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Spectral analysis of coastal vegetation and land cover using AISA+ hyperspectral data

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This paper describes a spectral analysis of several coastal land cover types in South Padre Island, Texas using AISA+ hyperspectral remote sensing data. AISA+ hyperspectral data (1.5 metre) were acquired throughout the area on 9 March 2005. Data over mangrove areas were converted to percent reflectance using four 8 × 8 metre reflectance tarps (4%, 16%, 32% and 48%) and empirical line calibration. These data were then compared to percent reflectance values of other terrestrial features to determine the ability of AISA+ data to distinguish features in coastal environments. Results suggest that these data may be appropriate to discriminate coastal mangrove vegetation and provide researchers with high resolution spatial and spectral information to more effectively manage coastal ecosystems.

Keywords: Hyperspectral data; AISA+; Black mangrove; Empirical line calibration

1. Introduction

As anthropogenic and natural environmental changes continue to alter the Earth's surface, the ability to map and monitor these changes using remote sensing data must improve. Traditionally, multispectral satellite remote sensors such as Landsat Thematic Mapper (TM), Multispectral Scanner (MSS), and Advanced Spaceborne Thermal Emission Radiometer (ASTER) have been used to map and monitor changes in the biosphere (Jensen *et al.* 2004, Hardin and Jensen 2005). However, while these sensors have proven robust for many applications, they often lack the spatial and spectral resolution necessary to differentiate characteristics of the Earth's surface—especially when the spectral changes are very small or in a very narrow area of the electromagnetic spectrum. For example, Landsat TM measures only seven discrete portions of the electromagnetic spectrum, SPOT (Satellite Probatoire d'Observation de la Terre) only measures in four discrete portions of the spectrum,

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and ASTER measures 14 portions of the electromagnetic spectrum (at differing spatial scales). In addition, these sensors measure reflected and emitted energy in relatively wide bandwidths (e.g. 80–100 nm) that may reduce or dampen spectral responses in discrete portions of reflected energy. Due to this low spectral resolution, new hyperspectral imaging systems have been developed that acquire images throughout the visible and near-infrared portions of the spectrum from airborne platforms with wavebands as small as a few nanometres. These relatively narrow spectral bands facilitate better discrimination between vegetation types, crops, and other earthly features (Gong *et al.* 1992). These sensors record spectral signatures with sufficient sampling to allow identification of ground targets and quantitative analysis of subtle spectral changes.

The narrow bandwidths of a hyperspectral sensor are sensitive to subtle variations in reflectance. These same reflectance characteristics are lost within the relatively coarse bandwidths in conventional multispectral scanners (e.g. MSS, Landsat TM). Thus, conventional multispectral sensors may under-sample the information content available by making only a few samples in spectral bands up to several hundred nanometres wide (Jensen 2000). For example, through laboratory and field studies, numerous narrow spectral band features have been shown to be related to changes in some vegetation biophysical variables (Treitz and Howarth 1999) such as chlorophyll amount and type (Yoder and Pettigrew-Crosby 1995) and canopy chemical characteristics and their relation to carbon cycling (Gao and Goetz 1995).

The large number of very narrow bands enables airborne hyperspectral remote sensing data collection to replace data collection that was previously limited to field site surveys or laboratory testing. Analysis of hyperspectral data allows extraction of detailed spectrum for each picture element in the image. Such spectra allow direct identification of specific materials based upon their spectral characteristics, including minerals, atmospheric gases, vegetation, dissolved material in water bodies, agricultural crop yield, and soil characteristics (Jensen 2000).

1.1 *Mangroves and coastal areas*

Mangroves are woody plants that are found in estuaries and intertidal zones in tropical and subtropical climates forming a unique coastal ecosystem that both terrestrial and aquatic species depend on for their survival (Lefebvre and Poulin 1997). The mangrove ecosystem can be so compact and diverse that in a small spatial scale (≤ 1 ha) one can observe the entire range of salinity (i.e. habitats) in which higher plants are found (Field *et al.* 1998). Unfortunately the mangrove ecosystem is disappearing rapidly (almost 50% of the original geographic range) due to invasive species and urban development (Field *et al.* 1998). There are many benefits to mangrove forests: their root systems trap debris and detritus brought in by tides; they serve as the breeding grounds for many fish, shellfish, birds and other wildlife; they provide flood and storm protection; sediment control; and honey production (Allen 1998, Ewel *et al.* 1998, Badola and Hussain 2005, Quarto 2005). Negative consequences occur when mangroves become invasive species. For example, in Hawaii they are playing a role in the recovery of native waterbird populations (Allen 1998). This paper describes the acquisition, initial processing, and analysis of hyperspectral data collected in a mangrove area on South Padre Island, Texas.

2. Methods

2.1 Study area

South Padre Island, Texas, USA (26.11° N, 97.15° W) is a popular resort town located in southeast Texas along the Gulf Coast that has been built up in recent years. Due to the rapid growth of the built environment, concern exists over the impact of this growth on the natural environment. South Padre Island is bordered by the Lower Laguna Madre to the west and the Gulf of Mexico to the east. Native plants include coastal mangrove species and dunes vegetation. The focal species in this study is the black mangrove (*Avicennia germinans*).

Black mangroves grow closer inland and are typically only reached by water during high tides. In the northern portion of its range, including the study area, the black mangrove is more of a shrub than a tree and it is not frost-tolerant. The key identifying feature of the black mangrove is the pencil-like breathing tubes, pneumatophores, which grow vertically to above the highest water level.

2.2 AISA+ hyperspectral sensor

AISA+ is one of the most compact airborne hyperspectral instruments in the world. Its small size makes it portable for use in various aircraft because the instrument can be mounted on a plate that is compatible with a standard aerial camera mount, available in virtually any airplane throughout the world (figure 1). Another advantage of AISA+ over other hyperspectral sensors is the flexibility in selecting the sensor's spatial and spectral resolution characteristics. For example, simple ASCII text files that can be written and loaded at any time control the sensor settings, bandwidth selections, and integration time. Multiple configuration files are

Figure 1. AISA+ hyperspectral sensor with attached GPS/INS system. The mount was made with 3/4 inch plywood.

loaded on the controlling computer and used interchangeably throughout the flight depending on the image targets or mission goals.

Reflected light from the target below the aircraft is transmitted through a camera lens and directed to a prism-grating-prism optical system, which splits the light into its component wavelength spectra. The refractive properties of the two opposing prisms allow for a linear projection of light onto the charged coupled device (CCD) array. Real time data that are being collected are displayed on a scrolling window to be certain that the area of interest is being imaged.

AISA+ is capable of collecting data within a spectral range of 400 to 970 nm. Although AISA+ is capable of collecting up to 244 spectral channels within this range, the data rate associated with the short integration times (sampling rates) required of the sensor in most operational/flight modes, limits the number of channels. The full spectral mode, however, is useful for acquiring 244 spectral signatures of specific targets that can be used to generate pure endmembers as well as for band selection purposes. Spatial resolution of AISA+ data depends on many factors including airplane height and sensor scan rate.

To provide accurate location of the hyperspectral data, an Inertial Navigation System (INS) and Global Positioning Systems (GPS) were integrated into the AISA+ sensor. The GPS/INS and AISA+ datastreams were combined in the collection computer to provide frame by frame georeferencing of the imagery. Pitch, roll, and yaw are encoded with the GPS/INS information to provide accurate locations. Using these data and other calibration files, hyperspectral data are radiometrically and geometrically post-processed using a proprietary add-on to the Environment for Visualizing Images (ENVI) software provided by Specim as part of the sensor package called CaliGeo.

Hyperspectral data have been used to discriminate vegetation in a large variety of areas and environments. Held *et al.* (2003) used the Compact Airborne Spectrographic Imager (CASI) to discriminate vegetation in a coastal marine environment. The authors used CASI (14 bands) and radar data to produce detailed habitat maps of an estuary.

2.3 Data

AISA+ hyperspectral data were acquired throughout the South Padre Island, Texas area on 9 March 2005. A flight height of 1067 m (3500 ft) above sea level and a speed of 192 kilometres per hour (120 miles per hour) were maintained throughout the flight. The sensor's adjustable scan rate was set to 36 ms to acquire 1.5 m² pixels (figure 2). The data were radiometrically and geometrically corrected using the CaliGeo add-on in ENVI (figure 3).

2.4 Empirical line calibration

Remotely sensed data must usually be converted to physical units, such as reflectance, for them to be of lasting quantitative value (Smith and Milton 1999). The empirical line calibration method assumes that there are one or more targets with different spectral reflectance ranges that encompass the same wavebands acquired by the sensor. To this end, the corrected hyperspectral data were converted to percent reflectance using four 8 × 8 metre reflectance tarps (4%, 16%, 32%, and 48%; figure 4) and empirical line calibration. Empirical line calibration forces the

Figure 2. Uncorrected AISA+ data acquired over South Padre Island, Texas. Note the straight line distortion caused by movement of the airplane (roll and pitch). The Laguna Madre is at the top of this image with the Gulf of Mexico (and breaking waves) at the bottom of the image.

image data to match *in situ* reflectance data obtained at the same time as the overflight (Jensen 2005). The reflectance of each target is measured on the ground with a field spectroradiometer and then applied to the entire image to generate reflectance values (Smith and Milton 1999). Further, Smith and Milton (1999) concluded that the empirical line method for converting remote sensing data to reflectance is simple and effective, and that errors of only a few percent can be achieved when using four targets.

Figure 3. Corrected AISA+ image acquired over South Padre Island, Texas. Note that the image has been corrected of all heading, roll, and pitch errors and is now in its correct planimetric organization with the Laguna Madre to the west and the Gulf of Mexico (with breaking waves) to the east.

Figure 4. Tarp placement on South Padre Island, Texas. Note the wet sandy area to the north of the tarps and the band of black mangrove beyond the sand. (Photo by P. Mausel.)

Empirical line calibration was implemented using spectrally ‘pure’ pixels acquired over the eight meter tarps and comparing these pixels to the spectroradiometer data acquired at the same time as the image flyover (figure 5) to generate an equation

Figure 5. Four 8×8 meter reflectance tarps (4%, 16%, 32%, and 48% reflectance) located adjacent to mangrove area at South Padre Island, Texas. Tarp pixels were used to calculate reflectance for the rest of the image. The bright pixels above the 16% reflectance tarp represent a truck used by the field team.

which predicts percent reflectance from radiance; a separate equation was calculated for each band (Smith and Milton 1999). These equations were then applied to the entire image. The image spectrometry of a healthy black mangrove patch adjacent to the Laguna Madre (figure 6) was then compared to that of other healthy vegetation to determine differences.

After empirical line calibration was performed on the image, four different land cover types were examined to determine any spectral differences between them. The four land cover types were: black mangroves, healthy grass, wet tidal sands, and asphalt road. These four land cover types were chosen because they are very common on South Padre Island.

3. Results and discussion

As expected, healthy black mangroves exhibited high reflectance in the near infrared with less reflectance in the visible portion of the electromagnetic spectrum (EMS; figure 7). This contrasted with the spectral reflectance properties of healthy grass (figure 8) which exhibited greater reflectance in the near infrared and visible portions of the EMS. The grass spectral profile is smoother than the mangrove spectral profile. This may be indicative of the more homogeneous environment in which grass grows. Conversely, the mangrove spectral curve contains many small spectral differences. This is probably representative of the diverse environment (sand, water, etc.) in which mangroves grow, and underscores the difficulty of using wide-band multispectral remote sensing data that are unable to map and model these small changes. These reflectance differences are probably sufficient for accurate image classification.

Both wet sand and the asphalt road had very compressed spectral response curves (figures 9 and 10). This is expected as wet sand has a much lower albedo

Figure 6. Stand of black mangrove with tidal lagoon in the background. Black mangroves ringed the tidal lagoon. (Photo by P. Mausel.)

Figure 7. Spectral reflectance curve of healthy mangroves. Note the small peak in green wavelengths and the much larger peak in near-infrared energy.

than dry sand (figure 11), and each of these terrestrial features could be statistically differentiated in any common supervised or unsupervised classification (figure 12).

Figure 8. Spectral reflectance curve of healthy grass. Note the greater reflectance in all areas of the spectrum—especially in the near-infrared – as compared to figure 7.

Figure 9. Spectral reflectance curve of wet sand. Note the mangroves and tidal lagoon in the upper left part of this image.

4. Conclusions

Narrow spectral bands that enable researchers to distinguish very small reflectance variations probably ensure that hyperspectral data will continue to be integrated into mainstream remote sensing. This is especially the case in sensitive environments where small spectral variations may be indicative of larger ecological processes.

This study has demonstrated that AISA+ hyperspectral data may be of use to discriminate between various types of vegetation found in coastal areas. Future research could focus on more specific hyperspectral bands to delimit coastal mangrove areas and the use of vegetation indices in this process. Also, mangrove biophysical parameters and their relationship to mangrove spectral characteristics could be investigated.

Figure 10. Spectral reflectance curve of asphalt road. Note the vehicles driving on the road.

Figure 11. Spectral reflectance of dry sand. Note the darker, wetter sand to the right of the point on the image.

One of the benefits of converting hyperspectral data into reflectance using calibration tarps, spectroradiometric measurements, and empirical line calibration is that researchers can use the corrected data in lieu of more costly large-area field surveys to generate spectroscopy. This would allow researchers to examine an area synoptically without concern for changing sun angles or other illumination conditions, and researchers could make simple spectral reflectance comparisons between different terrestrial features. These data can also be used as an example for students studying remote sensing, biogeography, and biology to better understand the relationship between an object and its spectral reflectance.

Future research could focus on determining which of the bands used in this project are the most effective for differentiating between the different land cover types. In addition, a future study could determine the optimum spatial resolution for mangrove and other coastal vegetation discrimination.

Figure 12. Spectral response curves of the five land cover types examined in this study.

Note: The AISA+ data used in this project can be downloaded from <http://wabashview.indstate.edu/>

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