Test, Evaluate, and Characterize a Remote-Sensing Algorithm for Optically-Shallow Waters

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LONG-TERM GOALS

The long-term goal of this project is to provide reliable inversions of water column and bottom properties when the hyperspectral inversion algorithm (HOPE) is applied to any coastal area that is interested by the Navy.

OBJECTIVES

The projected goal for this research is to test, and understand, the performance of the hyerspectral-optimization algorithm (HOPE) designed for derivation of water-column and bottom properties of optically-shallow waters from spectral remote sensing, with an eventual goal that the HOPE algorithm can be adopted and utilized by the Navy.

APPROACH

We, along with colleagues and international collaborators, will first determine a common data set of optically-shallow waters. This data set contains images of hyperspectral remote sensing as well as bathymetry and IOPs for validation. We will then conduct independent tests of HOPE [*Lee et al.*, 1999; *Lee et al.*, 2001; *Lee et al.*, 2007] using this data set to identify:

- where models do and don’t work (physical limitations, algorithms restrictions, dependencies on additional data sources)
- serviceable in terms of adaptability (to locations, sensors, optical properties)
- strengths and weaknesses of the model
- potential refinements of the algorithm
- development of standard products for mapping in optically shallow waters

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WORK COMPLETED

Two efforts were carried out during the course of this project. One was to evaluate the performance of HOPE with independently collected hyperspectral images; another was to search and identify robust, easy-access, optimization software for use by broader communities.

For the algorithm test and evaluation, two images (over Lee Stock Island, USA and Moretna Bay, Australia, see Fig. 1) were selected after discussion (workshop) with other colleagues and international collaborators. Lee Stock Island (LSI) was imaged with the Ocean Phills [*Davis et al.*, 2006], a hyperspectral (402-800 nm, with ~5nm step) imager; while Moreton Bay (MB) was imaged with the CASI system, which has 28 bands covering a range of 439.3-778.5 nm.

Before image-derived remote sensing reflectance (Rrs) were fed to HOPE (Hyperspectral Optimization Process Exemplar), a pre-process was done to improve/enhance Rrs quality. This pre-process has two aspects: 1) spatial smoothing for wavelengths longer than 600 nm; and 2) white correction for each pixel. Process 1 reduces image speckles resulted from low signals in the longer wavelengths of the study areas. Process 2, where the method was documented in *Lee et al* [2001], compensates, to a degree, the over- or under-corrections in the atmospheric-correction step (including surface reflectance). After these fine adjustments of the image Rrs, properties of the water column and the bottom (absorption coefficient, particle backscattering coefficient, bottom reflectance, and bathymetry) were derived with the HOPE algorithm from Rrs. The inverted results were further compared with in situ measurements (and results from other algorithms) to evaluate the algorithm performance, and results were reported in a workshop taken in February 2009.

The HOPE package uses commercially available software (Solver DLL, Solver Inc.) for the optimization execution. Solver is robust and efficient in handling such tasks. However, due to its relatively high price, Solver is not widely used by ocean color remote-sensing community. To overcome this barrier, and to test the impact of optimization code on remote sensing retrievals, two additional optimization routines (Levenberg-Marquardt and a routine (B2NLS) based on the Bounded Constrained Least Squares/Nonlinear Equations (DQED) [*Lawson and Hanson*, 1995]) were tested and evaluated. These two optimization routines were first tested with in situ measured Rrs (41 stations with bathymetry ranging from ~1.0 m to ~25 m) to select a proper one, and then applied to the LSI and MB images.

RESULTS

A few important results emerged from these efforts.

1) HOPE has wide applicability. HOPE uses a simplified analytical function to represent radiative transfer results in optically shallow environments, with parameters developed with data sources in the West Florida Shelf and the Gulf of Mexico. Apply HOPE to LSI and MB images, properties of the bottom and the water column were well retrieved. Fig. 2 and Fig. 3 present the retrieved properties, along with a quantitative comparison of bathymetry with acoustic measurements. The consistent bathymetry results suggest that HOPE is insensitive to location or data where HOPE is going to be applied. For the retrieval of bottom properties (depth and bottom reflectance), the key is to have enough bottom signal in Rrs. These results also showed that, as demonstrated in *Lee and Carder* [2002], number of spectral bands have only minor impacts on the quality of retrievals, as long as "enough" (~15 bands in the 400 – 800 nm range) well-positioned bands are available. There are no

obvious elements that require refinement for the HOPE algorithm, except in the future to add mixed bottom properties for a pixel. We are cautiously adding this feature as the number of bottom types could be resolved within one pixel is limited.

2) Optimization code does have impacts on efficiency and quality of retrievals. Fig. 4 and Fig. 5 compares the modeled and measured Rrs (from in situ measurements) when the optimization code “thinks” the objective function is “optimized”. Clearly, with the same set up and the same initial values, the two routines could have quite different results. From these comparisons, we concluded that the B2NLS routine fits better our objectives, and B2NLS was then applied to the LSI and MB images to retrieve water column and bottom properties.

3) The B2NLS routine produced nearly identical results compared to that from the Solver optimization for the two images (see Fig. 6 for retrieved bathymetry), and is efficient in processing (see Table 1 for processing time with a 2 quad-core processors at 2.66 GHz in Linux OS). With this routine, because of its availability with the IMSL Math&Stats Libraries package, the HOPE algorithm could be transitioned easier to the Navy users. Some speckles were found in the retrieved images though, and we are continuing the efforts to analyze the sources for such speckles and optimize the routine.

Table 1. Processing time with the B2NLS optimization routine.

Image	# Rows	# Columns	# Spectral bands	Time (seconds)
LSI	501	899	83	2922.46
MB	749	1132	28	5390.66

IMPACT/APPLICATIONS

The above results have been reported at the workshop held in February 2009, and will also be included in a journal article. The HOPE algorithm/model is used by the NRL and colleagues in Australia and other regions.

RELATED PROJECTS

3D Remote Sensing with a Multiple-band Active and Passive System: Theoretical basis

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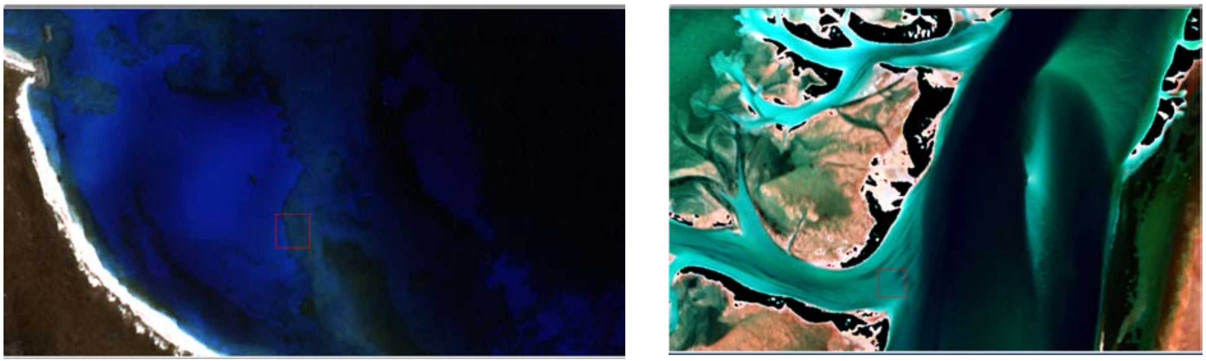

Figure 1. Images selected for evaluation of remote-sensing algorithms over optically shallow waters. Left: Lee Stock Island; Right: Moretna Bay, Australia.

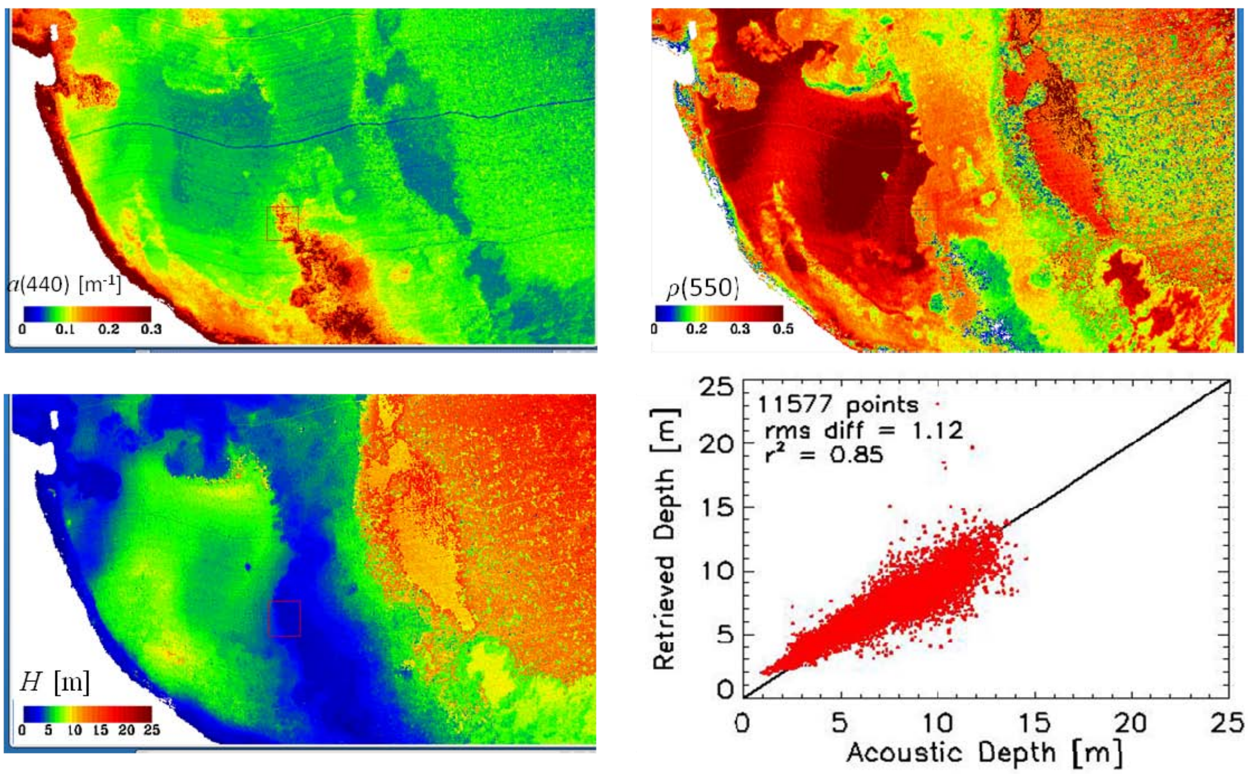

Figure 2. Retrieved properties of the LSI area. Lower right is a scatter plot between known and Rrs-derived bottom depth (H). Also note the clear contrast of bottom depth between the left side and the right side of the image (lower left), but no such contrast for water absorption coefficient (440 nm, upper left), consistent with the expectation that water column properties are less patchy than bathymetry.

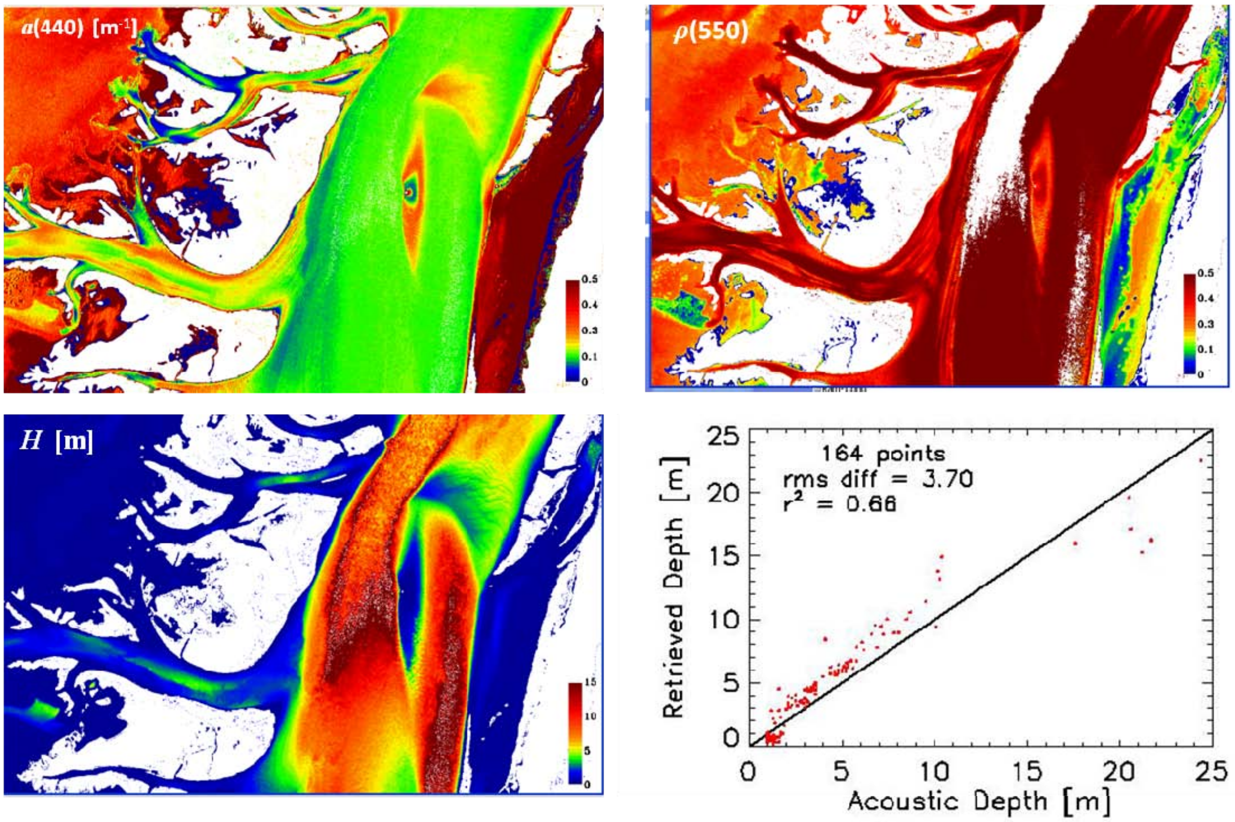

Figure 3. As Fig.2, but for the MB area.

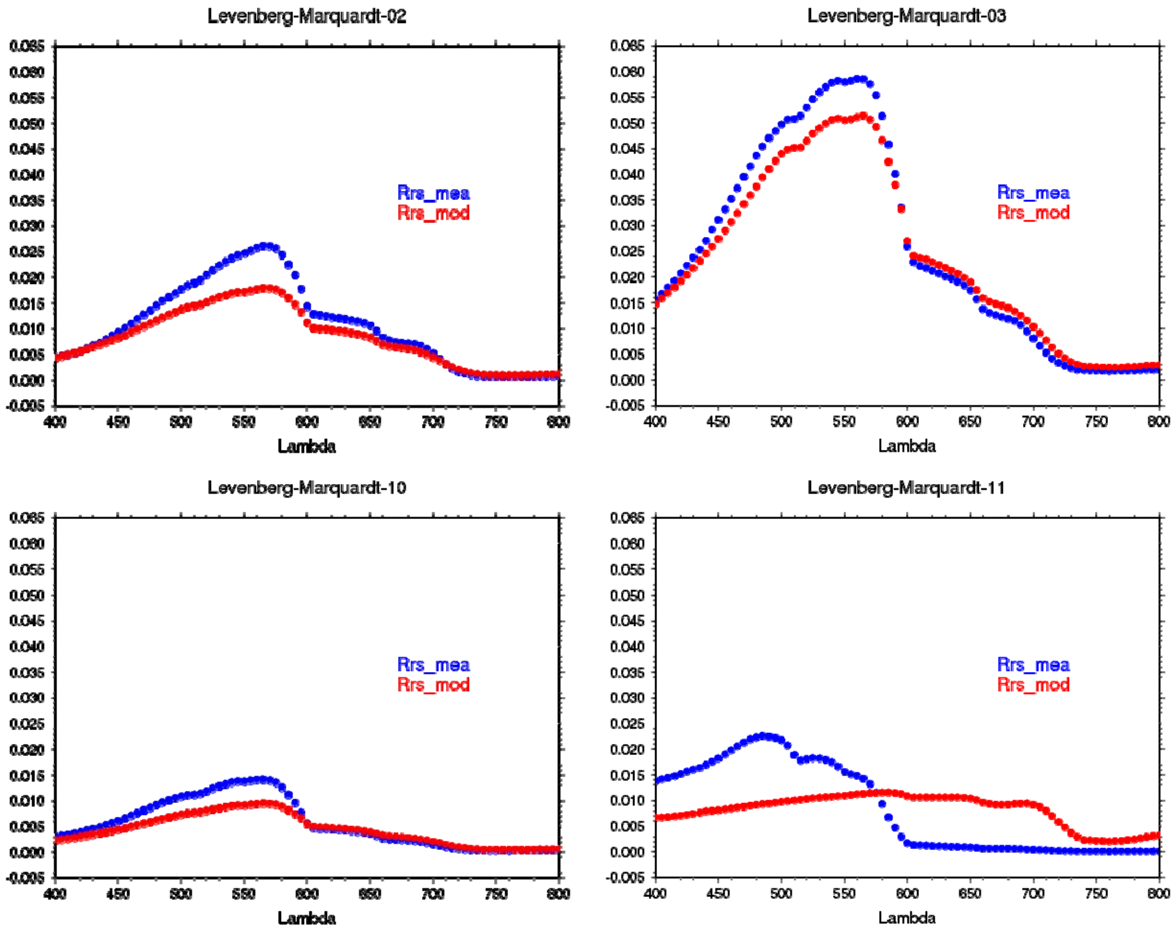

Figure 4. Examples of modeled and measured Rrs (ship-borne data) when "optimization" is reached with an L&M routine.

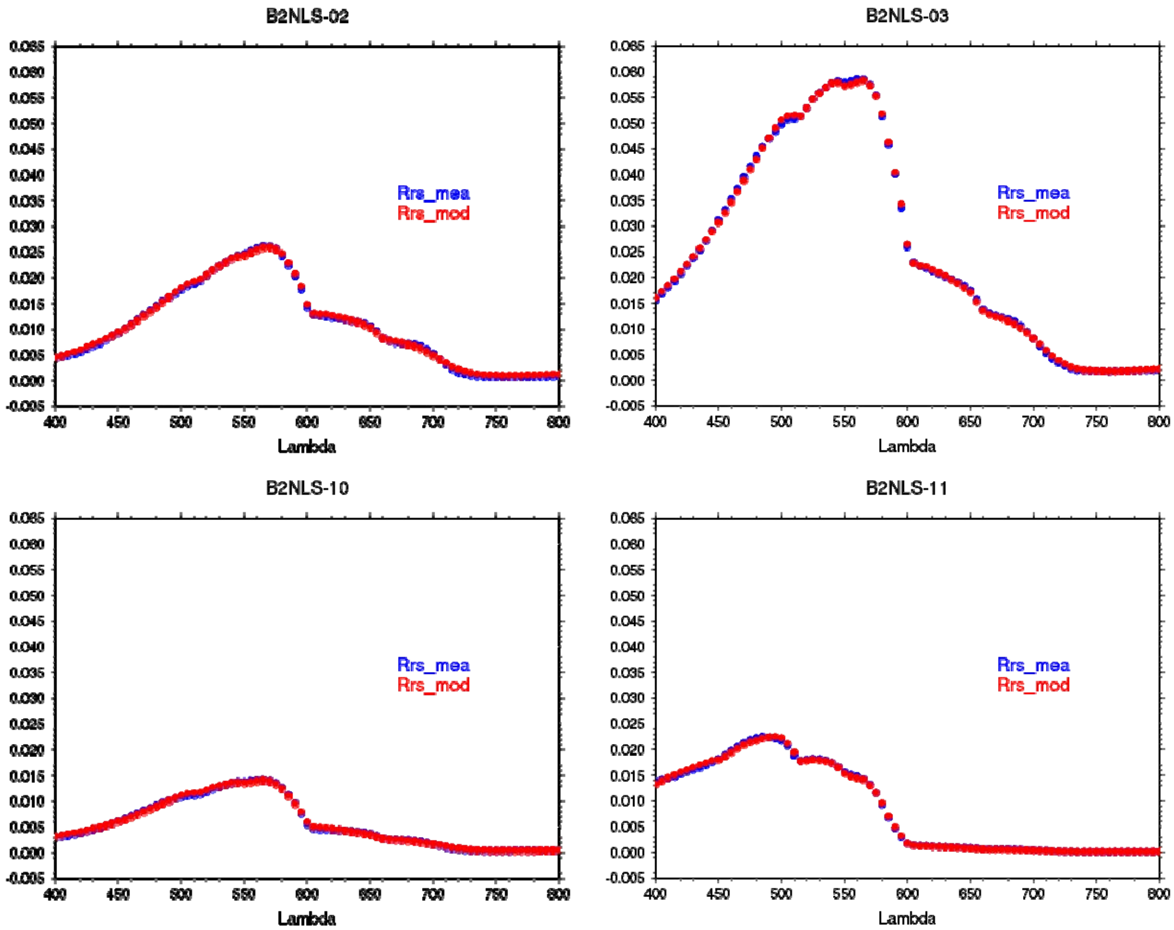

Figure 5. Examples of modeled and measured Rrs when "optimization" is reached with the B2NLS routine.

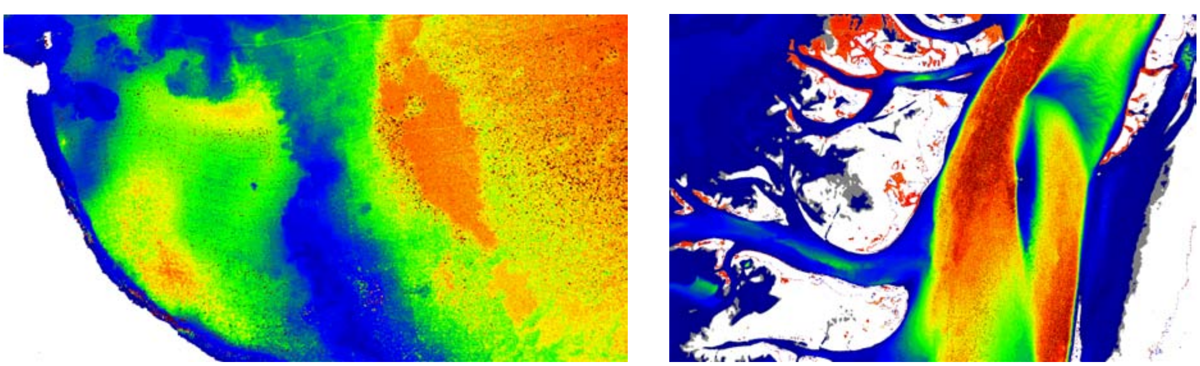

Figure 6. Bathymetry of LSI and MB retrieved with the B2NLS optimization routine.