Atmospheric Profile Variability Impact on the Performance of Hyperspectral Remote Sensing Detection Systems

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Atmospheric profile variability impacts the effectiveness of hyperspectral remote sensing systems to identify geological materials from space. This variability alters the "truth" spectrum (e.g. reflective or emissive) by modifying its spectrum through such atmospheric factors as transmissivity, upwelling radiance, and downwelling radiance. Incomplete characterization of these effects can lead to incorrect target assignments and therefore can impact subsequent quantification estimates.

It is thus necessary to understand the statistical variability of the atmosphere as seen from space and ultimately how it impacts uncertainty in the measured spectra of materials.

The scope of this paper is to:

1. **Estimate atmospheric profile variability over the Hawaiian Islands for a period of one year. This variability is compiled over a daily interval and reported for each month.**
2. **Estimate material spectral variability resulting from atmospheric temporal variance using 6 selected geological igneous rock classes across the VIS/SWIR region.**
3. **Evaluate the effectiveness of the *Spectral Angle Mapper* (SAM) to effectively discriminate between rock classes with limited *a priori* knowledge of atmospheric conditions.**

The ultimate goal of this effort is to assess to what level, if any, supplemental local meteorological data and/or *in situ* atmospheric retrieval methods are required to assure system discrimination/identification performance objectives.

Introduction

An important capability of hyperspectral imaging (HSI) remote sensing is the ability to geologically map mineral distributions across large areas of the Earth's surface. The accuracy of such maps is dependent upon the fidelity of accompanying atmospheric data. Specifically, an important issue facing the hyperspectral remote sensing community is the degree to which atmospheric profiles need to be characterized in order to process and exploit hyperspectral data. Such information is required to spectrally correct for atmospheric modification of ground materials. The required fidelity of such characterization is mission dependent and is a function of the level of quantitative demand placed upon the exploitation of such data. This functional dependence sets important requirements on the suite of sensors onboard the collection platform as well as on the complexity of processing algorithms. These requirements ultimately drive system configurations, concepts of operation, and cost.

One important factor that enters into atmospheric characterization is the amount of seasonal profile variability. By tracking slowly changing seasonal trends it may be possible to use monthly profile rather than *in situ* real-time measurements to successfully fulfill certain types of mission objectives (such as material classification from space).

The objective of this paper is to address the impact of atmospheric variability on spectral signature formation as seen from space and its subsequent impact on material classification. Results of this study suggest that class discrimination is possible provided that monthly-averaged atmospheric profile data is available. Yet many assumptions and approximations are implicit in this conclusion which are discussed in this paper. It is also premature to extend such a conclusion to mission objectives requiring quantitative material demixing.

The analysis consists of four steps: the acquisition of daily weather profile information, the mapping of the profile data into atmospheric transmissivity information, the estimation of the spectral signatures of target classes from space, and the quantification of class separability using mean monthly spectral characterization. Results are presented in terms of spectral correlation and plotted on a monthly interval.

This paper consists of two main sections. In Section I, the methodology used in this assessment study is presented. It details the capturing of daily weather data along with its integration into MODTRAN. It also discusses the estimation of spectral signatures using the MODTRAN results and subsequent spectral correlation and classification methods.

Section II, presents basic theoretical models used in the spectral signature estimation and the resulting simulation results. Class spectral variability is shown on a monthly basis and quantified in terms of auto- and cross-class correlation. In addition, approximations used in this analysis are reviewed and critiqued with interpretations of the simulated results.

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Methodology

The methodology consist of four steps: the retrieval of atmospheric data, the processing of this data with MODTRAN, the estimation of spectral signatures of target class materials, and the statistical assessment of spectral variability.

During the first step of processing, a one-year block of atmospheric profile data was obtained from the NOAA's Forecast Systems Laboratory (FSL) radiosonde database[1]. This block consisted of atmospheric profiles of the pressure, temperature, and dew point for various vertical heights measured at 0 and 12 hours Zulu at the Hilo, Hawaii station. Those profiles with recorded values for heights above 20 km were downloaded to a local computer, and the pressure, temperature, and dew point values were interpolated to constant height intervals. A total of 659 profiles were used for dates spanning 1 Jan 2000 to 1 Jan 2001.

The radiosonde data consist of thousands of altitude dependent points that were interpolated into 61 layers using the SNDTP5 program. These interpolated layers were evenly distributed between ground level and 25 km and consist of temperature, pressure, and partial pressure water data. These interpolated profiles were input into MODTRAN 4.0 where the upwelling radiance and transmission profiles were generated for each day. MODTRAN was run in a downward looking mode (sensor at 25 km and the target at ground level), with the target albedo set to zero (compensation for the zero albedo will be addressed in the analysis). A maritime extinction (visibility = 23 km) aerosol model was used with the sun located at 30 degrees from the zenith and 30 degrees azimuthally east of north. The spectral signature was obtained at a spectral resolution of 10 cm^{-1} across a spectral range of 3000 to 35000 cm^{-1}.

To compute the spectral signature of the target at the collection platform, one needs to consider contributions arising from at least four terms: the unscattered surface reflected radiation, the down-scattered surface-reflected skylight, the reflected background radiance, and the path-scattered radiance. In this study, it is assumed that the entire 2π steradian of the sky is seen so that reflected background radiance can be ignored. Adjacency effects due to seasonal variations in scene contrast are also neglected. Contributions from the path scattered radiance are usually small but has been estimated using MODTRAN and is included in this analysis. The down-scattered surface-reflected skylight has been set to zero in this analysis and will be a subject of future investigation.

Estimates for spectral radiance are next computed using surface reflectance, atmospheric transmission and path scattered radiance terms. Rock spectra supplied from the JPL ASTER Spectral library[2] were used as input to the reflectivity model.

Six igneous (volcanic) rock classes common in Hawaii were selected in this analysis. These class assignments were based on the amount of SiO_2 content found within the rock, spanning from Basalt (SiO_2 poor) to Rhyolite (SiO_2 rich) as well as by their alkali (Na_2O and K_2O) content (see Table 1). Sample spectra used in the assessment consisted of aphanitic specimens where crystal sizes were on the order of 75 micrometers or less. Figure 1 shows the percent reflectivity for each rock class.

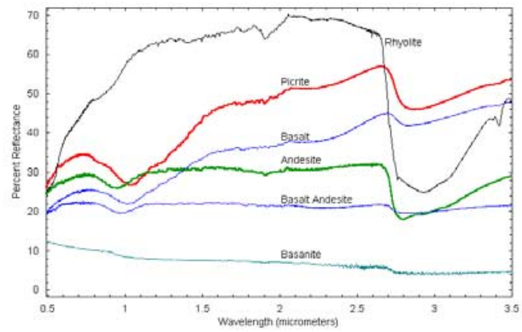

Figure 1. Reflectivity curves for the six classes of rocks investigated in this study.

Using both estimates of atmospheric transmission and upwelling radiance from MODTRAN and spectral reflectivity information supplied from the USGS database, the spectral signatures of each rock class were computed. These signatures were averaged on a monthly basis and used later as referenced *a priori* target signatures.

The daily and monthly average spectra were further processed to assess within-class and out-of-class spectral variability during each of the 12 months of the year. The variability was quantified by computing the angle between the mean monthly spectral signature vector to that of daily spectral vector estimates. Within-class variability measured the daily spectral angle variations of a given rock class to that of a referenced monthly averaged spectrum. Out-of-class variation again computed the angle between a reference spectrum and a given class of daily spectra. The reference class and the daily classes were however different and helped to later assess class-to-class discrimination.

Analysis

An extensive number of simulations were performed to assess the daily spectral variability of rock classes as seen from space. Simulation conditions for collection geometry, sensor conditions, and atmospheric conditions are summarized in Table I.

Table I. Simulation Conditions

Sensor Type:	Grating
Sensor Resolution:	14.25 nm
Spectral Bands:	200
Spectral Range:	0.45 – 3.3 micrometers
Sun-to-Nadir	30 degrees
Ground-to-sensor angle:	30 degrees from nadir @ 30 degrees north of east
Atmospheric Visibility	23 km
Aerosol scattering model:	Maritime
Atmospheric fill factor:	1.0
Downwelling Sky Radiance:	(Not Modeled)
Rock Classes:	Rhyolite, Picrite, Basalt, Andesite, Basalt Andesite, and Basanite

Using the methodology described in the previous section, spectral signatures of each rock class were generated for each day. An example of one month of spectral variation is shown in Figure 2. The figure shows the mean spectral signature for Picrite during the month of June (dark line) along with several overlay spectra corresponding to daily-simulated spectra for that month. The mean spectral signature is saved for each class and for each month, resulting in a total of 72 mean spectral for the year. These mean spectra are referred to as reference vectors during the remainder of this paper.

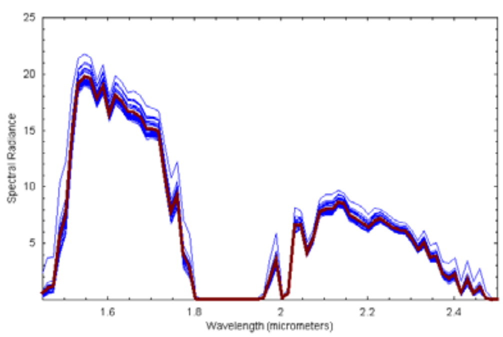

Figure 2. Estimate of the spectral radiance signature of Picrite using radiosonde data collected at Hilo, Hawaii for the month of June 2000.

Each reference vector is dotted with the corresponding daily spectrally estimated measurement to estimate monthly signature variability (e.g. the Spectral Angle Mapper – SAM algorithm)[3]. Results from this operation are shown for the Picrite reference class in Figure 3. As expected, in-class variability (the dark curve) shows smaller spectral angles than does the out-of-class members.

Further inspection of Figure 3 show that Picrite correlates best with Basalt with some potential confusion during month 11. Inspection of Figure 2 shows why this correlation is high for this class pair. Basalt and Picrite are adjacent curves showing much spectral similarities. However, with only marginal information of the atmosphere, class separation can be easily performed. Similar results have been observed for the remaining reference vectors. These results suggest that only marginal information of the atmosphere is required to separate rock classes from each other.

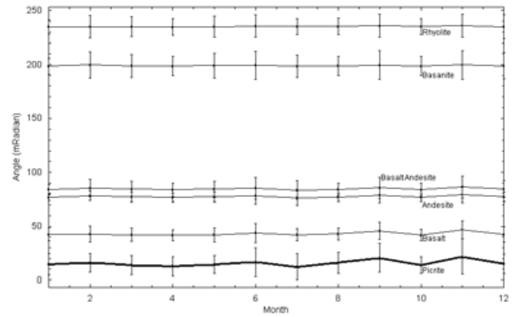

Figure 3. Results from the SAM algorithms showing the spectral angle between the reference spectrum, Picrite and each of the six classes of rock types as a function of the month index.

This analysis does not, however, account for several factors that may impact the conclusion of this study. First, the sky downwelling radiance, which is influenced by cloud location, sky fill, and cloud type is not included in this analysis. It is also depend upon the aerosol distribution within the atmosphere. Second, the study also does not include natural variations associated with geometric orientation of the reflection plane relative to the sensor line-of-sight. Third, the present model assumes that the ground normal-to-sensor line of sight is constant. Fourth, this study assumes that within any given pixel element, the spectral signature is only comprised of that single class material. Lastly, this study does not account for potential seasonal variability of the background scene which, would lead to variability of adjacency spectral signatures.

Conclusions

The variability of atmospheric profile data across a monthly interval is sufficiently small to allow for an effective means of identifying material classes from air- or space-borne vehicles. Simulations suggest that such class differentiation is possible provided the targets fill the entire pixel and atmospheric downwelling variance is small. Potential use of traveling average weather profile data may be sufficient for the exploitation of HSI data.

Several factors remain to be investigated before monthly averaged data is used. Specifically, studies are required to assess the impact of atmospheric downwelling radiance variability, adjacency, and pixel fill on class discrimination and identification.

References

[1] http://www.fsl.noaa.gov
[2] http://speclib.jpl.nasa.gov
[3] Center for the Study of Earth from Space (CSES), *SIPS User's Guide, The Spectral Image Processing System*, *Version 1.1*, University of Colorado, Boulder, p. 74, 1992