Article

Mapping Coral Reef Benthos, Substrates, and Bathymetry, Using Compact Airborne Spectrographic Imager (CASI) Data

Ian A. Leiper [1,2,*], Stuart R. Phinn [1], Chris M. Roelfsema [1], Karen E. Joyce [1,2] and Arnold G. Dekker [3]

[1] Centre for Spatial Environmental Research, School of Geography, Planning and Environmental Management, University of Queensland, St Lucia, QLD 4072, Australia; E-Mails: s.phinn@uq.edu.au (S.R.P.); c.roelfsema@uq.edu.au (C.M.R.); karen.joyce@cdu.edu.au (K.E.J.)

[2] Research Institute for the Environment and Livelihoods, Charles Darwin University, Casuarina Campus, Darwin, NT 0810, Australia

[3] CSIRO Earth Observation & Informatics Future Science Platform, Canberra, ACT 2601, Australia; E-Mail: Arnold.Dekker@csiro.au

* Author to whom correspondence should be addressed; E-Mail: ian.leiper@cdu.edu.au; Tel.: +61-8-8946-7290; Fax: +61-8-8946-6155.

Abstract: This study used a reef-up approach to map coral reef benthos, substrates and bathymetry, with high spatial resolution hyperspectral image data. It investigated a physics-based inversion method for mapping coral reef benthos and substrates using readily available software: Hydrolight and ENVI. Compact Airborne Spectrographic Imager (CASI) data were acquired over Heron Reef in July 2002. The spectral reflectance of coral reef benthos and substrate types were measured *in-situ*, and using the HydroLight 4.2 radiative transfer model a spectral reflectance library of subsurface reflectance was simulated using water column depths from 0.5–10.0 m at 0.5 m intervals. Using the Spectral Angle Mapper algorithm, sediment, benthic micro-algae, algal turf, crustose coralline algae, macro-algae, and live coral were mapped with an overall accuracy of 65% to a depth of around 8.0 m; in waters deeper than 8.0 m the match between the classified image and field validation data was poor. Qualitative validation of the maps showed accurate mapping of areas dominated by sediment, benthic micro-algae, algal turf, live coral, and macro-algae. A bathymetric map was produced for water column depths 0.5–10.0 m, at 0.5 m intervals, and showed high correspondence with *in-situ* sonar data (R^2 value of 0.93).

1. Introduction

Resource inventory and mapping is one of the most common applications associated with the remote sensing of coral reefs [1]. Viewing a true-colour moderate or high spatial resolution satellite image of a coral reef reveals valuable information on reef extent, configuration, and geomorphology at broad levels. It does not, however, enable accurate identification of benthos and substrate types; e.g., does a brown-coloured pixel represent live coral, dead coral covered with turf algae, or macro-algae. Spatial and textural context can aid image interpretation and reveal structures such as patch reefs, but the composition of those structures remain difficult to determine; e.g., is the patch reef covered in live coral or crustose coralline algae? Distinguishing between different types of benthos and substrate types relies on the unique spectral properties of those features. Therefore, obtaining image data of sufficient spectral and radiometric resolution is crucial, along with an understanding of the optical properties of coral reef environments [2].

Hochberg *et al.* [3] showed that 12 coral reef benthos and substrate types (fleshy brown, green, and red algae; non-fleshy encrusting calcareous and turf algae; bleached, blue, and brown live coral; soft/gorgonian coral; seagrass; terrigenous mud; and carbonate sand) could be identified through *in-situ* collected spectral reflectance data which were shown to be consistent globally. These spectra, which were considered as pure end-members, were measured with an Ocean Optics S2000 portable spectrometer, across a Ground Field Of View (GFOV) of 0.06–10.0 cm diameter with negligible water column attenuation.

Due to the high level of spatial heterogeneity of coral reef environments, even at a sub-metre scale, an image pixel from a high spatial resolution airborne or satellite image sensor will mostly be comprised of multiple coral reef benthos and substrate types, resulting in a mixed end-member spectral reflectance signature. Leiper *et al.* [4] showed that mixed end-member spectra measured within a 0.92 m diameter GFOV, that were dominated (greater than 65% cover) by a single benthos or substrate type, were similar in shape to the pure end-member spectra presented by Hochberg *et al.* [3]. In a local context, field surveys on Heron Reef, a platform reef in the southern Great Barrier Reef, Australia, showed that many areas were dominated by a single benthos or substrate type at a 1.0 m^2 spatial resolution [4]. This suggested that pure end-member spectral reflectance curves measured using the methods of Hochberg *et al.* [3] could be used to conduct a supervised classification of high spatial resolution hyperspectral image data, despite the disparity in spatial resolution between field (spectral reflectance measurements) and image data. This has two important implications: (1) mixed end-member spectra were difficult to measure for some assemblages, and collecting an appropriate representative spectral library would be challenging; pure end-member spectra are comparatively easy to collect, and many such spectral libraries already exist; (2) mixed end-member spectra could not be measured with consistent water depth and air-sea interface conditions, creating a challenge to solving the radiative transfer equation to calibrate field and image data; pure end-member spectra can

be measured consistently and are readily entered as the bottom boundary condition in radiative transfer models.

High spatial and spectral resolution remote sensing instruments can theoretically detect the subtle spectral differences between the different coral reef benthos and substrate types [5–7]. The Compact Airborne Spectrographic Imager (CASI) is a high spatial resolution hyperspectral airborne sensor, that has been used to map coral reef environments using both unsupervised [8] and supervised [9–11] classification approaches. Using a spectral reference library to supervise image classification has been shown to increase classification accuracy in comparison to supervised approaches using image-based statistics [12,13], and has the potential to automate coral reef mapping procedures independent of ancillary field surveys [2,14,15].

This study used a reef-up approach to map coral reef benthos, substrates, and bathymetry on Heron Reef, investigating a simple physics based inversion model for mapping using readily available software: HydroLight (Sequoia Scientific, Inc.) and ENVI (Exelis Visual Information Solutions). This was achieved by measuring *in-situ* pure end-member spectral reflectance signatures, processing them to be compatible with CASI-2 image data, and using them to supervise image classification. Previous studies using this approach acquired Hyperion image data, where 30 m pixels are seldom dominated by a single benthos or substrate type, yet the spectral reference library used to supervise classification was composed of pure end-members [14] or did not consider effects of water column attenuation [16]. A strong emphasis was placed on the ability to map live coral, macro-algae, and algal turf (which predominately covers dead coral substrate), because these benthos and substrate types can be used to identify coral/algal dominated community phase-shifts and indicate reef status [17].

2. Methods

This study used an established mapping algorithm, Spectral Angle Mapper (SAM), to map benthos and substrate type and bathymetry simultaneously. SAM has previously been used to map coral reef features from Hyperion satellite image data [14,16], a sensor with high spectral resolution (10 nm band width, 196 bands between the 400 nm and 2500 nm region) and moderate spatial resolution (30 m pixel size). We further developed this approach using CASI-2 image data with a 1 m pixel size, a more appropriate spatial resolution when considering the benthos and substrate types being mapped and the pure end-member spectral reflectance library used to supervise the classification [4].

In-situ spectral reflectance signatures of coral reef benthos and substrates were measured on Heron Reef, and modelled to reflectance just below the water surface using the HydroLight 4.2 radiative transfer model. The resulting spectral library was re-sampled to the CASI-2 sensor characteristics (wavelength and Full-Width Half Maximum) and used to classify CASI-2 image data with the SAM classification algorithm.

2.1. Study Site

Heron Reef is a lagoonal platform reef [18] approximately 27 km^2 in area [19], located at 23°45′S, 151°92′E in the Capricorn Bunker Group, Great Barrier Reef, Australia (Figure 1). Due to the presence of a research station on the island, Heron Reef is one of the most studied coral reefs in the world. Remote sensing research has been undertaken at Heron Island using data acquired by Landsat

Multispectral Scanner [20,21], Landsat Thematic Mapper [19], Landsat Enhanced Thematic Mapper [22], IKONOS [23], Quickbird-2 [24], CASI [25,26], and field spectrometry [22,27–30]. Extensive field surveys on benthos and substrate composition and acquisition of high spatial resolution image data have occurred at least annually since 2000. Heron Reef features benthos and substrate types that are dominated by live coral and macro-algae communities, making it a suitable location to test coral reef mapping of benthos and substrates. Water depths in the channels surrounding the reef are approximately 15–30 m; the sandy lagoon has an average water depth of 3.5 m at low tide [18].

Figure 1. CASI-2 image data mosaic of Heron Reef, Great Barrier Reef, Australia, displayed in RGB mode using bands with centre wavelengths of 664.5 nm, 564.0 nm and 478.8 nm, respectively. The locations where field data were collected to validate the classified images are shown.
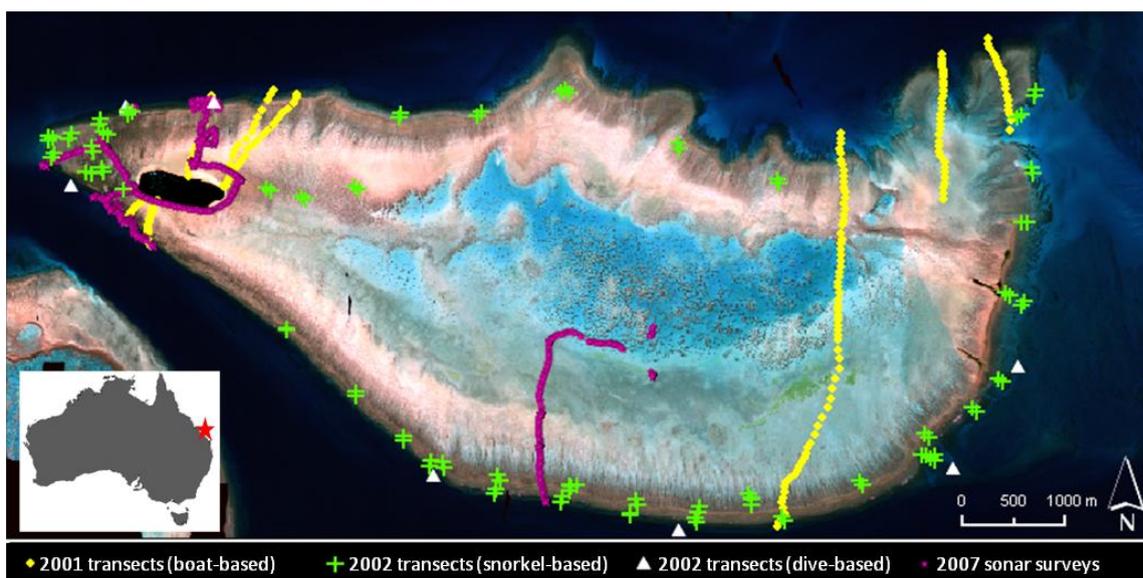
2.2. Acquisition and Pre-Processing of CASI-2 Image Data

CASI-2 hyperspectral data were acquired between 10:00 and 14:00 (+10 h GMT) on 1 and 3 July 2002. Data of the complete Heron Reef area was collected in 45 flight lines with a spatial resolution of 1 m across 19 spectral bands (Table 1). Extensive pre-processing converted the at-sensor radiance values to remote sensing reflectance, geo-referenced to UTM WGS84. The pre-processing included correction for cross-track illumination effects, atmospheric conditions, air-sea interface, sun glint, and geometric distortions [31]. Band 18 contained excessively noisy data (as it was positioned at a H_2O and O_2 atmospheric absorption feature) and band 19 was used to de-glint bands 1–17 [31]; therefore, only bands 1–17 were used for image data classification (Table 1). No water column correction was undertaken; instead, the effects of water column attenuation were incorporated into the reference spectral reflectance library using radiative transfer modelling.

Table 1. Spectral band centres and widths of the CASI-2 sensor used to acquire the Heron Reef images in 2002.

Band Number	Centre Wavelength (nm)	Full Width at Half Maximum (nm)
1	439.3	20.6
2	459.4	20.7
3	478.8	18.9
4	498.4	20.8
5	516.1	15.3
6	528.5	11.0
7	552.5	11.0
8	564.0	9.7
9	574.4	11.6
10	594.2	9.8
11	614.1	11.7
12	624.5	9.8
13	643.5	9.8
14	664.5	9.8
15	674.0	9.8
16	691.2	9.8
17	707.5	7.9
18	732.4	8.0
19	778.5	15.7

2.3. Creating the Reference Spectral Reflectance Library

Spectral reflectance measurements for 10 coral reef benthos and substrate types were measured *in-situ* at Heron Reef in June 2006 (sediment, benthic micro-algae (BMA), algal turf, crustose coralline algae, brown macro-algae, green macro-algae, red macro-algae, live coral (brown-mode), live coral (blue-mode), and soft coral). These benthos and substrate types were chosen because they have been reported as being optically separable based on *in-situ* spectral reflectance signatures collected globally [3,14,32–37]. Furthermore, they are found on Heron Reef dominating (greater than 65% cover) areas of at least 1.0 m^2 (which is appropriate considering the spatial resolution of the CASI-2 image data), and can indicate the health and status of a coral reef (especially the distribution of live coral, macro-algae, and algal turf which quickly covers dead coral substrate [17,33]).

Radiance was measured across an effective spectral range of 400–800 nm, using an Ocean Optics USB2000 spectrometer and a fibre optic probe attached to an artificial light source [38,39]. The spectrometer is enclosed in an underwater housing, and operated *in-situ* whilst SCUBA diving. Each spectral measurement was taken holding the optics and artificial light source about 5.0 cm from the target, ensuring a GFOV less than 0.1 m diameter and negligible water column attenuation. Before each measurement, a reference reading of a 99% Lambertian reflectance standard (Spectralon®, Labsphere Inc., North Sutton, NH, USA) was taken to represent solar irradiance conditions, along with a dark current reference reading, and used to transform the radiance measurements to reflectance units.

Reference readings were taken underwater adjacent to the benthos or substrate target. The resulting reflectance spectra were re-sampled to 1 nm intervals across a spectral range of 400–800 nm.

To simulate the effect an overlying water column would have on the *in-situ* spectral reflectance signatures, the HydroLight 4.2 radiative transfer model was used to create a spectral reference library reflectance from just below the water surface [40]. Haltrin's chlorophyll-based model of sea water optical properties was selected, which assumed that coloured dissolved organic matter and suspended scattering particles co-varied with a user specified chlorophyll concentration [31,41]. The HydroLight model was run for water depths from 0.5 m till 10 m with 0.5 m intervals using a chlorophyll concentration profile of 0.125 mg/m^3, constant with depth. This chlorophyll concentration was selected following measurements of the water optical properties at Heron Reef by Wettle [42]. The output from the model was subsurface reflectance across a spectral range of 400–799 nm, for each depth, modelled using the spectral reflectance of each benthos and substrate type in the spectral library as the bottom boundary reflectance.

2.4. Image Classification to Create a Benthos and Substrate Classified Image, and a Bathymetry Classified Image

Spectral Angle Mapper (SAM) is a method which focuses on the shape of spectral reflectance curves, and was considered a suitable algorithm for this study using a reference spectral reflectance library to classify hyperspectral image data. SAM calculates the angle between each image pixel and reference spectra, by treating each as vectors in an n-dimensional space equal to the number of image bands [43]. The angle between two vectors is insensitive to the length of each vector, so the method is sensitive to spectral shape and relatively insensitive to gain factors (illumination). The reference spectra vector with the smallest angle to the image pixel vector is considered the best match, and if an angle exceeds a threshold set by the user then the pixel remains unclassified. Joyce *et al.* [31] assessed a number of techniques for mapping live coral cover on Heron Reef, and reported that SAM produced the highest correlation with field survey data. SAM is a classification algorithm readily available within the software package ENVI.

Three main SAM classifications were performed during this study, with the third implementation providing the final benthos and substrate classified image.

First, using a single threshold angle set to 0.1 radians, the CASI-2 image data (bands 1–17) were classified with the reference spectral library described above; (0.1 radians was the minimum threshold angle tested by Kutser *et al.* [14]). A second SAM classification was performed using only image data bands 4–17, because wavelengths below 500 nm have few spectral features to differentiate between coral reef benthos and substrate types, and are most affected by atmospheric effects [14]; the threshold angle was kept at 0.1 radians. The output images from both the first and second SAM classifications were dominated by sediment and algal turf, and it was obvious that many sites were incorrectly classified as these two classes; of particular note, was the incorrect classification of areas known to be dominated by live coral and macro-algae.

These apparent errors led to a third SAM classification, using a multi-radians approach, which allowed the user to set a threshold angle for every input reference spectra. The threshold angles were refined by running individual SAM classifications for each benthos and substrate type in the spectral

reference library (using all depth modelled spectra), testing threshold angles between 0.03 and 0.1 radians. A series of classified images were produced for each benthos and substrate type, from which a suitable threshold angle was selected and used in the final (third) SAM classification (Table 2). To decide the best threshold angle for each benthos and substrate type, the output images were assessed for correlation with field data and knowledge of the study site. Based on the spectral reflectance properties of sediment, it was decided that SAM be used to classify sediment in deeper waters, and a density slice using band 4 (at 498.4 nm) to classify shallow water sediment based on its relatively high magnitude of reflectance.

Table 2. Threshold angle (in radians) for each benthos and substrate type in the multi-radians SAM classification using image data bands 4–17. The same angle was used for the 20 depth modelled classes within each benthos and substrate type.

Benthos or Substrate Type	Threshold Angle (Radians)
Sediment	0.04
Benthic micro-algae	0.07
Algal turf	0.07
Crustose coralline algae	0.05
Brown macro-algae	0.10
Green macro-algae	0.10
Red macro-algae	0.08
Live coral (blue-mode)	0.09
Live coral (brown-mode)	0.10
Soft coral	0.10

A classified image showing the distribution of benthos and substrates on Heron Reef was created by merging together all the depth classes within each benthos and substrate class in the SAM output image (for example, merging together the pixels classified as algal turf 0.5 m, algal turf 1.0 m algal turf 10.0 m, into a single algal turf class).

Conversely, merging all pixels classified with the same depth, regardless of benthos and substrate type, created a classified image showing the bathymetry of Heron Reef in 0.5 m intervals from 0.5 to 10.0 m depth. To avoid large regions of unclassified pixels, the classified image was created using the second SAM classification run (image bands 4–17 with 0.1 radians threshold angle). This output image had fewer unclassified pixels due to the lower threshold angle which resulted in more pixels being classified as an end-member, mainly sediment, which may exert a strong influence on spectral reflectance in mixed end-member spectra [4,5,44]. Because water attenuation has a strong influence on reflectance signatures, the benthos and substrate type was not particularly important for bathymetry classification, apart from being either bright (sediment) or dark (live coral, macro-algae *etc.*), and for this reason the lower threshold angle was justified.

2.5. Validation of the Benthos and Substrate Classified Image

In-situ validation data on the benthos and substrates of Heron Reef were collected in the form of 48 snorkel- and 29 dive-transects surveyed in November 2002 and eight boat-based transects surveyed in April 2001 [31] (Figure 1). These surveys involved taking photographs of the benthos and substrate using a downward looking digital camera whilst advancing along a transect, the geo-location of which was tracked using a Global Positioning System (GPS) in a dry-bag floating at the water surface and attached to the surveyor [31]. Based on the original photo analysis by Joyce [31], it was possible to assess the percent cover of six benthos and substrate types in our classified image: sediment, algal turf, crustose coralline algae, macro-algae, live coral and soft coral. It was not possible to assess blue- or brown-mode live coral distribution, or to separate macro-algae into the divisions brown (Phaeophyta), green (Chlorophyta) and red (Rhodophyta), because the *in-situ* validation data did not contain such detailed information. The *in-situ* validation data (percent cover of benthos and substrates along the geo-referenced transects) was not used to supervise image classification and was therefore independent of the classified image.

To validate the benthos and substrate classified image, *in-situ* validation data was used to create a standard error matrix, sites were analysed using *in-situ* transect data, and, where no *in-situ* data was available, site knowledge was used to assess classification results.

A standard error matrix was produced to provide a quantitative assessment of benthos and substrate mapping accuracy, from which user, producer, and overall accuracy statistics were calculated. Unfortunately, there was a limited number of data points and there was bias in the benthos and substrate types sampled (and not sampled), the spatial distribution of the data points was not even, and there was possible mis-registration between field and image data to consider [45–47]. In particular, no macro-algae or BMA data points were present in the *in-situ* validation data, and there were few crustose coralline algae and soft coral data points. Spatial mis-registration between field and image data was unavoidable due to the discrepancy between image data pixel size (1 m), the positional accuracy of the GPS instruments used during field work, and additional GPS instrument movement due to current, waves and swell [31]. This made it impossible to be sure that a point measured in the field was positioned with pixel-scale accuracy and precision when overlaid on the image data.

The classified image was also validated using a qualitative per-transect approach. The classified image was visually assessed against the 48 snorkel, 29 dive- and eight boat-based transects. The transects were overlaid on the classified image, with a 5.0 m diameter circular buffer on the snorkel-and dive-transects and a 20.0 m diameter circular buffer on the boat-based transects to account for spatial mis-registration of field and image data [31]. The classified image was then visually assessed against the field validation data for a match in benthos and substrate types. If the transect displayed a similar benthos and substrate pattern as the classified image, with an allowance for spatial misregistration, the transect was considered to match the classified image; if there was no match, or only a section of the transect matched with the classified image, notes were taken to describe the mis-match.

Due to the limited spatial coverage of the *in-situ* validation data, and missing categories including macro-algae and BMA, additional areas were also assessed based on site knowledge and field validation data collected during 2001–2009 (with due consideration given to temporal change that may have occurred in benthos and substrate type cover since image acquisition). For example, Shark Bay,

the area immediately east of Heron Island, is known to be dominated by red and brown macro-algae communities; and the lagoon is known to feature large areas of benthic micro-algae which appear bright green in true-colour images.

## 2.6. Validation of the Bathymetry Classified Image

Boat-based tide-corrected depth soundings using a single beam echo sounder, collected in 2007, were used to validate the bathymetric classified map [25]. These measurements surveyed a range of depths across geomorphic features including the reef slope, crest, lagoon, patch reefs, reef flat and harbour (Figure 1).

3. Results

3.1. Reference Spectral Reflectance Library

The mean spectral reflectance signatures collected *in-situ* for 10 coral reef benthos and substrate types on Heron Reef are presented in Figure 2. The number of spectral measurements taken were: sediment *n* = 1, benthic micro-algae (BMA) *n* = 1 , algal turf *n* = 10, crustose coralline algae *n* = 2, brown macro-algae *n* = 2, green macro-algae *n* = 13 , red macro-algae *n* = 5, live coral (brown-mode) *n* = 30, live coral (blue-mode) *n* = 11, and soft coral *n* = 1). Each benthos and substrate type showed spectral reflectance features consistent with those previously reported for pure end-member spectra of coral reef benthos and substrates [3]. Using these spectra as the bottom boundary reflectance condition in the HydroLight radiative transfer model, the effects of an overlying water column were simulated, creating a reference spectral library of subsurface reflectance for 10 coral reef benthos and substrate types at water depths of 0.5–10.0 m (0.5 m intervals) (Figure 3). Because no water column optical properties were measured during the field surveys, no assessment could be made between study location water spectral values and the Hydrolight modelling output. The form and magnitude of the simulated subsurface spectral reflectance library was consistent with the results presented in Lubin *et al.* [48] for upwelling spectral radiance at the air–water interface modelled for a number of coral reef benthos and substrate types. The most noticeable effect of the water column modelling was attenuation at wavelengths greater than 575 nm, and a reduction in magnitude of spectral reflectance features as the water column depth increased (Figure 3).

Figure 2. Mean spectral reflectance signatures measured *in-situ* at Heron Reef, and used as the bottom boundary layer in HydroLight modelling.
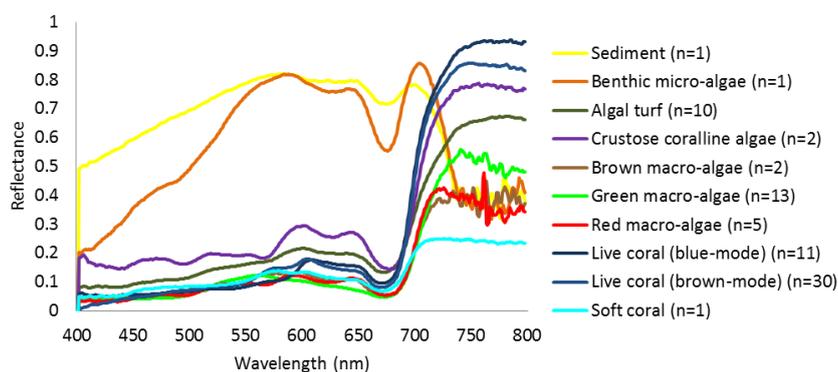
Figure 3. Subsurface reflectance curves for each benthos and substrate type at depths 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 6.0, 7.0, 8.0, 9.0, and 10.0 m. The coloured lines represent the full resolution (400–800 nm) spectra, the black lines represent the correspond curves integrated across the CASI-2 spectral response curves. Note that the scale of the y-axis changes between plots, to allow the shape of the spectra be better seen.
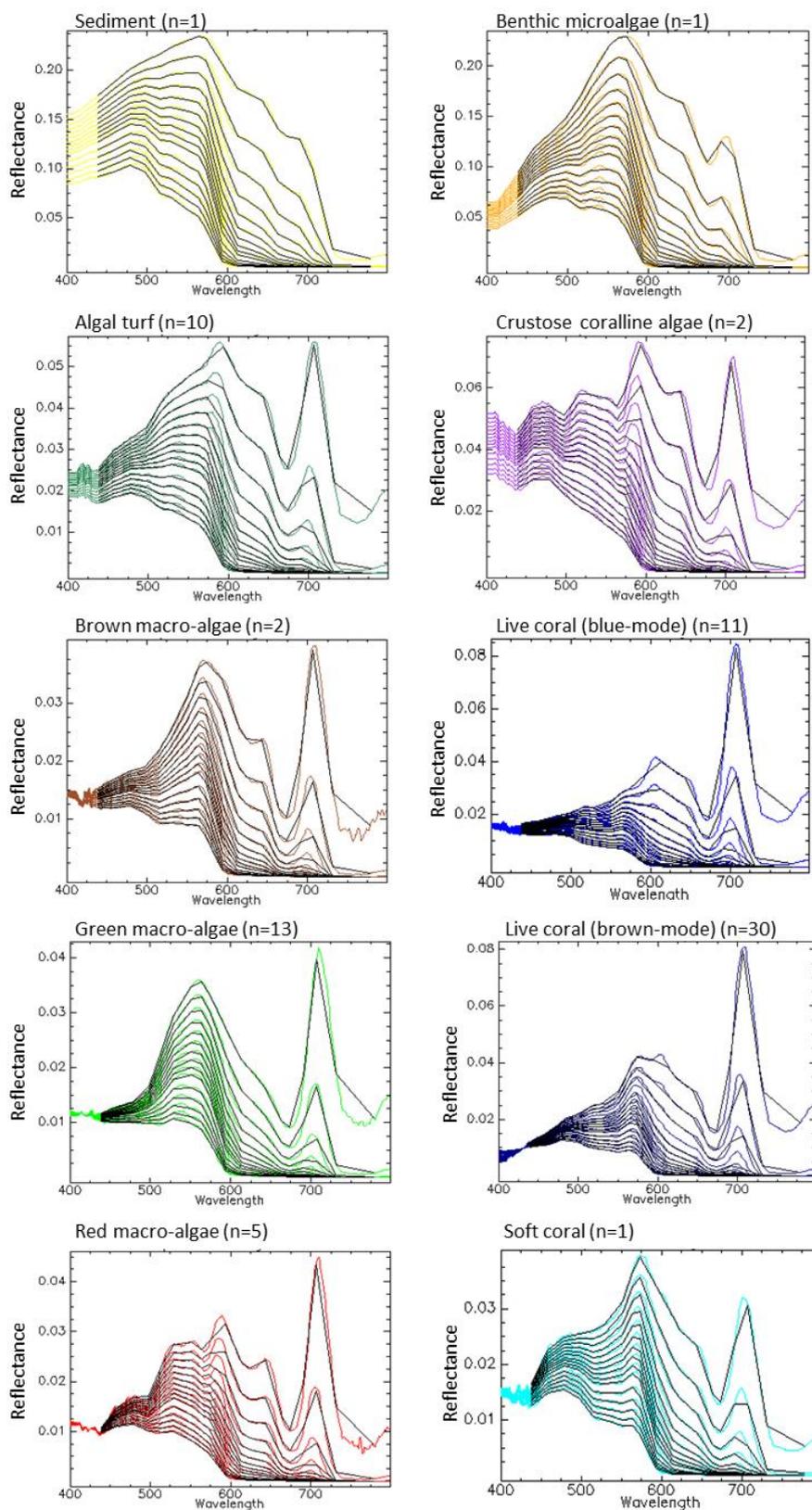
When the full-resolution subsurface spectral reflectance signatures were integrated across the CASI-2 spectral response curves, and plotted together, it was apparent that some prominent spectral features were either no longer evident or that their waveband position had shifted due to the integration process (Figure 3). Comparing the full resolution spectra to those integrated across the CASI-2 spectral response curves: sediment and BMA were well matched; algal turf and crustose coralline algae had absorption peaks at 590 nm omitted; brown macro-algae had a prominent peak at 575 nm altered; green macro-algae was well matched; red macro-algae had prominent features at 568 and 586 nm altered; live coral (blue- and brown-modes) had features at 540, 585, and 605 nm altered; soft coral had slight alterations near 585 and 605 nm.

Because the magnitude of reflectance for sediment was significantly greater than all other benthos and substrate types apart from BMA, a density slice was used to map sediment in shallow water. A density slice using image band 4 (498.1 nm) was selected because sediments contains relatively low amounts of photosynthetic pigments compared to BMA, which absorb light in this spectral region (along with some carotenoids and xanthophylls) [49]; this was evident in the spectral reflectance plots (Figure 3).

Bands 18 and 19 were removed from the image data due to noisy data and glint processing respectively, but were still present in the *in-situ* derived spectral library; these bands did not appear to contain any spectral features which would have aided in the identification or classification of any of the benthos or substrate types (Figures 2 and 3).

3.2. Image Classifications

### 3.2.1. Benthos and Substrate Classified Image

The CASI-2 image data were classified into 10 benthos and substrate type classes using the multi-radians SAM approach with image data bands 4–17 and a density slice to map shallow water sediment (Figure 4). Sediment was the dominant benthos and substrate type, with a strong presence of algal turf on the reef flat and a rim of live coral on the reef slopes. The classified image closely matched field data and expert knowledge of Heron Reef; four sites which highlight a variety of mapped benthos and substrate types are shown in Figure 4, including: (a) live coral habitat near the harbour and on the reef slope; (b) macro-algae and algal turf which covers dead coral structures in Shark Bay; (c) patch reefs with algal turf on the upper surface, surrounded by sediment and sparse live coral, and; (d) BMA in the lagoon. The presence of large areas of live coral near the harbour, and the absence of it in Shark Bay, indicated that a spectral reflectance difference between macro-algae and live coral was detectable by the CASI-2 sensor.

Unclassified pixels (Figure 4) represented image data which were outside the threshold angle set using the SAM classification and below the density slice threshold which mapped sediment in shallow water. In areas outside the reef slope, these pixels were located in water deeper than 10.0 m and were expected to be unclassified because the reference spectral reflectance library only contained signatures modelled to 10.0 m depth. The unclassified pixels in areas where the water column was known to be less than 10.0 m may have been unclassified due to the mixture of reef benthos and substrate types within those pixels, or due to pure end-member spectra missing from the reference spectral library

(e.g., cyanobacteria mats [7]), which then caused those pixels to be outside the minimum SAM threshold angle. Pure end-member spectra of benthos and substrate types have distinctly different signatures to mixed end-member spectra dominated by two or more benthos or substrate types [4,12,44].

The occurrence of unclassified pixels on the reef flat, in waters less than 10.0 m deep, could have been reduced if the threshold angle was increased; however, this would have led to an increase in commission errors. The optimal balance between omission and commission errors will depend on the mapping application. For this study, commission errors were reduced to ensure that a change in benthos and substrate type using temporal image data could infer a change in coral reef health using live coral and macro-algae as proxies. The spatial resolution of CASI-2 image data is high enough that pixels dominated by a single substrate will begin to dominate an area that has a significant change in benthos from live coral to macro-algae, and *vice versa*. By reducing commission errors, the risk of incorrectly relating a mapped change in substrate composition to a change in actual reef status is reduced.
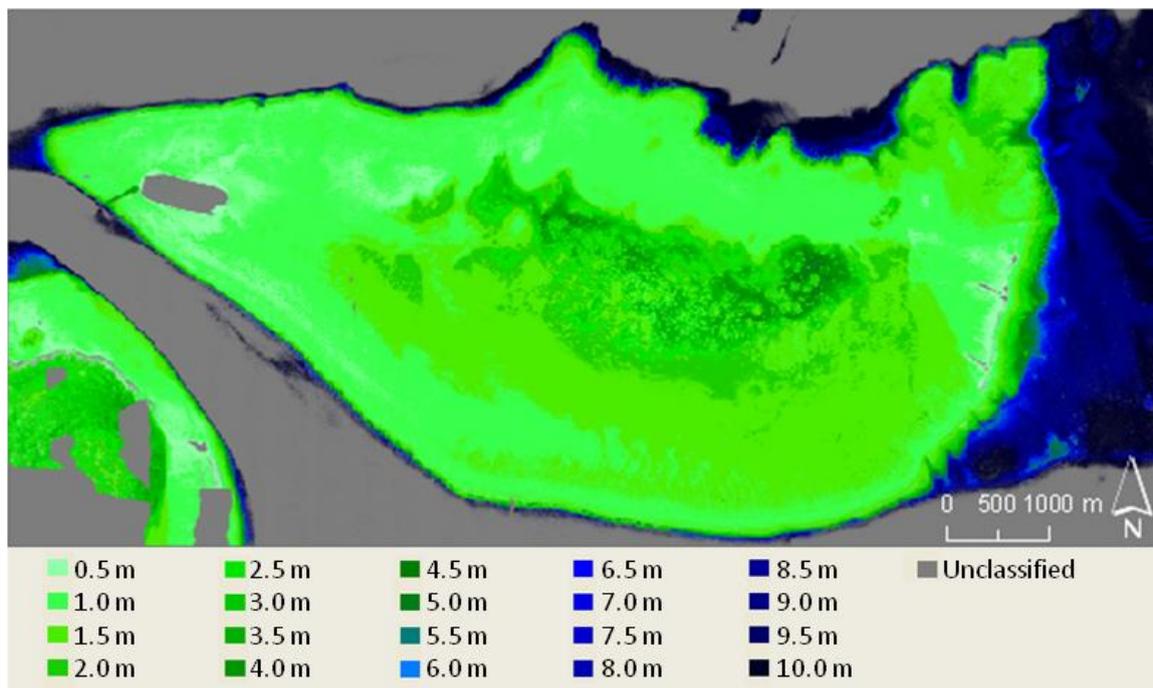
Figure 4. Classified image showing benthos and substrates on Heron Reef. Below the main figure are insets which show in more detail the mapping of zones dominated by (**a**) live coral; (**b**) macro-algae; (**c**) patch reefs; (**d**) spur and groove formations and; (**e**) benthic micro-algae. Inserts are also presented to show more detail of the bathymetry classified image (Figure 5), alongside the true-colour and benthos and substrate classified images.
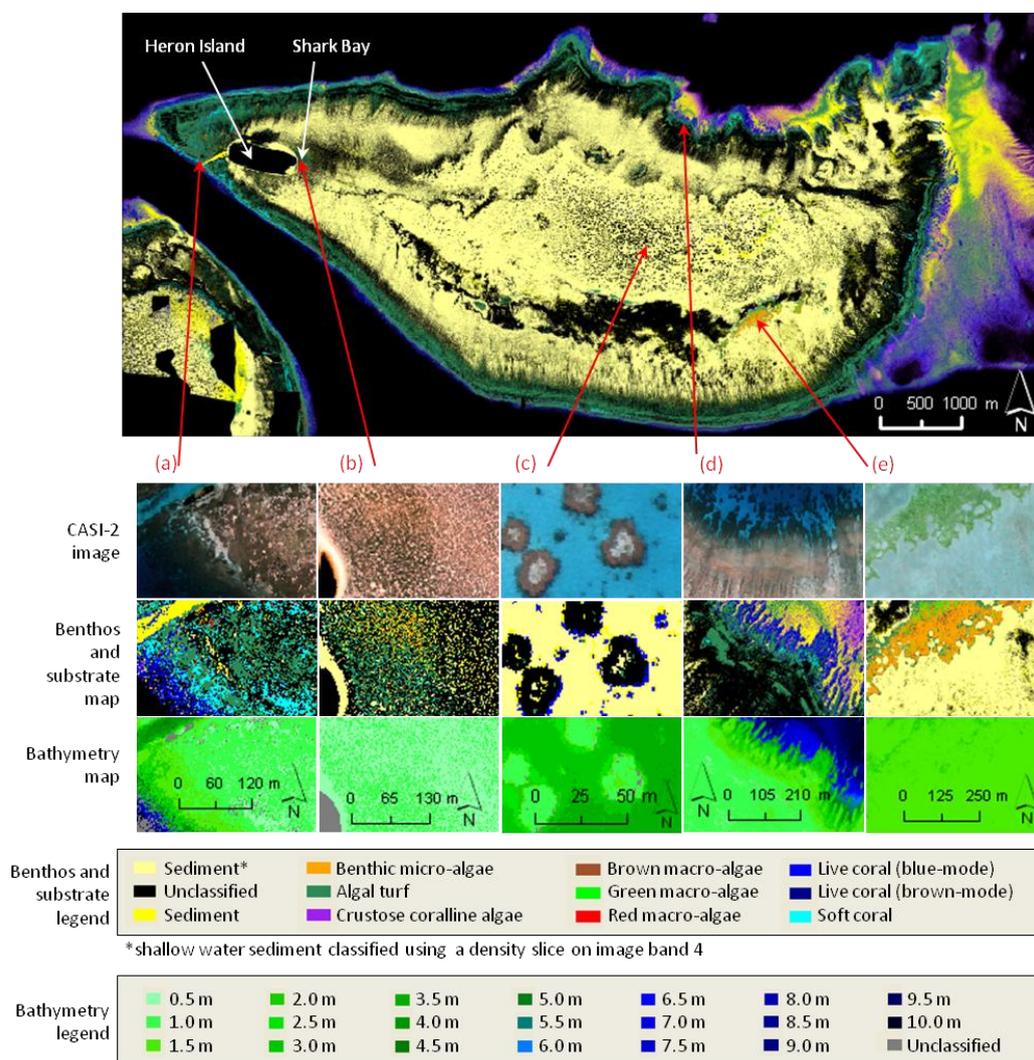
3.2.2. Bathymetry Classified Image

The bathymetry map (Figure 5) showed that Heron Reef is relatively flat and surrounded by waters greater than 10.0 m depth. Internally, there is a shallow lagoon with the deepest point on the eastern end at around 5.0 m deep and a harbour (west of the cay) which was 4.0 m deep on average. A shallow reef rim surrounding the reef flat was evident, and all zones matched known geomorphic features and recent bathymetric mapping [25]. The spur and groove formations on the seaward slopes of the reef rim were accurately mapped (Figure 4d). The waters beyond the Heron Reef slope, including the Heron-Wistari inter-reef channel, are known to be greater than 10 m deep [18], and were unclassified due to the absence of spectra modelled to these depths in the reference spectral library.

Figure 5. Heron Reef bathymetry classified image; showing the internal lagoon with a maximum depth of around 5.0 m, a shallower reef flat, and a harbour which is around 4.0 m on average. Waters beyond the reef slope, and known to be greater than 10 m deep, were unclassified.

3.3. Validation of the Classified Images

3.3.1. Benthos and Substrate Classified Image Validation

The overall accuracy of the benthos and substrate classified image was 65.13% (Figure 6). The producer's and user's accuracy for sediment and algal turf was relatively high; live coral had relatively low producer's and user's accuracy levels. Unfortunately, *in-situ* validation data were not available for benthic micro-algae or macro-algae, and very few data points were available for crustose coralline algae and soft coral. As mentioned in the methods section, the results shown in the error matrix must be considered with spatial mis-registration effects in mind; it is impossible to be sure that a point measured in the field was positioned with pixel-scale accuracy and precision when compared

against the classified image. Also note that pixels labeled as "unclassified" were not included in the error matrix because it was not possible to tell if this were a correct or incorrect classification (as described in Section 3.2.1).

Figure 6. Standard error matrix. The three divisions of macro-algae (Brown, Red, and Green), and two modes of live coral (blue and brown), were grouped together to form a single macro-algae and live coral group, respectively. Overall accuracy was 65.13%.

Benthos and substrate type	Sediment	BMA	Algal turf	Crustose coralline algae	Macro-algae	Live coral	Soft coral	Row totals	User's accuracy
Sediment	92	0	41	0	0	15	0	148	62%
BMA	0	0	0	0	0	0	0	NA	NA
Algal turf	19	0	508	4	0	60	0	591	86%
Crustose coralline algae	14	0	47	0	0	9	0	70	0%
Macroalgae	0	0	14	0	0	5	0	19	0%
Live coral	6	0	79	0	0	78	1	164	48%
Soft coral	1	0	26	0	0	22	0	49	0%
Column totals	132	0	715	4	0	189	1		
Producer's accuracy	70%	NA	71%	0%	NA	41%	0%		

Field validation data (column group header); Classified data (row group header).

Overall accuracy = 65.13%

Using a per-transect validation approach, and incorporating a suitable buffer area to account for spatial mis-registration, resulted in a good match between the classified image and the *in-situ* validation data on snorkel- and boat-based transects (Figure 7). Sediment, BMA, algal turf, macro-algae, and live coral were mapped in accordance with validation data and site knowledge. Of the 48 snorkel and eight boat-based transects, 49 were a good match and seven were only a partial-match. The partial-match occurred for two reasons: (1) some areas had an excess of red macro-algae in the classified image; and (2) some areas of the classified image were unclassified. Validation data collected on the dive transects matched poorly with the classified image; many pixels were unclassified—which was expected due to the depth of the dive transects and the depth of the water column modelled in HydroLight (maximum depth of 10.0 m). In areas which were classified, poor classification was evident by the presence of algal turf and crustose coralline algae in areas which appeared to be sediment in the true colour image (for example, the far eastern edge of the classified image (Figure 4). This highlighted an apparent depth limitation of the mapping approach to water column depths shallower than 8.0–9.0 m, determined by observing the bathymetric classified image values at the location of the poorly classified areas in the benthos and substrate classified images. Kutser *et al.* [14] also noted a limitation mapping coral reef benthos and substrates in water depths greater than 8.0 m, in contrast to theoretical detection limits of depths up to 25.0 m [36].

Figure 7. Examples of field validation transects, with a 5.0 m circular buffer around each point to account for spatial mis-registration. Transects were assessed for a match between the benthos and substrates within the buffer and the classified image. The snorkel transects shown above were considered to display a good match with the classified image, and were representative of the majority of transects.
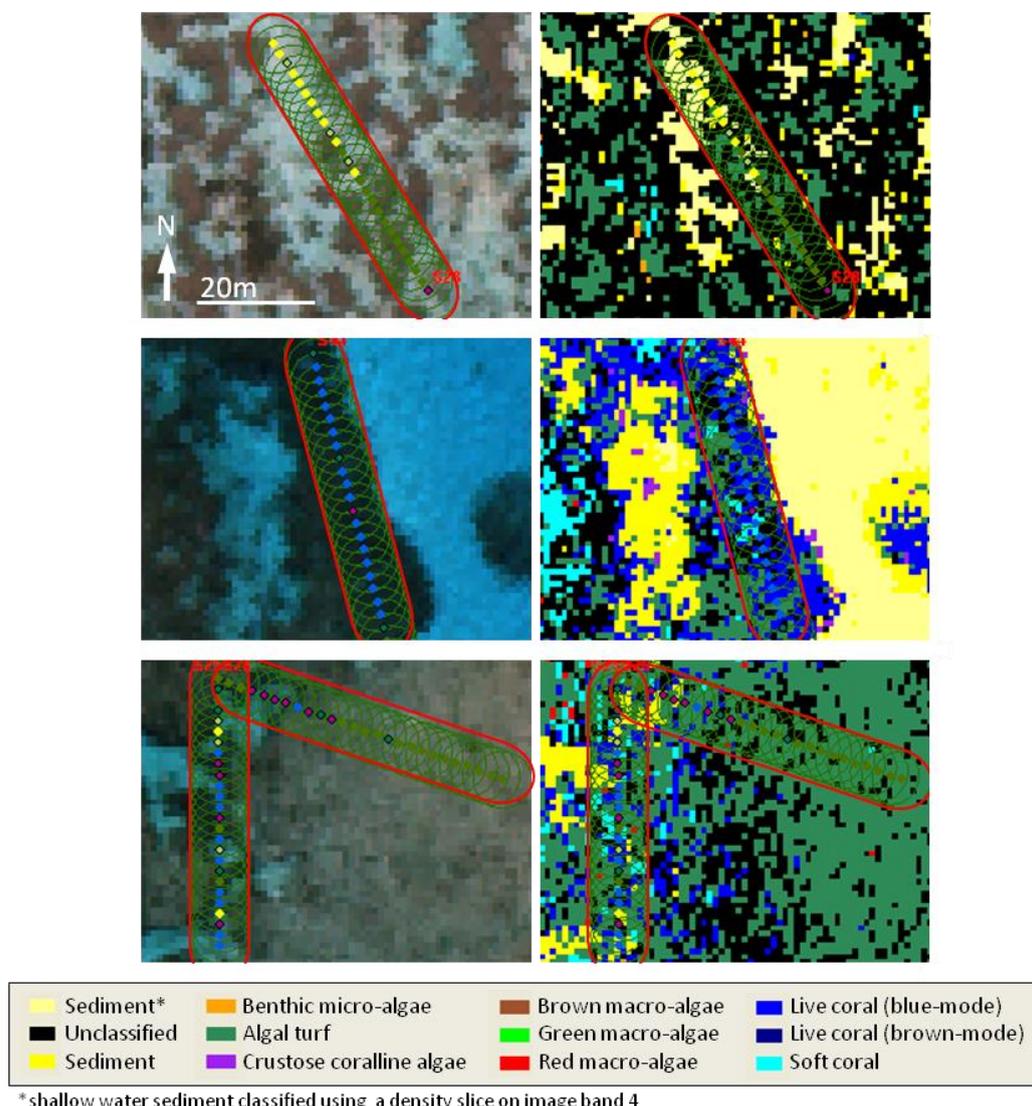

3.3.2. Bathymetry Classified Image Validation

The bathymetry image showed a high correspondence to the sonar data. Plotting the estimated depth from the classified image against the sonar depth collected *in-situ* resulted in a R^2 value of 0.93 (Figure 8). The maximum depth modelled in the *in-situ* library, and therefore the maximum estimated depth, was 10.0 m; this explains the upper depth limit for estimated depth values, which extends from around 10.0–20.0 m in the sonar depth measurements.

A plot of the water depths along one of the sonar tracks running from East to West, beginning to the West of Heron Island (shown in Figure 1), showed the high correspondence between field and classification results.

Figure 8. (**a**) The classified image of Heron Reef bathymetry was validated using boat-based sonar measurements. The estimated water depth from the classified image was plotted against the sonar depth measurements, and showed a high correspondence, with an R^2 value of 0.9285. The maximum depth modelled in the *in-situ* library, and therefore the maximum estimated depth, was 10.0 m; (**b**) Water depths along the boat-based sonar track and estimated from the classified image, running from east to west, beginning to the West of Heron Island (shown in Figure 1). Values of zero refer to unclassified areas in the classified image, which was only classified to depths of 10 m.
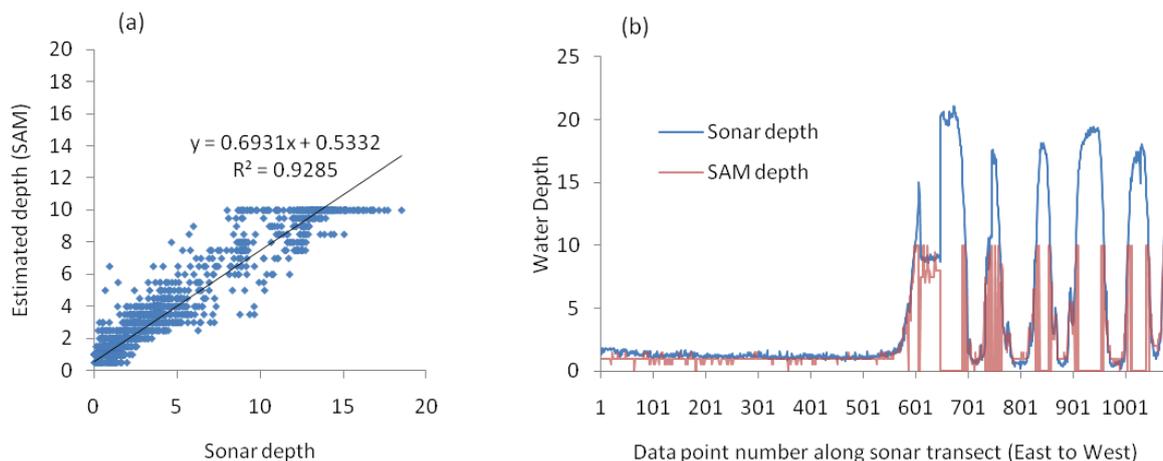
4. Discussion

Mapping coral reef benthos and substrates (in particular, live coral and macro-algae) using remote sensing techniques can provide information relevant to coral reef health. This is especially useful in their often remote locations, where *in-situ* methods are unsuitable due to limited spatial coverage, and there is limited ability to repeat observations or measurements. This study used a reef-up approach to map coral reef benthos, substrates, and bathymetry on Heron Reef, investigating a simple physics-based inversion model to extract ecologically meaningful information from airborne remote sensing data, with readily available software.

Spectral reflectance measurements collected in 2006 were used to supervise the classification of hyperspectral image data collected in 2002. This reef-up mapping approach accommodates retrospective mapping, where field data collected at a time concurrent with image acquisition are not available to supervise image classification [13], and provides a consistent method which can be used to classify temporal hyperspectral image data and determine reef status and trends. A drawback to retrospective mapping, highlighted in this study, can be a lack of suitable historical field validation data.

The accuracy of classified images must be assessed to provide confidence in the results and to inform users and producers of possible limitations; however, it can be difficult to collect sufficient validation data for traditionally accepted accuracy assessments, and this is an area of research that needs greater attention, critical analysis, discussion and innovation [45]. It is difficult to plan where sites of interest on a reef are, prior to image classification. With limited field time, often in remote and challenging environments, it is necessary to draw upon site specific expertise and knowledge to provide additional validation of classified images, where traditionally accepted accuracy assessment

protocols are not possible [45,50]; for example, sediment and BMA areas on the south-eastern reef flat (Figure 4e) were obvious from the true-colour image and site experience, and spending valuable field survey time to collect formal validation points in these areas was not justified due to time limitations during data collection. An advantage of the mapping approach presented in this paper, in contrast to retrospective mapping, is that a classified image could be created using an existing spectral reflectance library and a field survey could then be planned *a posteriori* with knowledge of the classified image and the requirements of a formal accuracy assessment in mind.

Some areas of the benthos and substrate classified image were validated by visual comparison with field validation transects, using an appropriate buffer distance to account for mis-registration effects between field and image data, and site knowledge. The classified image (Figure 4) matched well with the field validation data in depths shallower than 8.0 m; below this depth the classified accuracy decreased dramatically, as attenuation by the water column reduced the spectral features that were used to discriminate the benthos and substrate types at shallower depths (Figure 3). The ability to map benthos and substrates at depths greater than 8.0 m needs further research, as many important invertebrate and fish communities are located on and beyond reef slopes, in depths greater than 8.0 m.

The HydroLight radiative transfer model was used to create a spectral reference library of reflectance just below the water surface (Figure 3), calibrating *in-situ* spectral reflectance measurements with CASI-2 image data (after radiometric, atmospheric, and air-water interface corrections). The effect of water column attenuation changed the albedo and shape of the benthos and substrate spectra (compare Figures 2 and 3), particularly spectral reflectance features located at wavelengths longer than 575 nm. The influence of a water column on shallow reefs (less than 3.0 m water depth) has been reported as negligible by some researchers [5], which is not the case as shown by a water column of only 0.5 m depth (Figure 3) or even a wet target with no overlying water column [42]. Due to light attenuation in the water column, at depths of more than 5–6 m reflectance values at wavelengths greater than 575 nm are of limited value for mapping marine benthos and substrates even in very clear waters. Identification of spectral features in shorter wavelengths that can discriminate between benthos and substrates should be an important focus area for marine habitat mapping research.

Lubin *et al.* [48] modelled how the spectral signatures of coral reef benthos and substrate types would appear from space. The *in-situ* reflectance spectra measured in their study correspond well with those in Figure 2, apart from slightly different magnitude of reflectance values between the two studies. This has important implications because a lot of the reported differences by Lubin *et al.* [48] were apparent reflectance contrasts between substrates, and it highlights the value of classifiers such as SAM which are based on spectral shape and are relatively insensitive to illumination. Many supervised classification methods use Euclidean distance as the conceptual foundation for comparing image and training data [2,51]. In marine environments, such methods must be carefully approached to avoid depth dependency errors due to the effects of water column attenuation on the spectral reflectance magnitude of benthos and substrate types.

SAM has previously been used to map coral reef environments using high spectral resolution imagery. Kruse [16] classified Hyperion image data, creating a reference spectral library by selecting end-members directly from the imagery. The benthos and substrate type map showed a dependence on depth, which was likely due to the end-member selection process. The reference spectral library should have contained spectra for each benthos and substrate type at each depth mapped, which was not

the case. Using site specific optical differences, rather than location-independent spectral signatures, also limits the application of the mapping approach [8]. Kutser *et al.* [14] classified Hyperion image data using forward modelling of *in-situ* spectra to at-sensor radiance with raw image data, and remote sensing reflectance just above the water surface with atmospherically corrected imagery. Like the present study, Kutser *et al.* [14] did not need to measure the reflectance of each benthos and substrate type *in-situ* at each of the depths mapped, because water attenuation was modelled, and *in-situ* pure end-member spectral reflectance signatures appear to show no significant change with depth [52]. Unfortunately, their classified images had limited validation because their field data were limited in benthos and substrate types and spatial coverage, although their bathymetry estimates matched well with a nautical chart of the site. This study extended the work by Kutser *et al.* [14], testing the SAM algorithm with forward modelled spectra to subsurface reflectance and CASI-2 hyperspectral airborne image data. The CASI-2 image data was of a spatial resolution that is more commensurate with the pure end-member spectral signatures constituting the spectral reference library because benthos and substrate types are more likely to be dominated by these end-members of a 1 m pixel size than the 30 m pixel size of Hyperion. In this study, the validation of a greater variety of benthos and substrate types was possible, providing further evidence for the applicability of the approach for mapping coral reef environments. However, like Kutser *et al.* [14], the validation of this study was limited by the amount of *in-situ* field data that was available.

Kutser *et al.* [14] used a spectral angle threshold of 0.2 radians, which was at least double the greatest angle used in this study (Table 2). This was necessary to allow a 30 m Hyperion pixel to sufficiently relate to a pure end-member spectral reflectance signature originally measured within a 0.03 m wide GFOV. The threshold angle used in this study, whilst reducing commission errors, may also have resulted in a high rate of omission errors. The high number of unclassified pixels in the benthos and substrate classification image is an area that needs further investigation. Using mixed end-member spectra to supervise image classification could have classified pixels dominated by two or more benthos and substrate types, such as the heterogeneous upper surfaces of patch reefs (Figure 4c); this would likely result in fewer unclassified pixels in the benthos and substrate classified image.

The CASI-2 spectral response is adjustable, and is calibrated before image data are acquired. This allows the user to set the band locations and widths, a decision that is critical for the detection of spectral features to identify the different benthos and substrate types being mapped. The CASI-2 spectral response was selected using full resolution *in-situ* spectral reflectance signatures of pure end-members with negligible water column attenuation, for use with the semi-analytical model SAMBUCA [42]. Figure 9 shows the high retention of spectral features when the full resolution pure end-member spectra of bottom reflectance were integrated across the CASI-2 spectral response curves. For this study, however, the reference spectral reflectance library was reflectance just beneath the water surface, modelled to incorporate water column attenuation, which significantly modifies the spectral shape of the reflectance curves. Figure 3 shows that some features in the modelled full resolution spectral reference library were not captured by the CASI-2 spectral response used in this study. Future applications using the mapping approach presented in this study should ensure that if the sensor has a user defined spectral response, that it is optimised for the spectra in the spectral reflectance reference library. This should result in an increased ability to map benthos and substrate types, whose spectral features were not detected in this study due to the CASI-2 spectral response,

including live coral and benthos and substrate types with pigments from the division Rhodophyta (red macro-algae and crustose coralline algae).

Figure 9. The left column shows spectral reflectance signatures measured *in-situ* with negligible water column attenuation for red macro-algae, crustose coralline algae, and live coral (brown-mode). The coloured lines represent the full resolution (400–800 nm) spectra, and the black lines represent the corresponding curves integrated across spectral response curves of the CASI-2 sensor. The CASI-2 sensor was able to capture the (complex) spectral reflectance features that characterise these benthos and substrates. In comparison, many of these features were not captured when the subsurface reflectance spectra were integrated across the spectral response curves of the CASI-2 sensor (right column, taken from Figure 3).
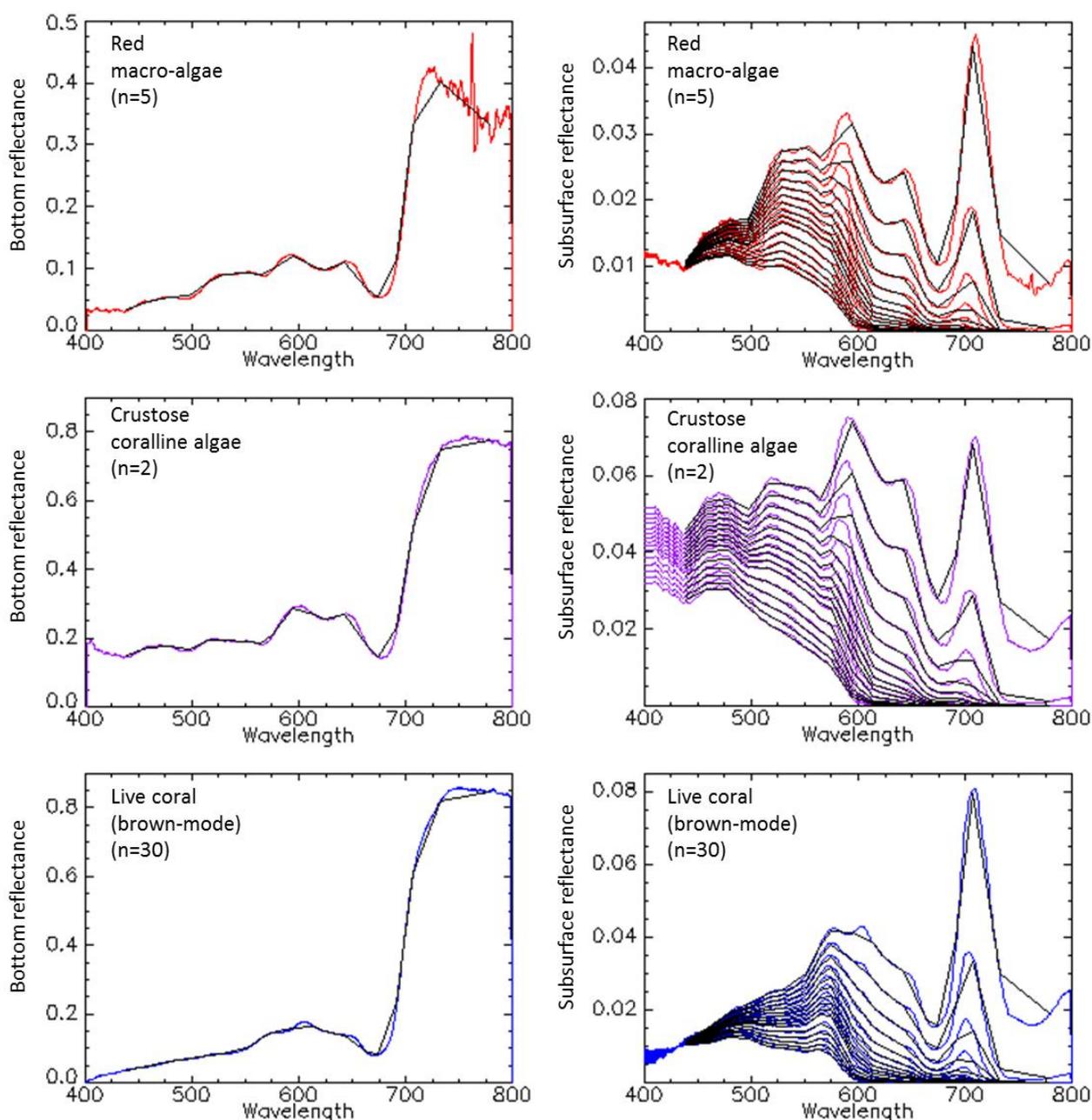
5. Conclusions

This study used a reef-up approach to map coral reef benthos, substrates, and bathymetry, investigating a physics-based inversion model for mapping. That both spatial and spectral resolution was commensurate between image data, the coral reef targets being mapped, and the reference spectral reflectance signatures, is notable for this study.

Bathymetry was mapped at 0.5 m intervals to a depth of 10.0 m, and showed high correspondence (R^2 value of 0.93) with *in-situ* sonar data. Sediment, benthic micro-algae, algal turf, crustose coralline algae, macro-algae, and live coral were mapped with an overall accuracy of 65%. The ability to map both live coral and macro-algae has important applications for monitoring reef health and status.

The amount of field data available for quantitative validation was a limitation of this study, and needs to be an important focus for future coral reef mapping studies. Using the reef-up mapping approach presented in this paper to classify images prior to fieldwork could assist survey planning. This would maximise chances of collecting a validation dataset for a comprehensive accuracy assessment of all benthos and substrate types, at a range of depths.

Light attenuation in the water column was shown to present a significant challenge for mapping marine benthos and substrates in water depths greater than 8.0 m. Future research is needed to identify spectral features in the lesser attenuated shorter wavelengths which may be used for discrimination. High spatial and spectral resolution sensors with an adjustable user-defined spectral response, such as the Compact Airborne Spectrographic Imager (CASI), could then be optimised according to such wavelengths and necessary bandwidths prior to data acquisition.

Author Contributions

Ian Leiper designed the study, conducted the analysis, and wrote the manuscript with contribution from all co-authors. Stuart Phinn, Karen Joyce, Chris Roelfsema, and Arnold Dekker were involved in CASI image data acquisition and processing. All authors were involved in field survey data collection. Ian Leiper, Stuart Phinn, and Arnold Dekker secured funding for this research.

Conflicts of Interest

The authors declare no conflict of interest.

References

1. Green, E.P.; Mumby, P.J.; Edwards, A.J.; Clark, C.D. A review of remote sensing for the assessment and management of tropical coastal resources. *Coast. Manag.* **1996**, *24*, 1–40.
2. Mobley, C.D.; Sundman, L.K.; Davis, C.O.; Bowles, J.H.; Downes, T.V.; Leathers, R.A.; Montes, M.J.; Bissett, W.P.; Kohler, D.D.R.; Reid, R.P.; *et al.* Interpretation of hyperspectral remote-sensing imagery by spectrum matching and look-up tables. *Appl. Opt.* **2005**, *44*, 3576–3592.
3. Hochberg, E.J.; Atkinson, M.J.; Andrefouet, S. Spectral reflectance of coral reef bottom-types worldwide and implications for coral reef remote sensing. *Remote Sens. Environ.* **2003**, *85*, 159–173.
4. Leiper, I.; Phinn, S.; Dekker, A.G. Spectral reflectance of coral reef benthos and substrate assemblages on heron reef, Australia. *Int. J. Remote Sens.* **2012**, *33*, 3946–3965.
5. Andrefouet, S.; Payri, C.; Hochberg, E.J.; Hu, C.; Atkinson, M.J.; Muller-Karger, F.E. Use of *in-situ* and airborne reflectance for scaling up spectral discrimination of coral reef macroalgae from species to communities. *Mar. Ecol. Prog. Ser.* **2004**, *283*, 161–177.
6. Mumby, P.J.; Hedley, J.D.; Chisholm, J.R.M.; Clark, C.D.; Ripley, H.; Jaubert, J. The cover of living and dead corals from airborne remote sensing. *Coral Reefs* **2004**, *23*, 171–183.
7. Andrefouet, S.; Hochberg, E.J.; Payri, C.; Atkinson, M.J.; Muller-Karger, F.E.; Ripley, H. Multi-scale remote sensing of microbial mats in an atoll environment. *Int. J. Remote Sens.* **2003**, *24*, 2661–2682.
8. Bertels, L.; Vanderstraete, T.; van Coillie, S.; Knaeps, E.; Sterckx, S.; Goossens, R.; Deronde, B. Mapping of coral reefs using hyperspectral casi data; A case study: Fordata, tanimbar, indonesial. *Int. J. Remote Sens.* **2008**, *29*, 2359–2391.
9. Mumby, P.J.; Green, E.P.; Clark, C.D.; Edwards, A.J. Digital analysis of multispectral airborne imagery of coral reefs. *Coral Reefs* **1998**, *17*, 59–69.
10. Mumby, P.J.; Green, E.P.; Edwards, A.J.; Clark, C.D. Coral reef habitat-mapping: How much detail can remote sensing provide? *Marine Biol.* **1997**, *130*, 193–202.
11. Hunter, E.L.; Power, C.H. An assessment of two classification methods for mapping Thames Estuary intertidal habitats using CASI data. *Int. J. Remote Sens.* **2002**, *23*, 2989–3008.
12. Purkis, S.J.; Pasterkamp, R. Integrating *in situ* reef-top reflectance spectra with Landsat TM imagery to aid shallow-tropical benthic habitat mapping. *Coral Reefs* **2004**, *23*, 5–20.
13. Purkis, S.J. A "Reef-Up" approach to classifying coral habitats from IKONOS imagery. *IEEE Trans. Geosci. Remote Sens.* **2005**, *43*, 1–16.
14. Kutser, T.; Miller, I.; Jupp, D.L.B. Mapping coral reef benthic substrates using hyperspectral space-borne images and spectral libraries. *Estuar. Coast. Shelf Sci.* **2006**, *70*, 449–460.
15. Lesser, M.P.; Mobley, C.D. Bathymetry, water optical properties, and benthic classification of coral reefs using hyperspectral remote sensing imagery. *Coral Reefs* **2007**, *26*, 819–829.
16. Kruse, F.A. Preliminary results—Hyperspectral mapping of coral reef systems using EO-1 hyperion, Buck Island, U.S. Virgin Islands. In Proceedings of the 12th JPL Airborne Geoscience Workshop, Pasadena, CA, USA, 24–28 February 2003.
17. Done, T.J. Phase shifts in coral reef communities and their ecological significance. *Hydrobiologia* **1992**, *247*, 121–132.

18. Jell, J.S.; Flood, P.G. *Guide to the Geology of Reefs of the Capricorn and Bunker Groups, Great Barrier Reef Province with Special Reference to the Heron Reef*; University of Queensland Press: Brisbane, Queensland, Australia, 1978.

19. Ahmad, W.; Neil, D.T. An evaluation of Landsat Thematic Mapper (TM) digital data for discriminating coral reef zonation: Heron Reef (GBR). *Int. J. Remote Sens.* **1994**, *15*, 2583–2597.

20. Jupp, D.L.B.; Heggen, S.J.; Mayo, K.K.; Kendal, S.W.; Bolton, J.R.; Harrison, B.A. *The Brian Handbook: An Introduction to Landsat and the Brian (Barrier Reef Image Analysis) Systems for Users*; Australia Commonwealth Scientific and Industrial Research Organisation Division of Water and Land Resources Natural Resources Series: Melbourne, Australia, 1985.

21. Jupp, D.L.B.; Mayo, K.K.; Kuchler, D.A.; Heggen, S.J.; Kendall, S.W.; Radke, B.M.; Ayling, T. Landsat based interpretation of the cairns section of the Great Barrier Reef Marine Park (Australia). *Remote Sens.* **1985**, *4*, 42–44.

22. Joyce, K.E.; Phinn, S.R.; Roelfsema, C.M.; Neil, D.T.; Dennison, W.C. Combining Landsat ETM plus and Reef Check classifications for mapping coral reefs: A critical assessment from the southern Great Barrier Reef, Australia. *Coral Reefs* **2004**, *23*, 21–25.

23. Andrefouet, S.; Kramer, P.; Torres-Pulliza, D.; Joyce, K.E.; Hochberg, E.J.; Garza-Perez, R.; Mumby, P.J.; Riegl, B.; Yamano, H.; White, W.H.; *et al.* Multi-site evaluation of IKONOS data for classification of tropical coral reef environments. *Remote Sens. Environ.* **2003**, *88*, 128–143.

24. Phinn, S.R.; Roelfsema, C.M.; Mumby, P.J. Multi-scale, object-based image analysis for mapping geomorphic and ecological zones on coral reefs. *Int. J. Remote Sens.* **2012**, *33*, 3768–3797.

25. Hedley, J.; Roelfsema, C.; Phinn, S.R. Efficient radiative transfer model inversion for remote sensing applications. *Remote Sens. Environ.* **2009**, *113*, 2527–2532.

26. Joyce, K.E.; Phinn, S.R.; Roelfsema, C.M. Live coral cover index testing and application with hyperspectral airborne image data. *Remote Sens.* **2013**, *5*, 6116–6137.

27. Joyce, K.E.; Phinn, S.R. Bi-directional reflectance of corals. *Int. J. Remote Sens.* **2002**, *23*, 389–394.

28. Joyce, K.E.; Phinn, S.R. Hyperspectral analysis of chlorophyll content and photosynthetic capacity of coral reef substrates. *Limnol. Oceanogr.* **2003**, *48*, 489–496.

29. Leiper, I.A.; Siebeck, U.E.; Marshall, N.J.; Phinn, S.R. Coral health monitoring: Linking coral colour and remote sensing techniques *Can. J. Remote Sens.* **2009**, *35*, 276–286.

30. Joyce, K.E.; Phinn, S.R. Spectral index development for mapping live coral cover. *J. Appl. Remote Sens.* **2013**, *7*. doi:10.1117/1.JRS.7.073590.

31. Joyce, K.E. *A Method for Mapping Live Coral Cover Using Remote Sensing*; The University of Queensland: St Lucia, Australia, 2005.

32. Kutser, T.; Jupp, D.L.B. On the possibility of mapping living corals to the species level based on their optical signatures. *Estuar. Coast. Shelf Sci.* **2006**, *69*, 607–614.

33. Clark, C.D.; Mumby, P.J.; Chisholm, J.R.M.; Jaubert, J.; Andréfouët, S. Spectral discrimination of coral mortality states following a severe bleaching event. *Int. J. Remote Sens.* **2000**, *21*, 2321–2327.

34. Holden, H.; LeDrew, E. Spectral discrimination of healthy and non-healthy corals based on cluster analysis, principal components analysis, and derivative spectroscopy. *Remote Sens. Environ.* **1998**, *65*, 217–224.

35. Holden, H.; LeDrew, E. Hyperspectral identification of coral reef features. *Int. J. Remote Sens.* **1999**, *20*, 2545–2563.

36. Kutser, T.; Dekker, A.G.; Skirving, W. Modeling spectral discrimination of great barrier reef benthic communities by remote sensing instruments. *Limnol. Oceanogr.* **2003**, *48*, 497–510.

37. Hochberg, E.J.; Atkinson, M.J.; Apprill, A.; Andrefouet, S. Spectral reflectance of coral. *Coral Reefs* **2004**, *23*, 84–95.

38. Lim, A.; Hedley, J.D.; LeDrew, E.; Mumby, P.J.; Roelfsema, C. The effects of ecologically determined spatial complexity on the classification accuracy of simulated coral reef images. *Remote Sens. Environ.* **2009**, *113*, 965–978.

39. Roelfsema, C.; Marshall, J.; Hochberg, E.; Phinn, S.; Goldizen, A.; Gill, T. Underwater Spectrometer System 2006 (UWSS04). Available online: http://ww2.Gpem.Uq.Edu.Au/crssis/ publications/uw%20spec%20manual%2029august06.Pdf (accessed on 8 May 2014).

40. Mobley, C. *Light and Water: Radiative Transfer in Natural Waters*; Academic Press: San Diego, California, 1994.

41. Haltrin, V.I. Chlorophyll-based model of seawater optical properties. *Appl. Opt.* **1999**, *38*, 6826–6832.

42. Wettle, M. *Monitoring Coral Reef Bleaching from Space a Feasibility Study Using a Physics-Based Remote Sensing Approach*; University of Hull: Yorkshire, UK, 2005.

43. Kruse, F.A.; Lefkoff, A.B.; Boardman, J.W.; Heidebrecht, K.B.; Shapiro, A.T.; Barloon, P.J.; Goetz, A.F.H. The spectral image-processing system (SIPS)—Interactive visualization and analysis of imaging spectrometer data. *Remote Sens. Environ.* **1993**, *44*, 145–163.

44. Hedley, J.D.; Mumby, P.J.; Joyce, K.E.; Phinn, S.R. Spectral unmixing of coral reef benthos under ideal conditions. *Coral Reefs* **2004**, *23*, 60–73.

45. Andrefouet, S. Coral reef habitat mapping using remote sensing: A user *vs.* producer perspective. Implications for research, management and capacity building. *J. Spat. Sci.* **2008**, *53*, 113–129.

46. Congalton, R.; Green, K. *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices*; Lewis Publishers: New York, NY, USA, 1999.

47. Congalton, R.G. A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sens. Environ.* **1991**, *37*, 35–46.

48. Lubin, D.; Wei, L.; Dustan, P.; Mazel, C.H.; Stamnes, K. Spectral signatures of coral reefs: Features from space. *Remote Sens. Environ.* **2001**, *75*, 127–137.

49. Hedley, J.D.; Mumby, P.J. Biological and remote sensing perspectives of pigmentation in coral reef organisms. *Adv. Mar. Biol.* **2002**, *43*, 277–317.

50. Andrefouet, S.; Gilbert, A.; Yan, L.; Remoissenet, G.; Payri, C.; Chancerelle, Y. The remarkable population size of the endangered clam Tridacna maxima assessed in Fangatau Atoll (Eastern Tuamotu, French Polynesia) using *in situ* and remote sensing data. *Ices J. Mar. Sci.* **2005**, *62*, 1037–1048.

51. Sohn, Y.; Rebello, N.S. Supervised and unsupervised spectral angle classifiers. *Photogramm. Eng. Remote Sens.* **2002**, *68*, 1271–1280.

52. Minghelli-Roman, A.; Chisholm, J.R.M.; Marchioretti, M.; Jaubert, J.M. Discrimination of coral reflectance spectra in the Red Sea. *Coral Reefs* **2002**, *21*, 307–314.