Offshore petroleum exploration from space: a developing capability at Geoscience Australia

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Abstract- **Natural seepage can generate hydrocarbon slicks on the sea surface that may provide petroleum explorers with direct evidence of oil and gas below the sea bed. Remote sensing has the potential to be used as a tool for detecting such sea surface slicks, thereby identifying areas in both producing and frontier basins that are prospective for hydrocarbons. We are developing a two-pronged, remote sensing-based approach for seepage slick studies in the Australian Marine Jurisdiction: 1) building a semi-automated processing and classification system in order to scan large numbers of Synthetic Aperture Radar scenes for potential natural slick targets, and; 2) investigating the potential of optical remote sensing as a diagnostic tool for further, targeted study.**

Using objected-oriented classification algorithms in a bulk processing environment, large Synthetic Aperture Radar data sets were able to be efficiently screened for potential natural oil slick targets. This processing system offers a range of outputs, including classification statistics for each scene studied, as well as geo-referenced shapefiles ready for analysis in Geographic Information System software, where it can be combined with ancillary data sets for contextual analysis.

Our research into the potential for optical remote sensing to enable further diagnostic study of identified, potential targets has shown that there are several commercially available, space borne sensors able to detect the types of oils found throughout the Australian Marine Jurisdiction, but that oil type is critical for this application. Further to this, we have developed an approach for performing a feasibility study of oil type versus sensor sensitivity prior to image data acquisition.

I. INTRODUCTION

Oil and gas naturally seeps through the seafloor from reservoirs below the sea bed which can result in oil slicks on the sea surface. Remote sensing is applicable to detecting and mapping natural seepage slicks due to the cost-effective ability to scan extensive and/or remote regions. However, the bulk of remote sensing of marine hydrocarbon slicks to date has focused on detecting and mapping relatively thick oil pollution and spills, often with a known extent, date, and/or location [1]. Utilizing remote sensing for petroleum exploration purposes poses significant additional challenges; natural, seepage-derived oil slicks are typically considerably thinner on the sea surface, and their timing, extent, location and chemical properties are often not known.

Remote sensing studies of oil slicks have been carried out using Synthetic Aperture Radar (SAR) [2][3]. Under suitable environmental conditions, a sea surface slick has a dampening effect on the capillary waves, thereby reducing the amplitude of the wave-dependant backscatter signal, which in turn is visible as a dark area (negative contrast) in SAR imagery.

SAR is highly effective in screening for seepage slicks as it covers large geographic areas and can image through clouds and at night-time. However, the large volume of data required to screen the Australian Marine Jurisdiction (AMJ), for natural slicks prohibits manual, operator-based analysis of the imagery, particularly where multi-temporal data sets are involved. Furthermore, new data are continuously being acquired. Hence, we have developed a bulk processing, semi-automated, SAR data classification system for broad scale, initial detection of slicks. The Semi-Automated Marine Slicks SAR Analysis (SAMSSARA), system is described in Section II.

A limitation of SAR for detecting hydrocarbon slicks is that it contains no diagnostic spectral information. Hence, other phenomena that cause dampening of capillary waves, such as natural film, bathymetric features, weather and even coral spawn, can lead to a range of false positive interpretations of natural oil slicks [4][5].

Although prohibitively costly for scanning large offshore areas, high spatial resolution optical remote sensing offers potential for further identifying and characterizing naturally occurring hydrocarbon slicks. Potential applications range from locally targeted airborne hyperspectral acquisitions to multispectral spaceborne sensors with global coverage. However, the feasibility of these types of optical data applications remains to be proven. We are currently investigating the sensitivity of high spatial resolution, commercially available sensors to oil types known to occur in the AMJ. By determining the optical properties of these oils and assessing the environmental signal to noise characteristics

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of the relevant sensors, we are able to: 1) constrain the feasibility of using a given sensor for further, targeted identification of a potential oil slick target and 2) prescribe a method for determining a-priori the potential and limitations of a given sensor and/or oil type for this type of application. This work is presented in Section III.

II. Broad Scale Detection System

A. Methodology

SAR data, such as those obtained from the European Space Agency's (ESA's) ERS-1 and ERS-2 sensors, have the necessary spatial and temporal coverage to monitor the AMJ for potential seep-derived slicks. Screening such data manually incurs a prohibitive cost due to the large size of such data sets. Our solution, SAMSSARA, which was developed using Definiens software, combines object-oriented data analysis and classification tools with batch-processing and thorough reporting schematics in order to provide a first screening of these large SAR data sets.

The object-oriented classification rule set incorporates both contrast and shape criteria, as well as performing object mergers based on proximity and orientation. To begin with, the classification is based on local contrast within subsets of a given SAR scene, in order to circumvent the gradients (scene-wide, gradual change in average contrast) typically found in this type of imagery. Several approaches to removing this gradient from the imagery were examined, but did not yield satisfactory results. Hence each SAR scene is divided into subsets, and contrast statistics are calculated locally. An identified object with contiguous, lower values (i.e. negative contrast as defined by local statistics) is considered a potential slick candidate object.

Further to this, the shape of each potential object is examined using a set of criteria that include length versus width and perimeter versus area. A natural slick is typically an elongated, thin form, with one or more twists (due to surface currents). In addition, identified objects are merged using a set criteria that include the object's orientation in relation to neighboring objects and the extent and orientation of shared perimeters. Merged objects are then re-classified based on the contrast and shape rules described above, and the process repeated iteratively until every subset in the scene has been classified.

The classification scheme currently uses three categories of potential slicks targets: 1 - dark feature; 2 - moderately slick shaped, and; 3 - slick shaped, with the latter being the highest probability slick target classification based on the defined criteria. SAMSSARA retains the number of classified targets in each category for each scene and outputs these project statistics in both csv and html format. Furthermore, for each scene, the geo-referenced location and classification category of each identified slick target is reported in separate, scene-specific csv and html files. In addition, the hyperlinked html reports contain thumbnail imagery of each identified target.

Finally, SAMSSARA outputs geo-referenced maps (shape files) of all classified potential targets.

B. Results and Discussion

Fig. 1 shows an example of an ERS-1 scene in, together with a magnification of a portion of the scene revealing a high probability hydrocarbon slick feature. Note the contrast gradient across the full scene (progressively lighter towards the Southeast) as well as several larger, circular features with negative contrast (shown circled). The relatively circular shape and large size of the features likely precludes them from being naturally occurring hydrocarbon slicks. However, the scene does contain several category 3 slick features, one of which is shown magnified in Fig. 1. An ERS scene of the same area from a different date was also acquired (not shown). A category 3 slick feature was identified by SAMSARRA in the same vicinity as the feature magnified in Fig. 1 for this alternate date.

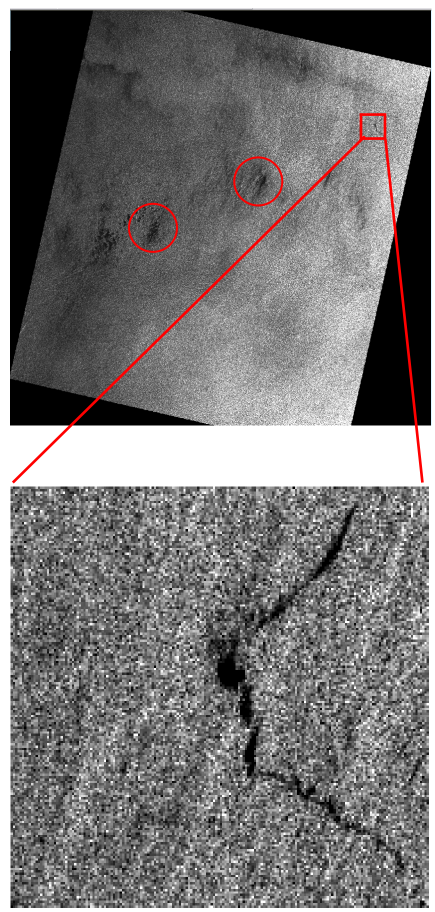

Figure 1. Full SAR scene (top) with a category 3 feature magnified (bottom). Negative contrast (dark) features with the wrong size and/or shape to be a typical hydrocarbon slick are shown circled.

Fig. 2 displays sample SAMSSARA GIS outputs for nine (9) ERS scenes, including the scene shown in Fig. 1. The classification results for the scene in Fig. 1 and the additional scene covering this area that was acquired on a different date, are shown in Fig. 2b. For both dates, blue and green targets denote category 1 and 2 features respectively (Fig. 2b). As an example, the features classified as category 1 can be seen to be either too large or to not have a characteristically elongated shape. Orange and red targets are category 3 features from the two alternate scenes. The orange colored slick feature in Fig. 2c is the classified target relating to the slick shown in Fig. 1. Note that the slick feature from the alternate date in Fig. 2c is classified as two targets (red and green slick features) indicating that further refinement may be needed in the merger rule set of the classification algorithm.

SAMSSARA's basic function is to perform an initial screening of large volumes of SAR scenes, thereby automatically discarding a (possibly substantial) volume of data requiring inspection by a trained operator. The outputs from this screening, statistics reporting and thumbnail imagery in the html output, provide a user with a first level of potential target features assessment.

The final stage of output assessment can then be done in a GIS, enabling the visualization of all identified potential slick features in a contextual, spatially coherent environment. The identified features can be assessed in relation to each other, and additional data sets, such as geological information, can be incorporated and overlaid.

Finally, the GIS enabled output can be analyzed from a multi-temporal perspective. The re-occurrence of category 3 features through both space and time, as shown in Fig. 2c, is a strong indicator of a potential natural seep.

C. Future work

We are currently developing improved classification methods in order to eliminate a greater number of false positives from the initial screening of these large data sets. In addition, we are investigating the potential for incorporating the multi-temporal analysis component in the object-oriented classification process. It is currently completed by an operator during the post-classification, GIS-based analysis. Furthermore, the SAR data require pre-processing, including geo-referencing and re-scaling to 8 bit data. The pre-processing component is currently not automated. A potential future direction is to develop SAMSSARA into a fully automated, operational system for monitoring offshore slick features in the AMJ.

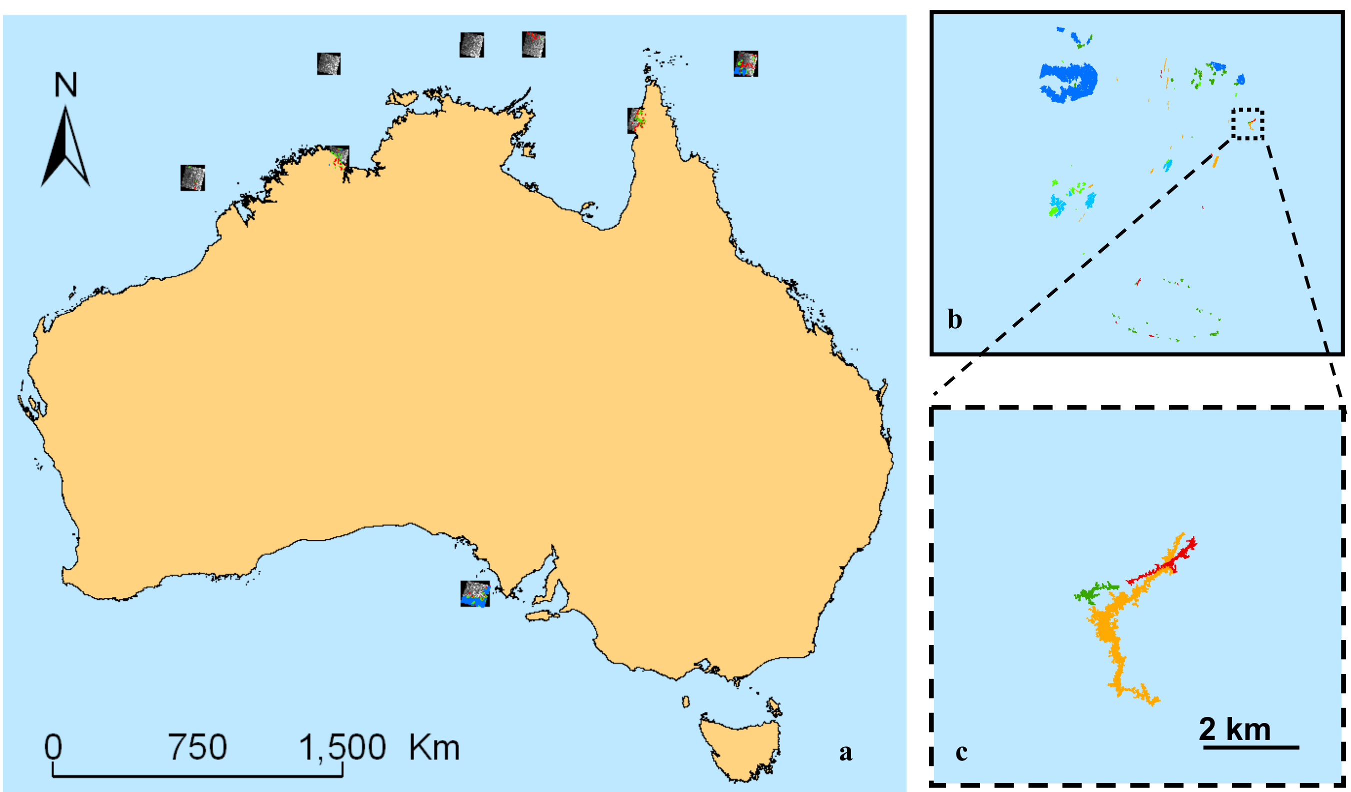

Figure 2. SAMSSARA classification output in GIS format for nine (9) ERS scenes (a). The results for the scene in Fig. 1 are shown magnified, both for the full scene (b) as well as the slick feature (c). Note that an additional slick shape, from SAR data of a different date, is also shown classified in (c). See text for further details.

III. TARGETED IDENTIFICATION

A. *Methodology*

The absorption of light by oil is dependent on both wavelength and oil thickness; there is an increase in absorption with increasing oil thickness, as well as an increase in absorption towards the blue end of the visible spectrum [6]. Petroleum is composed of complex mixtures of hydrocarbons, and the chemistry of individual oils can vary substantially. This variation in chemistry affects a variety of bulk properties such as density and viscosity, and has a direct effect on optical properties of oils. Thus, the chemistry of an oil can influence both the wavelength and thickness-dependent absorptive properties. However, the literature detailing investigations of this is sparse [7].

We examined the wavelength and thickness-dependent absorptive properties, through laboratory experiments, of two naturally occurring oils of differing chemistry. We then applied the results of these measurements in a sensitivity analysis, using image-derived performance limitations of two representative optical imaging sensors, to test how the contrasting characteristics of the oils would affect their ability to be detected with optical remote sensing.

We used two separate, laboratory-based methods for determining the light-absorptive properties of the two oils. One method (Approach 1) was relatively complicated to implement, prone to error, and required access to a high resolution spectroradiometer. This method was used to replicate, as closely as possible, remote sensing measurement conditions of oil film on water, in a controlled laboratory setting. The results from this method could be translated directly to sensor sensitivity response. The second method (Approach 2) utilized relatively common laboratory equipment and measurement protocols but required further conversion for use in a sensor sensitivity analysis.

The aim of this work was two-fold: 1) investigate the effects of oil type and film thickness on a remote sensing signal, specifically for representative, naturally occurring oils, and; 2) propose a relatively straightforward way of performing a sensitivity study based on sensor and oil type.

We selected two oil types that represented (from an optical perspective) end member-type extremes of Australian hydrocarbon oils: a Gippsland light crude oil and a North West Shelf light condensate. Samples of these oils were sourced from the Geoscience Australia archive created as part of the Offshore Petroleum Act of 2006. The light crude and the condensate had an American Petroleum Institute (API) gravity of 41.4º and 52.6º, respectively. The approximate location of sampling of the two oils is shown in Fig. 3.

The experimental set-up underpinning Approach 1 is shown in Fig. 4. An ASD FieldSpec Pro FR spectroradiometer was used to perform radiometric measurements through a fibre optic cable directed at the top of an illuminated beaker filled with water. A 3% reflecting panel was used to replicate typical background reflectance values in an open ocean environment [8]. For each oil type, known amounts were incrementally added to the water surface in the beaker and changes in reflectance measured, resulting in measurements of remote sensing reflectance that are a direct function of oil thickness.

Figure 3. Approximate location of the two oils sourced for the sensitivity analysis study: a) North West Shelf light condensate and b) Gippsland light crude

Approach 2 consisted of commissioning standard transmittance measurements of the two oils. Such measurements utilize relatively common laboratory equipment and measurement protocols. The scope of this paper precludes a detailed description of the experiment and we refer to [9] for further, detailed information.

B. *Results and Discussion*

1. Approach 1

The oil type- and oil thickness-dependant changes in reflectance measured in Approach 1 were convolved to relevant sensor channels using sensor filter functions [9]. These results were subsequently normalized to the radiometric sensitivity of the sensor as determined by [10].

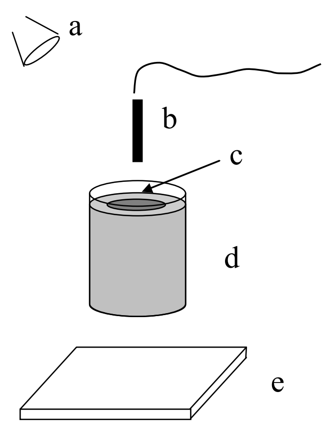

Figure 4. Experimental set-up for Approach 1: a) single, semi-collimated light source; b) fibre optic cable and fore optic; c) oil film on water surface; d) water-filled beaker, and; e) 3% reflecting panel.

Fig. 5 shows thickness dependent changes in reflectance for the two oils examined in this study, filtered and normalized for the response of the Quickbird sensor (a commercially available, spaceborne, multispectral sensor). The y-axis in Fig. 5 denotes discernable levels of information for the Quickbird sensor, in units of $NE\Delta R_E$ (Noise Equivalent delta Reflectance) [10]. For any given Quickbird sensor band, a difference in $NE\Delta R_E$ value greater than one implies that the difference is detectable.

The x-axis denotes wavelength, with the visible blue channel occurring around 480 nm and the visible red channel occurring around 660 nm. For the Gippsland light crude, Fig. 5a corroborates known theory [6]: there is increased absorption of light towards the blue end of the spectrum, and increasing absorption with increasing oil thickness. Importantly, the results show that the Quickbird sensor is able to detect this absorption.

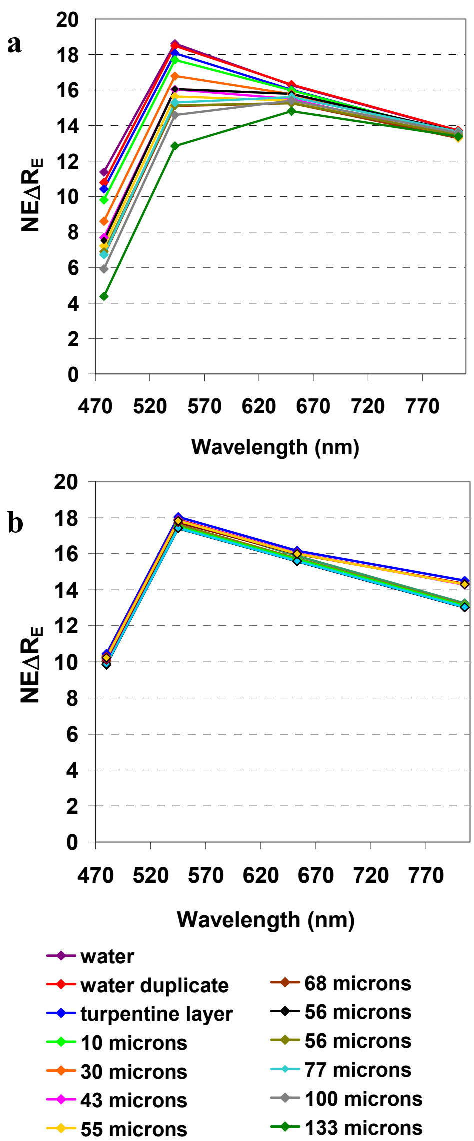

Figure 5. The thickness-dependent absorption of the Gippsland light crude (a) and North West shelf light condensate (b) as measured by Approach 1 and expressed in units of Noise Equivalent delta Reflectance.

As an example, a 30 micron thick layer of the Gippsland light crude is theoretically discernable in both the blue (approx. 480 nm) and green (approx. 550 nm) Quickbird channels (Fig, 5a), (it is more than one $NE\Delta R_E$ level apart from the water signal). In contrast, the North West shelf light condensate (Fig. 5b) is not able to produce an absorption effect measurable by the Quickbird sensor up to an oil thickness of 200 microns (the difference in absorption spectra are less than one $NE\Delta R_{E)}$, which is significantly thicker than typically occurring natural oil slicks.

These findings, together with additional work for a range of sensors and oil types, suggest that the chemistry of the oil may be critical to the application of optical remote sensing to natural oil slick detection. Hence, we recommend that a sensitivity study such as described above should be undertaken prior to using optical remote sensing for slick detection and identification. This would incorporate the characteristics of any potential sensors and optical properties of the oil types expected to be present in the region. As information on oil chemistry may not be available for areas of frontier petroleum exploration, the results we present in our studies provide guidance in assessing optical remote sensing data.

As an example, our findings here indicate that petroleum slicks derived from condensate seepage (oils of API gravity greater than 45º) may not be detected using optical properties. In contrast, light crude oils of lower API gravity (35º to 45º) may be detected but oil film thickness will need to be greater than a given threshold (30 microns in the case of the Gippsland light crude and the spaceborne Quickbird sensor).

2. Approach 2

The methodology used in Approach 1 is reasonably complex and requires access to specialist instrumentation. An alternative (Approach 2) involves estimating transmittance through absorbance measurements, which can be done using standard spectrophotometric measurements. The advantage of these types of measurements is that the required equipment and operator experience is relatively common in biology, chemistry and/or physics research institutions, including university laboratories. Transmittance measurements and results analogous to those reported here are therefore relatively straightforward to commission, provided access to suitable oil samples.

In order to utilise the standard transmittance measurements for the type of sensitivity analysis described here, the measured absorbance requires conversion to a quantity comparable to the oil-covered water reflectance values measured in Approach 1. The formulas for this conversion are outside the scope of this paper, and can be found in [9].

Fig. 6 shows the result of using Approach 2 to derive the airborne hyperspectral HYMAP sensor's sensitivity for a range of thicknesses (in 10 micron increments) of the Gippsland light crude. For example, Fig. 6 shows that the HYMAP sensor could theoretically discern (i.e. the difference in $NE\Delta R_E$ values are >1) the absorptive properties of a layer of Gippsland crude 10 µm thick in approximately five of the sensor channels (between approximately 470 nm – 550 nm).

Fig. 7 shows an example comparing the results of Approach 1 and Approach 2. Here, the absorption of the Gippsland light crude, as estimated by both approaches, for Quickbird's blue channel is shown as a function of oil thickness. Similar results are obtained for oil layers up to approximately 50 microns thick, but for thicker oil layers the results for the two approaches diverge. Note that the results do not diverge by significantly more that a Quickbird $NE\Delta R_E$ level. In other words, this divergence is theoretically not detectable by Quickbird. Furthermore, we postulate that this divergence is due to the gradual evaporation of the lighter fractions of oil, as the measurements progressed during the time-consuming reflectance measurements of Approach 1.

In summary, we conclude that the more accessible Approach 2 produces valid sensitivity estimates of oil layers on water. Indeed, under the assumption that the difference in results between the two approaches is due to the evaporation of the lighter fractions of oil, the transmittance-based approach is more accurate. An in-depth description and analysis of this work is available in [9].

C. *Future work*

Using the Approach 2 method prescribed above, we are currently undertaking sensitivity studies comprising five (5) sensor types and four different oil types from Perth Basin area. We anticipate that we will continue to gradually add results to a database of oil type versus sensor sensitivity. This will provide a reference for the applicability of a given optical remote sensing platform for detecting a given type of marine oil slick.

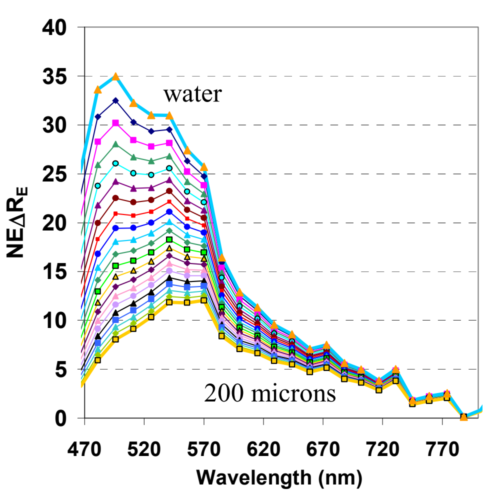

Figure 6. The thickness-dependent absorption of the Gippsland light crude as measured by Approach 2 and expressed in units of Noise Equivalent delta Reflectance. The simulated oil thickness varies from 0 – 200 microns in 10 micron increments.

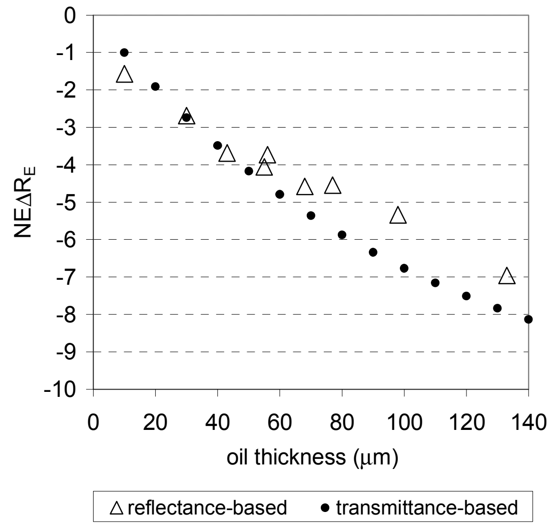

Figure 7. The absorption of the Gippsland light crude, as estimated by Approach 1 (reflectance-based) and Approach 2 (transmittance-based), for Quickbird's blue channel, shown as a function of oil thickness.

IV. Concluding Remarks

We are developing a two-pronged approach for detecting and monitoring naturally occurring oil slicks in the Australian offshore environment: broad scale initial detection using SAR data, and further targeted study using optical remote sensing-based techniques with diagnostic potential.

The extensive and repetitive coverage of SAR data, in combination with its sensitivity to slicks on the sea surface, has been harnessed in a semi-automated, object-oriented, classification and processing system in order to perform initial screening of large volumes of data. This system, SAMSSARA, offers a range of reporting and analysis outputs, including the highlighting of likely slick targets. Its benefits include: 1) the cost saving of discarding data which does not need to be assessed manually by a trained operator; 2) quick visualization of project statistics and identified targets, and; 3) providing geo-referenced maps of classified objects which can be directly input into a GIS for contextual analysis in combination with, for example, geological data.

Commercially available optical remote sensing data can be used for further targeted study on a case-by-case basis: the spaceborne Quickbird multispectral sensor and the airborne hyperspectral HYMAP sensor are able to detect the diagnostic absorption of light by a layer of hydrocarbon oil on a water surface, but this is critically dependent on oil type. We propose a relatively straightforward transmittance-based approach for estimating the absorptive properties of a targeted oil type, in order to perform the recommended sensor- and oil-specific sensitivity analysis prior to (potentially costly) image data acquisition and analysis.

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