Using Remote Sensing Images to Design Optimal Field Sampling Schemes

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Outline

Using Remote Sensing Images to Design Optimal Field Sampling Schemes

Debba

Introduction to hyperspectral remote sensing

Objective

Study Area

Data used

Methodology

Results

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

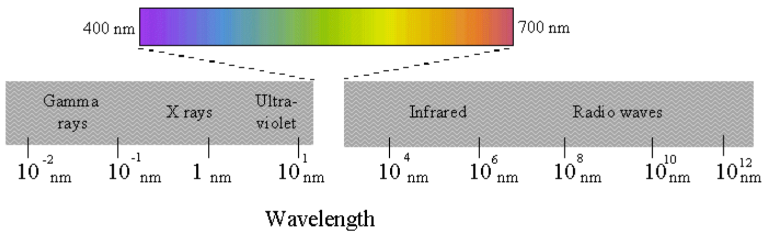

Figure: Spectral Range

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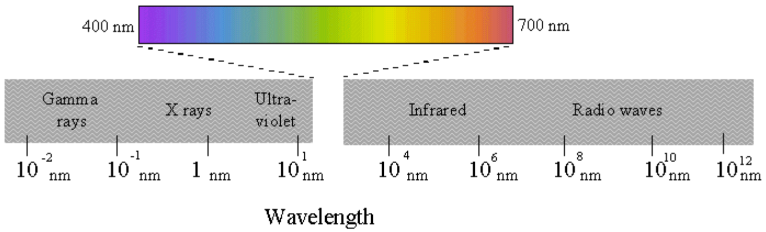

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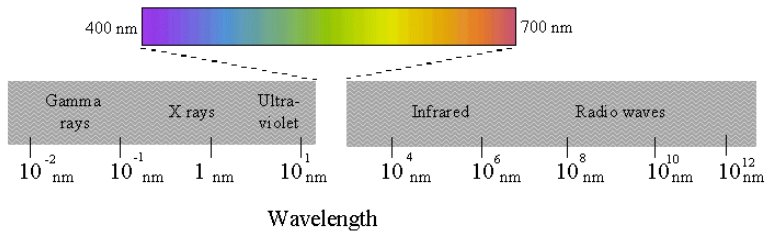

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OVERVIEW OF HYPERSPECTRAL REMOTE SENSING (cont...)

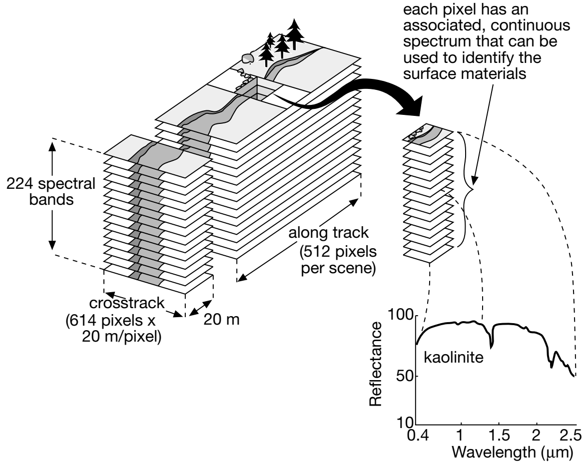

Figure: Hyperspectral cube

OVERVIEW OF HYPERSPECTRAL REMOTE SENSING (cont. . .)

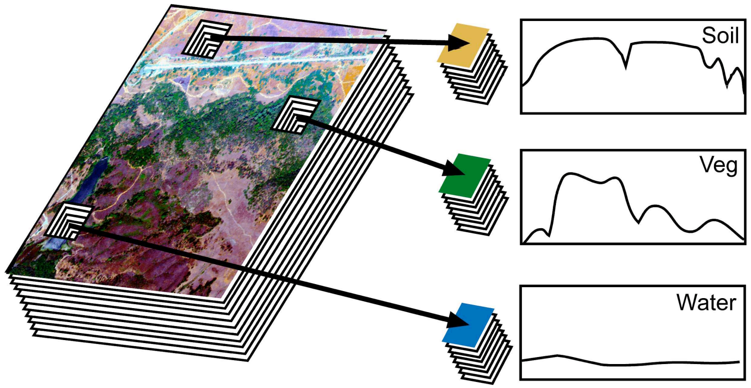

Figure: Pixels in hyperspectral image

OVERVIEW OF HYPERSPECTRAL REMOTE SENSING (cont. . .)

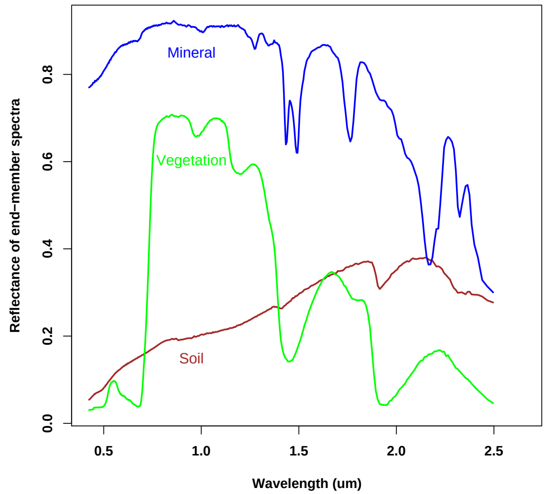

Figure: Example of 3 different spectral signatures

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

STUDY SITE

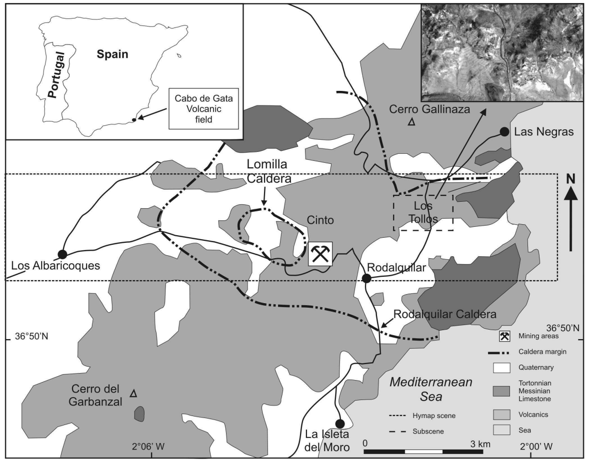

Figure: A generalized geological map of the Rodalquilar study area showing the flight line and the hyperspectral data

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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ENDMEMBER SPECTRA

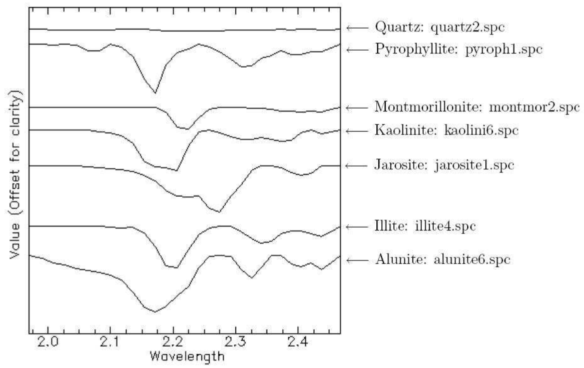


Figure: Plot of 7 endmembers from USGS spectral library for the 30 selected bands, enhanced by continuum removal.

CONTINUUM REMOVAL

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.

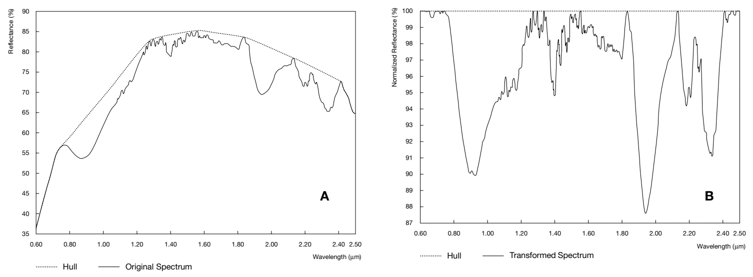
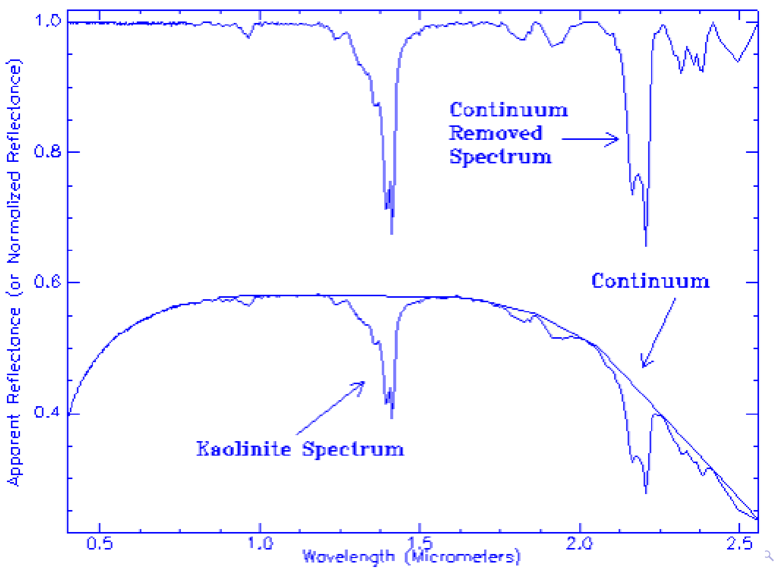


Figure: Concept of the convex hull transform; (A) a hull fitted over the original spectrum; (B) the transformed spectrum.

CONTINUUM REMOVAL (cont. . .)



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

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

  $f(\lambda)$ – image reflectance spectrum and $e(\lambda)$ – reference spectrum.
- Results in a gray-scale rule image – values are the angles

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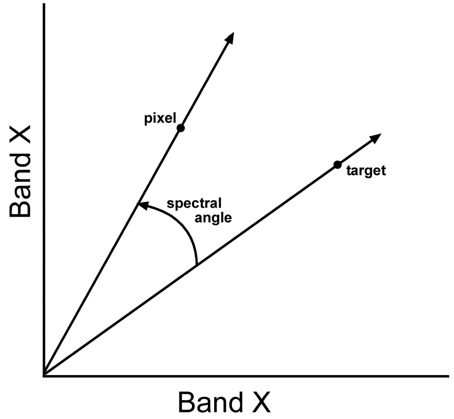

Figure: Spectral angle.

METHODS (cont. . .): SAM Rule Image for Alunite

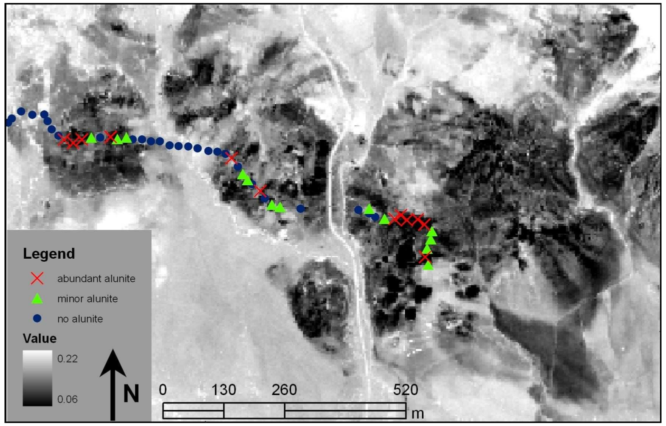

Figure: SAM classification rule image for alunite. Dark areas indicate smaller angles, hence, greater similarity to alunite.

METHODS (cont. . .): Spectral Feature Fitting (SFF)

- SFF – pixel based classification technique.
- Remove the continuum from both the reference and unknown spectra.
- SFF produces a scale image for each endmember selected for analysis by first subtracting the continuum-removed spectra from one (inverting it), and making the continuum zero.
- SFF determines a single multiplicative scaling factor that makes the reference spectrum match the unknown spectrum.

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METHODS (cont. . .): Spectral Feature Fitting (SFF)

- SFF then calculates a least-squares-fit, band-by-band, between each reference endmember and the unknown spectrum.
- The total root-mean-square (RMS) error is used to form an RMS error image for each endmember.
- Scale/RMS provides a fit image that is a measure of how well the unknown spectrum matches the reference spectrum on a pixel-by-pixel basis.

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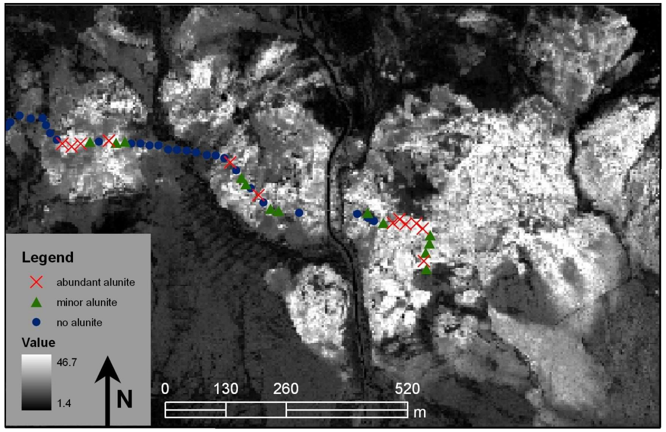


Figure: SFF fit image for alunite. Lighter areas indicate better fit values between pixel reflectance spectra and the alunite reference spectrum.

SAM values scaled to $[0, 1]$

$$w_1(\theta(\overrightarrow{\mathbf{x}})) = \begin{cases} 0\,, & \text{if} \quad \theta(\overrightarrow{\mathbf{x}}) > \theta^t \\ \dfrac{\theta^t - \theta(\overrightarrow{\mathbf{x}})}{\theta^t - \theta_{\min}}\,, & \text{if} \quad \theta(\overrightarrow{\mathbf{x}}) \leq \theta^t \end{cases} \tag{2}$$

SFF values scaled to $[0, 1]$

$$w_2(\tau_F(\overrightarrow{\mathbf{x}})) = \begin{cases} 0\,, & \text{if} \quad \tau_F(\overrightarrow{\mathbf{x}}) < \tau_F^t \\ \dfrac{\tau_F(\overrightarrow{\mathbf{x}}) - \tau_F^t}{\tau_{F,\max} - \tau_F^t}\,, & \text{if} \quad \tau_F(\overrightarrow{\mathbf{x}}) \geq \tau_F^t \end{cases} \tag{3}$$

METHODS (cont...): Fitness Function

Combination of SAM and SFF scaled to $[0, 1]$ is defined as

$$w(\theta(\overrightarrow{\mathbf{x}}), \tau_F(\overrightarrow{\mathbf{x}})) = \begin{cases} \kappa_1 w_1(\theta(\overrightarrow{\mathbf{x}})) + \kappa_2 w_2(\tau_F(\overrightarrow{\mathbf{x}})), \\ \quad \text{if } \theta(\overrightarrow{\mathbf{x}}) \leq \theta^t \text{ and } \tau_F(\overrightarrow{\mathbf{x}}) \geq \tau_F^t \\ 0, \quad \text{if otherwise} \end{cases} \quad (4)$$

$$\phi_{\mathrm{WMSD}}(\mathbf{S}^n) = \frac{1}{N} \sum_{\overrightarrow{\mathbf{x}} \in \mathbf{I}} w(\overrightarrow{\mathbf{x}}) \left|\left| \overrightarrow{\mathbf{x}} - W_{\mathbf{S}^n}(\overrightarrow{\mathbf{x}}) \right|\right| , \quad (5)$$

METHODS (cont...): Fitness Function

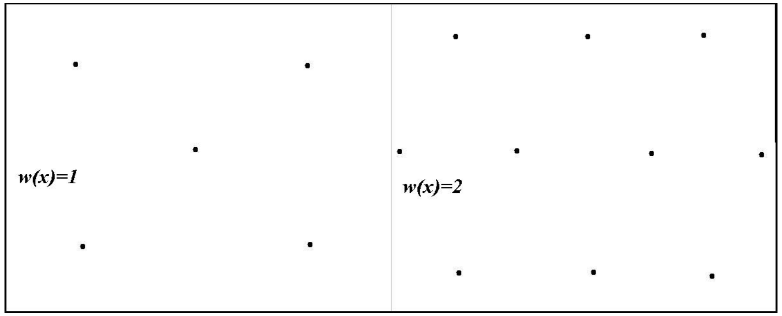


Figure: Fitness function with different weights for $N = 15$.

RESULTS OF THE OPTIMIZED SAMPLING SCHEME

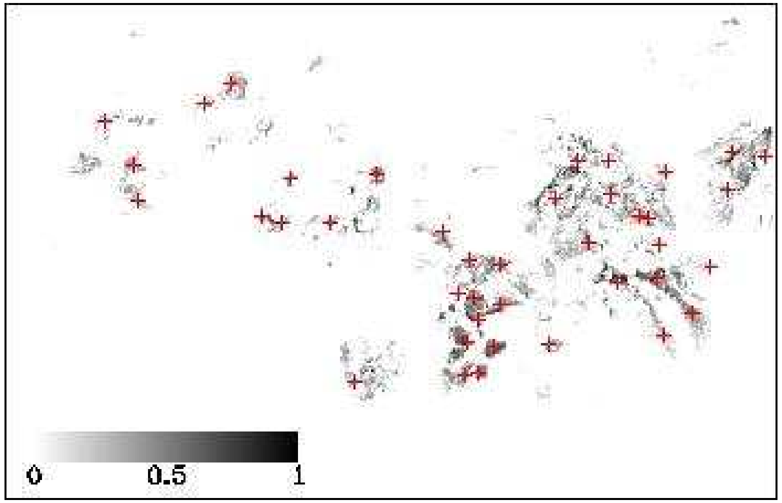


Figure: Optimized sampling scheme.

RESULTS (cont. . .): Distribution of 40 optimized sampling scheme

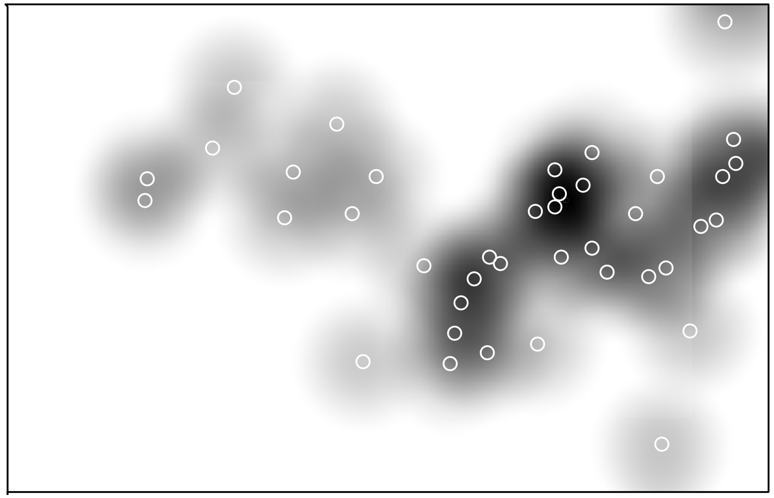


Figure: Distribution of 40 optimized sampling scheme

RESULTS (cont. . .): Distribution of 40 highest values

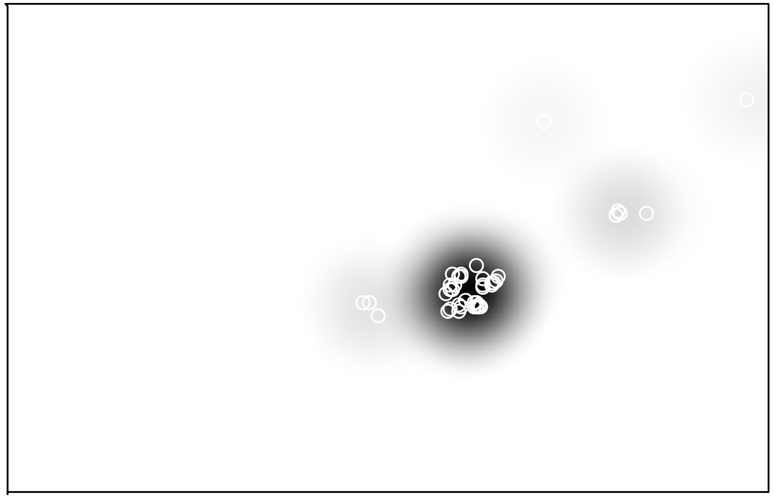
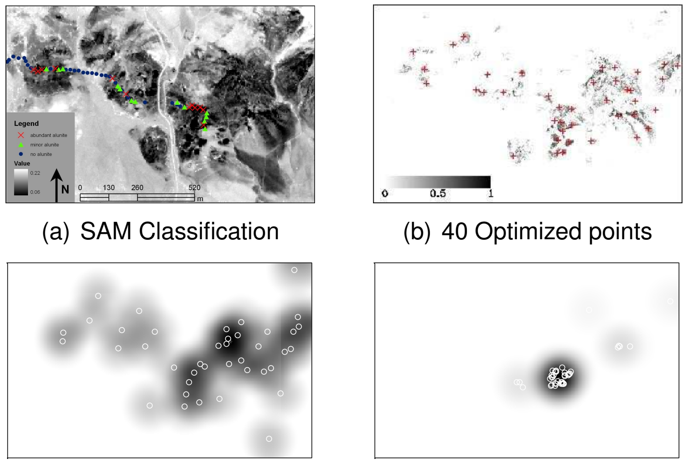


Figure: Sampling scheme: 40 highest values

RESULTS (cont...): SUMMARY COMPARISON



(a) SAM Classification (b) 40 Optimized points

(c) Distribution sampling pts (d) Distribution highest points

Figure: Summary comparison of the optimized sampling scheme.