RECONSTRUCTION OF SEAGRASS EXTENT FROM RETROSPECTIVE ANALYSIS OF LANDSAT IMAGERY

JANET M. ANSTEE
CSIRO Oceans and Atmosphere, CS Christian Laboratory, Canberra ACT 2601, Australia

KLAUS D. JOEHNK, SCOTT N. WILKINSON, FAZLUL KARIM & ZYGMUNT LORENZ
CSIRO Land and Water, CS Christian Laboratory, Canberra ACT 2601, Australia

Archival remote sensing imagery were used to reconstruct seagrass coverage and turbidity time-series for Western Port, Victoria. This enables investigation of the extent to which seagrass coverage and bay turbidity are, and have been, sensitive to river discharge and suspended solids or climatic fluctuations. Furthermore, the use of remote sensing to derive physical parameters that can be used to calibrate a hydrodynamic model is a new and novel approach, compared with the more traditional methods of model calibration using in-situ measurements.

Based on the relationship between the satellite derived reflectance and the inherent optical properties of the water column, semi-empirical algorithms can be derived for these optically complex waters to provide estimates of substrate composition and water quality information. The application of these methods for multispectral satellite imagery analysis has several limitations, however, the benefit of the hyperspectral models have been found to produce better results compared with alternative methods. Multi-temporal data from the Australian Geoscience Data Cube (AGDC) when combined with the optical modelling approach, enables consistent large scale spatio-temporal analysis of seagrass extent and of coastal water quality. These analyses are used in support of analysis of turbidity sources, hydrodynamic modelling and seagrass modelling activities, which are reported in separate abstracts.

Keywords: retrospective analysis, optical modelling, multi-temporal, remote sensing, seagrass mapping

1 INTRODUCTION

Satellite imagery is a valuable data type for monitoring coastal resources over large areas, as the spatial coverage provides contextual information often unavailable through ground based survey. Landsat satellite imagery provides medium resolution (spatial resolution of 25 meters) that is on an environmentally relevant spatial scale but requires a standardised approach in which to monitor temporal change [1]. Previous assessments have often suffered from sensor resolution limitations [2], but even so, they can be sufficient to highlight distributional ecosystem differences between successive image acquisitions.

A physics-based inversion model was developed for hyper-spectral data [3] to retrieve bathymetry, substrate composition and water quality information [(concentrations of chlorophyll-a (CHL), non-algal particulates (NAP) and colour dissolved organic matter (CDOM)]. Based on optical modeling, this approach requires an understanding of the interactions between light and the atmosphere, the water surface, water column constituents and the substratum, if optically shallow [4].

Retrieving information from satellite data on water quality and benthic substrata from (often multispectral) satellite data through the inversion of constituents and substratum is constrained by the spectral and spatial characteristics of the satellite imagery. The complexity of coastal environments where water constituents, benthic substrate and depth are all varying, means more spectral bands are required to sufficiently resolve details and to separate benthic habitat features.

2 DATA AND METHODS

2.1 Study Site

Western Port, in southern Victoria, Australia (area 270 km^2) is a relatively shallow embayment with important saltmarsh, mangrove and seagrass communities. Previous studies have shown extensive loss of seagrass coverage between the 1970s and 2000s [5]. Since this time, there have been previous studies showing progressive loss in some areas, while re-establishment in others. However, areas such as the upper north and eastern regions of the bay are chronically turbid and the intertidal substrate remains non-vegetated.

2.2 Satellite Data

It was proposed in this research to apply the optical modelling approach on archival Landsat data. Landsat 8, launched in 2013 provides this research with current imagery for assessment while Landsat 5 and 7 data provides archival imagery from 1987. Suitable Landsat images were acquired from both the USGS archive and the Australian Geoscience DataCube (AGDC) free of charge. Landsat 8 has an increased data capture capacity and an improved signal to noise performance compared to the older Landsat satellites.

2.3 Model for Substrate Retrieval

A physics-based model offers an objective and repeatable algorithm for retrieval of substratum-type information from remote sensing data. An inversion algorithm by [6,4,7] was developed for remote sensing data using an analytical model and optimisation routine. The algorithm expresses the subsurface remote-sensing reflectance r_{rs} as a function of a set of environmental variables, that is, measureable water properties which can be estimated from remotely sensed data. When the modelled remote sensing reflectance $r_{rs}^{modelled}$ is compared to the measured satellite remote sensing r_{rs}^{input} reflectance , the set of environmental variables that minimises the difference between the model and input reflectance provides the solution. This approach provides a physics-based analytical solution for retrieving environmental variables independently on a pixel-by-pixel basis. In [8] and [9], [10] and [4], the [6] algorithm was enhanced and evolved into SAMBUCA, a semi-analytical model for bathymetry un-mixing and concentration assessment. SAMBUCA was now able to retrieve simultaneous outputs of: 1) the water's optically active constituent concentrations (chlorophyll-a, Coloured dissolved organic matter and non-algal particulate), 2) the percentage substratum cover type (either as homogeneous or mixtures of two substrate types) and 3) metrics to assess the reliability of the retrieval.

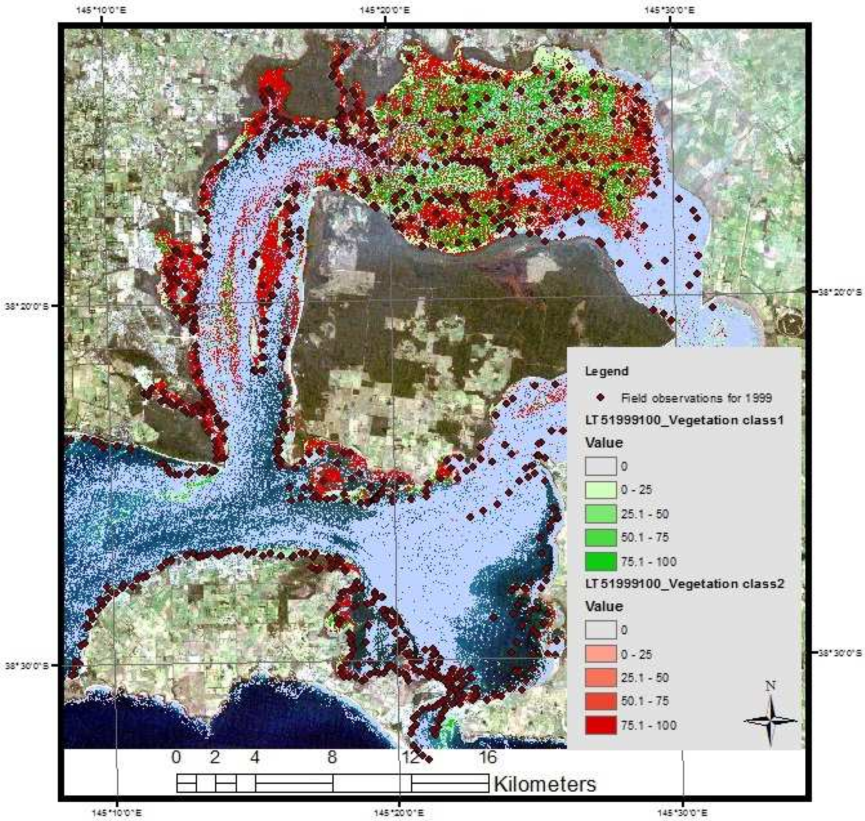
2.4 Parameterisation

The parameterization of SAMBUCA relies on the optical properties of the water body and substratum derived from field measurements. Inversion methods analysed in [4] showed increased accuracy of retrievals were obtained with improved optical parameterisation of the study site. An accurate parameterisation provides boundary conditions for the retrieval of the environmental variables. Field campaign measurements ensure the SAMBUCA parameterisation is as robust and comprehensive as possible, but when unavailable, the input (such as constituent concentrations, or absorption or backscattering information) is derived from archival field campaign measurements from similar environments. Once parameterised, SAMBUCA was run to estimate the concentrations of optically active constituents in the water column (chlorophyll-a, CDOM and NAP), water column depth, and benthic substratum composition on a pixel-by-pixel basis. Spectral reflectance measurements of a local seagrass and brown macroalgae show that the spectra are generally quite distinct, mainly due to a varying pigment composition as seen in the peaks and troughs in reflectance. Although these species may be spectrally distinct in hyperspectral imagery, the broad spectral bands of the multispectral Landsat indicate that species separability would be challenging.

3 RESULTS AND KEY FINDINGS

3.1 Physics-based retrieval of Landsat data

SAMBUCA was sensitive to the initial boundary conditions, that is, the starting value and range of the variables. A series of SAMBUCA tests were run using as input the two substrate (dark mud and bright sand) spectral libraries. The SAMBUCA-derived bathymetry estimates were compared at selected sites in Westernport where depth measurements obtained from prior studies were used. An accurate bathymetry layer would further constrain the model and could be integrated at a later stage. The best performing set of variables used in the parameterisation were used to constrain another SAMBUCA run using a three substrate library using a brown macroalgae, seagrass and sand spectra as possible substrates.



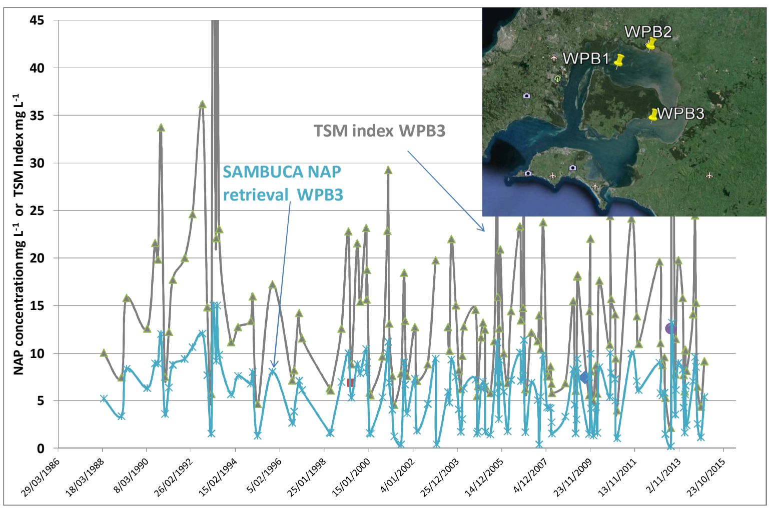
Seven Landsat images (acquired between 1985-2014), were selected to apply SAMBUCA and derive substrate maps. Figure 1, shows a subset of the derived substrate map for a 10 April 1999 Landsat 5 image. In Figure 1, the green class represents data retrieved as brown macroalgae and the red class represents seagrass. Each pixel of the Landsat imagery covers 625m^2, therefore each pixel contains a ‘mixture’ of the reflectance of all the substrates within that 625m^2. Together with this spatial heterogeneity, the broad bands of the Landsat sensor are probably unable to distinguish between the algae and seagrass spectra, therefore in (Figure 1, the red and green classes are labelled vegetated substrate rather than seagrass or macroalgae.

Figure 1: The Landsat 5 image of Westernport Bay from 10 April 1999 with the retrieved seagrass and algae classes overlaid in red and green, respectively. The field data are overlaid as dark red dots.

Accuracy of the Westernport SAMBUCA substrate retrievals (Figure 1) were assessed using field observation data collected between 26 July 1999 and 19 April 2000. As previously discussed, due to Landsat’s limited spectral resolution, the ability to separate species was restricted, therefore the SAMBUCA substrate retrievals were assessed after combining the seagrass and macroalgae classes with an overall accuracy of 71%.

3.2 Time Series analysis of satellite-derived water quality information

Analysis of remotely sensed data time series has the potential to augment the sparse in-situ total suspended matter (TSM) measurement records to provide a fuller understanding of the temporal dynamics of sediment transport within Westernport. Multi-decadal time series of Landsat data can be acquired from the AGDC [11]. Retrieving the concentration of TSM from Landsat data requires an understanding of its effects on the spectral signal measured by the sensor. An analytical relationship between TSM and the average of the reflectance for Landsat green and red bands was derived for several locations where field data was available. This algorithm was developed by [12] for highly turbid lakes, where the green and red Landsat bands were identified as most suitable for estimating variations in TSM (equation 1), but noting the errors increase with clearer waters, [12]. Both The TSM and SAMBUCA estimations appear to describe similar temporal behaviour with SAMBUCA’s retrievals underestimating the TSM estimates.



Equation 1:

$$\text{TSM index} = \text{mean}(\text{green} + \text{red})$$

Figure 2: A pixel drill of Landsat data obtained from the AGDC for the field site WPB3. The TSM index (green triangles) was derived using from [12] and for the same pixels the SAMBUCA NAP (non algal particulates) retrieval (blue crosses) for data from 1988 until 2014.

3.3 Summary

A map of vegetated substrate (seagrass and macroalgae) has been retrieved from the Landsat data using the SAMBUCA model objectively applied. Results indicate that the spatial patterns in the SAMBUCA predictions of vegetated substrate correlate with historical field mapping. The Landsat sensor appears to lack sufficient spectral sensitivity to distinguish between the spectral classes of seagrass and algae, unless it is in areas of significant homogeneity that encompass more than one Landsat pixel ($625m^2$).

Significant portions of the Westernport Landsat scenes were covered with optically deep water, that is, where the substrate reflectance cannot be determined either from the confounding effects of the water column depth or because of the water clarity. The SAMBUCA retrieval appears to adequately map the turbidity within each scene, when compared with the TSM index of the AGDC pixel drill, which enables the relative impact on bay turbidity of catchment sediment inputs and re-suspension to be investigated.

4 ACKNOWLEDGMENTS

This work was funded by Melbourne Water and CSIRO. Leo Lymburner provided valuable AGDC support.

REFERENCES

[1] Anstee, J. M., Dekker, A.G. and Brando, V. E., “Retrospective change detection in a shallow coastal tidal lake: Mapping seagrasses in Wallis Lake, Australia”, in *Analysis of Multi-Temporal Remote Sensing Images*, edited by P. C. Smits and L. Bruzzone, (2004),pp. 277-285.

[2] Botha, E. J., Brando, V.E., Anstee, J.M., Dekker, A.G. and Sagar, S., Increased spectral resolution enhances coral detection under varying water conditions, *Remote Sensing of Environment*, 131, (2013), 247-261.

[3] Lee, Z., Carder, K.L., Mobley, C.D., Steward, R.G. and Patch, J.F.,” Hyperspectral remote sensing for shallow waters: II. deriving bottom depths and water properties by optimization”, *Applied Optics*, 38(18), (1999), 3831-3843.

[4] Dekker, A. G., S. R. Phinn, J. Anstee, P. Bissett, V. E. Brando, B. Casey, P. Fearns, J. Hedley, W. Klonowski, Z. P. Lee, M. Lynch, M. Lyons, C. D. Mobley & C. Roelfsema,” Intercomparison of shallow water bathymetry, hydro-optics, and benthos mapping techniques in Australian and Caribbean coastal environments”, *Limnology and Oceanography: Methods*, 9, (2011),396-425.

[5] Shepherd, S. A., Watson, J.E., Womersley, H. B. S.and Carey, J. M., “Long-term changes in macroalgal assemblages after increased sedimentation and turbidity in Western Port, Victoria, Australia”, *Botanica Marina*, 52(3), (2009), 195-206.

[6] Lee, Z., Kendall, L.C., Chen, R. F. and Peacock, T. G., “Properties of the water column and bottom derived from Airborne Visible Imaging Spectrometer (AVIRIS) data”, *Journal of Geophysical Research*, 106(11), 11,(2001), 639-651.

[7] Lee, Z. P., Carder, K.L., Steward, R. G. Peacock, T.G., Davis, C.O. and Patch, J.S., “An empirical algorithm for light absorption by ocean water, *Journal of Geophysical Research*, 103(C12), 27, (1998), 967-978.

[8] Wettle, M. & Brando, V. E., “SAMBUCA - Semi-analytical model for Bathymetry, un-mixing and concentration assessment”. *CSIRO Land and Water Science Report No. 22/06*, CSIRO, Canberra (2006).

[9] Brando, V.E, Dekker, A.G. and Anstee, J.M. “Simultaneously Mapping Depth, Substratum Type and Water Quality in Cockburn Sound Using Hyperion Satellite Data”. *Ocean Sciences Meeting*, 20-24 February 2006; Honolulu, HI (USA), American Geophysical Union, *http://www.agu.org/pubs/agu_joureos.html*.

[10] Brando, V. E., Anstee, J. M., Wettle, M., Dekker, A. G., Phinn, S. R. & Roelfsema, C., “A physics based retrieval and quality assessment of bathymetry from suboptimal hyperspectral data”. *Remote Sensing of Environment* 113,4, (2009), 755-770.

[11] Purss, M.B., Lewis, A., Oliver, S., Ip, A., Sixsmith, J., Evans, B., Edberg, R., Frankish, G., Hurst, L., & Chan, T., “Unlocking the Australian Landsat Archive–From dark data to High Performance Data infrastructures”. *GeoResJ*, 6, (2015),135-140

[12] Dekker, A.G., Vos, R.J., & Peters, S.W.M., “Analytical algorithms for lake water TSM estimation for retrospective analyses of TM and SPOT sensor data”. *International Journal of Remote Sensing*, 23, (2002), 15-35.