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Habitat mapping in the Farasan Islands (Saudi Arabia) using CASI and QuickBird imagery

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Abstract. Map products derived from remote sensing technology increase our understanding and ability to manage tropical marine environments. The enhanced mapping capabilities of hyperspectral sensors are well understood; yet technology uptake, particularly for large scale tasks, has been slow. The study presented represents one of the largest hyperspectral projects to date, and paves the way towards increased use of this technology. Hyperspectral CASI-550 imagery and multispectral QuickBird imagery, was acquired over 3,168 km^2 of the Farasan Islands. In addition to the typical image processing steps, inopportune water condensation in the CASI sensors lens necessitated further processing to remove an across-track artifact. We present a simple protocol for correcting this abnormality, utilizing an abundance of optically deep water to model and correct the error. Investment in optical, bathymetric, and other supporting field data, along with the acquisition of the QuickBird imagery was vital. Data pre-processing facilitated thematic mapping with accuracy comparable to other studies, while allowing the use of spectral unmixing to discriminate coral from within algae dominated patches in shallow water (0-5 m) environments. The unmixing model proved robust, was readily adaptable to the CASI sensor and provides additional habitat information beyond the level of thematic mapping alone.

Keywords: CASI, QuickBird, remote sensing, coral reef, spectral unmixing

Introduction

The use of optical remote sensing technology to characterize reefscapes has increased in recent years. Drawing on a global dataset of reflectance spectra, Hochberg et al. (2003) showed that most reef components can be spectrally grouped into 12 fundamental categories; brown, green and red fleshy algae; calcareous and turf algae; brown, blue and bleached coral; gorgonian/softcoral; seagrass; terrigenous mud; and sand. As such, spectral discrimination is sufficient to classify basic reef components such as coral, algae, and sand, but insufficient at the species level. The vast majority of work to date has concentrated on multispectral, predominantly satellite based sensors (e.g. Landsat TM, IKONOS, QuickBird), which offer reliable data relatively cheaply. However, multispectral sensors collect data within only a few discrete bands and this spectral paucity may preclude discrimination of some habitat components. Hyperspectral sensors (e.g. AVIRIS, AISA, CASI, PHILLS), by contrast, provide higher levels of spectral detail. This may enable classification of image pixels into a greater number of descriptive classes, or facilitate deriving the relative fractional contribution of different spectral-endmembers (Goodman and Ustin 2007).

This study utilizes both Compact Airborne Spectrographic Imager (CASI)-550 hyperspectral imagery and QuickBird multispectral imagery. Using standard image processing techniques, a single integrated map product is achieved by merging classification output from the two different sensors. However, an unfortunate across-track spectral abnormality, later diagnosed as a lens condensation issue, was identified on receipt of the CASI-550 imagery. Across-track errors are typically caused by vignetting, instrument scanning, or non-uniform illumination effects, and can usually be corrected using standard processing algorithms. The across-track irregularity in this data proved more complex and necessitated a customized correction approach.

Studies to date mostly favor the descriptive class approach, where each pixel is assigned to a single thematic class, and forgo sub-pixel unmixing techniques. We examine both approaches in meeting two objectives: 1) the production of large-scale thematic habitat maps describing functionally important carbonate and sediment systems; and 2) an assessment of how spectral unmixing techniques might be applied to a CASI dataset to complement thematic information. To meet the latter objective, Goodman and Ustin's (2007) unmixing model

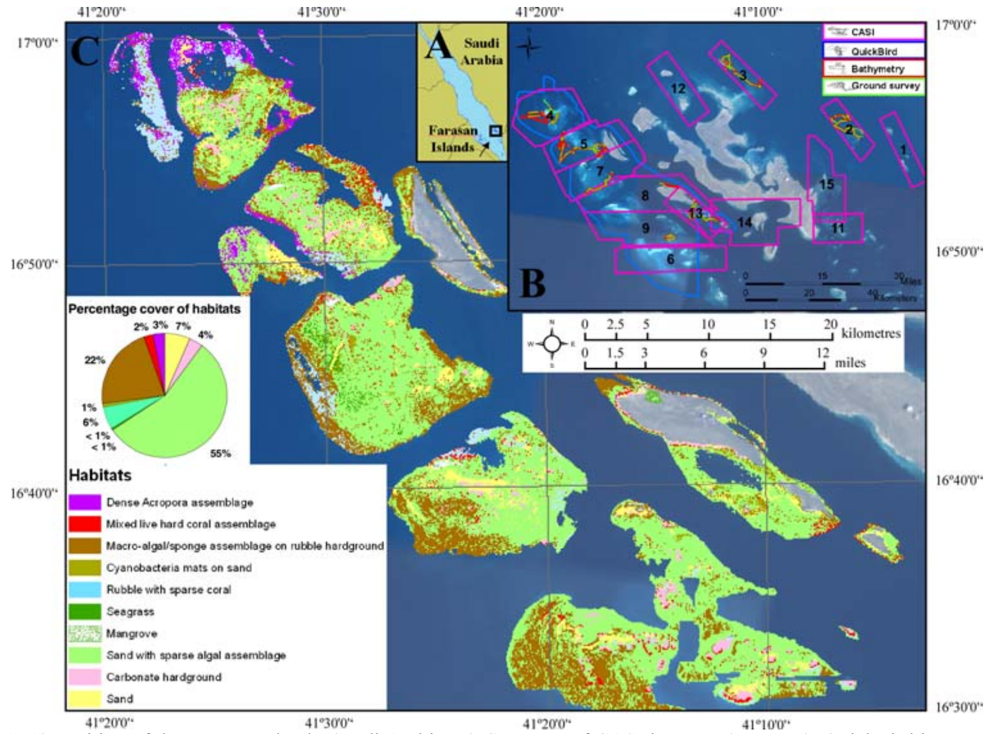

Figure 1: A) Position of the Farasan Islands, Saudi Arabia; B) Coverage of CASI imagery (magenta), QuickBird imagery (blue), bathymetric tracks (red) and ground survey points (orange); and C) Habitat map for the Western Farasan Islands produced using CASI hyperspectral and QuickBird multispectral imagery, along with percentage breakdown by habitat. Map accuracy: P_0= 82% (95% confidence intervals of P_0 are 77% and 86%), T= 79% (95% confidence intervals of T are 75% and 85%).

was employed. The approach combines a semi-analytical inversion model with linear spectral unmixing to extract sub-pixel information on sand, coral and algal composition, while simultaneously deriving information on water properties and bathymetry.

Materials and Methods

Image acquisition: In May 2006 3,168 km^2 of CASI image data were collected in the Farasan Islands, Saudi Arabia (Fig. 1A and 1B). The data presented here comprises the western bank region (Areas 4-9); approximately two thirds of the total area acquired. Data were collected at 1.5 m pixel resolution, with 19 bands assigned between 400 and 660 nm and 2 bands within the near-infrared (NIR) region, representing a non-contiguous 21 band hyperspectral dataset. Band width (FWHM) ranged from 3-7.6 nm. The instrument was mounted on a Cessna aircraft, fitted with differential Global Positioning System (dGPS), integrated to a gyroscope measuring aircraft position and movement. CASI imagery was corrected to scaled radiance prior to delivery. Augmenting this, 1,637 km^2 of high resolution QuickBird satellite data (eight scenes dating March 2004 through October 2006) were also acquired (Fig. 1B). QuickBird imagery has high spatial resolution (2.4 m pixel) comparable to CASI, but with fewer bands 4 vs. 21 and greater band width (60-140 nm).

Field survey: Field bathymetric, benthic and spectral data collection efforts were combined for maximum efficiency (Fig. 1B). Using Landsat imagery as a guide, ground tracks bisecting areas of high spectral heterogeneity, depth and exposure regimes were selected. This maximized the representativeness and diversity of habitat sampling. Single-beam acoustic sonar linked to dGPS was run continuously during the survey process, producing ~160,000 soundings, later adjusted for tidal height. A subset of 2,967 soundings were then set aside from model development and utilized exclusively for test purposes. A visual census incorporating percentage covers of major habitat contributors (corals, macro-algae, seagrass, sponges, etc) and base substrates was carried out using glass-bottom buckets, snorkel and SCUBA. Sites were chosen at random along the pre-selected ground tracks, though some spectrally distinct features were specifically targeted, producing 1604 ground truth points. A Dive-Spec underwater spectrometer (NightSea LLC) utilizing both artificial and incident light sources, calibrated against a white Spectralon panel (99% reflectance), was used to measure diffuse attenuation, marine and terrestrial endmember spectra, and deep water reflectance. Optical data described the water as intermediate between Jerlov type II and type III, indicative of a slightly turbid tropical environment.

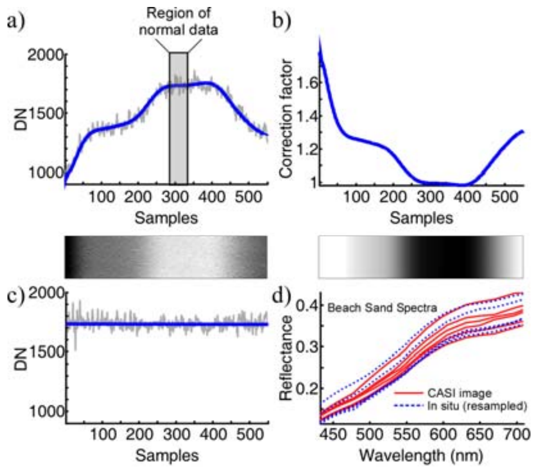

Figure 2: Across-track abnormality correction using optically deep water subset for a blue (506 nm) band. a) Across track abnormality; mean trend shown by bold line, along with region of normal data identified by field spectra comparison and image; b) Correction factor line and image; c) Corrected line and image; and d) Beach sand spectra from corrected imagery and *in situ* optics re-sampled to the CASI spectral response.

Abnormality correction: Fig. 2a illustrates the across-track abnormality, shown as the spectrum of a single band across a single line over deep water. Allowing for sea-surface and wave induced background-noise, this line is expected to have a relatively constant across-track response.

While a region of relatively flat data exists (as indicated in Fig. 2a), the spectral response drops precipitously towards both edges of the across-track array. It was further determined that this response varies across different flight-lines, thus ruling out an array sensitivity issue. Post-collection instrument analysis suggested a lens condensation problem, resulting in water pooling at the periphery of the lens. The greater affect noted towards the edges of the array, and at increased wavelengths, is consistent with this diagnosis. In the absence of a uniform solution based on the sensor, it is necessary to quantify and correct this effect based on the image data, which is difficult for areas with patchy habitats due to the inherently high spectral variation.

Optically deep water has proved useful in modeling within image spectral variation (Hedley 2005). Deep water fortunately exists in all flight-lines of the Farasan Islands. Subsets measuring 500 (along-track) × 550 pixels (across-track) were created and the across-track spectra from each subset were analyzed to determine the position of 'normal' data (Fig. 2a); typically ~70 pixels offset from centre. Mean 'normal' radiance was calculated using a 50 x 500 pixel subset from this region and divided by the mean spectrum of each sample, producing band specific across-track correction factors (Fig. 2b). The process was independently repeated for all 21 bands of each flight-line, and a correction image identical in size to the extent of each CASI flight-line created. Finally, each raw image was multiplied by its respective correction image, to normalize the peripheral regions to the spectral radiance of the central area (Fig. 2c).

Map products: Image processing followed the methodologies outlined in Fig. 3. A thematic map product was produced by first performing independent supervised classifications of the processed CASI and QuickBird imagery and then merging the results into an integrated product (Fig. 3). Field data were categorized into distinct habitat classes based on the dominant benthic coverage (see legend in Fig. 1C). A total of 800 points were used to train a maximum likelihood classification. When either sensor lacked adequate spatial coverage (or in cases where the distortion from the CASI abnormality was too high), the other sensor was used. The red and NIR bands from each sensor were used for mangrove classification and land masking, and benthic classification was based on bands from the blue-green region of the spectrum (CASI: 13 bands; QuickBird: 2 bands). A preliminary analysis was carried out for flight Areas 8 and 9 (Fig. 1B) before expanding the mapping protocols to the whole study area. Comparison of tau accuracy coefficients from 185 randomly chosen field observations suggested higher discriminatory ability using CASI in habitats shallower than 6 m (79% vs 74%) while QuickBird was the more accurate of the two sensors for habitats deeper than 6 m (80% vs 76%). Accordingly, two classifications were performed for each sensor, one classification for depths from 0-6 m and one classification for depths from 6-15 m. In the final map product, the various classifications were merged with reference to image availability, depth priority and context. For accuracy assessment of the final map, 300 points independent from the training process, distributed across the study area, were used. Most points (86%) were less than 6 m in depth, reflecting the dominance of shallow bank-top habitat.

Spectral unmixing: An additional image analysis procedure was used to examine sub-pixel habitat composition. Goodman and Ustin's (2007) spectral unmixing model was adapted to take account of the CASI band configurations. Results were evaluated using a single geocorrected flight-line with extensive ground and bathymetric data. Mean field spectra from the Farasan Islands for sand (n = 10), algae (n = 21) and coral (n = 29) were used as the spectral endmembers in the unmixing model. Derived bathymetry was compared to *in situ* depth soundings and endmember abundance maps were displayed as an RGB false-color composite for field data comparison. Accuracy was assessed using the *in situ* ground survey data.

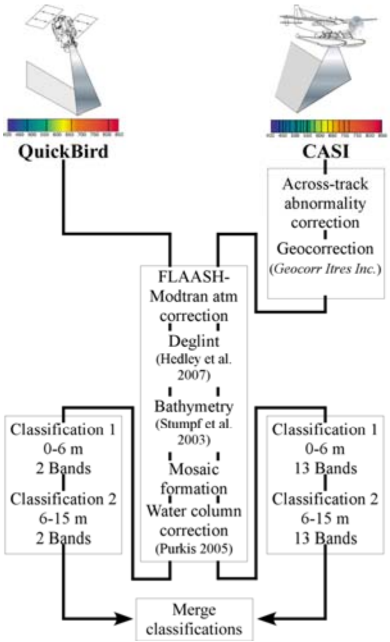

Figure 3: Processing stream for CASI and QuickBird data in producing thematic map product.

Results

The CASI across-track spectral abnormality was effectively removed using the derived correction factors, resulting in realistic spectral response across each flight-line (Fig. 2c). Background noise levels were comparable in magnitude to the raw image. Following further image processing (Fig. 3), image spectra also compared favourably to *in situ* beach sand spectra (Fig. 2d). This allowed creation of a radiometrically consistent mosaic for the study area. The method was successful in all bands for the majority of flight-lines; however, in 5% of cases, line correction was not possible as a flat region of 'normal' data could not be identified. These flight-lines were excluded from further analysis.

The combined sensor approach (Fig. 3) had a good overall accuracy (tau coefficient = 79%), mapping a total of 10 habitat classes. The western Farasan Islands are predominantly sedimentary in nature with 55% of benthos comprised of sand, or sand with sparse algae. Other areas include macro-algae/sponge atop rubble hardgrounds (22%); and rubble with sparse coral cover (6%), often intermixed with dense *Acropora* areas (3%) in the north-west. With the exception of *Acropora*, coral was only classifiable as a mixed assemblage. This comprised only (2%) of the substrate, mostly located in microatoll formations of 1-20 m diameter. Applied to Quickbird data the bathymetric model of Stumpf et al. (2003) compared favorably with actual soundings to a depth of 15 m (r = 0.91, p = <0.001, n = 2,967).

Application of the Goodman and Ustin (2007) unmixing model to the test CASI line was successful overall for investigating sub-pixel habitat composition. The comparison of predicted versus true depth (Fig. 4a) shows accurate depth determination to ~4.5 m (r = 0.83, p = <0.001, n = 161). Spectral unmixing within this depth threshold was also successful (Fig. 4b), having a high apparent overall accuracy of 76%. Small macroalgae patches (bright green) within a sand matrix (bright blue) are clear, as are transition pixels at fuzzy patch boundaries. Of particular note is the correct identification of small but abundant coral colonies at sub-pixel percentage cover, verified by field survey.

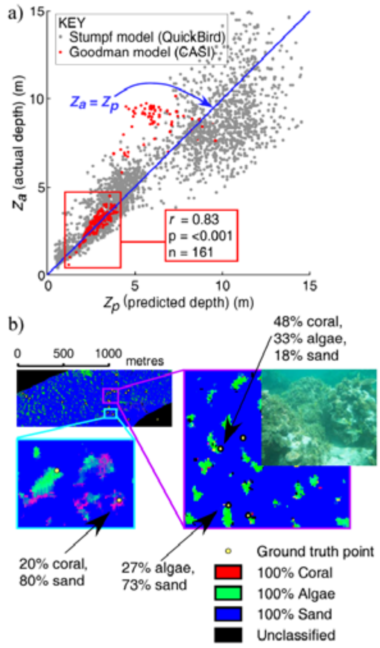

Figure 4: Goodman and Ustin (2007) model applied to CASI data showing: a) Comparison of model derived bathymetry and *in situ* soundings using Pearsons correlation; results of Stumpf et al. (2003) model applied to QuickBird also shown for comparison; and b) False color composite at differing resolutions with percentage coral, algal and sand in the red, green and blue channels respectively. Image typical of patches shown in upper right.

Discussion

The across track processing method (Fig. 2) represents a novel approach to a rare (or rarely disclosed) problem. The need for this correction is an exception and not needed for most hyperspectral acquisitions. The solution is simple, and when followed by standard atmospheric and water column corrections, a high quality image mosaic suitable for habitat mapping can be produced. The method has two processing requirements: 1) image data in a raw format uncorrected for geoposition, pitch, roll, or yaw; and 2) areas of deep water over which to model the spectral artifact. In most cases, the end users of hyperspectral imagery are not directly involved with image collection or pre-processing. Imagery is often delivered as radiometric and geocorrected flight-lines or a flight-line mosaic. In our case, we were able to liaise with our imagery supplier to acquire unprocessed imagery on which to derive a solution. Deep water is ubiquitous in our study area. This may not be the case for all study sites; however this study supports its inclusion where possible. As all lines were affected to some degree, quantifying the propagation, or not, of error through the above process is difficult. Field optical data compare favorably to fully processed imagery (Fig 2d), and the accuracy of the resultant maps lend support to our technique. Though partly automated, our solution operates on a band-by-band, line-by-line basis, and may therefore be time intensive for large datasets. Most significantly, we were able to recover data to a good standard, allaying any loss of capital investment.

The number of habitats (10), and overall accuracy (82%) compares favorably to CASI mapping elsewhere (e.g. Mumby et al. (1998) 81% for 9 classes, above 20 m depth; Bertels et al. (2008) 73% for 10 classes, above 15 m depth). Though overall accuracy may be biased towards shallow environments, our preliminary analysis suggests accuracy is likely to be >70% throughout. Bertels et al. (2008) demonstrate mapping to a higher number of classes, but there is a clear dichotomy between the number of classes mapped and overall accuracy. The different performance at depth of QuickBird vs. CASI is notable. Given the width of the QuickBird bands, signal is integrated over a greater portion of the spectrum than the selected CASI bands, which cover a more limited spectral range. While this effect is difficult to quantify, newer hyperspectral sensors record contiguous bands over a greater spectral range, have increased signal capacity and are thus expected to perform better. In the multi-sensor mapping approach presented, the use of 10 thematic classes is well suited to integration with QuickBird classifications. Though each sensor produced good classifications independently, the merged approach allowed adjustment for shortfalls in the coverage of either dataset.

Depth derived using the Stumpf et al. (2003) model showed a close relationship with true depth to 15 m. Both this model, and the Goodman and Ustin (2007) bathymetry model, were most accurate in shallow environments (<5 m). Correlation levels compare favorably to other datasets, as well as to similar inversion models (e.g. Bertels et al. (2008) ($r = 0.86$)). In both studies, model performance declined with depth. This is partially a function of increased light absorbance with depth, but with respect to CASI, there is also likely to be a decrease in the signal-to-noise ratio caused by the spectral artifact.

The outputs of Goodman and Ustin (2007) model indicate that spectral unmixing is both possible and accurate (apparent accuracy = 76%) in shallow environments (Fig 4b). The unmixing model concurs with field survey data in suggesting that an ecologically significant proportion of coral in the Farasan islands are located atop hardgrounds dominated by macro-algae. This is a dominant habitat across the western banks (Fig. 3).

This project demonstrates the utility of hyperspectral technology, despite encountering unexpected processing requirements due to the spectral artifact described above. Agencies often forgo hyperspectral sensors when mapping large geographic areas. However, the two approaches are complementary, providing ecologically relevant information at different hierarchical levels. Spectral unmixing of significant habitat components adds value to conventional mapping, and will lead to the better understanding, and management, of coral reef ecosystems.

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