Application of high spatial resolution, hyperspectral imagery to riparian mapping in Yellowstone National Park

W. Andrew Marcus
Department of Geography
University of Oregon

Outline of Presentation

• Goal of talk: Review data types and mapping approaches that have been most successful for us in riparian mapping
• Concept of high spatial resolution hyperspectral (HSRH) data
• Field area and data collection
• Research approaches and findings:
  • Data Decisions
    • choice of appropriate spatial resolution
    • choice of data compression approaches
  • Classification/Mapping Algorithms
    • spectral angle mapping for terrestrial landcover
    • maximum likelihood for in-stream habitats
    • regression analysis for stream depths
    • matched filtering for downed wood
• Summary

Collaborators on Image Acquisition, Data Collection, and Analysis

• Richard Aspinall, Montana State University
• Joe Boardman, Analytical Imaging Geophysics
• Robert Crabtree, Yellowstone Ecosystem Studies
• Don Despain, U.S. Geological Survey
• Earth Search Systems, Inc.
• Mark Fonstad, Southwest Texas State University
• Wayne Minshall, Idaho State University
• Chuck Peterson, Idaho State University

Field and Research Assistants: Robert Ahl, Kerry Halligan, Carl Legleiter, Jim Rasmussen

Research Objectives and Rationale

Overarching goal: determine if HSRH imagery can be used to map key environmental variables in complex stream settings.

What is Hyperspectral Imagery?

1999 Probe1 (solid lines) and TM5 spectra (symbols) for willow, cottonwood and aspen

Funding Sources:

The High Tech Landscapes Initiative of Yellowstone Ecosystem Studies, Bozeman, Montana

The NASA Earth Observations Commercial Applications Program (EOCAP) - Hyperspectral, Stennis Space Flight Center, Mississippi

The EPA bioindicators program
Rationale for using high spatial resolution

Detection of within-stream features like riffles requires HSR imagery.

High Spatial Resolution and Hyperspectral combined (“HSHR imagery”) provide more information on variables at the stream scale.

Field Area: Northeast Yellowstone

Landscape: Cooke City

Landscape: Round Prairie

Landscape: Lower Soda Butte Creek
Data Sets: Imagery and Field Data

1-m Imagery: Helicopter platform

To collect 1-m resolution data, the Probe-1 sensor was mounted on a helicopter and flown 600 m above the ground surface.

The helicopter platform created unique problems:
- more vibration, pitch, yaw and roll than fixed wing aircraft
- gyroscope overcompensation led to serious image swirl
- rotor blades blocked GPS signal, causing loss of coordinate data
- greater difficulty in coregistering field maps to imagery and GIS data
Methods: field mapping for image training and validation

Morphologic units, stream depth, substrate size, and vegetation communities and species were mapped directly to 1 m images to insure coregistration.

Data Decisions

Two key considerations:
- Different data compression approaches
- Effects of spatial resolution on feature detection

Hyperspectral data: reducing dimensionality

Goals of reducing dimensionality:
- Data compression and faster processing
- Signal enhancement
- Noise reduction

Approaches examined:
- Spectral selection
- Principal Component Analysis (PCA)
- Minimum Noise Fraction (MNF)

Possible future approach: Geostatistical filtering

Reducing Dimensionality: Selecting Spectra

If a feature has a unique spectral signal, selecting specific spectra may be an efficient approach for reducing dimensionality.

Reducing Data Dimensionality: PCA

Reducing Data Dimensionality: MNF
Reducing Data Dimensionality: PCA vs MNF

Data decision: spatial resolution

Findings: Reducing dimensionality

• Except with spectrally unique targets, spectral band extraction is generally not best approach as it discards the power of hyperspectral imagery. Exception is stream depth (to be discussed later).

• PC and MNF both reduce data size and processing time by an order of magnitude, but:
  • no a priori reason for favoring one over the other
  • each seems to work better for certain applications:
    • PCA best for instream classification
    • MNF best for terrestrial land cover

• Further work needed to:
  • determine why a given method works better in certain situations
  • evaluate alternative approaches—e.g., geostatistical filtering

Effects of spatial resolution: human features

Effects of spatial resolution: Streams

Finer scale spatial resolution better discriminates many features, but at the cost of:
• less area coverage for a given sensor
• greater data storage cost for a given area
Therefore one wants to choose coarsest pixel resolution that still meets mapping needs.
Effects of spatial resolution: Downed wood

- Requires 1-m resolution for detection.

Effects of spatial resolution: Vegetation type

- 4-m resolution provides valley wide coverage, while still detecting individual large trees.

Findings: Spatial resolution

<table>
<thead>
<tr>
<th>Feature</th>
<th>Required spatial resolution (m)</th>
<th>Accuracy at that resolution (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Human features</td>
<td>1</td>
<td>N.A.</td>
</tr>
<tr>
<td>In-stream habitats</td>
<td>1</td>
<td>76 to 91</td>
</tr>
<tr>
<td>Stream depth</td>
<td>1</td>
<td>67 to 99</td>
</tr>
<tr>
<td>Downed wood</td>
<td>1</td>
<td>82</td>
</tr>
<tr>
<td>Vegetation cover</td>
<td>2 to 10</td>
<td>92-99</td>
</tr>
</tbody>
</table>

General Rule: Pixel resolution should be 1/3 size of feature of interest. Realistic Rule: Pixel resolution should be approximately same size as feature of interest.

Hyperspectral Mapping

- Features of interest for riparian mapping:
  - Terrestrial land cover (vegetation, wetland, human features)
  - Stream habitats and depths
  - Downed wood

- Classification approaches used for final maps:
  - Spectral angle mapper (SAM) – land cover
  - Maximum likelihood – in-stream habitats
  - Matched filter (MF) – downed wood
  - Regression and hydraulic model – stream depths

- Also evaluated mixture tuned matched filters (MTMF), pixel purity indices (PPI), and pixel unmixing.

Evaluation site for land cover mapping

- Round Prairie, YNP

- 4-m imagery

Work by Kerry Halligan, YERC

- 30 sites visited for each category
Land cover mapping: Spectral Angle Mapper

Similarity between pixels is defined by the angle between their vectors. The advantage of this technique is that illumination differences across large landscapes (e.g., different aspects) do not create false differences between pixels of the same composition.

Land cover mapping: Data Processing

Data transformations prior to spectral angle mapping:
- None - use raw untransformed imagery
- Principal components (PCA) images
- Minimum noise fraction (MNF) images

The best classifications occurred with MNF transformed data. It is not immediately apparent why this is the case, but it seems likely that MNF does a better job of:
- Removing image-wide noise prior to data analysis
- Isolating signal related to subtle variations in vegetation cover

CRITICAL to using MNF - using an homogenous dark patch or dark bands for defining noise statistics.

Spectral Angle Mapping of Algae

SAM requires that the user define the threshold at which the feature is “found.” The user should therefore have knowledge about the landscape for feature ID to work.

Hyperspectral mapping: In-stream habitats

During the study, a number of floodplain stream habitats were identified. These were:
- High gradient riffle (white water)
- Low gradient riffle (no white water)
- Eddy drop zone (fine sediment accumulation)
- Scoot pool
- Glide
**In-stream habitats: Data processing**

Data transformations evaluated prior to mapping:
- None – use raw untransformed imagery
- Principal components (PCA) images
- Minimum noise fraction (MNF) images

The best classifications occurred with PCA transformed data. It appears the low reflectance from water causes MNF transforms to classify signal as noise, thereby reducing the spectral information available for analysis.

**CRITICAL** to using PCA in streams – calculate the covariance statistics using the water portion only of the stream (i.e., mask out remainder of image when calculating statistics).

**In-stream habitats: PCA images**

Take raw image

Mask to calculate covariance statistics for water

Create pc data that highlight within-stream variations

**In-stream habitats: Maximum likelihood approach**

Calculates the “distance” of a given pixel from the average based on statistical distribution of training sites in spectral space.

Example of maximum likelihood classification, (Lillesand and Kiefer, 1994, pages 590 & 596)

**Results of 4 Unit Stream Classification**

Field map

1 meter classification

<table>
<thead>
<tr>
<th>Turbulence Category</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Riffles/rapids</td>
<td>78.9</td>
</tr>
<tr>
<td>Glides</td>
<td>96.8</td>
</tr>
<tr>
<td>Pools</td>
<td>96.5</td>
</tr>
<tr>
<td>Eddy drop zones</td>
<td>84.8</td>
</tr>
</tbody>
</table>
**Hyperspectral mapping: stream depths**

Goal: determine if 1 m imagery can map continuous variations in depth.

Steps to reach this goal:
- Extract pc scores for depth pixels
- Conduct multiple regression analysis on depth vs. pc scores
- Error analysis
- Create depth image using regression results

**Multiple Regression Results, Lamar River, WY**

Summary statistics for multiple regression of depth (y) as a function of principal component scores (x₁, x₂, ..., xₙ):

<table>
<thead>
<tr>
<th>Depth Range</th>
<th>Number of sites</th>
<th>Number of pc bands in regression</th>
<th>R² adjusted</th>
<th>R² predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td>All depths</td>
<td>105</td>
<td>8</td>
<td>0.10</td>
<td>0.06</td>
</tr>
<tr>
<td>&lt; 60 cm</td>
<td>66</td>
<td>4</td>
<td>0.16</td>
<td>0.09</td>
</tr>
</tbody>
</table>

Cutoff of relation between depth and reflectance data at > 60 cm consistent with Winterbottom and Gilvear, 1998, but...

**Stream mapping: Depths in the Lamar River**

<table>
<thead>
<tr>
<th>In-stream habitat</th>
<th>Number of sites</th>
<th>Number of pc bands in regression</th>
<th>Adjusted R² (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eddy drop zone</td>
<td>17</td>
<td>2</td>
<td>93.8</td>
</tr>
<tr>
<td>High gradient riffle</td>
<td>35</td>
<td>6</td>
<td>67.0</td>
</tr>
<tr>
<td>Low gradient riffle</td>
<td>11</td>
<td>6</td>
<td>91.7</td>
</tr>
<tr>
<td>Pool</td>
<td>5</td>
<td>1</td>
<td>72.3</td>
</tr>
<tr>
<td>Rough water runs</td>
<td>10</td>
<td>3</td>
<td>82.5</td>
</tr>
<tr>
<td>Rums</td>
<td>9</td>
<td>4</td>
<td>93.1</td>
</tr>
<tr>
<td>Glides</td>
<td>17</td>
<td>11</td>
<td>98.6</td>
</tr>
</tbody>
</table>

**Stream depth mapping: The HAB-1 model**

Basis for model (developed by Mark Fonstad, SWTU):
- Manning equation
- Jarret’s roughness
- Q, S and W are measured

Key assumptions:
- roughness estimate is reasonable
- triangle approximation: \( D_{\text{avg}} = 2 \times D_{\text{max}} \)
- avg depth = avg reflectance signal (implies depth driving all variations in reflectance)

**Stream depth mapping: Input data**

Applying the HAB-1 Model:
- acquire Q and S from remote sources
- estimate \( D_{\text{ave}} \) and \( D_{\text{max}} \) at multiple cross sections
- determine avg, max, min reflectances at cross sections
- regress reflectance (x) vs depth (y)
- apply regression to remainder of remote sensing image
Results: Smooth and rough water

Discussion: Reasons for inaccuracies with in-stream mappings

Reflectance from streams may not be directly proportional to depth due to:
- variations in substrate
- turbulence and “false” turbulence
- viewing angle relative to sun
- variations in background (mixed pixels)
- turbidity

Reflectance variations from turbulence

Reflectance variations due to viewing angle

Reflectance variations due to substrate

Reflectance variations due to mixed pixels
Reflectance variations due to turbidity

Depth at both sites along Soda Butte Creek is ~1.5 m

Discussion: Are the depths accurate?

$\rho^2 = 0.30$, seems low, but
- general trend captured (slope $= 1$, y int. $= 0$)
- cross sections seem real
- hydraulics are correct

Hyperspectral mapping: Downed wood

Data transformations prior to matched filter mapping:
- None – use raw untransformed imagery
- Principal components (PCA) images
- Minimum noise fraction (MNF) images

The best classifications occurred with MNF transformed data.

Classification approaches used for final maps: matched filter (MF)
Also evaluated mixture tuned matched filters (MTMF), pixel purity indices (PPI), pixel unmixing, spectral angle mapper, maximum likelihood classification.

Discussion: The power of visualization

Downed wood: Matched filter mapping

Create pc image
Choose training sites, create matched filter images and assess accuracy at different thresholds.

Downed Wood: Matched filter mapping

Field map
Wood map
Downed wood

Proportion of wood in each pixel, red = high, green = medium, blue = low
**Summary:** high definition measurement

**Overall Accuracies:**
- In-stream habitats: 76% – 91%
- Depths: 67% – 99%
- Woody debris: 82%
- Algae: 75%
- Wetlands: 100%
- Vegetation: 93% - 100%

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**Summary: Sequence of steps & decisions**

1. **Data acquisition decisions**
   - Location and time
   - Spatial scale
   - Human features: 1 m
   - General land cover: 2 to 10 m
   - Streams: 1 m
   - Downed wood: 1 m
   - Spectral properties:
     - Optical for cover estimates and stream depths
     - Radar for biophysical measurements & moisture detection (not assessed in this study)

2. **Data preprocessing**
   - Atmospheric (not done for these studies)
   - Geometric (especially critical if coregistration to be done)
   - Data compression/separation of signal from noise:
     - Spectral extraction (biomass, unique spectral signatures)
     - PCA – for water features and noise statistics (develop covariance stats for features of interest only – mask out other features)
     - MNF – for terrestrial landcover features (develop noise stats over dark homogenous features)

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**Summary: Application of Classification/Mapping Algorithms**

- Terrestrial land cover over broad areas: SAM on MNF transformed data
- Downed wood: MF on MNF transformed data
- Streams:
  - In-stream habitats: Maximum likelihood on PCA data
  - Depths:
    - Multiple regression on PCA if ground data available
    - HAB-1 model on raw spectral bands if no depth data from ground

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**Summary: Map production**

- Assignment of data to classes (e.g. SAM rule images)
- Data overlays to generate comprehensive maps

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**Summary**

There is great potential for HSRH mapping of riparian environments.

But further work is needed:
- Rationale for choosing specific data compression and classification algorithms for different applications
- Evaluation of physical factors driving the signals
- Alternative modes of assessing accuracy
- Search for spectrally driven descriptors of streams
- High precision coregistration for change detection
- Incorporation of approaches into automated software sequences
- Ethics of remote measurement