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Hyperspectral Analysis of Columbia Spotted Frog Habitat

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ABSTRACT Wildlife managers increasingly are using remotely sensed imagery to improve habitat delineations and sampling strategies. Advances in remote sensing technology, such as hyperspectral imagery, provide more information than previously was available with multispectral sensors. We evaluated accuracy of high-resolution hyperspectral image classifications to identify wetlands and wetland habitat features important for Columbia spotted frogs (*Rana luteiventris*) and compared the results to multispectral image classification and United States Geological Survey topographic maps. The study area spanned 3 lake basins in the Salmon River Mountains, Idaho, USA. Hyperspectral data were collected with an airborne sensor on 30 June 2002 and on 8 July 2006. A 12-year comprehensive ground survey of the study area for Columbia spotted frog reproduction served as validation for image classifications. Hyperspectral image classification accuracy of wetlands was high, with a producer's accuracy of 96% (44 wetlands) correctly classified with the 2002 data and 89% (41 wetlands) correctly classified with the 2006 data. We applied habitat-based rules to delineate breeding habitat from other wetlands, and successfully predicted 74% (14 wetlands) of known breeding wetlands for the Columbia spotted frog. Emergent sedge microhabitat classification showed promise for directly predicting Columbia spotted frog egg mass locations within a wetland by correctly identifying 72% (23 of 32) of known locations. Our study indicates hyperspectral imagery can be an effective tool for mapping spotted frog breeding habitat in the selected mountain basins. We conclude that this technique has potential for improving site selection for inventory and monitoring programs conducted across similar wetland habitat and can be a useful tool for delineating wildlife habitats.

KEY WORDS amphibian habitat, Bighorn Crags, Columbia spotted frog, hyperspectral, *Rana luteiventris*, remote sensing.

Amphibian populations are declining, and large numbers of species are at risk of extinction around the world (e.g., Houlahan et al. 2000, Alford et al. 2001, Stuart et al. 2004). Although many factors are involved with these declines, none is more pervasive than wetland habitat loss or modification (Collins and Storfer 2003, Beebee and Griffiths 2005). The loss of wetland habitat and decline of amphibians has stimulated concern among herpetologists and conservation biologists and resulted in widespread implementation of inventory and monitoring programs for pond-breeding amphibians and their habitats over the last 2 decades (Semlitsch 2000).

A challenge to effective inventory, monitoring, and conservation of pond-breeding amphibians is the ability to accurately locate and gather habitat information on wetlands within a landscape. Amphibians use a variety of spatially discrete habitats seasonally and over their lifetime, but many of these habitats either are too small, ephemeral, or tree-covered to be identified in aerial photographs and, thus, are not mapped. Missing potential habitats, when designing sampling or surveying strategies for amphibian inventories, reduces inference, because a comprehensive sample or a random sample of all available wetland habitats within the study area cannot be completed (Fellers 1997). As such, many wetland sampling designs are biased toward known wetlands, which appear on United States Geological Survey (USGS) 7.5-minute (1:24,000) topographic maps, aerial photographs, or United States Fish and Wildlife Service National Wetland Inventory (NWI) maps (Cowardin et al. 1979). Underestimating the number of wetlands in an area could weaken estimates and inference of occupancy, abundance, and trends in these parameters.

Remotely sensed data have emerged as an important tool for mapping habitats and investigating ecological questions at a variety of spatial scales (Turner et al. 2003). Many scientists and resource managers are now familiar with multispectral sensors such as National Aeronautics and Space Administration's Landsat 7 Enhanced Thematic Mapper Plus (ETM; Raytheon Santa Barbara Remote Sensing, Santa Barbara, CA). Multispectral remote sensing refers to sensors that record the reflected, emitted, or backscattered energy from the Earth's surface in multiple bands (typically 4 to 7). Landsat ETM is useful for delineating general landscape patterns such as vegetation communities (e.g., Gap Analysis Program), which can form the basis for sampling designs and wildlife management considerations (Scott 1993). Hyperspectral remote sensing refers to sensors that record energy in many (sometimes hundreds) overlapping and narrow spectral bands across the visible and infrared wavelengths of the electromagnetic spectrum. The large increase in the range of spectral sampling and resolution over traditional multispectral sensors allows hyperspectral sensors to measure subtle energy absorptions needed to more accurately classify discrete fine-scale features (e.g., small habitat patches with specific soil and vegetation characteristics or small, isolated wetlands).

We assessed hyperspectral analysis as a tool for identifying inland wetlands and habitat features within those wetlands used by amphibians. Our goals were to compare the accuracy of hyperspectral imagery relative to other remotely sensed

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Table 1. Descriptive sensor comparison for Landsat 7 Enhanced Thematic Mapper Plus (ETM; Raytheon Santa Barbara Remote Sensing, Santa Barbara, CA), Airborne Data Acquisition and Registration 5500 (ADAR; Positive Systems, Inc., Whitefish, MT), and HyMap (Integrated Spectronics, Sydney, Australia) image datasets used to classify wetland habitat in the Frank Church-River of No Return Wilderness, Idaho, USA, in 2002 and 2006.

Sensor	Type of imagery	Spatial resolution (m)	Spatial extent[a] (km)	Bands	Spectral sampling	Spectral range (nm)
Landsat ETM	Multispectral	30	185 × 185	6	Band 1 (blue)	450–515
					Band 2 (green)	525–605
					Band 3 (red)	630–690
					Band 4 (near infrared)	750–900
					Band 5 (infrared)	1,550–1,750
					Band 7 (infrared)	2,080–2,350
ADAR 5500	Multispectral	2	2 × 3 (per frame)	4	Band 1 (blue)	460–550
					Band 2 (green)	520–610
					Band 3 (red)	610–700
					Band 4 (near infrared)	780–920
2002 HyMap	Hyperspectral	3.6	2.5 × 20	126	15 nm[b]	450–890
2006 HyMap	Hyperspectral	5	3 × 15	126	15 nm[b]	890–1,350
					13 nm[b]	1,400–1,800
					17 nm[b]	1,950–2,480

[a] Estimates are approx. spatial extent prior to the georeferencing process, which alters image area.
[b] Represents average spectral sampling interval for each spectrometer.

datasets and test whether hyperspectral imagery could be used to discriminate fine-scale microhabitat features such as those used by the Columbia spotted frog (*Rana luteiventris*).

We addressed 3 specific research questions:

1) How does accuracy of wetland classification based on hyperspectral data compare with classification accuracy based on USGS topographic maps and satellite and airborne multispectral data?
2) Among predicted wetlands, can wetlands used by Columbia spotted frogs for breeding be distinguished from nonbreeding wetlands?
3) Within predicted wetlands, can high-resolution hyperspectral data be used to identify locations likely to be used for deposition of egg masses?

STUDY AREA

Our study area was located in a region of the Salmon River Mountains known as the Bighorn Crags within the Frank Church-River of No Return Wilderness, Idaho, USA (45°6′36.80″N, 114°36′18.01″W). The Bighorn Crags is a 90-km^2 area of glaciated cirque basins characterized by steep headwall ridges that delineate upland watershed boundaries and varied topographic relief within watersheds. Ground elevations in the study area ranged from around 2,400 m to 2,900 m. Higher elevations were dominated by subalpine fir (*Abies lasiocarpa*) and whitebark pine (*Pinus albicaulis*), whereas lower elevation regions were primarily mixed stands of lodgepole pine (*Pinus contorta*) and Engelmann spruce (*Picea engelmanni*). Dominant understory vegetation was grouse whortleberry (*Vaccinium scoparium*) and beargrass (*Xerophyllum tenax*). Vegetation in more mesic open-canopy habitats was primarily dominated by grasses and sedges (*Carex* spp.).

The study area encompassed the headwater regions of 3 lake basins with 46 lentic water bodies within the extent of image coverage. Water bodies in the study area consisted of 32 permanent flooded lakes and ponds, 5 ephemeral ponds, 5 flooded meadows, and 4 streamside wetlands or pools. For simplicity, we refer to all the aforementioned habitats as wetland habitat, disregarding any formal definitions pertaining to water depth, soil type, or vegetation.

We focused on habitats of the Columbia spotted frog because of its close affiliation with wetlands and the availability of a 12-year dataset on spotted frog populations in the study area (Pilliod and Peterson 2001; Pilliod et al. 2002; D. S. Pilliod, USGS, unpublished data). At higher elevations (>2,000 m), the Columbia spotted frog typically breeds in ponds and lakes from June to July within areas of emergent vegetation, and tadpoles are strictly aquatic until metamorphosis (Munger et al. 1998, Bull and Hayes 2000, Pearl et al. 2007). Juvenile and adult frogs live along the margin of wetlands feeding on both aquatic and terrestrial prey and, from October to May, overwinter under ice in deeper lakes and ponds, in springs, and under stream banks (Bull and Hayes 2002, Pilliod et al. 2002). Some frogs move into meadows to feed and will travel ≥1 km through dry forests when traveling among water bodies (Pilliod et al. 2002).

METHODS

Hyperspectral Data and Classifications

The HyVista Corporation Pty Ltd collected hyperspectral image data with the airborne sensor HyMap (Integrated Spectronics, Sydney, Australia) on 30 June 2002 and 8 July 2006 (Cocks et al. 1998). HyMap collected 126 spectral bands of 12-bit data covering the 440–2,500-nm region of the electromagnetic spectrum with a spatial resolution or pixel size of 3.6 m (2002) and 5 m (2006) for our study area (Table 1). Raw radiance data collected by the HyMap sensor were atmospherically corrected by the vendor using a modified radiative transfer model.

We applied the same hyperspectral image classification methods to the 2002 and 2006 datasets to investigate their repeatability. Because this study describes a new mapping application, it is important to understand whether results are

comparable to a second independent hyperspectral dataset. We conducted all data processing and image classifications using ENVI® 4.1 (Research Systems, Inc., Boulder, CO).

The Standing Water (SW) classification method consisted of plotting 2 near-infrared bands (Band 20 and Band 33) as a 2-dimensional (2-D) scatter plot and selecting all image pixels exhibiting the lowest reflectance values near the plot origin. We iteratively refined the process of selecting plot pixels based on observed shoreline boundaries of large lakes in the imagery. We exported the final pixel selection to create the SW feature classification (Fig. 1).

Due to steep topography of the study area, there were substantial shadows in the imagery, and we mistakenly classified some shaded ridge pixels as SW, because shadows and water have similarly low spectral reflectance. We used a USGS 10-m-resolution digital elevation model to produce raster images of slope and screen for classification errors on steep slopes where water is unable to accumulate; consequently, we did not consider these areas in the accuracy assessment.

Emergent sedge (i.e., sedge that is partially submerged in standing water during at least part of the growing season) was the most common vegetation type of wetlands in our study area. Emergent sedge occurs around fringes of larger wetlands and also in small seasonal wetlands that lack standing water and primarily contain moist soils and vegetation. Some wetlands had submerged or shoreline grasses present in low density and others completely lacked aquatic vegetation.

The Emergent Sedge (ES) classification method consisted of an end member selection (pure pixels representing 100% of one feature such as sedge) and target-mapping methodology (see Aspinall et al. 2002 for a review). Target-mapping algorithms take the spectral response from the training pixel and select all other image pixels that contain a similar spectral profile across all bands.

We performed a spectral data reduction step using the Minimum Noise Fraction (MNF) transformation (Green et al. 1988) of the reflectance data to segregate the noise-dominated and redundant spectral bands from the bands contributing useful information. We selected the first 38 MNF bands (i.e., total no. of coherent MNF bands), which served as the input data for subsequent processing steps. We ran the Pixel Purity Index algorithm to identify potential ES end member pixels distributed within a well-studied wetland site (Boardman 1993). We used the Mixture Tuned Matched Filter (MTMF) algorithm to produce a classification map for the emergent sedge end member (Harsanyi and Chang 1994, Boardman 1998). Mixture Tuned Matched Filter performs a partial unmixing of the spectral response in each image pixel capable of detecting sub-pixel fractional abundances of the input end member.

The MTMF algorithm produces 2 continuous-scale output images: the Matched Filter (MF) image and an Infeasibility (INF) image. The optimal image classification benefits from the information in both of these images. We plotted the MF image data and the INF image data as a 2-D scatter plot and manually selected pixels that had high MF scores and low INF scores for the final ES classification (Fig. 1).

Multispectral Data and Classifications

We processed 2 multispectral datasets to compare to the hyperspectral data. The Landsat ETM satellite sensor collected multispectral data on 10 July 2002. The Landsat ETM sensor collects 6 spectral bands of 8-bit data in the visible and infrared region of the electromagnetic spectrum at a spatial resolution of 30 m (Table 1). We received the Landsat ETM data in units of digital number values and converted the data to at-sensor reflectance to account for absorptions from the atmosphere. The Airborne Data Acquisition and Registration (ADAR) 5500 system (Positive Systems, Inc., Whitefish, MT) collected the second multispectral dataset on 31 July 2002. The ADAR 5500 system incorporates a Kodak Professional DCS 420 (Eastman Kodak Company, Rochester, NY) digital framing camera and was configured to collect 4 spectral bands of 8-bit data in the visible and near-infrared regions of the electromagnetic spectrum with a spatial resolution of approximately 2 m (Table 1).

Water exhibits low reflectance in the near-infrared region of the electromagnetic spectrum. We selected and iteratively refined a group of pixels located in the lower left corner of the 2-D scatter plot of 2 Landsat ETM near-infrared spectral bands (i.e., Band 4 and Band 5) to map wetlands in the study area.

We used the Maximum Likelihood supervised classification algorithm to classify ADAR 5500 data. Wetland training data consisted of representative water pixels selected from field observations. We designated a probability threshold of 0.7 for each training class determined through repetitive classification attempts, and we classified any pixel falling within the designated threshold range as a wetland in the final wetland map.

Classification Accuracy Assessment

We performed accuracy assessment through a ground-truth validation effort conducted July 2003. We did not use a Global Positioning System (GPS) to locate validation points because of the combined inaccuracies of georeferencing high-resolution imagery and using GPS receivers in the field, particularly in areas of dense forest canopy cover and rugged topographic relief. We relied on classified imagery as a field map and navigated directly from it using obvious features (e.g., lake coves and rocky outcrops) as geographic reference points. Because we were familiar with the study area from previous research and with minimal year-to-year change in wetland extent, we were confident in our ability to locate validation sites.

We surveyed wetlands yearly during 1995 to 2006, which provided an extensive background record of wetland distribution. We conducted 2 additional field surveys specifically to validate predicted SW pixels occurring in contiguous patches >17 pixels (0.02 ha), and individual pixels of ES located within recognizable areas of wetland sites.

We assessed feature classification accuracy with an error matrix (Congalton and Green 1999). Producer's accuracy represents probability that a true positive location on the ground is correctly classified, and the inverse omission error

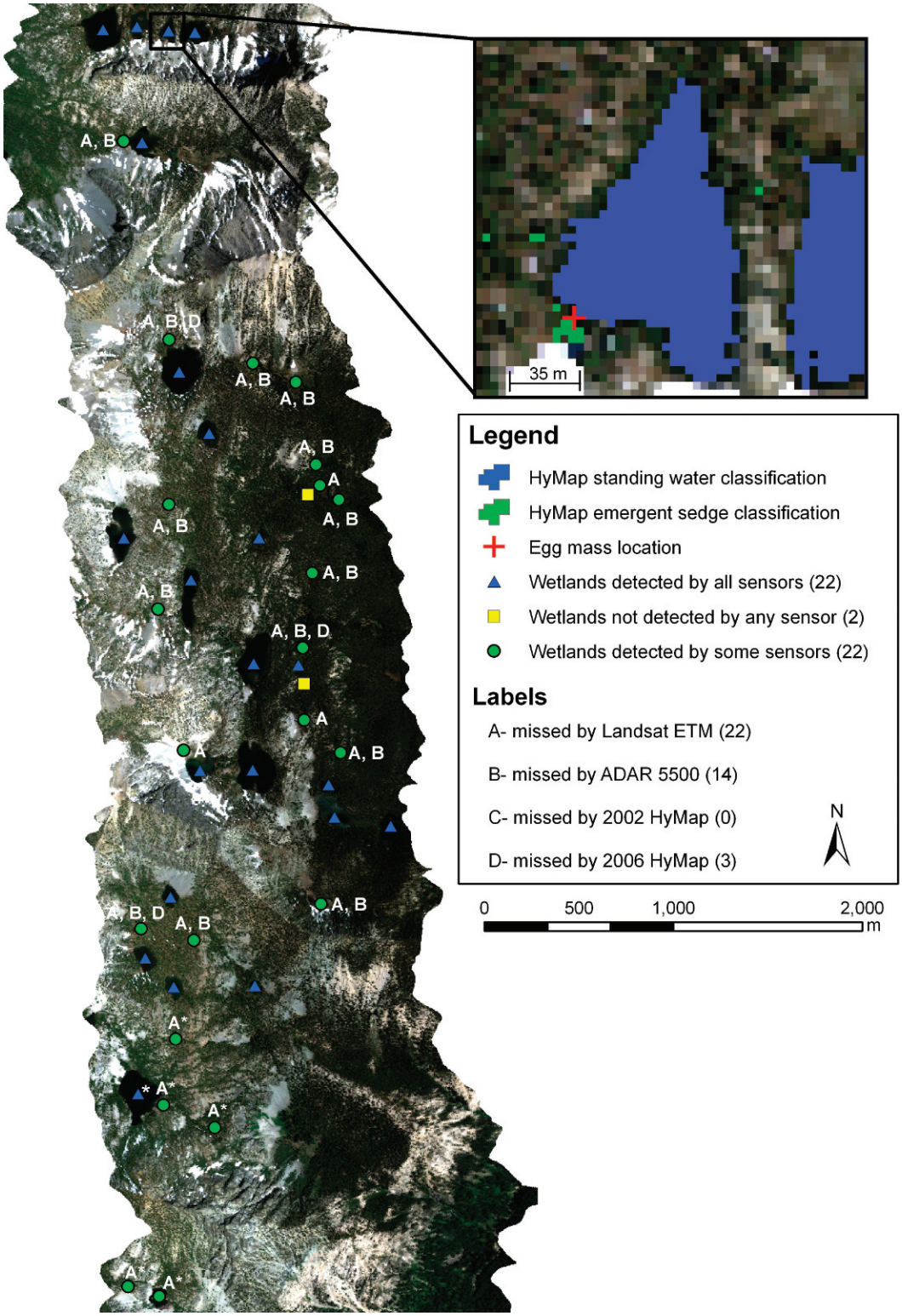

Figure 1. Wetland detection summary map of the study area in the Frank Church-River of No Return Wilderness, Idaho, USA, where we compared Landsat 7 Enhanced Thematic Mapper Plus (ETM; Raytheon Santa Barbara Remote Sensing, Santa Barbara, CA), Airborne Data Acquisition and Registration 5500 (ADAR; Positive Systems, Inc., Whitefish, MT), and HyMap (Integrated Spectronics, Sydney, Australia) image classifications from 2002 and 2006. Number of wetlands in each detection category is shown in parenthesis in the legend. The inset image shows an example wetland site with the 2002 HyMap standing water and emergent sedge classification result and an egg mass location plotted on the imagery. Asterisks denote all wetland sites that were outside the extent of the ADAR 5500 imagery.

Table 2. Wetland mapping accuracy for Landsat 7 Enhanced Thematic Mapper Plus (ETM; Raytheon Santa Barbara Remote Sensing, Santa Barbara, CA), Airborne Data Acquisition and Registration 5500 (ADAR; Positive Systems, Inc., Whitefish, MT), and HyMap (Integrated Spectronics, Sydney, Australia) image classifications from the Frank Church-River of No Return Wilderness, Idaho, USA, in 2002 and 2006. HyMap hyperspectral accuracies represent standing water (SW), emergent sedge (ES), and combined (SW+ES) wetland classifications.

Classification	Producer's accuracy (%)	User's accuracy (%)	Omission error (%)	Commission error (%)
Landsat ETM	47.8	100.0	52.2	0.0
ADAR 5500	60.0	100.0	40.0	0.0
2002 HyMap (SW)	78.3	94.7	21.7	5.3
2002 HyMap (ES)	73.9	89.5	26.1	10.5
2002 HyMap (combined)	95.7	89.8	4.3	10.2
2006 HyMap (combined)	89.1	93.2	10.9	6.8

rate represents a measure of the total percentage of true positive wetlands not correctly predicted (i.e., % of known wetlands missed; Congalton and Green 1999). User's accuracy represents probability that a classified image pixel is actually that category on the ground, and the inverse commission error rate represents a measure of the total percentage of false positive wetlands incorrectly classified as true positive locations (i.e., % of wetlands incorrectly classified as a wetland). We do not report an overall accuracy statistic, because this value is driven by the number of true negatives (i.e., pixels correctly not classified as wetland) and has little direct relationship to wetland detection performance we evaluated.

Breeding Wetland Predictions

Documenting the distribution of breeding habitats across a landscape is often a fundamental component of amphibian monitoring programs. Based on previous research from the study area, we defined potential spotted frog breeding habitat as all wetlands where both SW and ES were predicted to be present. We based these habitat-type criteria on general physical patterns we observed during field surveys in our study area, but these criteria do not define the realm of possible characteristics describing Columbia spotted frog breeding habitat across this species' entire range.

We also wanted to evaluate feasibility of predicting egg mass locations (oviposition sites) with the ES microhabitat classification, because ES is the most common location where we observed egg masses in our study area. We recorded egg mass locations almost yearly during 1995 to 2004 by marking locations on a USGS topographic map. We manually digitized egg mass deposition sites into a Geographic Information System (GIS) to compare them to ES classifications. In some cases the digitized egg mass locations were offset slightly from the predicted emergent sedge pixels because of differences between shoreline boundaries on USGS topographic maps and the imagery. We considered these locations true positives as long as predicted pixels were within 15 m of egg mass GIS points.

RESULTS

Wetland Identification and Delineation

We visually identified 28 wetlands from USGS 7.5-minute topographic maps representing 61% (28 of 46) of total wetland sites in our study area. Wetlands appearing on topographic maps primarily were lakes and open-canopy ponds >0.5 ha identified on aerial photographs. Landsat ETM wetland classifications successfully identified 22 wetlands (Fig. 1), but 24 small ponds (<0.3 ha) and wet meadows were not detected. The ADAR 5500 data accurately mapped 24 wetlands that tended to be larger lakes and ponds (Fig. 1), and 16 of the wetlands not detected with the ADAR 5500 data were also not identified on USGS topographic maps or predicted with the Landsat ETM wetland classification.

The 2002 hyperspectral data classification was the most effective remote sensing method, compared to both Landsat ETM and ADAR 5500 multispectral classifications, for identifying various types of wetland habitat. The SW classification method correctly classified 36 (78%) wetlands and falsely predicted 2 nonexistent wetlands (Table 2). Of the 2 falsely predicted wetland sites, one was located in a forested area and was misclassified shadow and the second site occurred on a flat meadow near a ridge pass. Because we had no field data to verify that the meadow site contained water during image data collection, we marked it as an error, but this site could have had an ephemeral pool present. The SW classification method was not effective at identifying small pools and flooded meadows.

The ES classification was useful for identifying small wetlands with sub-pixel scale abundances of ES present and too little standing water to be detected with the SW classification. The ES classification method correctly predicted 34 (74%) wetlands and overpredicted an additional four (Table 2). Overpredicted sites were drier meadows dominated by grasses or small areas of emergent grasses on pond shorelines. When we combined all true positive and false positive locations between the SW and ES classifications to produce the final comprehensive wetland classification, 44 (96%) wetlands were correctly predicted in our study area (Fig. 1). Two wetlands (a small forested ephemeral pond and a stream-side pool located in a densely forested riparian area) were not correctly classified with the combination of the ES and SW approaches. The combined SW and ES classification of 2006 hyperspectral data accurately identified 41 (89%) wetlands (Table 2; Fig. 1). Two wetlands misclassified in the 2006 imagery were moist meadows that lacked any standing water, as well as the same two that were misclassified in the 2002 image.

Predicting Use of Wetlands for Amphibian Breeding

Hyperspectral analysis was an effective tool at predicting which wetlands likely would be used by Columbia spotted frogs for reproduction. Considering criteria where both SW and ES were classified at one wetland site, we correctly predicted 14 of 19 (74%) Columbia spotted frog breeding wetlands. This combined classification approach overpredicted 3 breeding wetlands, all of which we field-verified to contain both SW and ES pixels but were not used by frogs for breeding.

Hyperspectral analysis was an effective tool at predicting where in wetlands Columbia spotted frogs would likely deposit eggs. Our field surveys identified 55 emergent sedge validation sites, which ranged from large continuous patches (0.08 ha) to discrete sub-pixel locations along shorelines. Classification accuracies for ES were high across the landscape, identifying most microhabitat sedge validation sites with a producer's and user's accuracy of 89% and 86%, respectively. Of the 32 egg mass locations identified in 19 wetlands over the last 12 years, we found that 23 of 32 (72%) fell within pixels predicted to contain ES (Fig. 1). The remaining 9 egg mass deposition sites were located in different microhabitat such as debris dams and subsurface vegetation.

DISCUSSION

Most previous wetland remote sensing applications have used black-and-white, panchromatic, or multispectral imagery for project-specific purposes. Black-and-white and color-infrared aerial photograph interpretation served as the basis for the development of the NWI maps available for many regions of the United States (Wilen and Bates 1995). Although NWI has been found to be accurate for some wetland types, minimum mapping units generally are large wetlands (>0.6 ha), and errors of omission can be substantial (Stolt and Baker 1995). Multispectral satellite remote sensing has been extensively investigated across a range of wetland habitats, showing a correspondingly wide range of classification errors (Johnston and Barson 1993, Jensen et al. 1995, Kindscher et al. 1998, Dechka et al. 2002). Classification accuracy in these studies can be a result of the purpose of the application or the intended use of the maps, which may or may not be helpful for the site-selection process of amphibian inventory and monitoring programs.

Results from both hyperspectral SW and ES classifications suggest hyperspectral remote sensing can provide an improved method for identifying wetland habitat distributions compared to multispectral imagery and traditional methods. When we combined the 2002 ES and SW classifications, we accurately mapped a near-comprehensive (96%) wetland distribution, exceeding typical classification results from multispectral remote sensing applications. More importantly, some wetlands identified with the hyperspectral data represent noteworthy amphibian habitat, such as the only known western toad (*Anaxyrus boreas*) breeding location, which was not mapped by any other dataset. However, it is important to note that some of the wetland sites in our study area were ephemeral or had portions that may dry over a short period during the summer. Because the remote sensing data were collected in June and July in 2 different years, the inter- and intra-annual variability in surface water presence could affect wetland and habitat detection accuracies.

When evaluating a new technology it is important to establish some repeatability of results before widespread confidence is gained. The hyperspectral wetland classification using the 2006 data closely matched the classification from the 2002 data, and the maps looked strikingly similar given the 4-year lapse between images and the slight decrease in spatial resolution in 2006. The high level of repeatable accuracy we demonstrated suggests this method would be appropriate as a tool for future wetland monitoring programs by producing habitat information not available on standard maps or imagery.

Our results suggest that hyperspectral data also can predict amphibian breeding habitats by incorporating knowledge of physical habitat attributes. We were able to correctly predict 74% of all known Columbia spotted frog breeding wetlands within the study area. Five breeding wetlands were incorrectly classified using the criteria we defined. All of those wetlands were small, emergent wetlands that lacked large areas of open, standing water but were still predicted as wetlands. Given the restrictive definition of potential breeding habitat as containing both SW and ES predicted pixels, we likely underestimated potential breeding habitat for Columbia spotted frogs in our study area. To assess the generality of our approach, future studies on other species are required. Emergent sedges, for example, may not be an appropriate microhabitat predictor for salamander species that prefer wood or other substrates for ovipositing. However, the spectral range and resolution of hyperspectral imagery may be adequate for modeling distribution and abundance of other microhabitat features important to different species, even under water.

The Landsat ETM data correctly identified large lakes and ponds, which explains the high user's accuracy. In other words, if a wetland was predicted, it was correct 100% of the time. However, Landsat ETM consistently missed smaller ponds, emergent wetlands, and wet meadows due to their small spatial extent relative to the large pixel size (30 m). The Landsat ETM classification missed the most productive breeding site for Columbia spotted frogs and the western toad breeding site in our study area.

The ADAR 5500 data were useful for identifying lakes and small ponds because of the high image spatial resolution. An omission error of 40% depicts some limitations of this dataset, even when the wetland features were large in size. The most productive breeding site for Columbia spotted frogs in our study area was identified, but several wet meadows and forested ponds were missed. Wet meadows were missed because we were unable to use an indicator, such as sedge presence, to assist in identification of shallow wetlands. Wet or flooded meadows were an important habitat type used by amphibian populations in our study area. These wetlands were difficult to predict using solely water features because the spectral response was

highly influenced by vegetation presence. The limited number of spectral bands of ADAR 5500 restricted the probability of correctly classifying these features.

Although still more expensive than some satellite multispectral sensors, hyperspectral imaging costs are becoming more affordable. Funding constraints for inventory and monitoring programs may limit the possibility of incorporating the expensive hyperspectral technology. The cost of the 2002 HyMap imagery was US$6,000 for one flight-line of data covering approximately 2.5 km × 20 km (at 3–4-m spatial resolution). In the last few years costs have declined, and the 2006 imagery cost US$8,250 to cover an area roughly 5 times that of the 2002 imagery. The 2006 costs include mobilization fees, which were shared among other group-shoot participants. Organizing data collection in conjunction with other regional projects can reduce overall costs and make hyperspectral image acquisition more affordable.

MANAGEMENT IMPLICATIONS

Recent studies have concluded that habitat alteration and environmental processes occurring at broad geographic extents can have significant effects on local amphibian populations (Houlahan and Findley 2003, Gibbs et al. 2005). Therefore, amphibian inventory and monitoring surveys should consider larger spatial coverage that is more likely to include foraging, breeding, and overwintering habitat (Semlitsch and Bodie 2003). We suggest that remotely sensed data could be used to improve designing inventory and monitoring programs across broad spatial scales.

We evaluated 3 remotely sensed datasets common or comparable to those being used for many natural resource applications today. The hyperspectral image processing results demonstrate an improvement over traditional methods of wetland site selection and multispectral remote sensing of detecting wetland habitat. The ability to predict amphibian breeding wetlands and egg mass locations within wetlands has profound implications for streamlining field-based surveys. Surveys constrained by a limited budget and time frame could benefit from not only knowing which wetlands to visit, but also the actual shoreline regions within a wetland that likely support amphibian breeding. This classification approach would be most useful for species with specific habitat requirements but may be difficult for species that are generalists or utilize more complex wetland microhabitat. Future studies in different landscapes will improve our understanding of the repeatability and generality of hyperspectral analysis for amphibian habitat studies. As hyperspectral imagery and analysis become more common and associated costs are reduced, hyperspectral data analysis may become an indispensable tool for delineating wildlife habitats and managing natural resources.

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LITERATURE CITED

Alford, R. A., P. M. Dixon, and J. H. K. Pechmann. 2001. Global amphibian population declines. Nature 414:449–500.

Aspinall R. J., W. A. Marcus, and J. W. Boardman. 2002. Considerations in collecting, processing, and analysing high spatial resolution hyperspectral data for environmental investigations. Journal of Geographical Systems 4:15–29.

Beebee, T. J. C., and R. A. Griffiths. 2005. The amphibian decline crisis: a watershed for conservation biology. Biological Conservation 125:271–285.

Boardman J. W. 1993. Automated spectral unmixing of AVIRIS data using convex geometry concepts. Summaries of the Fourth Annual JPL Airborne Geoscience Workshop, JPL Publication 93-26:11–14.

Boardman J. W. 1998. Leveraging the high dimensionality of AVIRIS data for improved sub-pixel target unmixing and rejection of false positives: Mixture Tuned Matched Filtering. Proceedings of the Seventh JPL Airborne Earth Science Workshop, JPL Publication 97-21:6.

Bull, E. L., and M. P. Hayes. 2000. Livestock effects on reproduction of the Columbia spotted frog. Journal of Range Management 53:291–294.

Bull, E. L., and M. P. Hayes. 2002. Overwintering of Columbia spotted frogs in northeastern Oregon. Northwest Science 76:141–147.

Cocks, T., R. Jenssen, A. Stewart, I. Wilson, and T. Shields. 1998. The HyMap airborne hyperspectral sensor: the system, calibration and performance. Pages 37–43 *in* M. Schaepman, D. Schläpfer, and K. I. Itten, editors. Proceedings from the first EARSEL Workshop on Imaging Spectroscopy. EARSeL, 6–8 October 1998, Zurich, Switzerland.

Collins, J. P., and A. Storfer. 2003. Global amphibian declines: sorting the hypotheses. Diversity and Distributions 9(2):89–98.

Congalton, R. G., and K. Green. 1999. Assessing the accuracy of remotely sensed data: principles and practices. CRC Press, Boca Raton, Florida, USA.

Cowardin, L. M., V. Carter, F. C. Golet, and E. T. LaRoe. 1979. Classification of wetlands and deepwater habitats of the United States. U.S. Fish and Wildlife Service Bulletin OBS-79/31, Washington, D.C., USA.

Dechka, J. A., S. E. Franklin, M. D. Watmough, R. P. Bennett, and D. W. Ingstrup. 2002. Classification of wetland habitat and vegetation communities using multi-temporal Ikonos imagery in southern Saskatchewan. Canadian Journal of Remote Sensing 28:679–685.

Fellers, G. M. 1997. Design of amphibian surveys. Pages 23–34 *in* D. H. Olson, W. P. Leonard, and R. B. Bury, editors. Sampling amphibians in lentic habitats: methods and approaches for the Pacific Northwest. Society for Northwestern Vertebrate Biology, Olympia, Washington, USA.

Gibbs, J. P., K. K. Whiteleather, and F. W. Schueler. 2005. Changes in frog and toad populations over 30 years in New York State. Ecological Applications 15:1148–1157.

Green, A. A., M. Berman, P. Switzer, and M. D. Craig. 1988. A transform for ordering multispectral data in terms of image quality with implications for noise removal. Institute of Electrical and Electronics Engineers Transactions on Geoscience and Remote Sensing 26:65–74.

Harsanyi, J. C., and C. I. Chang. 1994. Hyperspectral image classification and dimensionality reduction: an orthogonal subspace projection approach. Institute of Electrical and Electronics Engineers Transactions on Geoscience and Remote Sensing 32:779–785.

Houlahan, J. E., and C. S. Findley. 2003. The effects of adjacent land use on wetland amphibian species richness and community composition. Canadian Journal of Fisheries and Aquatic Sciences 60:1078–1094.

Houlahan, J. E., C. S. Findley, B. R. Schmidy, A. H. Meyer, and S. L. Kuzmin. 2000. Quantitative evidence for global amphibian declines. Nature 404:752–755.

Jensen, J. R., K. Rutchey, M. S. Koch, and S. Narumalani. 1995. Inland wetland change detection in the Everglades water conservation area 2A using a time series of normalized remote sensing data. Photogrammetric Engineering and Remote Sensing 61:199–209.

Johnston, R. M., and M. M. Barson. 1993. Remote sensing of Australian wetlands: an evaluation of Landsat TM data for inventory and classification. Australian Journal of Marine Freshwater Resources 44:235–252.

Kindscher, K., A. Fraser, M. E. Jakubauskas, and D. M. Debinski. 1998. Identifying wetland meadows in Grand Teton National Park using remote sensing and average wetland values. Wetlands Ecology and Management 5:265–273.

Munger, J. C., M. Gerber, K. Madrid, M.-A. Carroll, W. Petersen, and L. Heberger. 1998. U.S. National Wetland Inventory Classifications as predictors of the occurrence of Columbia spotted frogs (*Rana luteiventris*) and Pacific treefrogs (*Hyla regilla*). Conservation Biology 12:320–330.

Pearl, C. A., M. J. Adams, and W. H. Wente. 2007. Characteristics of Columbia spotted frog (*Rana luteiventris*) oviposition sites in northeastern Oregon, USA. Western North American Naturalist 67:86–91.

Pilliod, D. S., and C. R. Peterson. 2001. Local and landscape effects of introduced trout on amphibians in historically fishless watersheds. Ecosystems 4:322–333.

Pilliod, D. S., C. R. Peterson, and P. I. Ritson. 2002. Seasonal migration of Columbia spotted frogs (*Rana luteiventris*) among complementary resources in a high mountain basin. Canadian Journal of Zoology 80:1849–1862.

Scott, J. M. 1993. Gap analysis: a geographic approach to protection of biological diversity. The Wildlife Society, Bethesda, Maryland, USA.

Semlitsch, R. D. 2000. Principles for management of aquatic breeding amphibians. Journal of Wildlife Management 64:615–631.

Semlitsch, R. D., and J. R. Bodie. 2003. Biological criteria for buffer zones around wetlands and riparian habitats for amphibians and reptiles. Conservation Biology 15:1219–1228.

Stolt, M. H., and J. C. Baker. 1995. Evaluation of National Wetland Inventory maps to inventory wetlands in the southern Blue Ridge of Virginia. Wetlands 15:346–353.

Stuart, S. N., J. S. Chanson, N. A. Cox, B. E. Young, A. S. L. Rodrigues, D. L. Fischman, and R. W. Waller. 2004. Status and trends of amphibian declines and extinctions worldwide. Science 306:1783–1786.

Turner, W., S. Spector, N. Gardiner, M. Fladeland, E. Sterling, and M. Steininger. 2003. Remote sensing for biodiversity science and conservation. Trends in Ecology and Evolution 18:306–314.

Wilen, B. O., and M. K. Bates. 1995. The U.S. Fish and Wildlife Service's national wetlands inventory project. Vegetatio 119:153–169.

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