



Curtin University

Research Report

Examining the potential of detecting change in HICO-derived bathymetry: a case study of Shark Bay, Western Australia

HICO User's Annual Report II, April 2014

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Acknowledgements

Craig Marquardt is kindly thanked for assisting our understanding of the c-mpfit implementation of the Levenberg-Marquardt optimization algorithm. This work was funded in-part by an Australian Postgraduate Award administered by Curtin University.

Cover image

The cover image is a quasi-true colour HICO™ image of the Shark Bay World Heritage Area, Western Australia. The image was captured on 19 November 2011. Depicted is the Hopeless Reach embayment of Shark Bay, with the Peron Peninsula to the left, and the Wooramel bank to the right. The lower central part of the image shows Faure Island and to the right of it the Faure Sill – the gateway to Hamelin Pool that contains extant stromatolites. HICO™ Data provided by the Naval Research Laboratory.

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Executive summary

This report summarizes research outcomes for 2013 achieved by the Remote Sensing and Satellite Research Group (RSSRG), Curtin University, as an official HICO Data User. Since becoming an official HICO Data User in October 2011, the RSSRG has demonstrated HICO's capabilities for remote sensing optically shallow waters. Principally, the RSSRG's research efforts have focused on improving HICO retrievals of bathymetry within the Shark Bay Worlds Heritage Region, Western Australia. A particular emphasis has been placed on processing HICO data for the purpose of detecting changes in bathymetry through time.

The high spectral and spatial resolution offered by HICO surpasses current space-borne ocean color sensors. In addition, the high signal to noise ratio of HICO makes its spectral data ideal for observing the coastal ocean. However, processing HICO imagery from the distributed calibrated top-of-atmosphere radiance (L1B) product through to Level-2 (L2), sub-surface remote sensing reflectance imagery is a non-trivial task. These steps can add various amounts of noise that could render the retrieved geophysical L2 products, such as bathymetry, very imprecise. In this report we summarize recent research outcomes from the recent publication "*Detecting trend and seasonal changes in bathymetry derived from HICO imagery: A case study of Shark Bay, Western Australia*" published in Remote Sensing of Environment. We have also updated our previous HICO processing workflow, it now has a structure that incorporates:

1. atmospheric correction;
2. sunglint and air-to-water interface correction;
3. inversion using a shallow water algorithm to derive inherent optical properties (IOPs), depth and substrate albedos;
4. a method for propagating spectrally correlated noise through the inversion algorithm to estimate uncertainties in the IOPs, depth and substrate albedos;
5. image smoothing;
6. tide correction;
7. geo-registration, and;
8. temporal change detection analysis of the bathymetric product.

The updated processing workflow facilitates uncertainty estimates in HICO-derived bathymetry using a method that can be extended to planned hyperspectral ocean color missions such as the Pre-Aerosol, Clouds and ocean Ecosystem (PACE). Such estimates of uncertainties in satellite-derived geophysical products are highly important, particularly for environmental managers wishing to know if change is detectable above uncertainty.

Future research directions using HICO data will be tailored towards: improving the inversion solution of the shallow water model in the presence of spectrally correlated noise; analyzing the uncertainty in the benthic classification and assessing temporal change, and; applying this HICO processing workflow to other coastal regions in Western Australia.

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1 Introduction

Researchers from the Remote Sensing and Satellite Research Group (RSSRG) at Curtin University are presently involved in the HICO project as registered Data Users. The RSSRG has previously established expertise in processing, analysis and interpretation of airborne hyperspectral imagery over shallow marine waters. HICO was identified by the RSSRG as a space-borne sensor of interest particularly for environmental remote sensing of sensitive marine areas throughout Australia's coastline. The RSSRG's participation in the HICO project is possible only by in-kind contributions of time from research staff as there is presently no allocated funding for this project.

The RSSRG has developed a workflow to: (i) process HICO L1B calibrated top-of-atmosphere radiances to L2 above-water remote sensing reflectances using Tafkaa-6S, (ii) correct for sunglint contamination, (iii) mask cloud and land, (iv) derive inherent optical properties, water column depth and benthic classification maps using the BRUCE shallow water inversion algorithm; (v) propagate environmental and sensor noise through the BRUCE inversion algorithm to estimate the uncertainty of inherent optical properties, depth and benthic classification; (vi) geolocate L2 products using distributed geographic look-up tables (GLTs); (vii) tide correct raw bathymetry products, and; (viii) detect temporal changes in bathymetry.

Within this second HICO User Annual Report, the progress of the RSSRG's HICO project during 2013 is presented. Section 2 lists new project achievements for 2013. In section 3, a technical summary of the research achievements is given. A summary of new research results is presented in section 4. Finally, a summary of this report, future direction and current HICO-specific publications are given in section 6.

2 Project achievements

The RSSRG HICO Data User's Proposal was given approval on 5 October 2011. Since this time, much work has been done developing an appropriate workflow for access, processing and archiving HICO level-1B (L1B) data and derived level-2 (L2) products. Initial work during 2011-2012 focused on developing a logical procedure for atmospheric correction, L2 product processing of shallow water scenes, and geo-location of derived L2 products. New research completed during 2013 closely examined the combined effect of environment and sensor noise on HICO-derived geophysical parameters, an approach necessary for determining if change can be detected above uncertainty. These geophysical parameters consisted of inherent optical water properties (IOPs), water column depth, and benthic reflectance end-members, derived from a semianalytical shallow water inversion model.

Previous achievements (2011-2012):

- i. Development of a processing workflow;
- ii. Implementation of the Tafkaa-6S atmospheric correction scheme;
- iii. Successful inversion of HICO data to retrieve IOPs, bathymetry and benthic habitat maps, and;
- iv. Performed geo-location using Google Earth™ ground control points.

New achievements (2013):

- i. Successfully used spectrally correlated noise to determine uncertainty in the geophysical derived parameters;
- ii. Derived a time-series of bathymetry for Shark Bay World Heritage Area;
- iii. Developed an image based tide correction technique;
- iv. Investigated the potential for measuring change detection with HICO imagery;
- v. Examined improved methods for initialising the Levenberg-Marquardt optimization routine, and;
- vi. New research published in literature (Garcia et al. 2014; see reference list).

3 Technical summary

The first year of this project (2011-2012) focused on developing a HICO processing workflow from L1B data to above-water remote sensing reflectances, R_{rs} , that could be run in-house on a Linux-based computing platform. During the second year of this project (2013), the following were incorporated into the processing workflow: (1) propagation of total system (sensor + environmental) noise in order to estimate the uncertainty of the derived geophysical parameters; (2) post-processing image smoothing; (3) post-processing tide correction of bathymetry imagery, and; (4) bathymetric change detection. The basic structure of the workflow is shown schematically in Figure 1. In this figure the blue labels are the processing steps that were generated between 2011-2012, whilst the red labels are new steps created between 2012-2013.

3.1 Propagating spectral uncertainty through the BRUCE inversion algorithm

After atmospheric, sun-glint and air-to-water interface corrections, the HICO-derived sub-surface remote sensing reflectance (r_{rs}) image data will contain spectral noise from the sensor and from atmospheric fluctuations and sea surface state. Propagating this total system noise through the BRUCE inversion algorithm (BRUCE: Klonowski et al., 2007) is essential for estimating the uncertainty of the derived geophysical parameters. To achieve this, the uncertainty propagation technique developed by Hedley et al. (2010; 2012) was used. In this technique, the spectrally correlated noise, computed from the spectral covariance matrix of a dark homogeneous water region in the r_{rs} image, was used to generate 20 noise-perturbed $r_{rs} + \Delta r_{rs}$ spectra for each pixel within the scene. With the aid of the constrained Levenberg-Marquardt algorithm (Markwardt, 2009), the BRUCE algorithm was used to retrieve the values of $a_{\phi}(440)$, $a_{dg}(440)$, $b_{bp}(550)$, depth, $B_{sediment}$ and $B_{seagrass}$ for each noise-perturbed spectra. The mean average and standard error were then calculated for each geophysical parameter, where the latter was taken as the uncertainty. For a more detailed explanation see Garcia et al. (2014).

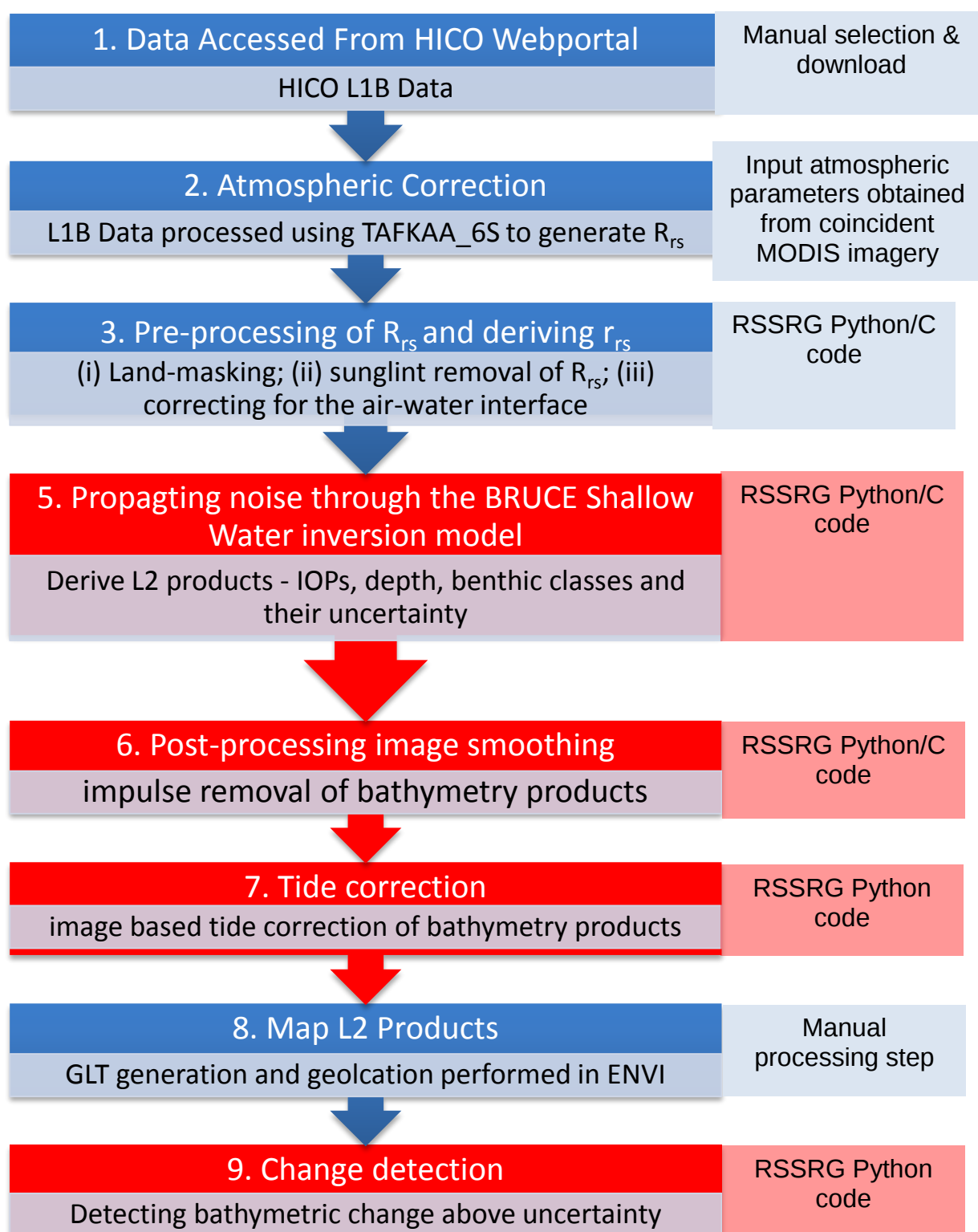


Figure 1: The present HICO processing workflow implement by the RSSRG. The blue and red panels are those processing steps developed during 2011-2012 and 2012-2013 respectively.

3.2 Improving the Levenberg-Marquardt optimization initialization

The Levenberg-Marquardt algorithm (L-M) is a type of local optimization algorithm and is understood to potentially converge to local minima – rather than the global minimum. In this case the global minimum would be those set of parameters whose modelled r_{rs} matches exactly with the sensor-derived r_{rs} . This method commences with the inversion of the sensor-derived r_{rs} spectrum of a given pixel to obtain an initial estimate of the inherent optical properties, depth and bottom albedo coefficients. If the Euclidean distance of this initial inversion was $\leq 1.0 \times 10^{-4}$, then the optimized model parameters formed the initial guesses for the inversion of the set of noise perturbed spectra. If the Euclidean distance of the initial optimization was greater than 1.0×10^{-4} , then the optimized parameters were randomly perturbed by 10% of their value and used as the initial guess for a subsequent inversion attempt. This inversion-perturbation step was repeated until either the Euclidean distance fell below 1.0×10^{-4} or if this step was repeated more than 4 times. In the latter, the optimized parameters that produced the lowest Euclidean distance formed the initial guess for the inversion of the set noise-perturbed spectra. We call this process the ‘update-repeat method’. Note that the Euclidean distance, is defined as,

$$Euclidean\ Distance = \sqrt{\sum_i^N (r_{rs,i} - \hat{r}_{rs,i})^2}$$

where $r_{rs,i}$ and $\hat{r}_{rs,i}$ are the sensor-derived and modelled reflectance respectively, at wavelength, i .

3.3 Image Smoothing

The retrieved bathymetry products contained various amounts of speckled salt-and-pepper noise pixels (henceforth referred to as impulse noise). To remove this effect whilst preserving image sharpness the following three step smoothing procedure was applied to the retrieved bathymetry product (image):

- (1) An impulse noise detection algorithm;
- (2) An adaptive median filter, applied to each identified impulse pixel from step (1), and;
- (3) The convolution of a second order binomial smoother with the resultant image from step (2).

The impulse noise detection algorithm simply tested if the central pixel of a 3×3 kernel had a magnitude that was substantially different from its surrounding 8 pixels. Specifically, the

central pixel was classified as impulse noise if the difference in depth between it and four or more of its surrounding pixels was greater than 2 meters. The threshold of 2 meters can be changed according to the scene or prior knowledge.

In the adaptive median filter stage, the kernel size of the median filter was iteratively changed according to the number of undesired pixels within the kernel. In this case, undesired pixels included cloud, land and other impulse noise pixels. We allowed the kernel size of the median filter to increase if more than 50% of the pixels in the kernel were undesired. Note that the undesired pixels were not included in the median calculation, and; a maximum kernel size of 15×15 was imposed to the adaptive median filter, whereby the calculation of the median was forced. The bathymetry uncertainty imagery were also modified during smoothing steps (2) and (3). In step (2) the uncertainty of the central impulse noise pixel was changed by the uncertainty of the selected median pixel.

3.4 Image based tide correction

Tide correction was performed in order to detect changes in the depth due to erosion, re-suspension, and/or sedimentation through time relative to a common datum. An image based tide correction technique was developed, whereby an offset was applied to each HICO-derived bathymetry image that in effect normalized the bathymetry time series to a reference depth. This reference depth was taken as the median of the shallow water pixels (< 3 meters in depth) across the all bathymetry images. The offset for each image was calculated by subtracting the median depth of the shallow water pixels for the given image from the reference depth. For a more detailed explanation see Garcia et al. (2014).

4 Application case study: Shark Bay World Heritage Area

Within this section, the processing capabilities developed within the second year (2013) of this project are demonstrated. The following case study focuses on a HICO scene captured over the Faure Sill, Western Australia.

4.1 Description of the Faure Sill

Shark Bay is a sub-tropical embayment that covers approximately 28,000 km² (Figure 2). The Shark Bay region is home to twelve species of seagrass that cover more than 4000 km² within the Bay (Walker et al. 1988). The presence of seagrasses, over a period exceeding 5000 years, has led to the development of sediment based structures such as the Faure Sill - a

shallow agglomeration of sand atop a sandstone ridge, located in the eastern inlet between Peron Peninsula and the mainland (see Figure 2). The Faure Sill is a shallow region with an average depth of 1 – 2 m with several deeper channels of 5 – 7 m in depth (Burling et al. 2003). The Faure Sill is a salinocline region between the hypersaline waters of Hamelin Pool, located to the south, and the metahaline waters of the Hopeless Reach, to the north. The presence of the Sill, which decreases interactions of the ocean with the waters of Hamelin Pool, combined with low rainfall and minimal runoff into Hamelin Pool, and the large annual evaporation, all combine to maintain extremely high salinity within Hamelin Pool (50 - 70 PSU). The unique hypersaline environment is suitable for rare stromatolites and algal mats.

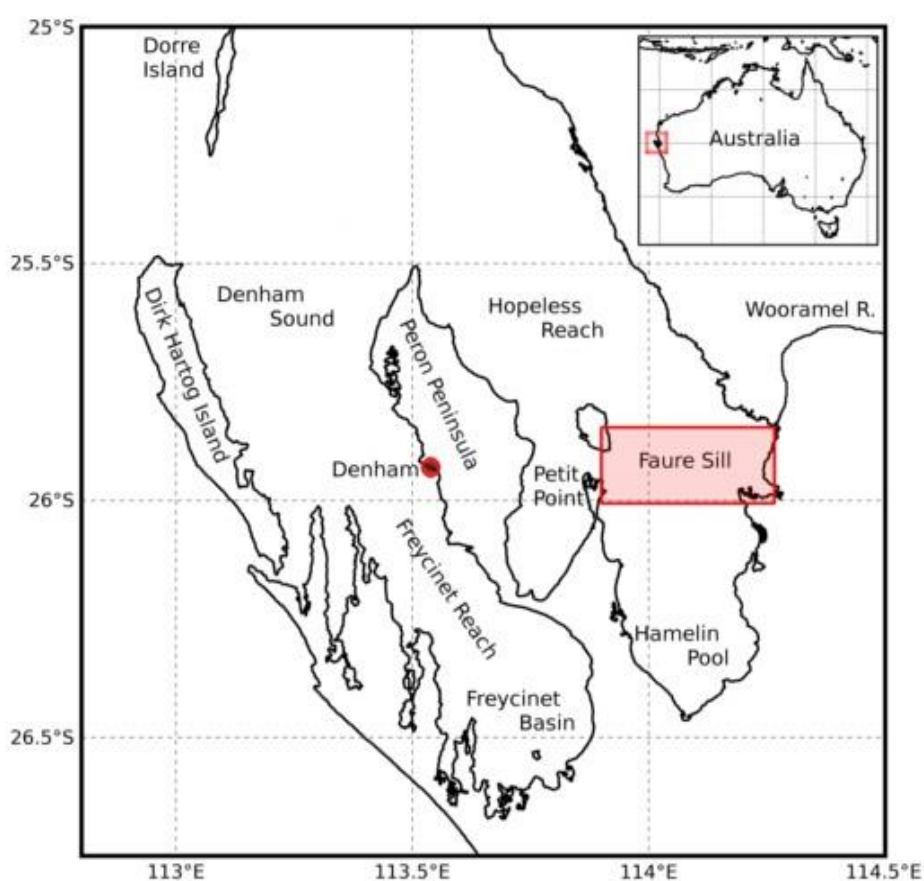


Figure 2: Location map of Shark Bay, Western Australia. The approximate position of the Faure Sill is highlighted in red.

4.2 HICO processing

4.2.1 HICO time series processing

To demonstrate the processing capabilities developed, we have selected nine HICO scenes of the Faure Sill captured from 19 November 2011 to 8 August 2012 (see Figure 3). For each HICO image, the L1B data were atmospherically corrected using Tafkaa 6S and a pixel-by-pixel sunglint correction was performed. After correction of the air-to-water interface, a dark water region was manually selected by 'eye' and used to extract the spectrally correlated noise. Each HICO-derived r_{rs} were then perturbed by this spectrally correlated noise of various magnitudes. The result was a set of $r_{rs} + \Delta r_{rs}$ spectra per pixel, which were inverted to derive the water column IOPs, water column depth and bottom albedo coefficients and their uncertainties. Here the BRUCE model was parameterized with two end-members albedo spectrum of sand and mixed seagrass (*Amphibolis antarctica* and *Posidonia australis*) respectively. These three benthic reflectances were measured during a field survey of Shark Bay, WA in May 2011. The total wall time for processing a single HICO scene from L1B to L2 products with their uncertainty is approximately 6 hours. It should be noted that the majority of this time is taken up by the propagation of noise through the inversion as a given HICO scene is effectively inverted 20 times (see section 3.1). Three examples of HICO-derived bathymetry and the associated uncertainties are shown in Figure 4.

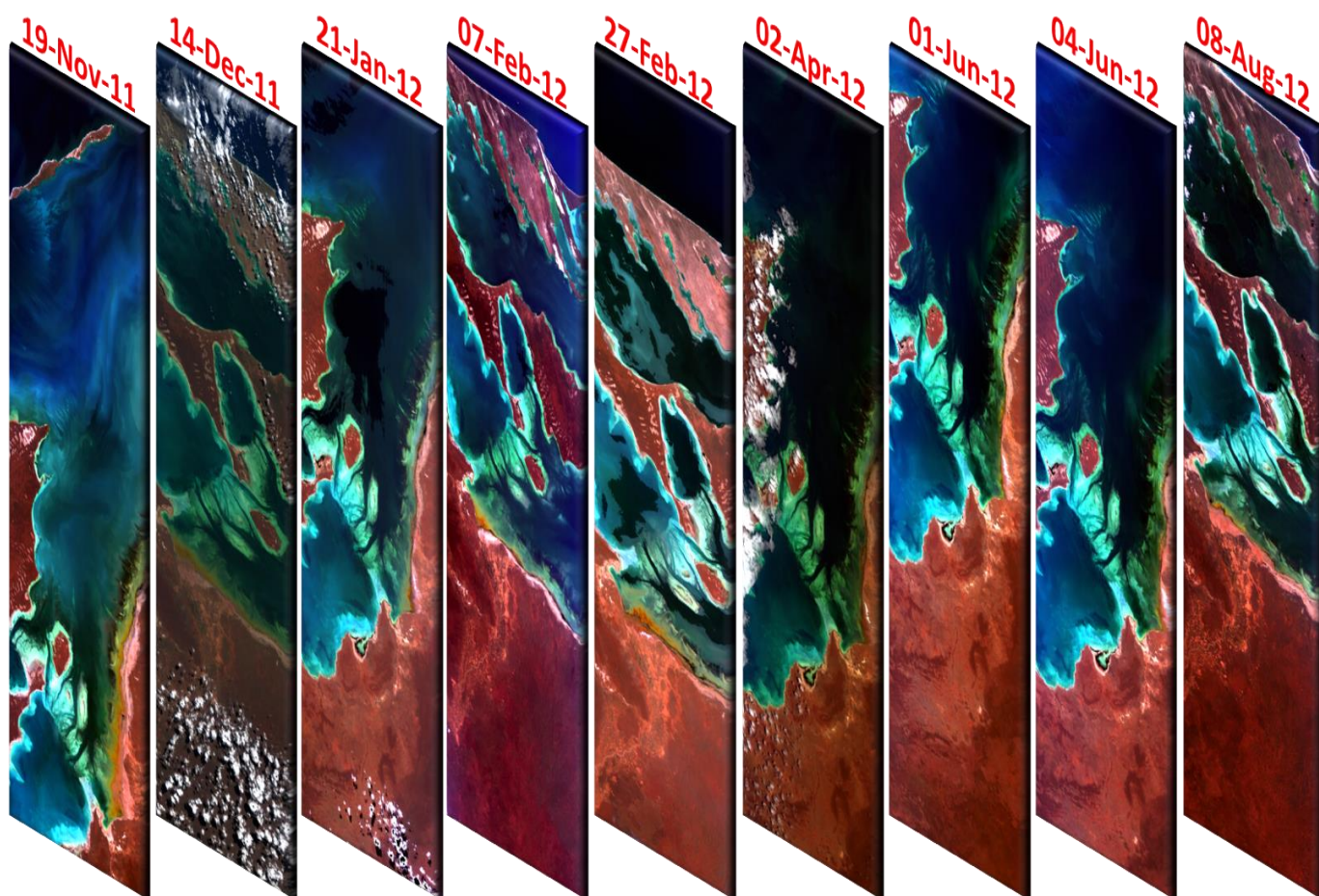


Figure 3: Pseudo true color imagery of the HICO derived sub-surface remote sensing reflectance, r_{rs} , for the nine overpasses of Shark Bay, Western Australia. Note that r_{rs} was only computed for the water pixels. Land pixels are displayed using their at-surface remote sensing reflectance.

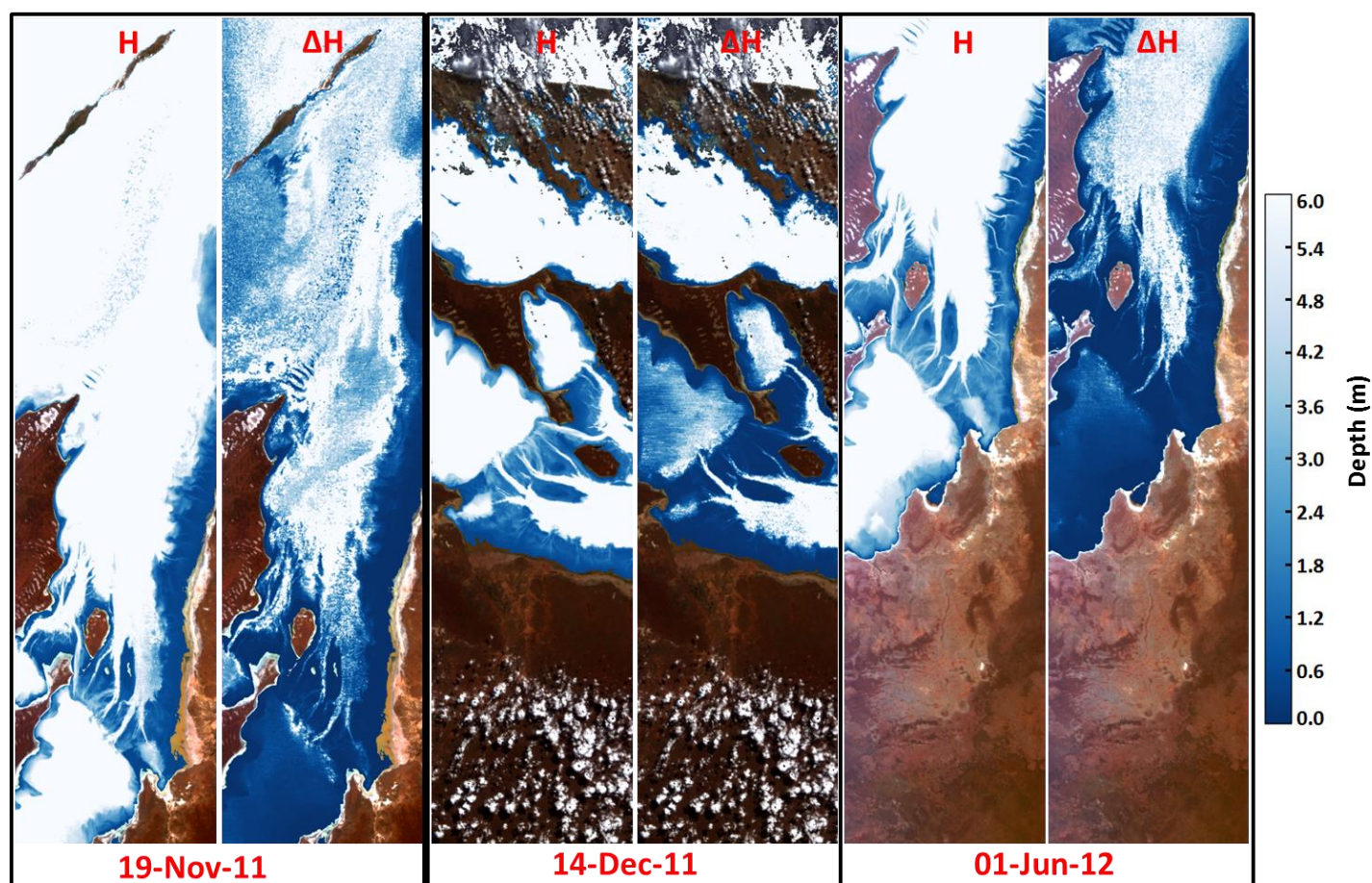


Figure 4: HICO-derived, smoothed bathymetry (H) and its uncertainty product (ΔH) of Shark Bay on 19 November 2011, 14 December 2011 and 1 June 2012. Dark blue region represent shallow water with a graduation to white representing deeper water. Various geomorphological features such as sub-tidal sand bars and flats, tidal-drainage channels and tidal-exchange channels can be resolved.

4.2.2 Effect of sensor-environment noise

The noise considered here arises from the HICO sensor and imperfect atmospheric/sun-glint/air-to-water interface corrections. As such this noise is predominantly unrelated to the signal magnitude, $||r_{rs}||$. Note that in shallow water, $||r_{rs}||$ varies according to the IOPs, depth and the substrate albedo (Hedley et al. 2012). Hence the relative uncertainty in r_{rs} would be larger for dark water targets (e.g. shallow water with a dark substrate), and smaller for bright water targets (e.g. shallow water with a bright substrate). The 'sensor + environment' noise was propagated through the shallow water inversion, where it was found that the relative uncertainty in the retrieved depth exponentially decreased as the pseudo signal-to-noise ratio (SNR) increased. In other words, lower relative uncertainties in the retrieved depth were obtained for bright shallow water pixels. Here the pseudo SNR was calculated on a per pixel basis from each HICO-derived r_{rs} image, i.e. the SNR after atmospheric/sun-glint/air-to-water interface corrections. Typically, a relative uncertainty of less than 10% in the retrieved depth were afforded for pixels with a pseudo SNR greater than 20. This was a promising outcome as the majority of the shallow water pixels (< 10 m) from the entire HICO-derived bathymetry dataset had a pseudo SNR greater than 20. For a more detailed explanation see Garcia et al. (2014).

4.2.3 Ability to detect change

Coastal marine managers require methods for detecting change from satellite-derived products over large areas. We have explored the ability to assess temporal change from HICO-derived tide corrected bathymetry products. Using a statistical analysis that incorporated the uncertainty of each bathymetry image, we were able to ascertain that a change in depth as low as 0.4 m is possible (under optimal conditions). Any changes in depth below 0.4 m are likely due to residual random fluctuations caused from imperfect atmospheric/sun-glint/air-to-water interface and tide corrections, and model parameterizations within the BRUCE inversion algorithm. This level of precision is encouraging given the amount of processing steps each HICO image underwent (see Figure 1). However, it is stressed that adequate sub-pixel geolocation accuracy is needed to detect real temporal changes in any satellite-derived product. Specifically, Dai and Khorram (1998) showed that to detect 90% of real temporal changes a geolocation accuracy of one-fifth the pixel size is needed which for HICO equates to approximately 20 m. Because the distributed geolocation look-up tables (GLTs) were insufficient, a substantial number of manual ground

control points were required in the geo-registration stage; not a trivial task when geo-registration has to be performed for multiple HICO scenes. For a more detailed explanation see Garcia et al. (2014).

5 Summary

This study has shown that, despite all the image processing steps HICO data underwent, it was possible to detect temporal changes in depth to as low as 0.4 m. This low detection limit was afforded by the relatively high precision of the HICO-derived bathymetry, which in turn depended on the optimization scheme implemented (results presented in Garcia et al. (manuscript under-review)). The accuracy of the bathymetric retrievals were not assessed in this study, however it was evident that the atmospheric correction introduced several spectral artifacts to the at-surface remote sensing reflectance (see Garcia et al. 2014), which can reduce the accuracy of the derived geophysical parameters. The magnitude of these spectral artifacts was comparable to the magnitude of the R_{rs} signal for optically deep-water pixels, though not so for bright shallow water targets.

Removing the atmospheric influence from HICO imagery of optically complex waters remains a challenging task. Many of the atmospheric correction algorithms, such as Taflaa (Gao et al. 2000), require wavebands in the SWIR to select the most appropriate atmospheric parameters in a per-pixel basis – bands that HICO does not have. This study has also shown that estimating these atmospheric parameters from coincident MODIS imagery and using them as inputs to Taflaa does not always yield adequate atmospheric correction. This could be due to poor estimation of the atmospheric parameters from MODIS or that the atmospheric/aerosol models used were not adequate for the semi-arid coastal region of Shark Bay.

Assessing temporal change in any derived geophysical parameter necessitates an estimation of the uncertainty to infer confidence. The method of propagating uncertainty (Hedley et al 2010; 2012), and the optimization scheme that is tailored toward improving the inversion solution in the presence of spectrally correlated noise, are transferable to any ocean color model as well as to other ocean color airborne/satellite sensors. Additionally, the image based tide correction scheme, and the statistical analysis used to infer a temporal change

can be implemented on any bathymetry time-series dataset derived from a variety of sensors/algorithms.

Within the next twelve months the RSSRG hopes to continue as HICO Data Users, with a focus on:

- Assessing the impact that sensor and environmental noise has on the classification of the benthos;
- Ongoing attempts at validating HICO-derived products;
- Implementing improved sunglint correction schemes (such as Hedley et al. 2005);
- Investigate alternative approaches for atmospheric correction such as 6SV (Kotchenova et al. 2008);

5.1 HICO-related publications

The following HICO-related publications have been published or are in the review process at the time of writing this report:

Garcia, R.A., Fearn, P.R.C.S. and L.I.W. McKinna (2014). Detecting trend and seasonal changes in bathymetry derived from HICO imagery: A case study of Shark Bay, Western Australia, *Remote Sensing of Environment*, 147C, 186-205, DOI: <http://dx.doi.org/10.1016/j.rse.2014.03.010>.

Garcia, R., McKinna, L.I.W, and P. Fearn (under review), Improving the optimization solution for a semi-analytical shallow water inversion model in the presence of spectrally correlated noise, *Limnology and Oceanography: Methods*.

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Dai, X., & Khorram, S. (1998). The effects of image misregistration on the accuracy of remotely sensed change detection. *IEEE Transactions on Geoscience and Remote Sensing*. 36(5), 1566-1577.

Egbert, G. D., and S. Y. Erofeeva. (2002). Efficient inverse modelling of barotropic ocean tides. *Journal of Atmospheric and Oceanic Technology*. 19(2), 183-204.

Gao, B., Montes, M. J., Ahmad, Z., and Davis, C. O. (2000). Atmospheric correction algorithm for hyperspectral remote sensing of ocean color from space. *Applied Optics*, 39(6), 887-896.

Hedley, J., A. Harborne, and P. Mumby. (2005). Simple and robust removal of sun glint for mapping shallow-water benthos. *International Journal of Remote Sensing*. 26, 2107-2112.

Hedley, J., C. Roelfsema, and S. Phinn. (2010). Propagating uncertainty through a shallow water mapping algorithm based on radiative transfer model inversion. *Proceedings of Ocean Optics XX*, Anchorage.

Hedley J., C. Roelfsema, B. Koetz, and S. Phinn. (2012). Capability of the Sentinel 2 mission for tropical coral reef mapping and coral bleaching detection. *Remote Sensing of Environment*. 120, 145-155.

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Kotchenova, S. Y., E. F. Vermote, R. Levy, and A. Lyapustin. (2008). Radiative transfer codes for atmospheric correction and aerosol retrieval: Intercomparison study. *Applied Optics*, 47, 2215-2226.

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Walker, D. I., Kendrick, G. A., & McComb, A. J. (1988). The distribution of seagrass species in Shark Bay, Western Australia, with notes on their ecology. *Aquatic Botany*, 30, 305-317.