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Signature ___________________________
Date ________________________________
MAPPING AMPHIBIAN HABITAT DISTRIBUTION IN THE FRANK CHURCH-
RIVER OF NO RETURN WILDERNESS, ID USING MULTIPLE SCALES OF
REMOTELY SENSED DATA

by

Jeremy P. Shive

A thesis submitted in partial fulfillment
of the requirements for the degree of
Master of Science in the Department of Biological Sciences
Idaho State University
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To the Graduate Faculty:

The members of the committee appointed to examine the thesis of Jeremy P. Shive find it satisfactory and recommend that it be accepted.

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I predicted Western Toad (*Bufo boreas*) and Columbia Spotted Frog (*Rana luteiventris*) habitat distribution at Big Creek and the Bighorn Crags, and compared the classification results from three different remotely sensed datasets: Landsat ETM+ and ADAR 5500 multispectral imagery and HyMap hyperspectral imagery. The hyperspectral data exhibited the highest classification accuracies with a producer’s accuracy of 83.3 % and 95.7% and a user’s accuracy of 75.8% and 89.8% in both study areas. I also found that the emergent sedge classification map in one study area directly predicted 72% (23/32) of the egg mass oviposition locations within lakes and ponds. The most important result is the four new amphibian sites identified with the hyperspectral data and not previously located through repeated ground-based surveys. The ability of hyperspectral data to identify near-comprehensive habitat distribution suggests that hyperspectral data analysis has the greatest potential for future widespread amphibian inventory and monitoring applications.
1.1.0. Thesis Introduction

1.1.1. Thesis Layout

Advances in remote sensing technologies provide new potential tools for identifying amphibian habitat distribution across large spatial scales. The rationale for this thesis was developed following an exploratory study testing new hyperspectral remote sensing technologies to identify amphibian habitat in an area of Yellowstone National Park (Crabtree et al. in press). The accurate preliminary classification results warranted further investigation to more thoroughly evaluate the potential for mapping amphibian habitat distributions using hyperspectral remote sensing technology.

The first chapter (2.1.0.) of this thesis describes the assessment of numerous image classification algorithms applied to multispectral and hyperspectral imagery. I created classification maps of different wetland habitat types using three different scales (i.e., spatial and spectral) of remotely sensed data. The goal of this chapter is to provide a quantified accuracy assessment of different types of remotely sensed data, and suggest the most appropriate data type for future amphibian conservation efforts such as inventory and monitoring programs. I compare the image classification results against traditional methods (e.g., topographic maps) for selecting amphibian sampling sites. I also evaluate the required processing time and cost of each dataset to further evaluate the most appropriate type of imagery for future inventory and monitoring programs.

The second chapter (3.1.0.) describes details from the hyperspectral data analysis of the Bighorn Crags study area. There are numerous years of ground-based
survey data collected in this study area (Pilliod and Peterson 2001, Pilliod and Peterson 2000, David Pilliod unpublished data) providing an ideal testing location with near-comprehensive documentation of amphibian habitat distributions and occurrence. I compare the classification accuracy of different emergent sedge spectral endmembers, and assess the ability to directly predict amphibian egg oviposition locations within a wetland site. I present some preliminary results for a wetland depth classification map, and discuss the potential for delineating specific amphibian habitat types, such as breeding and foraging habitat, with hyperspectral data.

1.2.0. Remote Sensing Data Descriptions

I will first describe the acquisition dates and sensor characteristics of all three remote sensed dataset used in this study, and refer to this section in subsequent chapters whenever necessary. Any preliminary image processing steps (e.g., atmospheric correction) applied to the multispectral data are explained after each dataset description. Following the hyperspectral data description, I elaborate in detail about the sequential image processing steps unique to hyperspectral data analysis.

1.2.1. Multispectral Data and Preliminary Processing

The first multispectral dataset was collected on July 10, 2002 by NASA’s Landsat 7 Enhanced Thematic Mapper Plus (ETM+) satellite. Landsat ETM+ uses an oscillating scanning mirror with +/- 5.78° angular displacement off-nadir, resulting in an image swath of approximately 185 km and an instantaneous field of view (IFOV)
(i.e., spatial resolution) of 30 m for all spectral bands (Jensen 2000). The Landsat ETM+ sensor collects six spectral bands of 8-bit data in the visible and infrared region of the electromagnetic spectrum (EMS).

The Landsat ETM+ data were received in the form of digital number (DN) values and were converted to at-sensor reflectance. The reflectance conversion process is calculated as:

\[ L_\lambda = \left(\frac{L_{\text{MAX}} - L_{\text{MIN}}}{255}\right) \cdot \text{DN} + L_{\text{MIN}} \]

where, \( L_\lambda \), is radiance (W/m\(^2\)/sr/\(\mu\)m) for each spectral band, LMIN and LMAX are the gains and bias information respectively that are obtained from the image header file, and DN represents the assigned digital number of a spectral band.

Reflectance, \( \rho_\lambda \), for each band is calculated as:

\[ \rho_\lambda = \frac{\pi \cdot L_\lambda}{\text{ESUN}_\lambda \cdot \cos \theta \cdot d_r} \]

where \( L_\lambda \) is the radiance for each spectral band, \( \text{ESUN}_\lambda \) is the mean exo-atmosphere irradiance for each band (Landsat 7 Science Users Handbook 2002) in units of W/m\(^2\)/\(\mu\)m, cosine \( \theta \) (\( \theta = 90^\circ - \beta \)) where \( \beta \) is the sun elevation angle. The term \( d_r \) is defined as \( 1/d_{e-s}^2 \) where \( d_{e-s} \) is the relative distance between the earth and sun in astronomical units (Duffie and Beckman 1980). The term \( d_r \) is calculated as:

\[ d_r = 1 + 0.033 \cos(DOY \ 2\pi/365) \]
where DOY is the sequential day of year.

The second multispectral dataset was collected on July 31, 2002 by Positive System’s Airborne Data Acquisition and Registration (ADAR) 5500 system. The ADAR 5500 system incorporates Kodak Professional DCS 420 digital frame cameras with a 39º across-track field of view and a 0.44 mrad IFOV for each pixel in the charge-coupled device (CCD) array (Jensen 2000). The ADAR 5500 was configured to collect four spectral bands of 8-bit data in the visible and near-infrared regions of the EMS with a spatial resolution of approximately 2 m.

1.2.2. Hyperspectral Data and Preliminary Processing

Hyperspectral data were acquired on June 30, 2002 by the airborne hyperspectral sensor HyMap (Cocks et al. 1998). HyMap uses a whiskbroom sensor with a 61.3º field of view (512 across track pixels) with an IFOV of 2.5 mrad along track and 2.0 mrad across track. HyMap is typically flown on a twin engine, fixed wing Cessna mounted with a gyro-stabilized platform and incorporates a Boeing C-MIGITS II Global Positioning System (GPS)/Inertial Monitoring Unit (IMU) that collects correction factors for aircraft roll, pitch, and yaw caused by turbulence. HyMap collects 126 spectral bands of 12-bit data covering 0.44 µm – 2.5 µm spectral region with a 15 nm average bandwidth. Spatial resolution of the hyperspectral data collected over the Big Creek and Bighorn Crags study sites were 4 m and 3.6 m, respectively.

The HyMap data are collected on a per pixel basis and therefore geometric corrections must be made to the data to insure that each pixel can be referenced to a
real-world coordinate system and used with other spatial datasets. All of the pixel coordinates recorded during the flight are organized into an Input Geometry File (IGM) that preserves the spatial integrity of the ground pixel relationships (Boardman 1999). Then a Geometry Lookup Table (GLT) is created which provides the measured coordinate positions supplied from the onboard C-MIGITS II GPS/IMU that corrects for platform motion and topography (Boardman 1999). I applied the geometric correction files to the reflectance data which eliminated overlapping redundant pixels and resampled “gaps” in the data, thus producing a geometrically corrected contiguous image.

I followed a hyperspectral image processing strategy developed by Analytical Imaging and Geophysics, Inc. (Center for the Study of Earth from Space 2002) for identifying image derived spectral endmembers (Figure 1). The purpose of this processing flow is to identify spectral endmembers without using ground based polygons or field spectra as training data. The results from each processing step feed directly into the next step until image endmembers are identified and are applied back to the entire image.

A preliminary step in the processing flow begins with the conversion process from radiance to apparent reflectance. To produce spectral signatures that can be compared with laboratory or ground-based spectra and quantitatively evaluated, the radiance data must be converted into apparent reflectance by applying atmospheric corrections. The raw radiance (µW/cm²/sr/nm) data collected by the HyMap sensor are influenced by incoming solar irradiance and atmospheric absorptions from gases such as water vapor, ozone, carbon monoxide, oxygen, carbon dioxide, nitrous oxide,
and methane (Gao et al. 1993). The data were delivered atmospherically corrected using a modified radiative transfer model (Gao et al. 1997). The reflectance data were also spectrally “polished” using the Empirical Flat Field Optimal Reflectance Transformation (EFFORT), which removes residual and cumulative calibration and model imposed errors (Boardman 1998a).

Figure 1. The “hourglass” hyperspectral image processing methodology (modified from Center for the Study of Earth from Space 2002).

The HyVista Corporation rescales the apparent reflectance data values from real numbers to integers to reduce the disk storage space needed for each hyperspectral image cube. True reflectance values are reported as a fractional percent from 0-1. To maintain the dynamic range of radiance values, spectral bands 1-62
(i.e., the VIS and NIR spectrometers) are multiplied by 1000 and bands 63-126 (i.e.,
the SWIR1 and SWIR2 spectrometers) by 4000 (HyVista Corp. 2002). The
converted data are considered to be apparent reflectance, opposed to true reflectance,
because in order to calculate true reflectance every change in terrain slope and aspect
would have to be accurately known. I maintained this data scaling format and all
hyperspectral plots in the following chapters report scaled apparent reflectance
values.

Many of the spectral bands in hyperspectral data contain redundant
information caused by the correlation between contiguous overlapping spectral band
sampling. Some spectral bands may also be dominated primarily by noise with low
signal content, especially wavelengths in the short-wave infrared region where
reflectance values are inherently low due to less incoming solar irradiance. I
performed a spectral data reduction step using the Minimum Noise Fraction (MNF)
transformation (Green 1988) of the reflectance data to segregate the redundant and
“noisy” uninformative bands from the bands contributing to true image variance. The
MNF transform can be considered a two-step principal components analysis that is
designed to decorrelate noise in the data based on local shift difference statistics to
create an isotropic noise structure. The first step calculates a noise covariance matrix
and decorrelates and rescales the estimated noise in the data (Green et al. 1988). The
second step is a standard Principal Component (PC) transformation where new
orthogonal axes of spectral information are identified and organized by decreasing
band variance (Green et al. 1988). I examined the MNF transformed spectral bands
using ENVI’s animation feature and considered the resulting eigenvalue plots to
determine the dimensionality of each dataset. The assigned image dimensionality (i.e., the total number of significant MNF bands) served as the input image data used for the subsequent hyperspectral processing steps.

The majority of image pixels represent spectral mixtures of background surface materials. There is a small subset of image pixels that are spectrally “pure” image endmembers or spectral signatures that represent 100% of a single feature (e.g., a species of vegetation). I ran the Pixel Purity Index (PPI) to identify potential image endmembers from the data that exhibited a spatial distribution within training site boundaries (i.e., top down approach). The PPI uses convex geometry concepts by fitting a simplex to the multidimensional cloud of spectral data points. PPI is an iterative process that cumulatively scores extreme pixels (i.e., pixel near simplex vertices) (Boardman et al. 1995). The simplex vertices represent theoretical image endmembers (Boardman 1993) that form the spectral mixtures comprising the majority of background image pixels. The PPI scores pixels within a defined standard deviation from the two most extreme pixels, sometimes causing an overestimation of scene endmembers in certain dimensional projections. The n-Dimensional Visualizer (n-DV) is an algorithm used as a secondary refinement of potential endmember pixels. I used the n-DV to interactively identify and refine the potential spectral endmembers by rotating the PPI pixels in variety of MNF dimensions (i.e., number of MNF bands) and observing selected endmember distributions in the original image.
2.1.0. Chapter 1 Introduction

2.1.1. Amphibian Declines

Amphibians are an integral component of numerous ecosystems worldwide, and as a taxonomic group they represent an important contribution to global biodiversity with over 4600 species worldwide (Pough et al. 2004). Many unique natural history traits of amphibian behavior, reproductive strategies, and anatomy and physiology have facilitated widespread global distribution and survival for millions of years. Unfortunately certain physical characteristics, such as semi-permeable skin, may increase amphibian susceptibility to harmful impacts from environmental pollutants caused by direct and indirect anthropogenic activities. Most amphibians also exhibit a biphasic life cycle demanding both aquatic and terrestrial habitat, which increases their vulnerability to impacts of habitat alteration or loss. Faced with numerous environmental challenges, amphibian occurrence and abundance patterns may provide biologists with a bioassessment tool for evaluating habitat quality and the presence of environmental stressors (Cooke 1981, Bowers et al. 1996).

Two decades of observations have documented widespread global amphibian population declines, which has stimulated concern among herpetologists and conservation biologists around the world. A number of hypotheses, such as increased ultraviolet radiation (Blaustein et al. 1994), global warming (Kiesecker et al. 2001), introduced predators (Knapp and Matthews 2000, Pilliod and Peterson 2001), disease (Berger et al. 1998), drought (Pounds and Crump 1994, Stewart 1995), and pollutants
(Carey and Bryant 1995) have been explored to help scientists understand observed population declines. Habitat loss or modification is an additional hypothesis investigated and recognized as an important contributing factor influencing population declines (Semlitsch 2000), suggesting the importance of understanding current habitat distributions and the potential repercussions resulting from future land management decisions.

2.1.2. Inventory and Monitoring Programs

In response to ongoing population declines, substantial effort has been invested in establishing broad scale inventory and monitoring initiatives to better understand amphibian population distributions and relative abundance across large landscapes. Commonly, inventory and monitoring programs have only recently begun and the collection of initial inventory data remains the primary objective. Following the inventory phase, repeated surveys can form the basis for a monitoring program. Monitoring specific key habitat features (e.g., shallow shorelines and emergent vegetation) can serve as a surrogate for amphibian response to habitat alteration over time. Modeling important habitat features may also provide insights concerning the effects of proposed management actions on population dynamics across broad spatial scales.

The design of inventory and monitoring programs requires thoughtful logistical considerations of sampling site selection, field data collection, and the temporal framework needed for thorough and repeatable surveys. The ideal scenario for an inventory and monitoring program would be to start with a comprehensive
survey of all available habitat within the study area (Fellers 1997), but this is rarely possible because current amphibian habitat distribution is usually unknown. Conventional methods of sampling site selection are based on the identification of lake and wetland sites through currently available spatial datasets such as U.S. Geological Survey topographic and U.S. Fish and Wildlife Service National Wetland Inventory (Cowardin et al. 1979) maps, or digital aerial photographs such as Digital Orthophoto Quarter Quadrangles (DOQQ). These datasets are frequently outdated and are derived from historic image interpretations influenced by interpreter bias, image data quality, and time of year when the images were collected. Small wetland sites (i.e., several m$^2$) are not regularly detected using traditional methods of environmental mapping, and this problem is exacerbated in regions with dense forest canopy cover and widely dispersed habitat locations. Yet, small ponds may serve as some of the most important habitat for breeding amphibians due to the lack of large predators, abundance of emergent vegetation used for egg attachment sites and cover protection, and the presence of algal mats for larval grazing.

Without the aid of standard imagery or maps to help identify crucial habitat distribution and assist a researcher in designing the most appropriate sampling scheme or site selection process, ground based surveys will be hindered due to the large number of hours needed to thoroughly inventory a forest or wilderness area. In most cases research or monitoring projects are limited by funding that restricts the spatial (e.g., area of study) and temporal scales (e.g., number of visits and duration) of a survey, emphasizing the need for a fast and efficient method of identifying potential survey sites. Thorough and comprehensive site sampling must be performed to
accurately assess current amphibian population distributions, and knowledge of habitat distribution across large landscapes can be incorporated into future conservation initiatives and management decisions (Pilliod and Peterson 2000).

2.1.3. Remote Sensing

Recent advances in remote sensing technologies, such as high spatial resolution hyperspectral data, provide an avenue to address ecological questions that occur at fine spatial scales and encompass large spatial extents (Aspinall et al. 2002, Crabtree et al. in press). The issue of determining an optimal sampling scale for remotely sensed data first received attention more than a decade ago when the options consisted of primarily coarse scale image data sources (Woodcock and Strahler 1987). The current variety of remotely sensed data scale options (i.e., spatial and spectral) significantly enhances the ability of a researcher to design studies and investigate biological or ecological questions that previously could only be considered with extensive ground-based sampling effort. Given the variety of spatial and spectral resolutions commercially available today, the most pertinent question becomes: What resolution(s) of remotely sensed data is the most appropriate to accurately address specific biological questions?

As soon as an ecological system is chosen for study there is an inherent scale imposed upon that system (Allen and Hoekstra 1992), and the selection of remotely sensed data will apply yet a separate scale of observation (Woodcock and Strahler 1987). The sampling scale of an investigation will ultimately determine the patterns and processes that can be detected within the system of study (Wiens 1989, Curran...
and Atkinson 1999). If an inappropriate scale of observation is chosen, the inherent system dynamics, patterns, and processes may not be explicitly evident (O’Neill et al. 1986). For example, watershed level distribution, lake or pond level abundance, and microhabitat level breeding habitat information all contribute different valuable insights used to understand and describe amphibian population status. Each level of information considered alone may provide an inaccurate portrayal of the true population status. Across the landscape, amphibians may occupy a wide distribution within a watershed, but if half the critical breeding sites have been lost or altered, remnant widespread occurrence may suggest the population is stable when in fact it may be in decline.

The goal of many field studies is to collect data at a limited number of sites over a short temporal frame throughout the duration of a survey. These results form the basis for extrapolation or “scaling up” the local observations into models or monitoring plans that encompass a much larger spatial extent. In many cases the extrapolation to higher levels is unwarranted due to the scale dependency of the data collected (Levin 1992). Researchers must begin to collect fine-scale information across large spatial extents, and produce large-scale models that reflect true system properties and not simply artifacts of the sampling scale.

2.1.4. Research Objectives

I have taken a multi-scale approach to assess the applicability of current remote sensing technologies to model wetland habitat distribution in a wilderness area. Three types of remotely sensed data, with varying spectral and spatial scales,
were considered to determine which scale of data most effectively predicts wetland habitat distributions across two distinct ecological landscapes. My specific research questions are twofold: (1) Does spatial or spectral scale contribute most importantly to wetland classification accuracies? (2) Considering the comparative accuracy results interpreted from an inventory and monitoring application perspective, the cost of each type of imagery, and the relative image processing time, what types of remotely sensed data are the most appropriate to efficiently map wetland habitat and be incorporated into future broad scale amphibian conservation programs? My research enhances the current understanding of the application of remote sensing for amphibian conservation and contributes to developing a practical and effective design of inventory and monitoring survey plans. This research has far-reaching conservation implications for amphibian populations in similar environments around the world, but also for wetland identification and delineation and conservation concerns for many other organisms with similar habitat requirements.

2.2.0. Methods

2.2.1. Study Area

Two ecologically different landscapes located in the Frank Church-River of No Return Wilderness, Idaho (Figure 2) were chosen as study areas. The U.S. Congress designated this region as a wilderness area in 1980; it spans 2.4 million acres and lies within four Idaho counties: Custer, Idaho, Lemhi, and Valley. Wilderness administration is shared primarily between the Challis, Nez Perce,
Payette, and Salmon National Forests with smaller portions falling under Bitterroot and Boise National Forest jurisdiction.

The first study area is located along Big Creek, a sixth or seventh-order stream and major tributary to the Middle Fork of the Salmon River with elevations ranging from approximately 1100 m to 1900 m. Douglas fir (*Pseudotsuga menziesii*) and ponderosa pine (*Pinus ponderosa*) are the dominant tree species within the drainage while black cottonwood (*Populus balsamifera*), water birch (*Betula occidentalis*), and green alder (*Alnus viridis*) represent the tree species most commonly found in the riparian areas along Big Creek and local tributaries. Rocky Mountain maple (*Acer glabrum*), syringa (*Philadelphus lewisi*), and prairie rose (*Rosa woodsii*) comprise the majority of understory vegetation in the riparian area, while Idaho fescue (*Festuca spp.*) and numerous forbs characterize the drier upland hillsides.

The second study area is located in the Bighorn Crags, a sub-alpine region of the wilderness characterized by high elevation glaciated cirque basins. Exposed rocky talus slopes dominate the skyline with high mountain lakes resting in glacial depressions below ridges and conifer forests residing on low angle slopes. Elevation in this area ranges from approximately 2400 m to 2900 m. Subalpine fir (*Abies lasiocarpa*), Engelmann spruce (*Picea engelmannii*), and whitebark pine (*Pinus albicaulis*) characterize the forested uplands and valley floors. Beargrass (*Xerophyllum tenax*) and grouse whortleberry (*Vaccinium scoparium*) dominate the forest understory and sedge (*Carex spp.*) is commonly associated with mesic meadows and wetland habitat.
2.2.2. Amphibian Species

Four species of amphibians are found within the study area including the Long-toed Salamander (*Ambystoma macrodactylum*), Western Toad (*Bufo boreas*), Columbia Spotted Frog (*Rana luteiventris*), and the Rocky Mountain Tailed Frog (*Ascaphus montanus*). Although Rocky Mountain Tailed Frogs are present within the study area, they are associated with high gradient streams and dense riparian canopy cover and do not utilize ponds or lakes during their life cycle. I did not attempt to identify this type of habitat and optical imagery may not be an effective approach to map and delineate Rocky Mountain Tailed Frog habitat requirements. The Western Toad is considered Sensitive by the Bureau of Land Management and a Species of
Special Concern by the Idaho Department of Fish and Game, and a current understanding of this species’ distribution and status is a relevant conservation concern. The Western Toad and Columbia Spotted Frog rely on lentic habitat for breeding and are commonly associated with small ponds and emergent vegetation in the study area. Long-Toed Salamanders are commonly found near shallow rocky shorelines and within submerged woody debris or terrestrially under rotten logs and bark (Stebbins 1985). Columbia Spotted Frogs can be found throughout the study area foraging in moist meadows dominated by grasses and sedges. It is believed that Western Toads and adult Long-Toed Salamanders overwinter terrestrially in animal burrows while Columbia Spotted Frogs and larval Long-Toed salamanders depend on deep or thermally influenced water bodies that remain unfrozen to survive the long harsh winters that occur in the study area.

2.2.3. Data Processing

I performed all image processing and image classifications using Research Systems Inc.’s ENVI® 3.5 (RSI, 2002). All GIS analyses were conducted using Environmental Systems Research Institute, Inc.® ArcGIS 8.2.

2.2.4. Remote Sensing Data

I assessed three different scales of remote sensing data in this study (Table 1). Refer to section 1.2.0. for image acquisition dates and a complete description of the sensor characteristics.
Table 1. A descriptive sensor comparison of the remotely sensed data used in this study.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Type of Imagery</th>
<th>Spatial Resolution</th>
<th>Spatial Extent*</th>
<th>Bands</th>
<th>Spectral Sampling</th>
<th>Spectral Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landsat 7 TM</td>
<td>Multispectral</td>
<td>30 m</td>
<td>185 km x 185 km</td>
<td>6</td>
<td>Band 1 (Blue)</td>
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<td></td>
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<td></td>
<td>Band 2 (Green)</td>
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<td></td>
<td></td>
<td></td>
<td>Band 3 (Red)</td>
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<td></td>
<td>Band 4 (Near Infrared)</td>
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<td></td>
<td></td>
<td></td>
<td>Band 5 (Infrared)</td>
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<td>Band 7 (Infrared)</td>
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<td>Multispectral</td>
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<td>2 km x 3 km</td>
<td>4</td>
<td>Band 1</td>
<td>460 nm - 550 nm</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(per frame)</td>
<td></td>
<td></td>
<td>Band 2 (Green)</td>
<td>520 nm - 610 nm</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Band 3 (Red)</td>
<td>610 nm - 700 nm</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Band 4 (Near Infrared)</td>
<td>780 nm - 920 nm</td>
</tr>
<tr>
<td>HyMap</td>
<td>Hyperspectral</td>
<td>3.5 - 4 m</td>
<td>2.5 km x 20 km</td>
<td>126</td>
<td>VIS 15 nm</td>
<td>450 nm - 890 nm</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>NIR 15 nm</td>
<td>890 nm - 1350 nm</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>SWIR1 13 nm</td>
<td>1400 nm - 1800 nm</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>SWIR2 17 nm</td>
<td>1950 nm - 2480 nm</td>
</tr>
</tbody>
</table>

* Estimates are approximate spatial extent; after georeferencing spatial extent may be reduced slightly due to topography

# Represents the average spectral sampling interval for each spectrometer
2.2.5.0 Multispectral Image Classification

The intent of the classification process is to map the distribution of wetland habitat as an indicator of potential amphibian habitat. I am not abiding to a strict definition of a wetland and from this point forward I will refer to a “wetland site” generically as any location of standing water in the form of permanent lakes or ephemeral ponds and pools, but also wet meadows where water presence may be no more than a thin film or moist soil holding small puddles. These site descriptions characterize typical amphibian habitat in the study area and hence are the focus of my classification efforts.

The topography throughout the study area is characterized by steep slopes and ridges that produce an abundance of shadow influenced locations within both study sites. Shadows and water exhibit a similar spectral response pattern of very low reflectance, and consequently these two classes were continually misclassified and confused in the multispectral imagery. I decided the most accurate classification of water features (i.e., wetlands) would be to distinguish them from the shadowed pixels in each image, and I paid close attention to selecting representative water and shadow training Regions of Interest (ROI’s). I selected pixels in multiple training sites across the extent of each dataset to develop statistically representative ROI’s needed for successful image classifications (Lillesand and Kiefer 1994). I was not concerned with the ability to correctly classify surrounding vegetation features and collapsed all other image features into a single class labeled “Everything Else”. This approach delineates a total of three spectral training ROI classes (i.e., water, shadow, and everything else) used to classify the Landsat ETM+ imagery. I attempted to classify
an additional feature, sedge, in the ADAR 5500 imagery, but following preliminary visual classification assessments I determined the results were below an acceptable level of accuracy caused by widespread obvious overpredictions. This resulted in a total of three ROI training classes (i.e., water, shadow, and everything else) used to classify the ADAR 5500 data as well.

I ran the Jeffries-Matusita ROI separability measure to quantitatively evaluate the statistical separability of the training ROI classes used for the multispectral image classifications (Richards 1999) (Table 2). The output separability values range from 0-2, with values falling below 1 indicating poor or unacceptable separability of training classes. Separability values above 1.9 indicate the classes are spectrally distinct and should contribute to an accurate classification of those classes (Richards 1999).

Table 2. Jeffries-Matusita ROI separability results for the multispectral training classes.

<table>
<thead>
<tr>
<th></th>
<th>Landsat ETM+</th>
<th></th>
<th>ADAR 5500</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Big Creek</td>
<td>Bighorn Crags</td>
<td>Big Creek</td>
<td>Bighorn Crags</td>
</tr>
<tr>
<td>Water</td>
<td>1.99</td>
<td>1.95</td>
<td>1.92</td>
<td>1.72</td>
</tr>
<tr>
<td>Shadow</td>
<td>1.99</td>
<td>1.99</td>
<td>1.97</td>
<td>1.99</td>
</tr>
<tr>
<td>Everything Else</td>
<td>1.99</td>
<td>1.99</td>
<td>1.97</td>
<td>1.99</td>
</tr>
</tbody>
</table>
2.2.5.1. Big Creek Study Area

I used the Spectral Angle Mapper (SAM) classification algorithm for both the Landsat ETM+ and ADAR 5500 datasets at the Big Creek study area. The SAM classification algorithm determines the similarity between image spectra and training ROI spectra based on the angle between them calculated as a vector in n-dimensional space, where “n” equals the number of input bands or dimensionality (Kruse et al. 1993). Smaller angles represent better matches to ROI reference spectra. I adjusted the maximum allowable angle across a range starting at 0.1 radians up to 3.0 radians to determine the best acceptable angular tolerance. This algorithm is relatively insensitive to changes in scene illumination and albedo effects (Kruse et al. 1993), which may have contributed to the success of this approach applied to a landscape that is highly influenced by drastic changes in image brightness caused by topography and shadows.

2.2.5.2. Bighorn Crags Study Area

Following numerous attempts to apply various supervised classification algorithms to the Landsat ETM+ data in the Bighorn Crags study area, I decided the best approach was to use a 2-Dimensional (2-D) scatter plot incorporating two near-infrared spectral bands (i.e., Band 4 vs. Band 5). Water exhibits a low spectral response pattern in the near-infrared region of the EM spectrum and would expectedly be located near the lowest spectral values on both axes of the scatter plot. By exploiting this known spectral feature characteristic, I subjectively selected and iteratively refined a group of pixels located in the lower left corner of the 2-D scatter
plot (Figure 3). I exported the selected pixels as ROI’s and produced a standing water classification image.

Figure 3. 2-D scatter plot used to create the Landsat ETM+ standing water classification map of the Bighorn Crags study site.

I used the Maximum Likelihood algorithm to classify the ADAR 5500 data. The Maximum Likelihood algorithm considers both spectral variance, plotted as a mean vector, and covariance of the training ROI’s (Lillesand and Kiefer 1994). The underlying assumption of this algorithm is a Gaussian distribution, which is a reasonable assumption for common spectral classes such as water (Lillesand and Kiefer 1994). Based on the spectral response pattern and associated statistics of the ROI training classes, a probability density function is created that assesses the
individual probability for each image pixel. I designated a probability threshold of 0.7 for each ROI training class determined through repetitive classification attempts, and any pixel falling within the designated threshold range is assigned to the corresponding ROI class.

2.2.6.0. Hyperspectral Image Classification

Given the unique attributes of hyperspectral data, such as the ability to map endmember sub-pixel fractional abundances, I tested the Mixture Tuned Matched Filter (MTMF) classification algorithm (Boardman 1998b). Initially, I ran MTMF on all image endmembers identified through the PPI and n-DV image processing steps. I also experimented with traditional supervised classification algorithms in attempt to produce the most accurate wetland classifications.

2.2.6.1. Big Creek Study Area

Given the increased spectral resolution and range of the hyperspectral dataset, I was able to identify much finer-scale wetland habitat features as endmembers than “water” alone. I identified Standing Water and Sediment (SWS) and Shallow Stream Water (SSW) image endmembers (Figure 4). The SWS endmember is characterized by shallow standing water with sediment substrate present. The SSW endmember is characterized by shallow flowing water and a variety of substrate types. I used these two endmembers to classify wetland habitats associated with floodplain and stream-associated features such as side-channels and backwater pools. I also identified a wet
meadow (WM) endmember representative of a mixture of sedges and grasses directly associated with water presence (Figure 5).

![Figure 4. Standing Water and Sediment (SWS) and Shallow Stream Water (SSW) endmember spectral profiles.](image)

I used the SAM classification algorithm to classify the SWS and SSW endmembers. The characteristics of the SAM algorithm (i.e., insensitivity to changes in illumination and albedo) likely contributed to the classification success for these features that commonly exhibit variable reflectance patterns due to the surface turbulence of flowing water. I experimented with the same angular ranges described previously for the multispectral datasets, to assign the angle that produced the most accurate classifications while minimizing classification errors.
I used the MTMF algorithm to produce a classification of sub-pixel fractional abundances for the WM endmember. Although the goal was not to quantify the accuracy of estimated fractional abundance, this classification algorithm is potentially the best approach to identify small wetland features common to this study area. MTMF builds upon the strengths of both matched filtering and spectral unmixing algorithms while avoiding the disadvantages of both (Boardman 1998b). Matched filtering performs partial spectral unmixing and identifies the fractional abundance of a spectral endmember on a continuous scale without knowing all of the background endmember signatures (Harsanyi and Chang 1994, Boardman et al. 1995). Spectral unmixing takes advantage of the hyperspectral leverage (i.e., an overdetermined solution caused by a greater number of spectral bands than unknowns) to solve the linear mixed pixel problem (Boardman 1993). The combined strengths of these two algorithms provides a powerful approach to map individual endmember fractional
abundances while simultaneously reducing the rate of false positive predictions (Boardman 1998b).

The MTMF algorithm produces two continuous scale output images: the Matched Filter (MF) result and an Infeasibility (INF) image. The MF values are scaled so that positive values estimate sub-pixel fractional abundance of the endmember. True positive MF scores typically range from around 0.2 – 1.0 (i.e., 20-100% pixel abundance). MF scores below 0.2 can be unreliable because these pixels are located close to the background spectral mean of zero, and classification of these pixels can introduce false positive errors. The INF values can be interpreted as standard deviations from the background spectral mean with the lowest values representing higher probability endmember pixels. The range of INF values vary with each scene based on the amount of spectral variability present within the image. True positive INF scores can commonly range from 0 – 40.

An optimal image classification benefits from the useful information of both resulting MTMF images. To exploit the true strength of this algorithm, I plotted the WM MF image data and the INF image data as 2-D scatter plot. I selected pixels that had high MF scores and low INF scores (Figure 6), and these pixels were exported to create the final endmember classification map. Due to the spectral similarities in the vegetation present across the Cabin Creek floodplain, I was forced to select image pixels with a minimum MF threshold of 0.6 because lower MF values overpredicted other floodplain vegetation pixels.
2.2.6.2. Bighorn Crags Study Area

I was unable to identify any image endmembers that classified all water bodies (i.e., lakes, ponds, pools) well with the hyperspectral data, and consequently I classified standing water in the hyperspectral data using the same strategy described for delineating water in the Landsat ETM+ data. I plotted band 20 (0.727µm) and band 33 (0.9047µm), two near-infrared spectral bands, as a 2-D scatter plot and selected the pixels located in the lower left corner of the plot (Figure 7). The 2-D scatter plot is interactively linked to the displayed image, and I focused on known...
areas of standing water (i.e., large ponds and lakes) to decide when the pixel selection began to overpredict non-target pixels.

Figure 7. 2-D scatter plot showing the pixel selection used to create the HyMap standing water class. Final water pixels are shown in blue while all background image pixels are shown in white.

I identified an Emergent Sedge (ES) endmember (Figure 8) located in the sedge- dominated periphery of a well-described training site. This endmember was mapped and used as a proxy to help locate small emergent wetland sites and also wet meadow areas typically associated with amphibian foraging habitat in this study site. I used the MTMF algorithm to map sub-pixel abundances of the ES endmember. I plotted the MF and INF images as a 2-D scatter plot and subjectively selected the
pixels that exhibited high MF scores and low INF scores (Figure 9) to produce the final ES classification. Emergent sedge is spectrally unique in this study site, and consequently I was able to select pixels with a minimum MF score of 0.2 without creating obvious commission errors.

![Emergent Sedge (ES) endmember spectral profile.](image)

2.2.7. Accuracy Assessment

Error matrices serve as the basis for descriptive statistical techniques used to evaluate classification accuracy (Congalton and Green 1999). Producer’s accuracy is calculated by dividing the total number of correct pixels in a category by the total number of pixels actually identified from ground truth reference data (Congalton and Green 1999). Producer’s accuracy represents the probability a true positive location on the ground is correctly classified. User’s accuracy is calculated by dividing the
total number of correctly classified pixels by the total number of pixels classified in that category (Congalton and Green 1999). User’s accuracy represents the probability that a classified image pixel is actually that category on the ground (Story and Congalton 1986). Omission and commission errors are calculated by subtracting producer’s and user’s accuracy from 100%, respectively.

Figure 9. 2-D scatter plot of the MF and INF results from the MTMF classification algorithm applied to the ES endmember. Final classified pixels are shown in green while the remaining background image pixels are shown in white.
Currently the ability to perform advanced image classifications has progressed in parallel to technological advances, but the corresponding ability to quantify accuracy has not followed this progression (Lillesand and Kiefer 1994). High spatial resolution data (i.e., 5 m or less) commercially available from numerous sensors challenges the capability of GPS receivers to accurately locate points on the ground when the topography is complex and canopy cover disrupts a clear view of the sky. Along with the technical limitations of using GPS in many field study areas, image georeferencing procedures of airborne high spatial resolution data sometimes fail to provide highly accurate corrections. Even with a sophisticated GPS/IMU and ray-tracing program recording X, Y, and Z coordinates for every image pixel, drastic fluctuations in ground elevations cause significant error in the georeferencing process (Boardman 1999). Thus the coordinates of certain image pixels may be spatially skewed in a non-systematic direction, which makes locating individual pixels on the ground extremely difficult if not impossible. Similar to other validation studies involving high spatial resolution data (Aspinall 2002, Marcus 2002, Crabtree et al., in press), I used the classified imagery as a field map and navigated directly from it using obvious features (e.g., lake coves, stream bends, and rocky outcrops) as geographic references.

I chose to use groups or clusters of pixels as the sampling unit for the high spatial resolution (i.e., ADAR 5500 and HyMap) classification validation. Single pixels were validated when they were predicted in an obvious shoreline location that I could confidently identify in the field. The Landsat ETM+ spatial resolutions are
within an expected positional range of accuracy common with current GPS receivers, so I considered individual pixels as a sampling unit for this dataset.

There are a number of suggestions published for developing a validation site selection scheme, each with their own advantages and disadvantages see, for example, Congalton 1991. Because the primary goal of this study was to identify wetland habitats that are low in abundance and widely dispersed throughout the scene, I felt the most appropriate validation was to visit all of the classified potential wetland sites. I walked the shorelines of lakes and visually searched meadows and backwater areas while in transit between predicted sites, and used previously collected field data from the study area (Pilliod and Peterson 2002, Pilliod and Peterson 2001, Charles R. Peterson, David S. Pilliod, Crystal Strobl, and Jeremy P. Shive, unpublished data) as ground truth to evaluate omission errors.

2.3.0. Results

2.3.1. Big Creek Accuracy Assessment

A total of 30 wetland sites exist within this study area based on past field surveys and newly located sites. Both multispectral datasets performed poorly at this study site while the combined producer’s accuracy of the hyperspectral data was more than three times greater (Table 3).

The Landsat ETM + water classification produced the poorest accuracy results possible for a remote sensing application with a producer’s and user’s accuracy of 0%. Even the largest pond within the study site (i.e., Bufo-Moose pond,
approximately 1400 m² in size) was not detected due to the low spatial resolution of the imagery.

Table 3. Accuracy assessment summary table for the Big Creek study area.

<table>
<thead>
<tr>
<th></th>
<th>Producer's Accuracy</th>
<th>User's Accuracy</th>
<th>Omission Error</th>
<th>Commission Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landsat ETM+ (Water)</td>
<td>0.0%</td>
<td>0.0%</td>
<td>100.0%</td>
<td>100.0%</td>
</tr>
<tr>
<td>ADAR 5500 (Water)</td>
<td>26.7%</td>
<td>72.7%</td>
<td>73.3%</td>
<td>27.3%</td>
</tr>
<tr>
<td>HyMap (SWS)</td>
<td>43.3%</td>
<td>92.9%</td>
<td>56.7%</td>
<td>7.1%</td>
</tr>
<tr>
<td>HyMap (SSW)</td>
<td>23.3%</td>
<td>100.0%</td>
<td>76.7%</td>
<td>0.0%</td>
</tr>
<tr>
<td>HyMap (WM)</td>
<td>30.0%</td>
<td>56.3%</td>
<td>70.0%</td>
<td>43.7%</td>
</tr>
<tr>
<td>HyMap (Combined)</td>
<td>83.3%</td>
<td>75.8%</td>
<td>16.7%</td>
<td>24.2%</td>
</tr>
</tbody>
</table>

Surprisingly, the high spatial resolution of the ADAR 5500 data did not contribute to a successful classification of wetland habitat. The calculated producer’s and user’s accuracy were 26.7% and 72.7%, respectively. Eight wetland sites were successfully identified, while three wetland sites were falsely overpredicted and confused with the shadow class.

The HyMap hyperspectral data produced some of the highest classification accuracies for individual endmembers, and a combined accuracy that exceeds the results from either multispectral dataset. I calculated a producer’s and user’s accuracy for the SWS endmember at 43.3% and 92.9%, respectively. The SWS endmember accurately identified thirteen wetland sites, while one site in a riparian area was overpredicted. The producer’s and user’s accuracy for the SSW endmember were 23.3% and 100%, respectively. This SSW endmember correctly identified seven wetlands with no false positive errors. The producer’s and user’s accuracy for
the WM endmember were 30% and 56.3% respectively. The WM endmember successfully predicted nine wetland sites, and falsely predicted seven sites.

I calculated a combined HyMap endmember producer’s accuracy of 83% (25/30) by summing all of the true positive locations among endmembers and divided by the total number of wetland sites. I added up all of the commission errors and a total of eight sites were overpredicted.

### 2.3.2. Bighorn Crags Accuracy Assessment

A total of 46 wetland sites are present within this study site based on previous field surveys and one additional site identified through this research. All datasets had higher classification accuracies in this study area, but the hyperspectral data identified nearly all wetland sites (Table 4).

<table>
<thead>
<tr>
<th></th>
<th>Producer's Accuracy</th>
<th>User's Accuracy</th>
<th>Omission Error</th>
<th>Commission Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landsat ETM+ (Water)</td>
<td>47.8%</td>
<td>100.0%</td>
<td>52.2%</td>
<td>0.0%</td>
</tr>
<tr>
<td>ADAR 5500 (Water)</td>
<td>60.0%</td>
<td>100.0%</td>
<td>40.0%</td>
<td>0.0%</td>
</tr>
<tr>
<td>HyMap (Water)</td>
<td>78.3%</td>
<td>94.7%</td>
<td>21.7%</td>
<td>5.3%</td>
</tr>
<tr>
<td>HyMap (ES)</td>
<td>73.9%</td>
<td>89.5%</td>
<td>26.1%</td>
<td>10.5%</td>
</tr>
<tr>
<td>HyMap (Combined)</td>
<td>95.7%</td>
<td>89.8%</td>
<td>4.3%</td>
<td>10.2%</td>
</tr>
</tbody>
</table>

The Landsat ETM+ imagery produced the lowest classification accuracies in this study area with a producer’s and user’s accuracy of 47.8% and 100%, respectively, but improved substantially over the results from the Big Creek Study
area. The Landsat ETM+ data successfully identified 22 wetlands site with no falsely predicted sites. Many small forested ponds and wet meadows were not detected using this dataset.

The ADAR 5500 data produced slightly better results with a producer’s and user’s accuracy of 60% and 100%, respectively. The ADAR data accurately found 24 wetland sites with no false positive predictions. This dataset was able to identify many lakes and medium sized ponds, while missing small ephemeral ponds and wet meadows.

The HyMap hyperspectral data again produced the highest classification accuracies of the datasets compared in this study area. The water feature alone correctly classified more true positive sites than either multispectral datasets with producer’s and user’s accuracy of 78.3% and 94.7%, respectively. The HyMap water feature successfully identified 36 wetland sites, and two sites were inaccurately overpredicted (i.e., 5.3% commission error) and confused with shadow. The sites missed by this dataset primarily consisted of wet meadows.

The ES endmember yielded a slightly less accurate classification compared to the water feature with a producer’s and user’s accuracy of 73.9% and 89.5%, respectively. I assessed the accuracy of this feature explicitly (i.e., a predicted sedge site was evaluated as sedge and not a wetland) to assess how well the sedge classification actually performed at predicting sedge presence. I visited a total of 55 predicted sedge sites and calculated a producer’s and user’s accuracy of 89.1% and 86%, respectively.
I added all of the true positive predictions and divided by the total number of wetland sites present in the study site to calculate a combined producer’s accuracy of 95.7% (44/46). All overpredicted sites that led to non-wetland locations were added to calculate a combined user’s accuracy of 89.8%.

2.4.0. Discussion

2.4.1. Big Creek Study Area

The wetland sites within the Big Creek study area are a combination of small ponds, wet meadows, and stream-associated features such as pools and backwater channels. Many of the wet meadow sites have small ephemeral pools of water that were difficult to accurately detect by all of the datasets.

The Landsat ETM+ failed to successfully predict any wetland sites within this study area including a large pond located on the floodplain of Cabin Creek. The omission error at Bufo-Moose pond is likely due to mixed pixels of water and shoreline, and without a single pixel that encompasses only water, the spectral response of the this site no longer “looks” like standing water. This site is a major source breeding pond for Western Toads and Columbia Spotted Frogs. The inability of this dataset to identify even a single large wetland site strongly recommends against the use of this imagery for inventory and monitoring efforts.

The ADAR 5500 imagery best identified stream-associated features, such as side channels and pools, but did not identify wet meadows and small pool locations adequately. My attempts to map an indicator variable, sedge, were not successful and consequently I was unable to accurately identify wet meadow features with the water
class alone. The single largest pond, Bufo-Moose pond, was accurately identified while a smaller exposed pond located on the Cabin Creek floodplain was unexpectedly missed likely due to the influence of surrounding vegetation on the spectral response of this site.

The clear advantage of the hyperspectral data is the ability to identify multiple wetland features and indicator variables such as sedge presence to identify small ephemeral wetland sites. The SWS endmember was used to complement the SSW classification by primarily identifying stream associated features, particularly side channels and backwater pools that I observed as late season Western Toad breeding sites in 2002. The SWS and SSW endmembers did not accurately identify wet meadows or small emergent ephemeral pools. The WM endmember was instrumental in identifying the wet meadow and ephemeral pool sites commonly missed by the SWS and SSW endmembers. The WM user’s accuracy was the lowest reported at this study site, illustrating the difficulty of accurately mapping this feature without overpredicting false positive sites.

Individually, each HyMap endmember did not perform particularly well, but the utility of this imagery is that all of the features can be combined to produce one superior image classification. From an inventory and monitoring perspective the omission error rate is the most important measure of success. The combined HyMap omission error of 16.7% suggests that regardless of the difficulties in detecting wetland sites with individual endmembers, the collective classification results approach comprehensive identification in a challenging environment. Some
commission errors are acceptable if the goal of the project is to identify all potential amphibian habitat in a study area.

From the standpoint of a herpetologist, the most significant result of the HyMap classification is identifying new sites that were not previously known from field surveys. I found a new backwater channel with breeding Western Toads and larval Columbia Spotted Frogs present. I also discovered a second new backwater channel on the Cabin Creek floodplain that was not previously recognized through on-the-ground visual-assessment of the area. I also identified a moderate sized forested pond representing a new potential breeding site with shallow water depths and an abundance of emergent vegetation. These results suggest hyperspectral data analysis is capable of meeting the common goals of amphibian inventory and monitoring programs.

2.4.2. Bighorn Crags Study Area

The Bighorn Crags study area is characterized by an abundance of high mountain lakes with forested pools and wet meadows dispersed throughout the landscape. The majority of wetland sites are lakes that on average are larger than the largest site in the Big Creek study area, and as a result the corresponding classification accuracies are much higher for all datasets in this study area.

The Landsat ETM+ data correctly identified wetland sites consisting of large lakes and ponds, while smaller ponds, emergent wetlands, and wet meadows were consistently missed likely due to their small spatial extent. The main source breeding site for Columbia Spotted Frogs, known as Frog Pond, was missed and as a
consequence the local population status would be misunderstood based on these results. A second crucial site not identified was a smaller emergent wetland, named Axe Handle Meadow, and is the location of the only known Western Toad breeding site in the basin (David S. Pilliod, unpublished data).

The ADAR 5500 data were useful for identifying lakes and small ponds because of the high spatial resolution. An omission error of 40% depicts some limitations of this dataset, even when the wetland features are relatively large in size. Frog Pond, the critically important Columbia Spotted Frog breeding site, was accurately identified while numerous wet meadows and forested ponds were missed. Axe Handle Meadow was missed again with this dataset and represents a significant error at a site essential for understanding local Western Toad population status. The primary reason many of the wet meadow sites were missed is because I was not able to use an indicator variable, such as sedge presence, to assist in the identification of important wet and flooded meadow sites. Wet and/or flooded meadows are an important habitat type utilized by amphibian populations in the study area. These sites are extremely difficult to predict using solely water features because the spectral response is highly influenced by vegetation presence. The limited number of spectral bands restricts the probability of correctly classifying these features, and imagery that provides an increased spectral range and spectral resolution will ultimately be needed to successfully model these types of wetland sites.

The HyMap water feature proved to be valuable for identifying the majority of small ponds and lakes present within the study area. I evaluated the accuracy of the ES endmember as a predictor of wetland presence and calculated accuracy statistics
based on ground truth data of all known wetland sites (i.e., a predicted sedge site was viewed as a predicted wetland site). This feature did not correctly classify large deep lakes that lacked shallow shorelines with sedge present, but was extremely effective at identifying wet meadows and ephemeral pools missed by all other datasets. The high accuracy of this feature supports future considerations to use sedge presence as a predictor variable for wetland identification, at least in the regions of the western U.S. where sedge presence is highly correlated to wetland and amphibian presence.

Although both the water feature and ES endmember produced higher accuracies than the multispectral datasets, the real advantage of the hyperspectral data is the capability to combine individual feature results for unparalleled accuracy results. This level of accuracy provides a near comprehensive prediction (44/46) of all wetland sites present within the study site providing the detailed information necessary for effective inventory and monitoring programs.

One of the most significant results from the HyMap classification is the discovery of a new forested pond. A thorough and detailed understanding of the wetland habitat available in this study site exists as a result of ongoing long term repeated surveys (Pilliod and Peterson 2002, Pilliod and Peterson 2001, David Pilliod unpublished data). In fact, other than a single new pond discovered this summer every other wetland location was previously identified and surveyed. No amphibians were observed at this new site, but the characteristics of the pond (e.g., fishless) suggest that amphibians may utilize this location sometime during their active season.
2.4.3. Comparison Against Traditional Methods

For a comparison to traditional site selection processes I used USGS 7.5 minute topographic maps and DOQQ’s to identify all wetland sites labeled on the map or clearly visible in the aerial photographs (Figures 10 and 11). The DOQQ’s used in this study are black-and-white, but color DOQQ’s are becoming available in many areas providing a more useful dataset for identifying wetland habitat. The Landsat ETM+ classification produced fewer true positive sites than the total recognized from topographic maps and DOQQ’s (note: no DOQQ’s exist over the Bighorn Crags study site). Across our study area, more wetlands would be accurately located if we used traditional sources instead of expending effort to classify the Landsat ETM+ imagery.

The ADAR 5500 data successfully identified more wetland sites than traditional topographic maps, but slightly less than the DOQQ’s in the Big Creek study site (Figures 10 and 11). The combined processing time required to georeference the imagery and classify the ADAR 5500 data far exceeds the total amount of time needed to visually interpret DOQQ’s. The greatest limitation of the ADAR 5500 data is the inability to accurately identify indicator variables, such as sedge presence, that can be used as a proxy for predicting wetland distributions.

The HyMap hyperspectral data clearly produced the greatest accuracies while providing a fine-scale level of information instrumental to understanding amphibian habitat distributions in the study area. Each individual endmember did not produce classification accuracies significantly better than the other datasets in this study, excluding Landsat ETM+ (Figures 10 and 11). However, when all of the endmember
accuracies are combined, this dataset yields the greatest accuracies accomplished in this study.

Figure 10. A comparison of correctly classified sites resulting from different data sources. The numbers above each dataset represents the total number of true positive sites predicted by each classified dataset of the 30 total wetland sites present in the Big Creek study area.

2.4.4. Assessment of Error and Bias

I performed all image classification efforts following a preliminary site survey and ground training data campaign. In addition, background knowledge of the study area compiled through multiple years of prior field based surveys provided an informed perspective of the current amphibian habitat distributions. I made a number of subjective decisions concerning classification thresholds, training data pixel selection, and decisions on the final “best” classification map. These decisions are influenced by my familiarity with the study area and may differ from a classification
effort performed with no background knowledge. Typically, prior to inventory surveys little or no detailed background information is available for a study area thus complicating the effort required to create an accurate classification. It would be beneficial to repeat this study in an unfamiliar region and compare the results to determine widespread application in inventory and monitoring programs.

![Bighorn Crags Study Area](image)

Figure 11. A comparison of correctly classified sites resulting from different data sources. The numbers above each dataset represents the total number of true positive sites predicted by each classified dataset of the 46 total wetland sites present in the Bighorn Crags study area. (* note: the ADAR 5500 coverage did not extend over the entire Bighorn Crags study area and consequently the total number of wetlands sites was reduced to 40).

I chose to navigate to all predicted sites using the final classification map as a reference as opposed to using GPS and navigating using site coordinates. The high spatial resolution of the ADAR 5500 and HyMap imagery require coordinate accuracies consistently within 5 m of absolute true ground position. Without real-time differential correction capabilities, GPS coordinates collected in a region with
rugged topography and forest canopy will rarely be accurate to within 5 m of absolute error. The georeferencing process contributes additional errors to image pixel coordinates and further lowers the probability of confidently locating individual pixels in the field. Until GPS accuracies increase and georeferencing algorithms advance, the assessment of high spatial resolution imagery will remain difficult and influenced by error.

2.4.5. Costs of Imagery

The total cost of each remotely sensed dataset needs to be evaluated if these technologies are going to be considered or actually become incorporated into inventory and monitoring programs typically constrained by funding. The financial reality of many long-term research initiatives limits the possibility of incorporating expensive technology that may only perform marginally better than a less expensive approach. A cost comparison of the imagery provides a perspective to consider accuracy and knowledge gained from a financial perspective.

Satellite based data will normally cost less than airborne imagery because many of the mobilization costs and acquisition logistics are no longer a substantial consideration. The Landsat ETM+ data was the most inexpensive data set acquired, regardless of the geographic location of the study area that spans two adjacent Landsat scenes boundaries. A Landsat scene costs $600 for a Level 1G radiometrically and geometrically corrected dataset with each additional scene offered at a reduced rate of $250 (http://edcdaac.usgs.gov/pricing_policy.html).
Considering the additional handling fee of $5, the total cost of the Landsat ETM+ data was $855 (Table 5).

Table 5. A comparison of imagery costs.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Costs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landsat ETM+</td>
<td></td>
</tr>
<tr>
<td>Single Scene</td>
<td>600</td>
</tr>
<tr>
<td>(x2 w/ reduced cost)</td>
<td>250</td>
</tr>
<tr>
<td>Handling Charge</td>
<td>5</td>
</tr>
<tr>
<td>$855</td>
<td></td>
</tr>
<tr>
<td>ADAR 5500</td>
<td></td>
</tr>
<tr>
<td>Mobilization*</td>
<td>4000</td>
</tr>
<tr>
<td>Image Acquisition*</td>
<td>7660</td>
</tr>
<tr>
<td>Post Capture Processing*</td>
<td>2000</td>
</tr>
<tr>
<td>DIME Software</td>
<td>1700</td>
</tr>
<tr>
<td>$15,360</td>
<td></td>
</tr>
<tr>
<td>HyMap</td>
<td></td>
</tr>
<tr>
<td>Single Flightline*</td>
<td>6000</td>
</tr>
<tr>
<td>(x3)</td>
<td>18000</td>
</tr>
<tr>
<td>$18,000</td>
<td></td>
</tr>
</tbody>
</table>

* Reported costs are variable

The ADAR 5500 dataset is the second most expensive imagery collected and has a number of acquisition fees and financial considerations associated with a specific contracted collection. Many of the costs I am reporting reflect the logistical considerations for the contracted data collection of this project, and the costs may be variable depending on a different contract and extent of data collection. Mobilization fees that cover the estimated number of images contracted, and the corresponding estimated number of flight and standby days required, totaled $4,000. The image acquisition fees for the total area contracted in this data collection cost $11,500, and includes expenses for flight operations engineer, insurance, and associated costs for the data capture. It is important to note that the contracted data collection covered a much larger spatial extent than this study area alone, and much of the data collected
were not used for this research. This would lower the category total but it is hard to estimate how much cost would appropriately be deducted, so I approximated a cost of about 2/3 the total equaling $7,660. There are also post capture processing fees of $2,000 for vignetting corrections and band-to-band coregistration for all images performed by Positive Systems.

The ADAR data are collected as individual overlapping frames imposing a large amount of processing time needed to georeference and mosaic the scenes into one image. Positive Systems, Inc. offers the DIME software package that is designed specifically for georeferencing and mosaicking ADAR 5500 data and costs $1,700 for the site registration and on-site training. There are 25 free processing credits provided with the site license, but additional costs of “image credits” for $5 each are needed to process and save output images. I could not use this program for the Bighorn Crags study site (i.e., DOQQ’s are required as a basemap layer), so I did not consider any additional image credit costs because they were not needed for this research. These additional costs are mentioned as considerations for larger studies incorporating this data type. Adding up all of acquisition expenses sums to a total of $15,360 for the entire study area (Table 5).

The HyMap hyperspectral data were the most expensive dataset collected over the study area. HyMap data are priced in this study on a per flightline basis of $6,000; included in these costs are image post-processing services such as atmospheric and geometric corrections. One flightline of hyperspectral data was collected over the Bighorn Crags study area and two flightlines were collected over the Big Creek study area, creating a total cost of $18,000 (Table 5). It is important to
note that the Big Creek study area could have been covered in a single flightline if appropriately planned, and this would have reduced the total number of flightlines, dropping HyMap behind the ADAR 5500 sensor in total costs. The reported costs reflect the value at the time of data acquisition and have since lowered in price with cost reduction incentives for larger data collections.

2.4.6. Processing Time Evaluation

This category is an additionally important consideration that must be evaluated when suggesting the most appropriate imagery for amphibian inventory and monitoring initiatives. Total processing time is very difficult to evaluate because I expect considerable variability in the length of time needed for different image analysts to perform the same processing steps. This will certainly influence the amount of time and effort needed to accomplish the necessary image processing steps. I provide a summary of the time expended to process and produce a classification from each dataset.

I made some background assumptions while comparing the total processing time for each dataset. First, I assumed that an image analyst is already trained in traditional remote sensing principles, processing, and applications, and I did not account for learning time except when necessary (i.e., hyperspectral image processing). Secondly I also imposed as a requirement, and part of preliminary processing steps, seven days of ground training data collection and/or ground reconnaissance at each study site to become familiar with the study area prior to any image processing effort.
The Landsat ETM+ data took the least amount of time to process and classify. The data were provided already mosaicked and the remaining image processing time consisted of converting the DN values to at-sensor reflectance. I estimated this step to take about two days. The image classification process includes time for ROI training class selection and refining, and experimental testing of classification algorithm applications that I estimated to total ten days. Including the initial ground truth campaign, total time expenditure results in 19 days, or 152 hours, to fully process and classify the Landsat ETM+ data (Table 6).

Table 6. A comparison of categorized image processing times and associated time.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Processing Step</th>
<th>Time (days)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Landsat ETM+</strong></td>
<td>Ground Training</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>Reflectance Conversion</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>Image Classification</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>19</strong></td>
</tr>
<tr>
<td><strong>ADAR 5500</strong></td>
<td>Ground Training</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>Georeferencing/Mosaic</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>Image Classification</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>20</strong></td>
</tr>
<tr>
<td><strong>HyMap</strong></td>
<td>Ground Training</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>Hyperspectral Training</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>Georeferencing</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>Data Reduction</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>Image Classification</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>47</strong></td>
</tr>
</tbody>
</table>

The ADAR 5500 data took the second greatest amount of time to process and was almost identical to the amount of effort expended on the Landsat multispectral dataset. The DIME software training took two days to complete in which time the
Big Creek scenes were georeferenced and mosaicked. I spent an additional day attempting to manually mosaic the Bighorn Crags images before deciding to leave them in the raw format due to undesirable results. Similar to the Landsat data, I estimated ten days for image classification time including ROI selection and the testing numerous classification algorithms. Including the time needed for the ground truth campaign, the total estimated processing time for the ADAR 5500 data was 20 days, or 160 hours (Table 6).

The HyMap hyperspectral data took the greatest amount of time to process and classify because of the total time required to learn hyperspectral data analysis techniques. Many of the common hyperspectral image processing steps are unique to this data type, and are not encountered working with multispectral data. I attended an hyperspectral training short-course that occurred over five days, and formed the foundation of my knowledge of hyperspectral analyses. I suggest this training as a precursor for efficiently processing hyperspectral data, and consider this training part of the processing effort that should be included in the estimate of total processing time. I estimate the georeferencing procedures lasted ten days with the majority of the time attributed to learning the correct processing steps specific to hyperspectral data and understanding various results. I performed data reduction techniques, such as the MNF transform, PPI, and the n-D Visualizer, which lasted 15 days with much of the processing time a result of redundant testing of processing steps to better understand intermediate results. Finally, I estimate the image classification procedure took a total of ten days of time to complete with many repetitive steps interpreting the
results and refining the input parameters. This results in a total of 47 days, or 376 hours, to complete the hyperspectral data analyses (Table 6).

### 2.4.7. Spatial vs. Spectral Scale

This study evaluated three remotely sensed datasets commonly used for natural resource applications. Based on the results of this study, spectral scale seems to contribute more substantially to classification accuracy than spatial scale. This assertion must be held within context of the relative spatial grain of the features that are being classified (Woodcock and Strahler 1987). For example, the 30 m (i.e., the grain) spatial resolution of the Landsat ETM+ data is larger than the spatial extent of many wetland sites, and consequently these features are not successfully classified with this dataset because the sampling unit is much larger than the features being studied. Spatial scale becomes a critically important factor when pixel resolutions surpass the spatial extent of the features of interest, but if pixel resolutions are close to the spatial scale of the features of interest, spectral scale and resolution become increasingly important and override the contribution of high spatial resolution data. This is shown in the direct comparison between the 2 m resolution ADAR 5500 and 3.6-4.0 m HyMap classification results. Both types of imagery are of comparable spatial resolution, but differ greatly in spectral scale (i.e., range and resolution). The superior classification accuracies exhibited by the HyMap data in both study sites clearly demonstrates how spectral scale contributes to classification accuracies, while higher spatial resolution data lacking large numbers of spectral bands has a difficult time identifying wetland features.
Similar results have been found in other remote sensing projects focusing on the delineation and classification of hydrologic features. Wright et al (2000) used high spatial resolution multispectral data (i.e., 1 m ADAR 5500) to map stream morphological units in third and fourth order streams. Classification accuracies in this study ranged from 11-53%, with some of the observed error attributed to the inability to spectrally distinguish habitat types. Marcus (2002) conducted a similar analysis in the same watershed on a fifth order stream using 1 m resolution hyperspectral data, and found much greater classification accuracies ranging from 85-91%. A comparison between these two results conducted at the same spatial resolution suggests that the spectral resolution may be the contributing factor driving higher classification accuracies. Marcus (2002) also concluded that higher spatial resolution (5 m) hyperspectral data over the same study site produced lower classification accuracies, but at this resolution the spatial grain is approaching or exceeds the spatial extent of the features of interest (i.e., morphological units) and may not be a valid comparison of spatial versus spectral scales.

My results support the theory that spectral scale is one of the primary factors contributing to successful image classification of hydrologic features, potentially outweighing the contribution from high spatial resolution. Further research needs to be conducted explicitly designed to test the influence of spectral and spatial scale in a variety of habitat types and landscapes before broad conclusions can be made. Many ecologists still do not appreciate how crucial considerations of scale are when designing experiments, and this subject may remain to be “the fundamental conceptual problem in ecology” (Levin 1992). There is no single correct scale or
level in which to study or best describe a natural system. As remote sensing
technologies continue to advance and applications become more common, researchers
need to recognize that, aside from spatial considerations, spectral scale is a
fundamental consideration that can no longer be overlooked.

2.4.8. Sensor Comparisons

The results from this study confirmed that different scales of remotely sensed
data produce varying classification accuracies within the same study area. From an
inventory and monitoring perspective, the dataset that provides the most cost-
effective and comprehensive habitat information is the most desired. These results
provide insight into the relative performance of three vastly different datasets for
predicting amphibian habitat and I offer some suggestions for further evaluation and
future inventory and monitoring applications.

The Landsat ETM+ sensor has traditionally been viewed as a valid resource
for numerous natural resource applications due to the consistency and availability of
data. For some applications (e.g., forest fragmentation studies) the 30 m spatial
resolution of this dataset may be appropriate because the scale of observation
correctly corresponds to the scale of processes governing the feature of interest.
Unfortunately, many wetland sites most important for amphibians are typically not
large lakes but smaller isolated ponds less than 900 m² in area. The results from both
study sites reveal a significant limitation of this imagery for accurate identification of
wetland habitat thus rendering the inexpensive costs of these data irrelevant.
The ADAR 5500 data performed below expected levels of accuracy even though this imagery exhibits the highest spatial resolution compared in this study. Given the fact that many of the wetland sites within the study are small in spatial extent, this dataset had the highest spatial resolution and would likely classify these locations most accurately. I feel that the limited number of spectral bands contributed to the difficulties of distinguishing water features from other spectral classes such as shadow. The ADAR 5500 sensor collects only a single band in the near-infrared spectral wavelengths. I found that the near-infrared region was paramount in providing spectral information necessary for delineating water from other features, and because these data lack multiple near-infrared spectral bands, classifying water features was more difficult. Coupled with the poor accuracy statistics is the expense associated with this dataset. Total costs rival that of the hyperspectral data, putting into question the applicability of ADAR 5500 data for inventory and monitoring applications.

Aside from considering the accuracy statistics, potentially the most important result from the HyMap image classification is that new previously unknown wetland sites were discovered in areas that have been repeatedly surveyed on the ground. These results are similar to another study in Yellowstone National Park where new amphibian breeding sites were located in unexpected areas (Crabtree et al., in press). The ultimate goal of an inventory program is to comprehensively survey all available habitats within a study area, and the HyMap hyperspectral data exhibit the best potential for accomplishing this goal. One goal of monitoring programs is to understand how particular habitat features are changing in extent and composition
over time. Given the ability to map fine scale wetland features, we can begin to subdivide predicted habitat into specific types of amphibian habitat such as breeding, foraging, and overwintering. These wetland features can be used as a surrogate to infer changing population status and habitat conditions across large landscapes. By identifying particular habitat features, such as the abundance of emergent sedge, testable hypotheses can be posed by remotely predicting occurrence and distribution in areas where there are no field data.

The costs associated with hyperspectral data are large and image processing can be time consuming and complex. This limits widespread application of this technology for inventory and monitoring programs. As hyperspectral data become more common, less expensive, and processing techniques are standardized, future applications may not have to face the numerous impediments common today.

Hyperspectral data have the capability to be successfully incorporated into inventory and monitoring programs, but this approach warrants additional research to assess repeatability and application in diverse environmental landscapes. One immediate limitation is the large cost and processing time associated with collecting hyperspectral imagery over large spatial extents. Hyperspectral imagery should be considered a valuable tool for future inventory and monitoring programs with new potential applications yet to be explored and evaluated.

2.4.9. Future Research

This research has shown that hyperspectral data analysis has the greatest potential for future widespread inventory and monitoring applications, but before new
technologies can be implemented in an operational context more research must be performed. First, there should be a repeat project performed in the same study area to assess how reliable and consistent results are between years. If this type of technology will ever be incorporated into long-term monitoring programs, there must be results showing wetland distributions and subsequent habitat changes can be accurately detected over time. Second, this type of analysis should be repeated in similar ecological landscapes located in different geographic regions to understand how robust this type of application is regionally before it is applied to entirely different environments. An optimal location would be a site where no background data have been collected describing amphibian habitat distributions and occurrence patterns, hence removing investigator bias associated with the familiarity of a study area. Lastly, similar studies should be performed in new geographic regions of the country that have less biological similarities to the original study area. This type of analysis needs to be assessed for different types of wetland systems (e.g., coastal wetlands and swamps) and the diverse number of amphibians inhabiting these environments. This approach would further test the potential of using hyperspectral data analysis as a method to delineate and monitor all types of amphibian habitat across large spatial extents in varied geographic locations.
Chapter 2 Introduction

3.1.1. Inventory and Monitoring

In light of ongoing global amphibian population declines, the need for inventory and monitoring programs has been recognized and programs have been initiated in many geographic regions facilitated by local, state, and federal organizations. One successful example is the Amphibian Research and Monitoring Initiative (ARMI) implemented by the Department of the Interior and led by the U.S. Geological Survey in cooperation with the National Park System, U.S. Fish and Wildlife Service, and the Bureau of Land Management (http://armi.usgs.gov/other.asp). The National Park Service also started the Natural Resource Challenge, initiating the collection of scientifically sound natural resource inventory information across numerous U.S. parks, with the goal of providing up-to-date baseline data that can be used to monitor environmental changes in the future.

Successful documentation of amphibian population dynamics, such as declines, requires a thorough and comprehensive understanding of current population status and distributions at local and broad spatial scales. Unfortunately there are a large number of locations in the U.S. and around the world where there are no historical reference data and the current understanding of amphibian presence, relative abundance, and distribution is limited. Initial inventory data are critical for establishing a comprehensive baseline dataset that can be used to quantify population changes through time.
Inventory surveys and the future monitoring plans require substantial costs associated with the extensive amount of time and effort needed to successfully accomplish broad scale amphibian surveys. In some cases, due to limited funds and personnel availability, a single seemingly thorough field study may serve as the sole source of baseline data for a large region. Studying amphibian populations at large spatial scales should be considered a program objective, and can provide a level of information essential for effective management practices (Pilliod and Peterson 2000). A key component to properly monitoring and managing a species is to understand how a particular population utilizes available habitat across large landscapes. Information about habitat use patterns may assist land managers in developing the most appropriate conservation strategies or better understand the implications of proposed management plans. This scenario stresses the development of fast and efficient field sampling methods to allow large spatial scales to be effectively studied and monitored.

3.1.2. High Spatial Resolution Hyperspectral Data

The application of high spatial resolution hyperspectral (HSRH) data has recently emerged as an important tool for investigating a variety of ecological questions (Crabtree et al. in press). Aspinall et al. (2002) suggested guidelines that define HSRH data as having spatial resolutions of 5 m or less and greater than 48 spectral bands with spectral resolution of 20 nm or finer. HSRH data have been used to successfully map a number of hydrological features. Marcus (2002) used HSRH data to map the distribution of stream morphological units (e.g., pools, riffles, and
glides) with greater accuracies in transition zones than are commonly mapped by field crews. Coarse woody debris was mapped along a stream floodplain in Yellowstone National Park with accuracies encompassing spatial distributions that may exceed the capabilities of field-based surveys (Aspinall 2002). Crabtree et al. (in press) reported results from an exploratory study mapping wetland habitat along Cache Creek in Yellowstone National Park that successfully used hyperspectral data to predict the location of unknown wetland sites yielding new amphibian locations.

Hyperspectral sensors collect large numbers of contiguous, overlapping, narrow spectral bands across the visible and near infrared wavelengths of the electromagnetic spectrum. The large increase in spectral resolution over traditional multispectral sensors provides the capability for hyperspectral sensors to measure and distinguish subtle spectral absorptions and produce spectral “signatures” for discrete surface features. The fine scale discrimination of spectral differences allows the identification of species of vegetation even at fractional scales within a pixel. Specific classification algorithms, such as Mixture Tuned Matched Filter (MTMF) (Boardman 1998b), have been developed for hyperspectral data that allow sub-pixel abundance classification of surface features across the image extent. Such algorithms present the possibility to collect fine-scale microhabitat information across large spatial extents, which is necessary for many ecological studies including inventory and monitoring projects.

This study describes the application of HSRH data analysis to identify amphibian habitat distributions within a forested high mountain lake landscape. I have developed two specific questions addressed through this research. First, can
HSRH data accurately identify multiple scales of amphibian habitat features (e.g., basin scale habitat distribution or local scale within site microhabitat) across a large and complex landscape? Secondly, can HSRH data be used indirectly through microhabitat feature classifications to differentiate amphibian breeding habitat from other wetland sites?

3.2.0. Methods

3.2.1. Study Area

The study area is located in a region known as the Bighorn Crags, within the Frank Church-River of No Return Wilderness, Idaho (Figure 12). The landscape is characterized by glaciated cirque basins with steep headwalls that delineate the upland watershed boundaries. The elevation throughout the study area ranges from 2400 m to 2900 m with the higher elevations dominated by subalpine fir (Abies lasiocarpa) while the lower elevations are mixed stands of whitebark pine (Pinus albicaulis), lodgepole pine (Pinus contorta), and Engelmann spruce (Picea engelmannii). The understory vegetation is dominated by grouse wortleberry (Vaccinium scoparium) and beargrass (Xerophyllum tenax), while more mesic wetland habitat is dominated by sedges (Carex spp.).

This study encompassed the headwater regions of three lake basins with a total of 46 lentic sites within the area of data coverage. Of the total sites, there are 32 permanent flooded lakes and ponds, five ephemeral ponds, five flooded meadows, and four stream-side wetlands or pools. For simplicity, I will be referring to all lentic sites found within the study area generically as “wetland” habitat (i.e., lakes, ponds,
and wet meadow), disregarding any formal definitions pertaining to depth or indicative vegetation.

Figure 12. The Bighorn Crags study area in the Frank Church-River of No Return Wilderness, ID (displayed in green in the left image). A Triangulated Irregular Network (TIN) elevation model depicts the rugged topography in the study area (elevation reported in meters) and lists the three lake basins studied.

### 3.2.2. Hyperspectral Imagery

Refer to section 1.2.2. for the imagery acquisition date and a description of the hyperspectral data used in this study.
3.2.3. Image Processing

I performed all image processing data analyses using Research Systems Inc.’s ENVI 3.5 (RSI 2000). All Geographic Information System (GIS) analyses were conducted using ESRI’s ArcGIS 8.2. I geometrically corrected the data using Input Geometry (IGM) and Geometry Lookup Table (GLT) files processed from the onboard GPS/INS data recorded (Boardman 1999). The data were georeferenced to the World Geodetic System (WGS-84) datum and Universal Transverse Mercator (UTM) zone 11N coordinate system.

3.2.4. Standing Water Classification

Standing water has a unique spectral response pattern of low reflectance, particularly in the near-infrared wavelength region. Following exploratory attempts to classify standing water, I determined the most accurate method of identifying standing water was to take advantage of this feature’s known spectral characteristics. I plotted Band 20 (0.727µm) and Band 33 (0.9074µm) as a 2-D scatter plot and selected all image pixels exhibiting the lowest reflectance values near the plot origin (Refer to Figure 7). The process of selecting plot pixels is interactively linked to the image display, and I iteratively refined the extent of selected pixels based on the shoreline boundaries of known sites. The pixel selection was exported and used to create the final Standing Water (SW) image classification.
3.2.5. Endmember Selection

I followed a hyperspectral image processing strategy developed by Analytical Imaging and Geophysics, Inc. (Refer to Figure 1). This processing flow is used to identify image-derived spectral endmembers (Refer to Section 1.2.2.) that feed directly into hyperspectral classification algorithms.

Emergent sedge- sedge that is partially submerged in standing water- is a feature highly correlated with wetland presence in the study area, and can be used as an indicator variable for small wetland sites and inundated meadows. Three different potential emergent sedge (ES) endmember groups were identified through the processing steps described above. The three different endmember groups, each consisting of multiple pixels, were distributed within the periphery of a well-studied breeding site known as Frog Pond (David Pilliod, unpublished data) (Figure 13). The spectral profiles exhibit many similarities, but most notably the large water absorption features located at 0.95µm and 1.25 µm. I used the average spectral profile for each endmember class as well as the average profile of all potential endmember pixels (Figure 14) and applied the MTMF classification algorithm.

I used the MTMF algorithm to produce a classification of sub-pixel fractional abundances for each emergent sedge endmembers. Although the goal was not to quantify the accuracy of fractional abundance estimates, this classification algorithm provided the best approach to identify small wetland features common to the study area. This algorithm builds upon the strengths of both matched filtering and spectral unmixing while avoiding the inherent disadvantages of both methods (Boardman...
Matched filtering performs a partial unmixing of image spectra and identifies pixel abundance of spectral endmember signatures without requiring all background image endmembers (Harsanyi and Chang 1994, Boardman et al. 1995). Spectral unmixing takes advantage of the hyperspectral leverage to solve the linear mixed pixel problem (Boardman 1993). This method incorporates feasibility constraints that restrict spectral mixtures to only non-negative and unit-sum solutions, which helps identify false positive classifications (errors of commission).

Figure 13. a) The western shoreline of Frog Pond with emergent sedge shown dominating the surrounding meadow (photo taken looking east from the region of endmember pixels). b) A hyperspectral image subset of the Frog Pond site. The light colored region around the standing water (blue polygon) is almost entirely emergent sedge. The spatial distribution of the three emergent sedge endmembers are shown.

The MTMF algorithm produces two continuous scale output images: the Matched Filter (MF) result and an Infeasibility (INF) image. The MF values are scaled so that positive values represent estimates of endmember sub-pixel fractional abundances. The INF values can be interpreted as standard deviations from the background spectral mean with the lowest INF values representing higher probability
endmember pixels. An optimal image classification benefits from the useful information of both resulting MTMF images. In order to exploit the true strength of this algorithm, I plotted the MF image data and the INF image data as 2-Dimensional (2-D) scatter plot. I selected pixels that had high MF scores and low INF scores (Refer to Figure 9), and these pixels were exported to create the final emergent sedge endmember classification map.

Figure 14. The emergent sedge endmember spectral profiles (ES1, ES2, ES3). The ES4 spectrum is the average spectral profile for all emergent sedge endmembers combined.

Egg mass oviposition locations were collected by David Pilliod across the study area from 1995 through 2003, except in 2001 due to wilderness closure caused by wildfire danger (David Pilliod, unpublished data). Amphibian egg mass
oviposition sites are commonly found in shallow water with submerged and emergent vegetation. Amphibians rely on submerged and emergent vegetation as egg attachment sites, cover protection, and larval grazing. In this study area, emergent sedge is highly correlated with wetlands and mesic meadows, suggesting the potential for egg oviposition prediction using emergent sedge as an indicator variable. The egg mass oviposition data were digitized into a GIS vector layer and overlaid onto the emergent sedge classifications to evaluate the feasibility of predicting oviposition location by mapping emergent sedge distributions.

3.2.6. Lake Depth Classification

The intent of this portion of the study was an exploratory effort to identify water depths that may assist in distinguishing potential breeding habitats from non-breeding wetland sites. Because water is the only spectral feature of concern for this part of the analysis, I created an image mask of the background terrestrial features. I used the final SW classification as an image mask (i.e., further processing only considered mask pixels) restricting the inclusion of terrestrial image pixels into statistical analyses. This allows the subtle variance in water reflectance values to be expressed proportionately to the total range of water pixel variance and not scene variance.

I ran the MNF transform on the SW masked image and examined the transformed spectral bands and eigenvalue plot to determine the SW image dimensionality as described above. Initially I ran the k-means unsupervised classification algorithm to estimate the number of spectrally distinguishable depth
classes present. I chose depth training class Regions of Interest (ROI’s) from areas of
known depths observed during ground truth validation. Training ROI’s were also
selected from large homogenous classified regions in the unsupervised classifications
results. I focused on selecting representative spectral variations for each depth
training class that encompassd the range of variation in observed scene illumination
across all three basins to develop image wide ROI’s needed for a successful
classification (Lillesand and Kiefer 1994).

I ran the Maximum Likelihood supervised classification algorithm on four
final depth training classes: <1.5 m, 1.5-2.5 m, 2.5-4 m, and >4 m (Figure 15). The
Maximum Likelihood algorithm considers both spectral variance, plotted as a mean
vector, and covariance of the training ROI’s (Lillesand and Kiefer 1994). The
underlying assumption of this algorithm is a Gaussian distribution, which is a
reasonable assumption for common spectral classes such as water (Lillesand and
Kiefer 1994). Based on the spectral response pattern and associated statistics of the
ROI training classes, a probability density function is created that assesses the
individual probability for each image pixel. I designated a probability threshold of
0.6 for each ROI training class determined through repetitive classification attempts,
and any pixel falling within the designated threshold range was assigned to the
corresponding ROI class creating a final lake depth classification map (Figure 16).
Figure 15. The average spectral profile for each lake depth training classes. Note: The reported negative scaled apparent reflectance values are a result of atmospheric correction induced errors that can be common over water surfaces.

Figure 16. a) True-color reflectance image over Skyhigh basin. b) Standing water classification created from the 2-D scatter plot and used as an image mask for the depth profile classification. c) Lake depth classification result (red = < 1.5 m, green = 1.5 - 2.5 m, yellow = 2.5 - 4 m, blue = > 4m).
3.2.7. Accuracy Assessment

Accuracy assessment was conducted through a ground truth validation effort during July, 2003. I used a traditional method for assessing classification accuracy, the error matrix. Error matrices serve as the basis for descriptive statistical techniques used to evaluate classification accuracy (Congalton and Green 1999). Numerous statistical measures can be derived from an error matrix, and I am reporting the measures that make sense from the perspective of an ecologist conducting field surveys. Producer’s accuracy represents the probability a true positive location on the ground is correctly classified (Congalton and Green 1999). Omission error is calculated by subtracting producer’s accuracy from 100%. The omission error is a measure of the total percentage of true positive sites that were not correctly predicted (i.e., the percentage of known wetlands missed). User’s accuracy represents the probability that a classified image pixel is actually that category on the ground (Story and Congalton 1986). Commission error is calculated by subtracting the user’s accuracy from 100%. The commission error is a measure of the total percentage of false positive sites incorrectly classified as true positive locations (i.e., the percentage of sites classified as a wetland, but are not wetlands).

Currently the ability to perform advanced image classifications has progressed in parallel to technological advances, but the corresponding ability to quantify accuracy has not followed this progression (Lillesand and Kiefer 1994). High spatial resolution data (i.e., 5 m or less) commercially available from numerous sensors, challenges the capability of GPS receivers to accurately locate points on the ground.
when the topography is complex and canopy cover disrupts a clear view of the sky. Aside from the technical limitations of using GPS in many field study areas, image georeferencing procedures of airborne high spatial resolution data sometimes fail to provide highly accurate corrections needed for pixel-based accuracy assessment (Wright et al. 2000, Marcus 2002). Even with a sophisticated GPS/IMU and ray-tracing program recording X, Y, and Z coordinates for every image pixel (Boardman 1999), drastic fluctuations in ground elevations introduce significant error into the georeferencing process. This means the coordinates of some image pixels may be spatially skewed in a non-systematic direction, which makes locating individual pixels on the ground extremely difficult, if not impossible. Similar to other validation studies involving high spatial resolution data (Marcus 2002), I used the classified imagery as a field map and navigated directly from it using obvious features (e.g., lake coves, stream bends, and rocky outcrops) as geographic reference points.

There are a number of suggestions published for developing a validation site selection scheme, each with their own advantages and disadvantages (Congalton 1991). Because the primary goal of this study was to identify wetland habitats that are low in abundance and widely dispersed throughout the scene, the most appropriate validation was to visit all of the classified potential wetland sites. Due to low confidence in accurately locating isolated individual pixels in the scene, I chose to use clusters of pixels as the sampling unit. I walked the shorelines of lakes and visually searched meadows and backwater areas while in transit between predicted sites. I did assess individual classified pixels located on or near the shoreline proximity when these locations were easily recognized in the field. Numerous
ground surveys have been completed since 1995 (Pilliod and Peterson 2001, Pilliod and Peterson 2000, David Pilliod unpublished data) and these data served as a ground truth database, which was extremely valuable for evaluating classification errors by alleviating the amount of time needed to thoroughly inventory a rugged wilderness landscape.

3.3.0. Results and Discussion

3.3.1. Standing Water Accuracy Assessment

A total of 46 wetland sites were identified within the image extent. The SW classification proved to be an effective method for identifying various types of wetland habitat such as large lakes and forested ponds (Table 7). The SW classification method alone missed 21.7% (10 sites) of the total wetlands sites present. This method was not effective at identifying some small pools and mesic meadows. There were very few overpredictions, 5.3 % commission error, that warranted any attention during field validation. A number of shadowed ridge pixel locations were incorrectly predicted as water. I used USGS 30 m Digital Elevation Models (DEMs) to assess the feasibility of the minor SW predicted locations. I used the DEMs to produce raster images of slope and aspect using ArcMap’s Spatial Analyst extension. The majority of overpredictions occurred on steep slopes which can easily be recognized as classification error due to the inability of water to accumulate on slopes; consequently, these sites were not considered in the assessment.
Table 7. Wetland site comparative accuracy assessment summary table. The ES 1 category represents the accuracy statistics for an emergent sedge endmember used to predict basin scale wetland distributions.

<table>
<thead>
<tr>
<th></th>
<th>Producer's Accuracy</th>
<th>User's Accuracy</th>
<th>Omission Error</th>
<th>Commission Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>SW</td>
<td>78.3%</td>
<td>94.7%</td>
<td>21.7%</td>
<td>5.3%</td>
</tr>
<tr>
<td>ES1</td>
<td>73.9%</td>
<td>89.5%</td>
<td>26.1%</td>
<td>10.5%</td>
</tr>
<tr>
<td>Combined</td>
<td>95.7%</td>
<td>89.8%</td>
<td>4.3%</td>
<td>10.2%</td>
</tr>
</tbody>
</table>

3.3.2. Emergent Sedge Accuracy Assessment

A total of 55 emergent sedge validation sites were identified from the ground validation surveys ranging in spatial extent from large relatively continuous patches to discrete sub-pixel locations along shorelines. All emergent sedge endmember classification accuracies were high, identifying near comprehensive sedge distributions (Table 8). There was some observed local variability in the classification results of different emergent sedge endmembers, but across the entire landscape predicted patterns were very similar, if not identical, in many regions.

Table 8. Comparative accuracy assessment results of the emergent sedge endmember classifications.

<table>
<thead>
<tr>
<th></th>
<th>Producer's Accuracy</th>
<th>User's Accuracy</th>
<th>Omission Error</th>
<th>Commission Error</th>
<th># Oviposition Sites Correctly Predicted</th>
<th>% Oviposition Sites Correctly Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td>ES1</td>
<td>89.1%</td>
<td>86.0%</td>
<td>10.9%</td>
<td>14.0%</td>
<td>23</td>
<td>71.9%</td>
</tr>
<tr>
<td>ES2</td>
<td>78.2%</td>
<td>84.3%</td>
<td>21.8%</td>
<td>15.7%</td>
<td>20</td>
<td>62.5%</td>
</tr>
<tr>
<td>ES3</td>
<td>87.3%</td>
<td>87.3%</td>
<td>12.7%</td>
<td>12.7%</td>
<td>20</td>
<td>62.5%</td>
</tr>
<tr>
<td>ES4</td>
<td>81.8%</td>
<td>84.9%</td>
<td>18.2%</td>
<td>15.1%</td>
<td>22</td>
<td>68.8%</td>
</tr>
</tbody>
</table>

The ES1 and ES3 endmembers produced the greatest accuracy results with omission and commission errors under 15% (Table 8). The ES1 and ES3
classifications only missed 6 and 7 emergent sedge locations, respectively. These results suggest that the ability to map emergent sedge distributions is a valid and practical method for identifying small wetland habitat and microhabitat features within larger sites. The ES1 endmember was instrumental in identifying small wetlands with sub-pixel scale abundances of standing water and mesic meadows that were commonly missed by the SW classification (Table 7). Using this endmember as a proxy for finding small emergent wetland sites has led to near comprehensive correct classification of wetland habitat within the study area. When all true positive and false positive locations are combined between the SW and ES1 classifications, omission and commission error rates are decreased to 4.3% and 10.2% respectively (Table 7). Only two wetland sites within the entire study area were not correctly classified with the combined strengths of these two informative wetland predictor variables. Of the two wetland sites not correctly identified, one was a small forested ephemeral pond and the second was a stream-side pool located in a forested riparian area.

A total of 32 observed egg mass locations were distributed across a total of 19 different wetland sites. I assessed the accuracy of egg mass oviposition sites from the perspective of an ecologist conducting field surveys. In some cases the digitized egg mass locations were offset from the actual emergent sedge predicted pixels. I considered these locations as true positive predictions as long as predicted pixels were within 15 m proximity to egg mass points. Again, all emergent sedge endmembers accuracies performed similarly, and all showed promise for identifying egg mass oviposition sites (Table 8). In addition to having the highest emergent sedge
3.3.3. Lake Depth Accuracy Assessment

Predicted depth class contours followed visual estimations of depth interpreted while surveying numerous sites. Lake depth classification was explored to address the applicability it may lend to inventory and monitoring initiatives that require fine-scale habitat information across large spatial extents. I recorded depths along a limited number of transects across representative lakes and ponds using a handheld sonar device, but the spatial accuracy of these transects are unknown. Little effort was expended to insure that transect start location coordinates were collected due to difficulties with GPS reception in the study area. This type of ground truth collection does not abide to any rigorous quantifiable accuracy assessment standards, and I want to acknowledge that my estimates are only a qualitative evaluation. However, these data do form the basis for understanding relative accuracies of lake depth classifications that might help determine the potential for further investigations and future applications.

I calculated the total area of each SW site as well as each predicted depth class. I divided the area of each depth class by the total predicted wetland area, and determined the total percentage of each individual depth class (Table 9). Even though a statistical assessment of the depth classifications was not possible, some important information can be gained through descriptive interpretations. For example, if I estimate the total area of the <1.5 m depth class, the proportion of littoral zone habitat
in each site can be estimated. This type of habitat is important for breeding amphibians and may serve as an additional piece of information used to distinguish breeding habitat from other wetland sites.

Table 9. The predicted area of the shallow depth categories at each SW wetland site. The two oviposition sites noted with the asterisk have breeding sites located in adjacent habitat that is not reflected in the reported area. The number in parenthesis represents the total oviposition locations within the site.

<table>
<thead>
<tr>
<th>Site Name</th>
<th>% of total area &lt;1.5 m</th>
<th>% of total area &lt;2.5 m</th>
<th>Total Area (m²)</th>
<th>Oviposition Site</th>
</tr>
</thead>
<tbody>
<tr>
<td>Barking Fox</td>
<td>41.02</td>
<td>54.55</td>
<td>15228.00</td>
<td>no* (2)</td>
</tr>
<tr>
<td>Buck</td>
<td>20.62</td>
<td>21.42</td>
<td>17664.48</td>
<td>no</td>
</tr>
<tr>
<td>Cache</td>
<td>92.82</td>
<td>92.82</td>
<td>2527.20</td>
<td>yes</td>
</tr>
<tr>
<td>Doe</td>
<td>57.54</td>
<td>75.64</td>
<td>24844.32</td>
<td>no</td>
</tr>
<tr>
<td>Echo</td>
<td>22.82</td>
<td>23.38</td>
<td>20619.36</td>
<td>no</td>
</tr>
<tr>
<td>Egg White</td>
<td>39.23</td>
<td>76.99</td>
<td>4393.44</td>
<td>yes</td>
</tr>
<tr>
<td>Fawn</td>
<td>98.20</td>
<td>98.40</td>
<td>6467.04</td>
<td>yes</td>
</tr>
<tr>
<td>Figure Eight</td>
<td>98.08</td>
<td>98.08</td>
<td>673.92</td>
<td>no</td>
</tr>
<tr>
<td>Frog Pond</td>
<td>63.11</td>
<td>66.99</td>
<td>1334.88</td>
<td>yes (7)</td>
</tr>
<tr>
<td>Glacial</td>
<td>49.61</td>
<td>77.65</td>
<td>13452.48</td>
<td>yes (2)</td>
</tr>
<tr>
<td>Greggs</td>
<td>28.46</td>
<td>68.27</td>
<td>6739.20</td>
<td>yes</td>
</tr>
<tr>
<td>Homer</td>
<td>68.42</td>
<td>68.42</td>
<td>246.24</td>
<td>no</td>
</tr>
<tr>
<td>In and Out</td>
<td>25.36</td>
<td>78.41</td>
<td>11702.88</td>
<td>yes</td>
</tr>
<tr>
<td>Little Snake</td>
<td>92.59</td>
<td>92.59</td>
<td>349.92</td>
<td>yes</td>
</tr>
<tr>
<td>Moose</td>
<td>82.53</td>
<td>97.38</td>
<td>2967.84</td>
<td>yes</td>
</tr>
<tr>
<td>Mosquito</td>
<td>41.05</td>
<td>100.00</td>
<td>7672.32</td>
<td>yes</td>
</tr>
<tr>
<td>Ramshorn</td>
<td>10.30</td>
<td>10.95</td>
<td>35730.72</td>
<td>no*</td>
</tr>
<tr>
<td>Reflection</td>
<td>20.38</td>
<td>22.30</td>
<td>35095.68</td>
<td>no</td>
</tr>
<tr>
<td>Skyhigh</td>
<td>9.08</td>
<td>10.59</td>
<td>40396.32</td>
<td>no</td>
</tr>
<tr>
<td>Skyhigh Wetland</td>
<td>100.00</td>
<td>100.00</td>
<td>194.40</td>
<td>no</td>
</tr>
<tr>
<td>Terrace 1</td>
<td>16.31</td>
<td>19.38</td>
<td>15577.92</td>
<td>no</td>
</tr>
<tr>
<td>Terrace 2</td>
<td>15.68</td>
<td>30.55</td>
<td>6363.36</td>
<td>no</td>
</tr>
<tr>
<td>Terrace 3</td>
<td>64.99</td>
<td>79.36</td>
<td>9292.32</td>
<td>yes</td>
</tr>
<tr>
<td>Terrace 4</td>
<td>12.29</td>
<td>15.28</td>
<td>32477.76</td>
<td>yes</td>
</tr>
<tr>
<td>TipTop</td>
<td>32.01</td>
<td>99.34</td>
<td>9758.88</td>
<td>yes (3)</td>
</tr>
<tr>
<td>Turquoise</td>
<td>31.69</td>
<td>48.06</td>
<td>26749.44</td>
<td>no</td>
</tr>
<tr>
<td>Twin Cove</td>
<td>10.04</td>
<td>10.26</td>
<td>41420.16</td>
<td>no</td>
</tr>
<tr>
<td>Upper Cache</td>
<td>95.45</td>
<td>97.73</td>
<td>1140.48</td>
<td>yes</td>
</tr>
<tr>
<td>Upper Echo</td>
<td>100.00</td>
<td>100.00</td>
<td>194.40</td>
<td>no</td>
</tr>
<tr>
<td>Upper Glacial</td>
<td>18.31</td>
<td>61.97</td>
<td>1840.32</td>
<td>no</td>
</tr>
<tr>
<td>Upper Skyhigh</td>
<td>100.00</td>
<td>100.00</td>
<td>194.40</td>
<td>no</td>
</tr>
<tr>
<td>Upper Walkabout</td>
<td>93.10</td>
<td>100.00</td>
<td>751.68</td>
<td>no</td>
</tr>
<tr>
<td>Walkabout</td>
<td>24.86</td>
<td>48.17</td>
<td>6726.24</td>
<td>yes</td>
</tr>
</tbody>
</table>
The lake depth data exhibit the potential to contribute complementary information in addition to emergent sedge distributions, which is useful for identifying amphibian breeding habitat. I selected all wetland sites that had 25% or more of the total area designated as the shallow depth class of <1.5 m. If these results are compared to the known distribution of egg mass locations, 14 of 19 (74%) breeding locations were accurately predicted. Nine locations were overpredicted (commission error) and 1 breeding location was missed (omission error). Of the 32 total oviposition locations, 23 (72%) locations can be indirectly identified using the predicted depth classification assuming a thorough survey is performed at each predicted site.

3.3.4. Basin Scale Wetland Distributions

The results from both the SW and ES classifications suggests that hyperspectral remote sensing can provide an efficient method for identifying amphibian habitat distributions in similar ecological landscapes. When the ES1 and SW classifications were combined in this study, 96% of all known wetland sites were accurately predicted. Aside from the impressive accuracy statistics, the most potentially interesting result was the identification of a previously unknown forested pond. After more than seven years of extensive ground based surveys (Pilliod and Peterson 2001, Pilliod and Peterson 2000, David Pilliod, unpublished data), I was able to identify a location that was previously unidentified. This is a shallow depth site that lacks fish and represents adequate characteristics of potential amphibian
habitat. This result demonstrates the potential strength of hyperspectral remote sensing for inventory and monitoring purposes that require comprehensive information across large spatial extents.

The most challenging wetland feature to classify is the shoreline boundary. The SW classification requires non-mixed pixels of water to accurately identify shoreline extents. In many areas, the shoreline is located in close proximity to the forest causing mixed pixels of vegetation and water. These areas will not be correctly classified using the methods I described, and may pose problems for detecting subtle changes in wetland extent potentially required for monitoring programs.

3.3.5. Amphibian Microhabitat Distributions

Visual assessment of sub-pixel abundance estimates suggest the MTMF algorithm can be used effectively to map fine scale wetland microhabitat features. It is extremely difficult to quantify sub-pixel estimates because the pixel spatial boundaries on the ground are unknown and GPS technology is hindered in regions like this study area. I recognized a number of locations where the classification predicted true positive locations of emergent sedge well below the spatial extent of a 3.6 m pixel. Similar to other studies applying the MTMF classification algorithm (Aspinall 2002), I also noticed considerable error between the predicted pixel abundance and true ground abundance. Some locations were predicted to have MF scores as high as 0.8 (i.e., analogous to 80% within pixel abundance), but appeared to have a much lower local abundance. Conversely, there were a number of locations where the extent of emergent sedge distributions was underestimated due to low
densities and open water patches. The emergent sedge endmembers were selected from a region where standing water depth was relatively low and vegetation density masked the spectral signature of standing water. In areas where emergent sedge density is lower than the training sites and there are widespread patches of standing water, classification results continually underestimate true ground densities. Future studies would benefit greatly from selecting image endmembers from different training locations that represent the variability of water and vegetation densities to see if abundance can be predicted more confidently.

Despite slight variability between emergent sedge endmember classification accuracies, there was some similarity between the correctly classified sites as well as the incorrectly classified sites. There were five sites that were consistently overpredicted by either three or all four emergent sedge endmembers. The overpredicted sites are interpreted as errors based on the ground validation survey which took place the year following the image acquisition. Interannual moisture variability may have contributed to these errors because seasonal flooding of meadows will vary in response to total snow pack and spring melt runoff. Consistent commission errors occurred in open meadows that showed some signs of historic inundation and flooding. Based on the extremely high level of accuracy exhibited in other locations, these classification errors may have been correct if the validation was conducted concurrently with the hyperspectral data collection and not the following year. A goal for future studies should be the collection of training and validation data within the timeframe of image acquisitions.
Preliminary results suggest that predicting water depths as a proxy to classify amphibian breeding habitat is not only possible but also accurate. Although not addressed in this study, it was recognized from the initial unsupervised classifications that information beyond water depths is present within the hyperspectral data. It appears as though substrate can be identified in water depths less than 2.5 m. I noted the substrate composition along the shoreline of most sites visited and it seems that rock and sediment dominated substrate are spectrally unique enough to warrant additional research. Coupling substrate composition with water depths provides an even greater ability to predict microhabitat feature distribution indicative of amphibian breeding locations.

3.3.6. Hierarchy Theory

Hierarchy theory provides a consistent method for examining ecological systems that exist across many spatio-temporal scales (O’Neill et al. 1986). For a holistic understanding of the focal scale in a study (e.g., wetlands in this study), hierarchy theory requires studying three levels at once to thoroughly place the observed phenomena in context of the larger system (O’Neill 1989, Allen and Hoekstra 1992a). Besides the focal level, researchers must also incorporate observations from the surrounding lower and upper levels. The lower level provides explanations about mechanisms and dynamics that are observed on the focal level, but also impose “initiating conditions” onto higher levels (O’Neill and King 1998). The grain (i.e., pixel spatial resolution) of the study will determine limits on the lowest level of organization that can be examined by the data. The upper level will
provide significance or context for the focal level within the larger system, and this upper level provides “environmental constraints” which define the range of possibilities. The extent of the study (i.e., image footprint) defines the highest level of organization that can be assessed (Allen and Hoekstra 1992b).

Although a sound theoretical foundation has been built for incorporating hierarchy theory into ecological studies, many projects cannot meet the requirements of investigating three separate scales simultaneously due to financial constraints. Hyperspectral data are unique by providing multiple scales of information within a single dataset. In this study the focal level, a wetland site, can be sampled and site characteristics such as size, shape, and spatial context can be derived or measured directly. The lower level, microhabitat features, can also be identified and features such as water depth, substrate, and emergent sedge presence can all be measured. The upper level, basin or watershed, can be studied and relationships such as site isolation and proximity to nearest sites can be measured with metrics commonly employed in landscape ecology studies. Approaching a research project from this perspective will likely yield relationships and explanations not explicitly evident with a single focal scale study. This unique characteristic of hyperspectral data, to my knowledge, has not been explored and presents an interesting avenue to pursue in future research projects.

3.3.7. Inventory and Monitoring Applications

The results of this study suggest that hyperspectral data analysis can be an effective tool for monitoring wetland habitat. Classifications across large landscapes showed that wetland predictions yielded a near comprehensive inventory of available
habitat within the study area. To have a complete understanding of amphibian presence and distribution, comprehensive surveys that encompass large spatial extents are ideal (Fellers 1997). Preliminary surveys in the study area conducted by sub-sampling wetlands within a basin provided an incomplete description of amphibian status because a major source population was not identified (Pilliod et al. 1996). In following years, comprehensive surveys conducted across watersheds provided a more complete and accurate understanding of population status (Pilliod and Peterson 1997). This level of detail is critical for effectively managing and understanding the impacts that habitat alteration or changing environmental conditions may have on local amphibian populations.

The ability to predict amphibian oviposition locations at the microhabitat scale has profound implications for streamlining field-based surveys. Surveys that have a limited budget and time frame could benefit greatly from not only knowing which potential sites to visit, but also the actual shoreline regions within a wetland site that likely support amphibian breeding. Microhabitat features can be periodically monitored to estimate how amphibian populations may be changing over time, or to help explain the mechanistic factors responsible for future declines.

A single hyperspectral dataset is capable of providing multiple scales of information across large spatial extents and may assist scientists in managing natural resources more effectively. Additional studies need to be conducted to understand the repeatability of hyperspectral analysis in similar and diverse ecological landscapes. As hyperspectral imagery and analysis becomes more common and
associated costs are reduced, I believe hyperspectral data analysis will become an indispensable tool for managing natural resources at large spatial scales.
Appendix A. The Big Creek study wetland classification error matrices.

<table>
<thead>
<tr>
<th></th>
<th>Landsat ETM+</th>
<th>ADAR 5500</th>
<th>HyMap SWS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Water</td>
<td>Other</td>
<td>SWS</td>
</tr>
<tr>
<td>Water</td>
<td>0</td>
<td>4</td>
<td>9</td>
</tr>
<tr>
<td>Other</td>
<td>30</td>
<td></td>
<td>21</td>
</tr>
<tr>
<td></td>
<td>30</td>
<td></td>
<td>30</td>
</tr>
<tr>
<td>Producers Accuracy (0/30)</td>
<td>= 0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Users Accuracy (0/4)</td>
<td>= 0</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>HyMap SSW</th>
<th>HyMap WM</th>
<th>HyMap Combined</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>STW</td>
<td>WM</td>
<td>Combined</td>
</tr>
<tr>
<td>SSW</td>
<td>7</td>
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<td>25</td>
</tr>
<tr>
<td>Other</td>
<td>23</td>
<td>7</td>
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</tr>
<tr>
<td></td>
<td>30</td>
<td></td>
<td>30</td>
</tr>
<tr>
<td>Producers Accuracy (7/30)</td>
<td>= 0.233</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Users Accuracy (7/7)</td>
<td>= 1</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Producers Accuracy (9/30) = 0.3
Users Accuracy (9/11) = 0.82
Producers Accuracy (13/30) = 0.433
Users Accuracy (13/14) = 0.929
Appendix B. The Bighorn Crags wetland classification error matrices.

<table>
<thead>
<tr>
<th></th>
<th><strong>Landsat ETM+</strong></th>
<th></th>
<th><strong>ADAR 5500</strong></th>
<th></th>
<th><strong>HyMap Water</strong></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Water</td>
<td>Other</td>
<td>Water</td>
<td>Other</td>
<td>Water</td>
<td>Other</td>
</tr>
<tr>
<td>Water</td>
<td>22</td>
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Producers Accuracy (22/46) = 0.478
Users Accuracy (22/22) = 1

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Producers Accuracy (34/46) = 0.739
Producers Accuracy (44/46) = 0.957
Users Accuracy (34/38) = 0.895
Users Accuracy (44/49) = 0.898
Appendix C. The Bighorn Crags emergent sedge error matrices.

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Producer's Accuracy (49/55) = 0.891
Producer's Accuracy (43/55) = 0.782
Producer's Accuracy (48/55) = 0.873
Producer's Accuracy (45/55) = 0.818

User's Accuracy (49/57) = 0.86
User's Accuracy (43/51) = 0.843
User's Accuracy (48/55) = 0.873
User's Accuracy (45/53) = 0.849
References Cited


