Using Remote Sensing Images to Design Optimal Field Sampling Schemes

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1. Introduction

2. Optimized sampling schemes case studies
   - Optimized field sampling representing the overall distribution of a particular mineral
   - Deriving optimal exploration target zones
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IMPORTANCE OF OPTIMAL SAMPLING SCHEMES

- Sample - small subset of the population of interest.
- Sample should represent the characteristics of the population (parameters / distribution).
- Environmental studies:
  - where to sample?
  - what to sample?
  - and how many samples to obtain?
- Remote sensing as ancillary information in the design of optimal sampling schemes.
- Advantages of using remote sensing images:
  - Provides a synoptic overview of a large area
  - Wealth of information over the entire area
  - In these methods sampling avoids subjective judgement
  - Reduces costs and saves time on the field (fewer samples)
OVERVIEW OF HYPERSPECTRAL REMOTE SENSING

Hyperspectral sensors
- record the reflectance in many narrow contiguous bands
- various parts of the electromagnetic spectrum (visible - near infrared - short wave infrared)
- at each part of the electromagnetic spectrum results in an image

Figure: Spectral Range
OVERVIEW OF HYPERSPECTRAL REMOTE SENSING (cont...)

Figure: Hyperspectral cube

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OVERVIEW OF HYPERSPECTRAL REMOTE SENSING (cont. . . )

Figure: Pixels in hyperspectral image
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Figure: Example of 3 different spectral signatures
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OBJECTIVE OF STUDY

Using a hyperspectral image, to guide field sampling collection to those pixels with the highest likelihood for occurrence of a particular mineral, for example alunite, while representing the overall distribution of alunite.

Usefulness: To create a mineral alteration map
Figure: A generalized geological map of the Rodalquilar study area showing the flight line and the hyperspectral data.
DATA USED

- HyMap: 126 bands – 0.4–2.5 μm
- Geology: 30 bands – 1.95–2.48 μm
- Distinctive absorption features at wavelengths near 2.2 μm
- We collected field spectra during the over-flight using the Analytical Spectral Device (ASD) fieldspec-pro spectrometer – 0.35–2.50 μm
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Figure: Plot of 7 endmembers from USGS spectral library for the 30 selected bands, enhanced by continuum removal.
Figure: Concept of the convex hull transform; (A) a hull fitted over the original spectrum; (B) the transformed spectrum.
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CONTINUUM REMOVAL (cont...)

Spectral Feature Fitting (SFF) is an absorption-feature-based method for matching image spectra to reference endmembers, similar to methods developed at the U. S. Geological Survey (Clark et al., 1990, 1991, 1992; Clark and Swayze, 1995).

Most methods for analyzing hyperspectral data still do not directly identify specific materials. They only indicate how similar a material is to another known material or how unique it is with respect to other materials. However, techniques for direct identification of materials — via extraction of specific spectral features from field and laboratory reflectance spectra — have been in use for many years (Green and Craig, 1985; Kruse et al., 1985; Yamaguchi and Lyon, 1986; Clark et al., 1987). Recently, these techniques have been applied to imaging spectrometer data, primarily for geologic applications (Kruse et al., 1988; Kruse, 1988; Kruse, 1990; Clark et al., 1990, 1991, 1992; Clark and Crowley, 1992; Kruse et al. 1993b, 1993c; Kruse and Lefkoff, 1993, Swayze et al., 1995).

All of these methods require you to reduce data to reflectance and to remove a continuum from the reflectance data prior to analysis. A continuum is a mathematical function used to isolate a particular absorption feature for analysis (Clark and Roush, 1984; Kruse et al, 1985; Green and Craig, 1985). A continuum corresponds to a background signal unrelated to specific absorption features of interest. Spectra are normalized to a common reference using a continuum formed by defining high points of the spectrum (local maxima) and fitting straight line segments between these points. The continuum is removed by dividing it into the original spectrum.

SFF requires you to select reference endmembers from either the image or a spectral library, to remove the continuum from both the reference and unknown spectra, and to scale each reference endmember spectrum to match the unknown spectrum. SFF produces a scale image for each endmember selected for analysis by first subtracting the continuum-removed spectra from one endmember (inverting it), and making the continuum zero. SFF determines a single multiplicative scaling factor that makes the reference spectrum match the unknown spectrum. Assuming that a reasonable spectral range has been selected, a large scaling factor is equivalent to a deep spectral feature, while a small scaling factor indicates a weak spectral feature.
METHODS: Spectral Angle Mapper (SAM) Classifier

- SAM – pixel based supervised classification technique
- Measures the similarity of an image pixel reflectance spectrum to a reference spectrum
- Spectral angle (in radians) between the two spectra

\[ \theta(\mathbf{x}) = \cos^{-1} \left( \frac{f(\lambda) \cdot e(\lambda)}{||f(\lambda)|| \cdot ||e(\lambda)||} \right), \] (1)

- \( f(\lambda) \) – image reflectance spectrum and \( e(\lambda) \) – reference spectrum.
- Results in a gray-scale rule image – values are the angles
METHODS (cont...): Spectral Angle Mapper (SAM) Classifier

Figure: Spectral angle.
METHODS (cont. . . ): SAM Rule Image for Alunite

**Figure**: SAM classification rule image for alunite. Dark areas indicate smaller angles, hence, greater similarity to alunite.
METHODS (cont. . . ): Spectral Feature Fitting (SFF)

- SFF – pixel based supervised classification technique
- Measures the similarity by examining specific absorption features in the spectrum after continuum removal has been applied to both the image and reference spectrum
- Performs a least squares fit on the absorption feature
- Results in a gray-scale rule image – values in the image are the fit
Figure: SFF fit image for alunite. Lighter areas indicate better fit values between pixel reflectance spectra and the alunite reference spectrum.
Combination of SAM and SFF scaled to $[0, 1]$ is defined as

$$ w(\theta(\vec{x}), \tau_F(\vec{x})) = \begin{cases} \kappa_1 w_1(\theta(\vec{x})) + \kappa_2 w_2(\tau_F(\vec{x})), & \text{if } \theta(\vec{x}) \leq \theta^t \text{ and } \tau_F(\vec{x}) \geq \tau^t_F \\ 0, & \text{if otherwise} \end{cases} \quad (2) $$

$$ \phi_{\text{WMSD}}(S^n) = \frac{1}{N} \sum_{\vec{x} \in I} w(\vec{x}) \left\| \vec{x} - W_{S^n}(\vec{x}) \right\|, \quad (3) $$
METHODS (cont...): Fitness Function

Figure: Fitness function with different weights for $N = 15$. 
RESULTS (cont...): OPTIMIZED SAMPLING SCHEME

Figure: Optimized sampling scheme.
RESULTS (cont...): Distribution of 40 highest values

**Figure:** Sampling scheme: 40 highest values
RESULTS (cont. . . ): Distribution of 40 optimized sampling scheme

Figure: Distribution of 40 optimized sampling scheme
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The location of known mineral occurrences (mines/prospects) are used for training in data-driven predictive mapping of prospective ground. Particular methods for obtaining a mineral prospective map are:

- the weights-of-evidence (WofE) method
- logistic regression
- canonical favorability analysis
- neural networks
- evidential belief functions
Mineral prospectivity maps are then usually used to guide further mineral exploration. A logical question regarding efficacy of mineral prospectivity maps is: “Where should targets of exploration for undiscovered mineral occurrences be focussed?”

The objective of this study is to demonstrate a methodology that we have developed in order to provide a plausible answer to the above question in a district-scale case study.
Figure: A generalized geological map of the Rodalquilar area mineral district.
Two sets of locations of mineral deposit occurrences, from different sources, were used in WofE modeling.

Set 1: 14 epithermal deposits and set 2: 36 epithermal deposits.

Set 2: Training set for WofE and designing optimal exploration target zones.

Set 1: Validation of WofE and optimal exploration target zones.

- **HyMap**: 126 bands – 0.4–2.5 \( \mu m \)
- **Geology**: 30 bands – 1.95–2.48 \( \mu m \)
- Distinctive absorption features at wavelengths near 2.2 \( \mu m \)
Figure: Plot of seven endmembers from USGS spectral library in the spectral range 1.95–2.48 $\mu$m. Vertical lines indicate the band centers used to obtain band ratio images (see text for further information).
DATA USED (cont...): CREATION OF BAND RATIO AS EVIDENCES

Figure: Band Ratio 1: arctan transformation on bands 103/107 (2.100/2.171 \(\mu m\)).
Figure: Band Ratio 2: arctan transformation on bands 107/109 (2.171/2.205 µm).
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Data Used (cont. . . ): Creation of Band Ratio as Evidences

Figure: Band Ratio 3: arctan transformation on bands 118/112 (2.357/2.258 µm).
Figure: Distance to fault and fracture. Increasing pixel brightness in this image indicates increasing distance from a fault or fracture.
METHODS

Figure: Flow diagram describing the process.
METHODS (cont...): ESTIMATION OF THE NUMBER OF EXPLORATION FOCAL POINTS

To estimate the number of exploration focal points, we used the binomial distribution – mineral deposit occurrence is a binary variable, being either present or absent. Thus, estimation of $n$ exploration focal points so as to yield (or discover) at least $r$ mineral deposit occurrences, with a probability of success $p$, at a 95% confidence, requires a solution for the following equation:

$$\sum_{i=r}^{n} \binom{n}{i} p^i (1 - p)^{n-i} = 0.95.$$  \hspace{1cm} (4)
METHODS (cont. . . ): FITNESS FUNCTION

\[ \phi_{WMSD+V}(S^n) = \frac{\lambda}{N(A)} \sum_{\vec{x} \in A} P(\vec{x}) \| \vec{x} - Q_{S^n}(\vec{x}) \| \\
+ (1 - \lambda)s^2(O_{S^n}) , \] (5)

where \( Q_{S^n}(\vec{x}) \) is the location vector of an optimal exploration focal point in \( S^n \) nearest to \( \vec{x} \), and \( s^2(O_{S^n}) \) is the variance of the posterior odds.
RESULTS: ESTIMATION OF THE NUMBER OF EXPLORATION FOCAL POINTS

Assume

- $r = 9$ based on the nine predicted out of 14 undiscovered epithermal occurrences in training set 1
- $p = 0.0025$ based on the average posterior probabilities of prospective pixels in the input WofE prospectivity model

With these assumptions we derive $n = 6280$.

Instead of $p = 0.0025$, we used $p = 0.6$ based on the approximate prediction rate of the input WofE model. Accordingly, $n = 22$
RESULTS (cont...): OPTIMIZED TARGET ZONES

Figure: Optimal exploration target zones defined by buffering to 238 m each of the optimal exploration focal points.
RESULTS (cont. . .): OPTIMIZED TARGET ZONES

- Total area represented by the 6280 unit cells is approximately $6280 \times 25^2 = 3925000 \text{ m}^2$.
- Delineated sub-area of $\frac{3925000}{22} = 178409 \text{ m}^2$
- If assumed undiscovered deposit is within a radius of $\sqrt{\frac{178409}{\pi}} = 238 \text{ m}$ (area of circle $= \pi \times \text{radius}^2$) around a derived optimal exploration focal point – then close.