Seagrass Mapping

Geographe Bay 2004 - 2007

Prepared for:

Southwest Catchment Council

Prepared by:

Dr KP Van Niel
Dr KW Holmes
Dr B Radford
School of Earth and Environment
The University of Western Australia

January 2009
# Table of Contents

Executive Summary ........................................................................................................ 4

1 Introduction ................................................................................................................. 5

Project Objective .......................................................................................................... 5

2 Background .................................................................................................................. 6

3 Image classification method ......................................................................................... 9

4. Seagrass maps ............................................................................................................ 14

5. Seagrass change .......................................................................................................... 20

6. Conclusions and Recommendations .......................................................................... 23

7. Acknowledgements ................................................................................................... 24

8. References .................................................................................................................. 25
List of Tables

Table 1. Summary of area by habitat in Geographe Bay for 2004 (GEM 2007) and 2007, as classified using supervised classification techniques...........14
Table 2. Summary of classification accuracy for the 2004 (GEM 2007) and 2007 image classifications.................................................................14
Table 3. Seagrass change 2004-2007 ..............................................................20

List of Figures

Figure 1. Location, showing 2004 imagery (GEM 2007)........................................8
Figure 2. Training data for supervised classification (1063 points). Training
tlocations were selected across depth gradients for classification.........11
Figure 3. Field data point locations (gathered in 2008)........................................12
Figure 4. Validation data for testing the accuracy of the 2007 classification........13
Figure 5. Map of seagrass distribution in Geographe Bay in 2004, using the
maximum likelihood classifier technique.......................................................15
Figure 6. Map of seagrass distribution in Geographe Bay in 2007, using the
maximum likelihood classifier technique.......................................................16
Figure 7. Per pixel confidence based on the probability of mapped seagrass
occurrence in Geographe Bay in 2007. Areas of low confidence were
cause by poor image quality and visibility (depth). .................................17
Figure 8. Per pixel confidence of mapped seagrass occurrence in Geographe Bay
in 2007. Overall, areas of low confidence were caused by poor image
quality and visibility (depth). In the northeastern part of the image, low
confidence was due to the need to use multiple classes of seagrass, so
that each seagrass signature competed against other seagrass signatures.
While this created low probabilities, it ultimately greatly improved the
classification in that area.................................................................18
Figure 9. Per pixel confidence of mapped seagrass occurrence in Geographe Bay
in 2007, based on distance from signature vector.........................................19
Figure 10. Change in seagrass 2004 – 2007.......................................................21
Figure 11. Example of the effect of spatial error on seagrass changes detected
between 2004-2007. Note that the “growth” occurs on one side of the
patch and the “loss” on the other and that both are similar in size and
extent........................................................................................................22
Figure 12. Example showing differences in misclassification in the 2004 and 2007
classifications in shallow waters near the marina just north of Geographe.
The 2004 and 2007 classifications both over and under predicted the
seagrass extent in different areas, leading to a change detection of both
seagrass gain and loss.................................................................22
Executive Summary

Seagrasses are common in nearshore, subtidal sand habitats in temperate southern Australia. This study documents an analysis using aerial photography of the distribution of *Posidonia* and *Amphibolis* seagrass in nearshore shallow (<10m depth) in Geographe Bay in 2004 and 2007. These studies are part of several ongoing investigations that together will assist assessment of development impacts on the marine environment in Geographe Bay.

In 2004, two methods were used to map seagrass distributions, classification accuracies were assessed, and a spatial assessment of classification certainty was also developed. 77% of the study was covered by seagrass, equating to 9699ha. For the area that was spatially coincident with the 2007 imagery equated to 9495ha. Future recommendations at the time included development of nearshore bathymetric data and future field survey data collection (GEM 2007).

In 2009, mosaicked aerial photography flown in 2007 was used to assess seagrass cover using the best methodology determined from the 2004 study. Spatial assessment of classification certainty was also analysed again. 71% of the study area (as defined by the coincident coverage for both sets of aerial photos) was covered in seagrass, equating to 8726ha.

An assessment made of the change in seagrass cover between the two time frames, as well as an assessment of the accuracy of the change detection. The analysis showed a gain of 1101ha and loss of 1870 ha across the study area covered by both images. 9383 ha remained unchanged. Inspection of the outcome showed that although an overall loss of seagrass cover of 769ha was found, but this was mainly due to (1) spatial displacement errors in the imagery as delivered, (2) distortions in the images as delivered due to sun glare and the mosaicking process, and (3) differences in the predictions between the two classifications (2004, 2007). In particular, improvements in the prediction of deeper water sand in the northeastern part of the study area led to an incorrect prediction of seagrass loss in the change detection analysis. Visual inspection of both images in the areas detected as change, as well as near shore areas, showed no visible loss of seagrass cover in a contiguous area >1ha.
1 Introduction

Seagrasses are common in nearshore, subtidal sand habitats in temperate southern Australia. In temperate Western Australia, seagrasses occupy approximately 20,000 km² of shallow coastal habitat (Walker, 1991) in water depths ranging from the intertidal zone to 35 m (Cambridge and Kuo, 1979). These seagrass meadows create a characteristic landscape visually identifiable using aerial photography and satellite imagery. This study documents an analysis using aerial photography of the distribution of seagrass in Geographe Bay in 2007 (Figure 1) and the change in seagrass cover between 2004 and 2007. This region supports a variety of seagrasses, predominantly from the genera *Posidonia* and *Amphibolis* (McMahon and Walker, 1998). Development along the coast can affect river and nearshore water quality and sedimentation, and may potentially affect marine ecosystems. Seagrasses tend to respond rapidly to environmental change, thus providing a useful indicator of the state of the marine environment. One example of this occurred near Perth in Cockburn Sound where there were large losses of seagrass meadows in the late 1960’s and early 1970’s. These losses were attributed to several factors, including increased nutrient loads which caused increased epiphyte biomass, resulting in shading of the seagrasses (Kendrick et al., 2002). During the same time period, nearshore areas in Geographe Bay were also documented as experiencing seagrass cover loss, while deeper water seagrasses appeared stable (Conacher, 1993). The spatial patterns and rates of change of seagrass loss and revegetation are critical information for environmental planning and management of this important recreational and commercial area.

The present study is one of several ongoing investigations that together will assist assessment of development impacts on the marine environment in Geographe Bay, including detailed analysis of seagrass species and patch dynamics, water quality, and regional change in seagrass distribution. This particular study will provide a snapshot of dense-canopy seagrass distribution in 2007 and change in seagrass distribution from 2004 to 2007.

Project Objective

The Geographe Catchment Council aims to assess the impact of development on marine ecosystem processes in Geographe Bay. Establishment of a baseline distribution of seagrass in Geographe Bay is essential for evaluating regional implications of environmental change, which affects ecosystems important for commercial, recreational, and intrinsic biological activities. The objective of this study was to determine the distribution of seagrass in the shallow, near shore waters of Geographe Bay in 2007 and to assess change in seagrass cover from 2004 to 2007. This will assist efforts to evaluate ecological function and changes in ecological function over time. These objectives were met via classification of
the 2007 aerial photograph mosaic and overlay of the 2007 seagrass extent with the classified 2004 aerial photograph mosaic previously reported (GEM 2007).

2 Background

2.1 Environmental setting

Geographe Bay is a wide embayment facing north, forming a relatively protected, shallow water marine environment popular for recreational activities and commercial fishing, located in south-west Western Australia approximately 200 km south of Perth (Figure 1). The present study extended from Peppermint Beach, north of Capel River (33°30’59.6”S, 115°30’49.6”), west to the eastern edge of Eagle Bay, at Cape Naturaliste (33°25’23.5”S, 111°58’05.6”) in near shore waters at 10m or less depth. The depth gradient is low along the eastern and southern portions of the bay (average of 1.6 m per km to 30-m water depth), and increases rapidly to the western most edge at Cape Naturaliste (22.5 m per km over 30-m water depth). The majority of seafloor is covered by unconsolidated sediments, deposited over older clay layers and limestone formations which are exposed at the surface in various positions throughout the bay. The nearshore sandy substrate is colonised by extensive seagrass beds, which patchily extend into deeper water as far as sufficient light is available for photosynthesis.

Seagrasses in the subtidal region (2 - 4 m) have been well characterised (Walker et al., 1987; McMahon et al., 1997). These shallow water areas are dominated by *Posidonia sinuosa* (60% cover), and the second most common species, *Amphibolis antarctica* is found around the edges of *P. sinuosa* meadows, as well as on limestone outcrops (McMahon and Walker, 1998). In recent tow video footage in deeper water (15-40 m) in the western portion of the field area, *Zostera* has also been identified, as well as patchy distributions of dense epiphytes (Marine Futures NHT II Project, 2006, unpublished data).

In this study, aerial photography classification was used to map *Amphibolis* and *Posidonia* cover, as they have high leaf-area indices (LAI = leaf area (in m²) per unit area of sea bed). The high LAI’s of *Amphibolis* (3.4–18.0) and *Posidonia* (1.9–3.5), (G. Kendrick, UWA, unpublished data), result in a large difference in the phototonal density between these seagrasses and unvegetated sediments. This contrasts with less dense seagrass genera, such as *Zostera*, which consequently cannot be distinguished from unvegetated sand in the analysis of aerial imagery. The nearshore marine environment was assessed to a water depth of 10 metres, and further where the aerial photography was of sufficiently high quality.

2.2 Data availability

A number of spatially referenced datasets were assessed for inclusion in the study to facilitate the detection of seagrass and evaluation of the resulting maps for Geographe Bay. The aerial photography is the most critical dataset, and two mosaics were evaluated for (1) image quality, which is affected directly by sun
glare, wave glint, and wave distortion, and (2) the quality of the mosaic production, particularly edge effects between the mosaicked photos, colour balancing, and most complete coverage of the study area.

2.2.1 Aerial photography

The aerial photography mosaic used for this analysis was constructed by the Department of Land Infrastructure (DLI), and made available through Landgate (Figure 1). The photography (1:25,000) was flown in March 2007 and in February 2008 and scanned at 1279 dpi producing a final digital image file with 0.5m resolution pixels. During the mosaic production, image selection and colour balancing were undertaken. This process involved colour balancing and feathering of adjacent photographs. This process provides a more visually appealing image but can result in obscuring some of the overlap between images, affecting classification accuracy. The spatial accuracy of the mosaicked image is 10m.

Prior to classification, the imagery was resampled using nearest neighbour interpolation to a pixel resolution of 1-m x 1-m. Pixel resolutions smaller than 1 m were found in an earlier study (GEM 2007) to introduce artefacts associated with the refraction of light across the air/water interface.

The 2008 imagery that was available covered little of the area classified in 2004, as much of the imagery extent was on land rather than over the near coastal waters. However, the 2007 imagery provided a good, but not complete, match to the 2004 imagery. Thus, the 2007 imagery was used for the analysis.

2.2.2 Bathymetry

Critical to the image processing in marine applications is a bathymetric model (delineating seafloor depth) at a similar spatial resolution to the imagery. There were no high resolution (5 – 15 m) bathymetry data sets available for the full extent of Geographe Bay. For partitioning the full study site into depth classes to improve classification accuracy, the National Oceans Office 250-m bathymetry was used (Heap et al., 2007). Because of the low topographic gradient in Geographe Bay and the coarse resolution of the DEM, this was not optimal.

2.2.3 Field validation data

Georeferenced field information on seagrass distribution was collected in 2008, which limits their usefulness as validation of the 2007 imagery (Barnes et al 2008). The dive sites were included as validation data for assessment of the classification accuracy.
Figure 1. Location, showing 2004 imagery (GEM 2007).
3 Image classification method

Aerial photograph classification enables the definition of vegetated and unvegetated areas of the imagery using the red, green and blue spectral bands. Automated classification approaches can be divided into the following methods: (1) unsupervised classification examines the groupings of spectral values in the image to define classes that the operator then correlates with known habitat types; while (2) supervised classification uses training data to systematically assign known habitat types to spectral groups in the image.

The previous study (GEM 2007) showed that the supervised classification outperformed the unsupervised classification. Thus, in this study, only the supervised classification methodology was employed, using the Maximum likelihood method.

3.1 Evaluation of classification techniques

The image classification result was evaluated with two datasets: (1) manually selected from the aerial photography and (2) georeferenced habitat classifications from 22 field data points collected in 2008 (Barnes et al 2008). These were compared to the 2007 imagery to assess whether any changes between 2007 and 2008 might have affected their validity (2 points were deleted based on this assessment). The study site was also subdivided and sampled by depth for both sand and seagrass to assess the effects of water depth on seagrass identification. These subdivisions were then used to assemble (1) a training dataset, originally developed in 2004, was checked for accuracy with the 2007 imagery, and modified and supplemented with new data (total 1063 points) for the supervised classification procedure and (2) a test dataset (397 points, which includes 20 of the field data points) for assessing the accuracy of both classifications.

For each dataset, a confusion matrix was assembled which presents the number of pixels correctly and incorrectly classified in each habitat, providing a means of assessing the classification and quality of the maps. Spatial assessment of classification confidence is provided for both 2004 and 2007 classifications as an assessment of per pixel probability. Also, for the 2007 classification, an alternative confidence assessment is provided based on the distance from each pixel in multidimensional space to the mean vector in the signature file.

3.2 Change detection over time

Change detection can either be analysed using two or more previously classified images or by using spectral pattern recognition across two or more images. Both methods are reliant on a georectification that matches both images closely. Otherwise, much of the change detected can actually be errors due to spatial displacement. Post classification change detection also relies on good classification accuracies across both time frames. Spectral pattern recognition is strongly affected by any distortions in the imagery. The data
provided had distortions caused by both sun reflection and the mosaicking process. Given the distortions in the imagery data, the post classification process was used in this study.

3.3 Assessment of change detection

Change detection analyses are not generally assessed for errors per se. This is often because these analyses are often post hoc and no data exists for the previous time frame. When they are assessed, it is usually via classification accuracy of each of the time frames or by (often small) sets of field data. Each image classification would then carry its own error, and multiple overlays can compound or reduce the overall level of errors, depending on their spatial distribution, magnitude and probability of co-location across images (Van Niel 2003). In this study, we use both the spatially explicit prediction confidence maps as well as descriptive interpretation to assess the accuracy of the change detection.
Figure 2. Training data for supervised classification (1063 points). Training locations were selected across depth gradients for classification.
Figure 3. Field data point locations (gathered in 2008).
Figure 4. Validation data for testing the accuracy of the 2007 classification.
4. Seagrass maps

In 2007, the mapped area was dominated by seagrass, classified with the supervised method as 71% seagrass (Table 1; Figures 5 and 6).

The accuracy of the 2007 classification was assessed using a new dataset of separate validation points, supplemented with a small amount of available field data. Increasing water depth changes the spectral signature of benthos, making it difficult to use fully automated unsupervised methods. The supervised classification method provided the ability to train the classifier to deal with the depth gradient at the study site. Visual inspection determined that the classification performed better in shallow water. This method also gave the added benefit of being able to develop a spatial representation of classification confidence and probability of prediction, which also provide a spatial measure of confidence in the prediction.

31 of the 397 validation sites had an incorrect classification. Of these, 3 were developed from field data. Two issues may contribute to this misclassification, spatial error and scalar assessment. The imagery has a spatial error of +/- 10m. Similarly, the GPS reading from the field data (pulled on a tether by divers) could also have this level of spatial error.

Overall, areas of low confidence in the confidence maps (Figures 7 and 8) were caused by poor image quality and visibility (depth). In the northeastern part of the image, low confidence was due to the need to use multiple classes of seagrass, so that each seagrass signature competed against other seagrass signatures. While this created low probabilities and thus low confidence maps, it ultimately greatly improved the classification in that area.

Table 1. Summary of area by habitat in Geographe Bay for 2004 (GEM 2007) and 2007, as classified using supervised classification techniques

<table>
<thead>
<tr>
<th>Year</th>
<th>Seagrass (ha)</th>
<th>Non-seagrass (ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2004 classification</td>
<td>9494.89</td>
<td>2859.51</td>
</tr>
<tr>
<td>2007 classification</td>
<td>8726.36</td>
<td>3628.05</td>
</tr>
</tbody>
</table>

Table 2. Summary of classification accuracy for the 2004 (GEM 2007) and 2007 image classifications

<table>
<thead>
<tr>
<th>Year</th>
<th>Seagrass</th>
<th>Producer’s accuracy</th>
<th>User’s accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>2004</td>
<td>Absence</td>
<td>98.4%</td>
<td>96.2%</td>
</tr>
<tr>
<td></td>
<td>Presence</td>
<td>96.5%</td>
<td>98.5%</td>
</tr>
<tr>
<td>2007</td>
<td>Absence</td>
<td>95.5%</td>
<td>96.7%</td>
</tr>
<tr>
<td></td>
<td>Presence</td>
<td>96.2%</td>
<td>95.5%</td>
</tr>
</tbody>
</table>
Figure 5. Map of seagrass distribution in Geographe Bay in 2004, using the maximum likelihood classifier technique.
Figure 6. Map of seagrass distribution in Geographe Bay in 2007, using the maximum likelihood classifier technique.
Figure 7. Per pixel confidence based on the probability of mapped seagrass occurrence in Geographe Bay in 2007. Areas of low confidence were caused by poor image quality and visibility (depth).
Figure 8. Per pixel confidence of mapped seagrass occurrence in Geographe Bay in 2007. Overall, areas of low confidence were caused by poor image quality and visibility (depth). In the northeastern part of the image, low confidence was due to the need to use multiple classes of seagrass, so that each seagrass signature competed against other seagrass signatures. While this created low probabilities, it ultimately greatly improved the classification in that area.
Figure 9. Per pixel confidence of mapped seagrass occurrence in Geographe Bay in 2007, based on distance from signature vector.
5. Seagrass change

Seagrass change was detected across the site. Table 4 shows the tabulation of seagrass loss and gain. Figure 10 shows the mapped results of the change detection analysis. While the overall analysis shows a loss of 768.28ha of seagrass coverage, this result is misleading. In Figure 10, there are clear areas of “change” detected, which coincide spatially with the worst distortions in the areas where two aerial photographs have been mosaicked or there were large areas of sun glare on the imagery. The notable “loss” of seagrass in the northeastern part of the study area is due to improvements made in the discrimination between deeper water seagrass and sand in the 2007 classification. As a result, the 2007 image classification process identified more extensive beds of deep water sand than was identified in 2004, which the change detection then incorrectly predicted as seagrass cover loss.

Figure 11 illustrates the “changes” detected when georeferencing (spatial error) affects the spatial coincidence of two aerial images in a time series. Note that on one side, the patch appears to be shrinking, while on the other it is growing. This is caused by a misregistration and/or spatial error (reported as +/- 10m for this data set).

Due to past work (Conacher 1993) suggesting that shallow water seagrass were being lost faster than deeper seagrass, the areas of change identified in the shallow waters were closely examined visually. Figure 12 shows the results from the change detection analysis, as well as the seagrass presence prediction from both 2004 and 2007. This figure illustrates well that even in relatively shallow waters, water turbidity, variable depth, and the potential presence of other elements spectrally similar to seagrass (eg. wrack, algae) in the image make it difficult to predict the seagrass cover accurately, which can affect change detection studies. Visual assessment of the imagery from both time frames in those areas shown to potentially be experiencing change and in all nearshore water showed no large areas of seagrass loss.

Table 3. Seagrass change 2004-2007

<table>
<thead>
<tr>
<th>Seagrass Change</th>
<th>Area (ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loss</td>
<td>-1869.83</td>
</tr>
<tr>
<td>No change</td>
<td>9383.29</td>
</tr>
<tr>
<td>Gain</td>
<td>+1101.28</td>
</tr>
<tr>
<td>Overall change (total)</td>
<td>-768.28</td>
</tr>
</tbody>
</table>
Figure 10. Change in seagrass cover 2004 – 2007.
Figure 11. Example of the effect of spatial error on seagrass changes detected between 2004-2007. Note that the “growth” occurs on one side of the patch and the “loss” on the other and that both are similar in size and extent.

Figure 12. Example showing differences in misclassification in the 2004 and 2007 classifications in shallow waters near the marina just north of Geographe. The 2004 and 2007 classifications both over and under predicted the seagrass extent in different areas, leading to a change detection of both seagrass gain and loss.
6. Conclusions and Recommendations

This study examined the distribution of seagrasses in shallow near shore waters of Geographe Bay using aerial photography. Full maps of seagrass distribution were developed for nearshore waters of 10m depth or less for 2004 and 2007. Excellent classification accuracy was attained for both years. Classification confidence was also provided as an estimation of the certainty of correctness of the classification. This allows for data quality assessment and future field survey and aerial data collection planning.

The change detection analysis found an overall loss of seagrass cover of 768.55ha, but this was mainly due to (1) spatial displacement errors in the imagery as delivered, (2) distortions in the images as delivered due to sun glare and the mosaicking process, and (3) differences in the predictions between the two classifications (2004, 2007). Improvements in the prediction of deeper water sand in the northeastern part of the study area led to an incorrect prediction of seagrass loss in the change detection analysis.

**For future studies, well georeferenced field data across the full extent of the study area would improve outcomes and provide independent data for classification accuracy assessment.** This should be considered for future studies if the same type of analysis is conducted for other dates. This is especially true if separation of seagrass, reef, wrack, and macroalgae, in addition to bare sediment is a priority. Wrack may be identified by annual classifications, as their distribution can change much more quickly than other classes. This type of analysis might provide a useful tool for removing error due to image classification confusion between wrack and seagrass. These seafloor elements can have very similar spectral signatures, especially at depth. Bathymetric data at an appropriate scale for the area would also greatly improve the ability to distinguish benthos at different depths.

In this study, the aerial photography was not purpose flown for marine mapping, nor was a high resolution DEM available during processing. This affected the extent over which seagrass could be mapped accurately. Most aerial photography is flown to capture terrestrial areas rather than marine. This often means that the images available over the ocean contain a large amount of sun glare or other disturbances that can be avoided or at least minimised using purpose-flown imagery. **We strongly recommend that purpose-flown imagery be used in the future.** In this case, the time of day (sun angle) and wave conditions can be assessed and appropriate conditions chosen for capturing images.

Georegistration issues are common in most imagery and are likely to exist in the image provided by DLI for this study. The georeferencing was reported to be +/- 10 m, with 0.5m pixels. **The use of detailed bathymetric data for the area and its use in orthorectification of aerial photography would greatly increase spatial accuracy and reduce spatial displacement.** In using the final maps, especially the change detection outcomes, developed by this study, it is important to consider the potential spatial displacement caused by this level of georeferencing accuracy.
7. Acknowledgements

The remote sensing analysis for the 2004 report was conducted at The University of Western Australia by Ben Radford; the 2004 report was drafted by Karen Holmes; and final assessment and data interpretation of the 2004 report was completed by Kimberly Van Niel. The remote sensing analysis for the 2007 imagery and the change analysis were conducted at The University of Western Australia by Kimberly Van Niel. To provide a complete report covering both time frames and the change detection, this report as developed as an amalgamation of both the prior (2004) report and the new 2007 imagery classification and 2004-2007 change detection outcomes and was written by Kimberly Van Niel.

The Busselton 2004 aerial photography mosaic was developed by DPI and provided through the DLI data distribution system (DOLA). The 2007 imagery was mosaicked and provided by Landgate. Field data was collected by Kurt Wiegele, Jordan Goetze and Owen O'Shea.
8. References


