species (NPS, 1999). The rush cover type is not mapped, probably because of the rareness of the cover type in the study area. It tends to occur as very small patches in close proximity to the waterlogged sedge sites. The sedge types represent multiple spectral conditions, apparently due to variations in site moisture. In effect, the sedges occur on wet to very wet sites with standing water apparent in the extreme cases. The classification does not map wetland forest (cottonwood) and shrub (willow) types as well as desired, in part due to the rarity and very small patch size of these features within the AVIRIS scene. The largest patch of willow observed in the study area is only 10 meters by 10 meters, which is much smaller than a 0.25-acre minimum-mapping unit. The time of year probably imposes a negative influence on the detection of willow communities. The willows tend to occur among sedges that are spectrally similar to willows on the AVIRIS scene. A scene acquired later in the year probably would have better separation, based on the fact that these types are distinct on October multispectral data from Positive Systems' ADAR system. Undoubtedly, the undersampling of the AVIRIS data in the along-track direction also impeded the detection of these very fine-scaled features.

In general, this author found the non-forested wetland cover types to have impressive exploitable spectral variability, but they posed great difficulties in mapping because of the spectrally subtle tones of certain wetland types on the CIR aerial photographs and because of the fine-scaled nature of many wetland sites (Figure 3). Certain AVIRIS RGB displays show wetland types better than the CIR aerials do, although it was best to view both data types compared to ground reference data. While we had considerable in-situ data, the description and accuracy assessment of the wetland types would benefit greatly from additional field validation.

The AVIRIS classification also largely identifies live and dead softwood forest, plus dead woody debris. The last tends to be a fine-scaled feature occurring on alluvial surfaces, such as gravel and sandbars (Figure 3). Mapping woody debris is important to the NPS for enhanced understanding of the region's riparian ecology and for better park management (NPS, 1999). The attempt to map aspen yielded mixed success, again apparently because of very small patch size and rarity within the scene. The AVIRIS also readily identifies many non-vegetated surfaces, such as multiple alluvium types, surface water, pavement, and bare rock outcroppings. Pavement is mapped well, though doing so required considerable additional effort using subset AOI's in conjunction with masking and reclassification. The classification shows a very small amount of non-forested shadow. The shadowed forest largely pertained to softwood forest and subsequently recoded as such in the final classification.

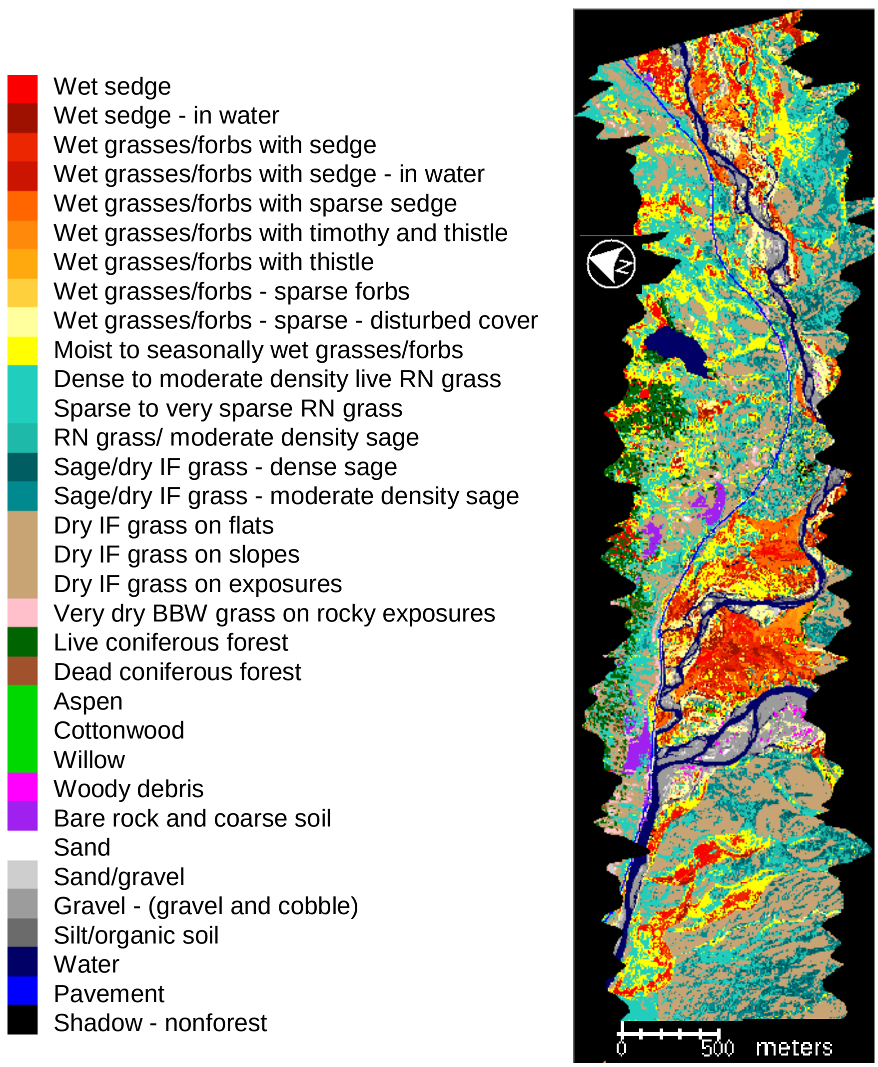

Figure 2. AVIRIS-based final classification with 33 map categories.

Table 4. Summary area for map categories in final classification.

Category #	Cover Type Category	Hectares	% Total Area
1	Wet sedge	13.62	2.69
2	Wet sedge - in water	7.19	1.42
3	Wet grasses/forbs with sedge	17.53	3.47
4	Wet grasses/forbs with sedge - in water	7.76	1.53
5	Wet grasses/forbs with sparse sedge	14.17	2.80
6	Wet grasses/forbs with timothy and thistle	3.14	0.62
7	Wet grasses/forbs with thistle	0.72	0.14
8	Wet grasses/forbs - sparse forbs	4.69	0.93
9	Wet grasses/forbs - sparse - disturbed cover	20.22	4.00
10	Moist to seasonally wet grasses/forbs	60.52	11.96
11	Dense to mod. dense live RN grass[1]	36.17	7.15
12	Sparse to very sparse RN grass	46.56	9.20
13	RN grass/moderate density sage	14.45	2.86
14	Sage/dry IF grass - dense sage[2]	18.43	3.64
15	Sage/dry IF grass - moderate density sage	39.47	7.80
16	Dry IF grass on flats	52.84	10.45
17	Dry IF grass on slopes	53.05	10.49
18	Dry IF grass on exposures	12.93	2.56
19	Very dry BBW grass on rocky exposures[3]	3.91	0.77
20	Live coniferous forest	14.40	2.85
21	Dead coniferous forest	1.98	0.39
22	Aspen	0.33	0.06
23	Cottonwood	0.14	0.03
24	Willow	0.05	0.01
25	Woody debris	1.15	0.23
26	Bare rock and coarse soil	4.83	0.95
27	Sand	0.62	0.12
28	Sand/gravel	2.54	0.50
29	Gravel - (gravel and cobble)	17.39	3.44
30	Silt/organic soil	6.24	1.23
31	Water	23.01	4.55
32	Pavement	3.40	0.67
33	Shadow – nonforest	2.38	0.47
N/A	Grand Total	505.82	100.00

[1]RN denotes grassland community with Richardson's needlegrass
[2]IF denotes grassland community with Idaho fescue grass
[3]BBW denotes grassland community with bluebunch wheatgrass

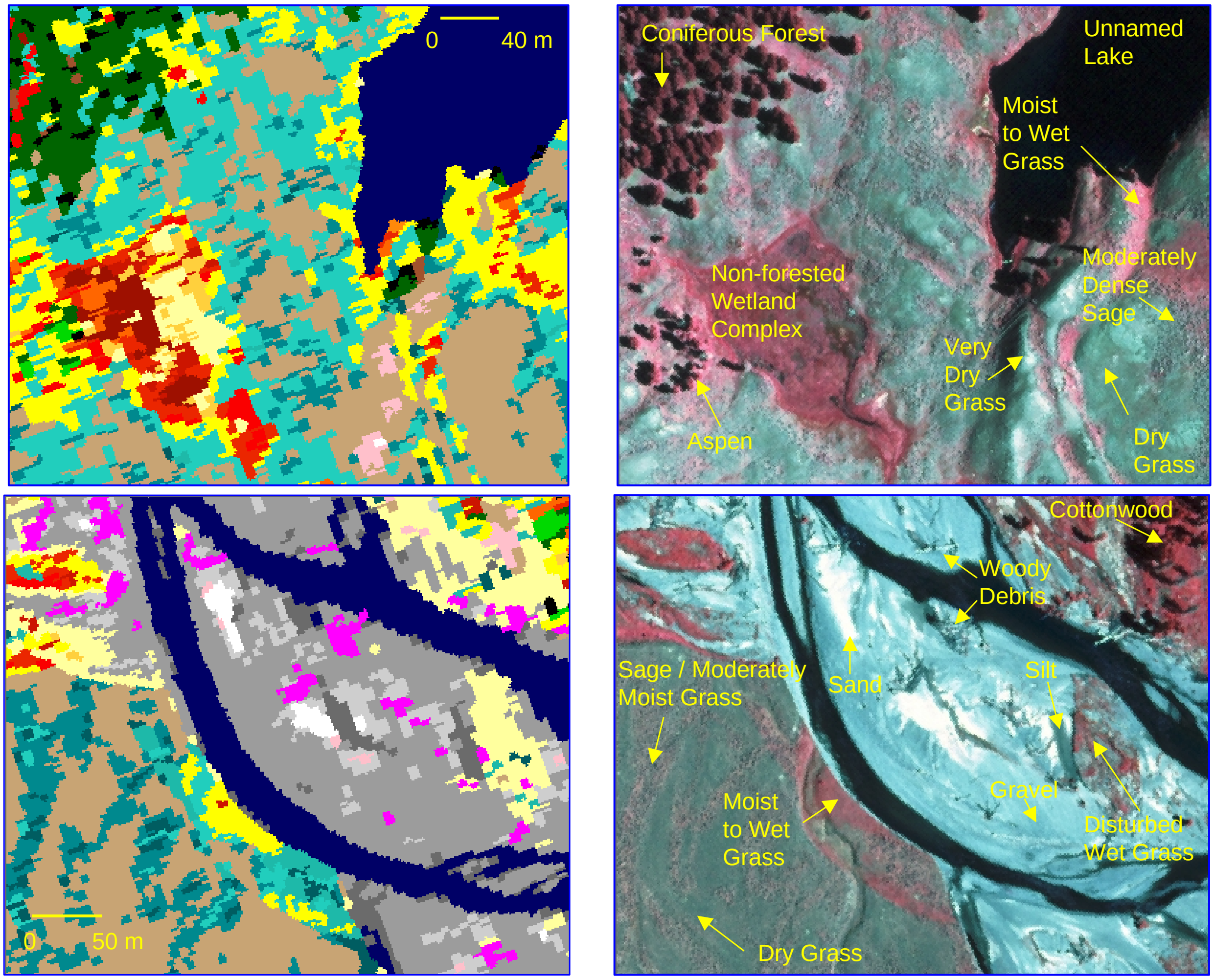

Figure 3. Visual comparison of final classification to scanned 1:8,000 color infrared aerial photographs.

6. CONCLUDING REMARKS

The results of this study provide insight into the apparent feasibility of using an 11-band subset of AVIRIS data and ISODATA techniques for classification of forest, range, and wetland habitats. The author observed consistent classification success for the most common cover types based on qualitative comparison to ground reference data. Classification success also occurred for some scarce, fine-scaled and/or comparatively rare habitats. However, classification confusion took place for other scarce, fine-scaled cover types. Herb-dominated wetlands appear to be well classified in general, although additional ground reference data is needed to determine the level of detail that can be extracted with the ISODATA classification approach as well as through interpretation of the CIR aerial photographs.

The ISODATA classification approach appears to be quite useful for computing wall-to-wall land cover maps from AVIRIS-quality hyperspectral data. The approach does not require all the bands and may or may not be improved using more bands. In terms of a first-cut classification, ISODATA classification using all bands did not appear to improve results when compared to ISODATA classification of 11 select bands. In addition, using all the bands takes about 20 times longer to perform a classification run and requires much more disk space to run. The disk space requirement for running ISODATA cluster busting on all the bands is probably too great for usage in an operational setting. However, an 11-band subset or a similar sized subset would be much easier to process from a data volume management perspective.

It is quite possible that there are other comparable or even better ways to compute wall-to-wall land cover maps from AVIRIS data. For example, some preliminary work by the author indicates that use of the 15 most signal-rich MNF bands instead of 11 select bands may improve ISODATA classification success. It also maybe possible to increase the number of raw bands to 25 without significantly slowing run times and without increasing data volumes to excessively large amounts. There are other bands that probably would be useful for band selection in regard to ISODATA classification. For example, Kokaly and Clark (1999) identify spectral regions important for estimating nitrogen, lignin, and cellulose levels in vegetation. Additional bands from these spectral regions could help improve classification results. Some of the bands selected for classification may not have been optimal. Consequently, better band selection may also improve results.

The classification of problematic scarce, fine-scaled features maybe better mapped with subpixel classification techniques. ISODATA may not always provide a sufficiently effective means to map rare and spectrally subtle features, although it appears to be well suited for land cover classification of common types within the scene. The study area of Northeast Yellowstone National Park largely consists of cover types common to the Northern Rocky Mountains. Consequently, the results from this study should be quite applicable to comparable mapping studies in this region of North America.

Additional work is being done to complete a quantitative map accuracy assessment, using a stratified random sampling of the classification in conjunction with CIR aerial photograph interpretation and field surveys. The results of this assessment will be reported at later date.

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