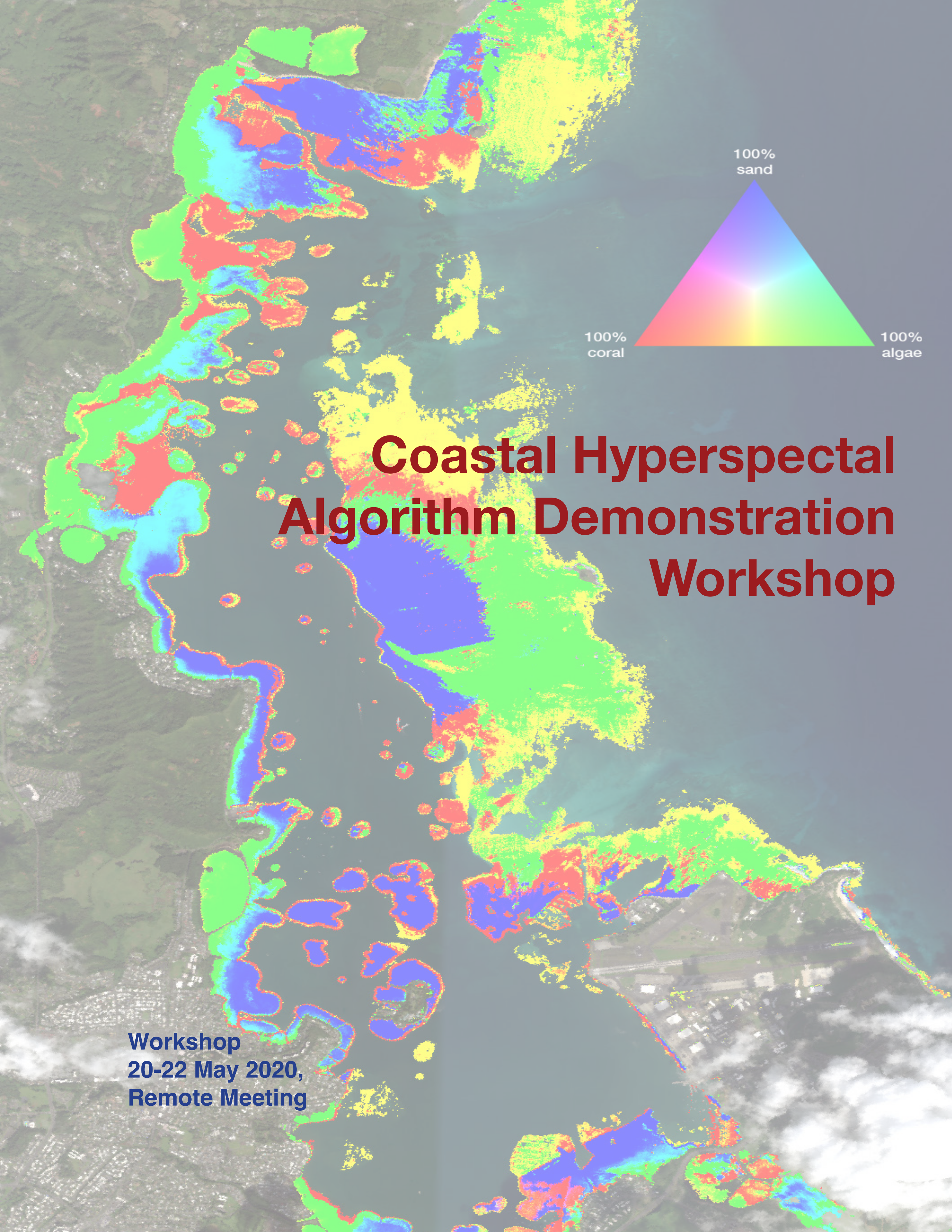

Coastal Hyperspectal Algorithm Demonstration Workshop

Workshop
20-22 May 2020,
Remote Meeting

September 2020
ALLIANCE FOR COASTAL TECHNOLOGIES
Ref.No.[UMCES] CBL 2020-013

Workshop Proceedings
Alliance for Coastal Technologies

COASTAL HYPERSPECTRAL ALGORITHM DEMONSTRATION WORKSHOP

Remote Meeting
20 - 22 May 2020

This workshop was organized and hosted by the Alliance for Coastal Technologies (ACT) and sponsored by the National Oceanic and Atmospheric Administration (NOAA)/US Integrated Ocean Observing System (IOOS)

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Following the "Hyperspectral Imaging of Coastal Waters" workshop in Honolulu on May 2018, the Alliance for Coastal Technologies (ACT, www.act-us.info) organized a coastal hyperspectral algorithm demonstration activity, in which participants were invited to participate in an algorithm round-robin using a hyperspectral image data sets from varying coastal environments (i.e., coral reefs, seagrass and harmful algal blooms) with available in-water validation data. Sponsored by the National Oceanic and Atmospheric Administration (NOAA)/US Integrated Ocean Observing System (IOOS), ACT and the participants convened for the "Coastal Hyperspectral Algorithm Demonstration Workshop" remotely on May 20-22nd 2020. The overarching goals of the workshop were to share progress updates from the individual teams and to facilitate a conversation around next steps for ACT. Focus was given to the potential for community publications on method considerations and best practices for Coastal Hyperspectral Remote Sensing.

ALLIANCE FOR COASTAL TECHNOLOGIES

One of the greatest challenges that NOAA faces in incorporating advanced technologies is bridging the Technology Readiness Level gap between developmental and operational instrumentation. Efforts dedicated to maturing observing technologies to operational readiness through rigorous and relevant testing, while simultaneously building user confidence and capacity, continue to be critical. Building on almost two decades of experience in facilitating the development and adoption of environmental observing instrumentation, the Alliance for Coastal Technologies (ACT, www.act-us.info), proposes to work in collaboration with U.S. IOOS Program Office and Regional Associations (RAs), IOOS federal and non-federal partners, local and regional resource managers, academic researchers, and the private sector to improve operational observation capabilities through the quantification of existing instrument performance, the introduction of new technologies, and enhanced communications. ACT's mission is to foster the creation of new ideas, new skills, new technologies, new capabilities, and new economic opportunities in support of the sustained national IOOS.

ACT was established by NOAA in 2001 to bring about fundamental changes to environmental technology innovation and research to operations practices. ACT achieves its goal through specific technology transition efforts involving both emerging and commercial technologies with the explicit involvement of resource managers, small and medium-sized firms, world-class marine science institutions, and NOAA and other Federal agencies. ACT's core efforts are:

1. Technology Evaluations for independent verification and validation of technologies,
2. Technology Workshops for capacity- and consensus-building and networking, and
3. Technology Information Clearinghouse including an online Technologies Database.

ACT is a leader in the evaluation of commercial and emerging ocean, coastal and freshwater sensing technologies. ACT's Technology Evaluations employ an ISO/IEC 17025:2017 compliant process to generate sensor performance data of known and documented quality through an open, inclusive, and transparent process that is responsive to the *users' operational needs*. Evaluations focus on classes of instruments to demonstrate capabilities/potential of emerging technologies, provide unequivocal verification of performance specifications for commercial technologies, and/or provide validation of instrument operational qualifications that meet users or observing system requirements. Laboratory and field testing are carried out under reproducible, well-understood conditions, which allows manufacturers to assess and improve components, configurations, and designs, as necessary. Since 2004, ACT has evaluated nearly 90 sensors from 32 international companies. Results of ACT Technology Evaluations also have provided important insights to users on how to interpret data provided by *in situ* instrumentation and thus how to appropriately quantify various environmental parameters. The ACT Evaluations provide independent assurance that basic science understanding, forecasting, and management decisions are based on accurate, precise, and comparable observing data, while minimizing the risk of artifacts and problems associated with young technology.

ACT Technology Workshops have addressed the capabilities of existing operational technologies (e.g., dissolved oxygen and salinity) and needs for new technological solutions to address specific global environmental issues (e.g., nutrients pollution and ocean acidification). Encouragement of the private sector as participants not only provides users with opportunities to better understand technology options, but also helps technology providers to better understand customers' needs.

The ACT Information Clearinghouse includes all Technology Evaluation and Workshop reports (as downloadable PDFs) and a stakeholder driven database that compiles and inventories information on observing technologies. The Technology Database now connects users with over 400 companies and nearly 4,000 commercial instruments, which increases awareness of technology customers, users, regulators, and policymakers of available technology options.

EXECUTIVE SUMMARY

This workshop was organized and hosted by Alliance for Coastal Technologies (ACT) members at the University of Hawaii at Mānoa (UHM) and sponsored by the National Oceanic and Atmospheric Administration (NOAA)/US Integrated Ocean Observing System (IOOS) on May 20 – 22, 2020. A Technical Advisory Committee comprised of leading experts who use hyperspectral imaging in coastal waters [Dr. Steve Ackleson (NRL), Dr. Kyle Cavanaugh (UCLA), Dr. Heidi Dierssen (University of Connecticut), Dr. Michelle Gierach (NASA/JPL), Dr. Jonathan Kok (AIMS), Dr. Sherry Palacios (CSUMB), Dr. Blake Schaeffer (EPA)] assisted ACT [Dr. Margaret McManus (UHM), Mr. Daniel Schar (HIMB), Dr. Mario Tamburri (UMCES), Dr. Tom Johengen (Sea

Grant), Dr. Andrea VanderWoude (NOAA), and Dr. Eric J. Hochberg (BIOS)] in planning the workshop.

The workshop was opened with welcome by Dr. Margaret McManus, who introduced the ACT and Technical Advisory Committee members. Further, the participating team leaders were introduced. This included: Wes Moses (NRL), Peter Gege (DLR Earth Observation Center), Luba Reshitnyk (Hakai Institute), Mike Sayers (MTU-MTRI). Additional guests participating were Tom Bell (UCSB), Susanne Craig (NASA), Stefan Plattner (DLR), Steve Lohrenz (UMass Dartmouth), and Clarissa Anderson (UC San Diego). It should be noted that due to the global pandemic this workshop was held online. In addition, due to the pandemic the progress of some teams was understandably delayed. The team leaders for these teams: Nima Pahlevan (NASA), Paul Gader/Susan Meerdink (University of Florida), and Rodrigo Garcia (UMass) will follow up later in the year. This report focuses only on the teams that were able to participate May 20-22, 2020.

Following introductions, a brief review of the outcomes of the last ACT workshop on "Hyperspectral Imaging of Coastal Waters" that took place in Honolulu in May 2018 was given: The goal of the past workshop had been to examine present hyperspectral imaging technologies in coastal environments, to explore future requirements for hyperspectral imaging and to determine if it would be appropriate for ACT to undertake a demonstration of these technologies and data processing methods. The recommendations emerging from the 2018 workshop included a list of possible demonstration projects that ACT might undertake:

1. An algorithm round-robin with outside participants using a hyperspectral image data set from varying coastal environments with available in-water validation data (i.e. harmful algal blooms, corals, kelp beds etc.).
2. Mooring calibration/validation of hyperspectral remote sensing with a set of hyperspectral optical sensors deployed on moorings along with coincident flyovers with a hyperspectral imager(s), (partnering with IOOS).
3. Controlled mesocosm(s) tank experiments with a suspended boom to 'fly' manufacturers hyperspectral imagers over the tanks to show the imagers capabilities.
4. Flight comparison with a sensor like PRISM (Portable Remote Imaging Spectrometer) as a standard.

Dr. Eric Hochberg (Bermuda Institute of Ocean Sciences/ACT) then introduced overarching goals of the three-day May 20-22, 2020 ACT workshop:

1. To exchange details on progress, data validation, lessons learned and possible future collaborations among participant teams that have been working since June of 2018 on this demonstration project.
2. To discuss the potential for community publications on method considerations and best practices for Hyperspectral Remote Sensing.

On the first and second day of the workshop, each of the teams presented their work and addressed the following in their team presentations:

1. Brief overview of study area and datasets used
   a. What was the application objective?
   b. What data were used, both remote sensing and otherwise?
2. Algorithm applied (including any preprocessing corrections if needed)
   a. What was the processing/analytical approach?
   b. What was the validation approach?
3. Results – Mapped products and graphical results of the validation
   a. Was the objective met?
   b. What were accuracy/uncertainty levels (quantitative or graphical)?
   c. What worked well with respect to the data and approaches?
   d. What challenges and limitations were encountered? Overcome?
4. Next steps (including the potential journal for submission)
   a. What are some recommendations to improve the data set, processing, and validation?
   b. Do you want to be part of a community paper(s)?
   c. Is there anything else to cover?

Presentations were grouped by data set: coral reefs, seagrass and harmful algal blooms (HABs). Each group of talks was followed by questions and a group discussion. On the second and third days of the workshop, a detailed outline for community publications on method considerations and best practices for coastal hyperspectral remote sensing was established and reviewed. Further, next steps for ACT in the upcoming 1-2 years were presented by Dr. Mario Tamburri including plans for an in-person workshop in Hawaii and a vendor demonstration in the Great Lakes in 2021.

GROUP PRESENTATIONS – CORAL PROJECT DATASET

A Spectral Optimal Estimation Approach for Retrieving Bottom Characteristics in Shallow Water Environments – Dr. Wesley Moses (Naval Research Laboratory, Washington, D.C., USA)

The goal of this work was to test an optimal estimation (OE) approach for retrieving multiple biophysical parameters of shallow waters using hyperspectral imaging data. OE is (1) based on the physics of radiative transfer; (2) capable of exploiting spectrally rich information; (3) computationally fast without compromising accuracy; (4) globally applicable, with limited need for local adjustments/re-parameterization; and (5) able to account for and provide estimates of uncertainties in retrievals.

The measured remote sensing signal is expressed as a function of various optically relevant variables that contribute to the measurement and perturbation in the signal due to measurement uncertainties:

Measured Signal, $y = f(x) + \varepsilon$, where x is a state vector consisting of optically relevant variables related to the atmosphere (aerosol type, aerosol optical thickness, etc.), water column (concentrations and absorption/scattering coefficients of optically active materials in water), and bottom (bottom depth and bottom type); ε is a measure of uncertainties in the measurement.

OE is a statistically rigorous method that exploits spectral information, taking into account prior estimates of x as well as uncertainties in measurement. The theoretical robustness, the effectiveness in using *a priori* information, and error analysis are advantages of this approach. Disadvantages are the need for judicious selection and parameterization of the forward model, the intensive and time-consuming computational labor, and the challenge of operational pixel-by-pixel implementation on a satellite image. We also explored a computationally less time-intensive approach that classifies the image into numerous classes of spectrally similar pixels and subsequently applies the algorithm to each class, as opposed to every pixel.

This study used PRISM data from Heron Reef, Australia, acquired on 16/17 September 2016 as part of NASA's Coral Reef Airborne Laboratory (CORAL) mission. The focus of the retrievals was on bottom depth and bottom type (coral, turf algae, and coral sand). We used atmospherically corrected data and assumed predetermined constant values across the whole image for concentrations of optically active constituents in the water column (chlorophyll-*a*, colored dissolved organic matter, and suspended particulate matter). The purpose of fixing constituent concentrations at predetermined, low constant values was to reduce the degrees of freedom in the retrieval and enable a quicker and more robust retrieval of bottom characteristics. This was deemed reasonable given that the images were from clear, shallow waters. In addition, we also applied OE by allowing the constituent concentrations to vary within narrow ranges and retrieving them along with bottom characteristics.

Two radiative transfer models were considered: Hydrolight-Ecolight and a simple Shallow Water Radiative Transfer (SWRT) model (Ackleson et al. 2017). The algorithm was applied in two ways, first to the whole image and then to specific pixels corresponding to *in situ* measurements. For the former case, the image was pre-classified into 70 classes, with the classification parameters set to result in spectrally tight classes that altogether represent the overall variation in the image but individually have minimal within-class variation. OE was applied to representative spectra from each class instead of each individual pixel in the image, and the biophysical parameters retrieved from each representative spectrum were assigned to all pixels in the corresponding class. This is based on the assumption that pixels with similar spectral properties likely contain similar biophysical properties and obviates the need for applying OE on a per-pixel basis for the whole, thereby saving significant computational time. The classification also enabled easy identification and removal of pixels not relevant to bottom retrievals (cloudy, terrestrial, and optically deep). Separately, OE was applied exclusively to pixels with corresponding *in situ* measurements for the purpose of direct comparison. There were 32 pixels with corresponding *in situ* measurements.

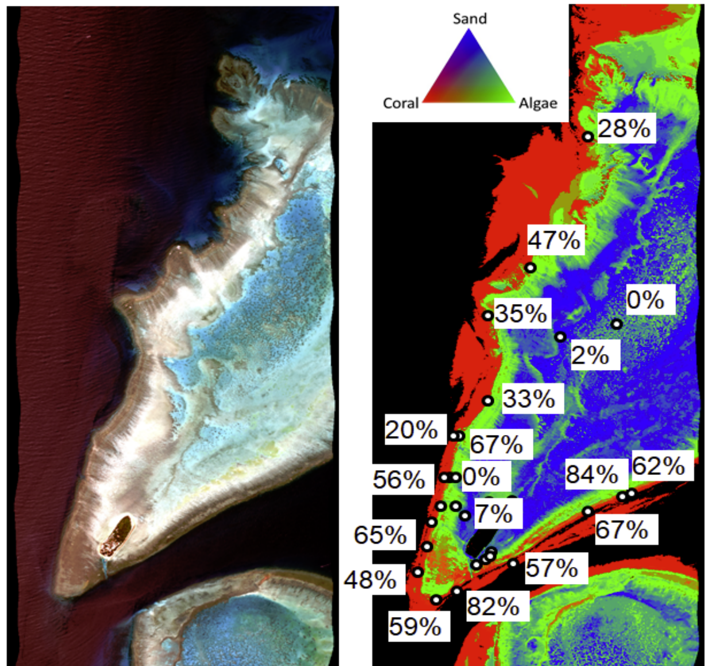

Figure 1. Left: A PRISM image of Heron Reef; Right: Bottom types retrieved using SWRT as the forward radiative transfer model; the percentages annotated are the percent coral cover measurements from *in situ* data.

For the PRISM data used in this study, OE retrievals of bottom characteristics based on SWRT were more accurate than those based on Hydrolight-Ecolight. A direct comparison of SWRT-based OE retrievals of bottom type with *in situ* measurements for the 32 pixels showed a bottom type detection accuracy of 78.125%. Applying OE to the entire image after pre-classification resulted in a slight decrease in the bottom type detection accuracy, at 68.75%. The decrease is understandable because, in this case, OE is not applied to actual reflectance spectra of pixels corresponding to *in situ* stations but to representative spectra from the classified image. Retrievals based on Hydrolight-Ecolight fared worse for both cases, with accuracies less than 50%. Analysis of the results showed that erroneous bottom type detections were mostly due to confusion between coral and turf algae bottoms. There was some sensitivity to water column properties. Knowledge or *in situ* measurements of absorption/scattering properties of the water column and constituent concentrations would help improve accuracy. Retrieved bottom depths compared reasonably well with *in situ* measurements. Though the comparison of absolute depths was not remarkable, the relative variations in depth were captured quite well.

In summary, the optimization approach generally yielded reasonably accurate retrievals of bottom characteristics. Further, the simple SWRT model was much faster to execute and generally yielded a higher accuracy. It appears that rigorous models such as Hydrolight-Ecolight are very sensitive to parameter initialization. Optimization-based approaches hold promise, but accurately retrieving multiple parameters requires reliable ancillary data. Next steps would be to (1) use data from other available sources to get as much *a priori* information as possible to constrain the retrieval; (2) use information on PRISM's radiometric characteristics and SNR to model uncertainties in retrievals; (3) revisit PRISM atmospheric correction based on *in situ* R_{rs}; and (4) apply the algorithm to *in situ* R_{rs} to test retrievals.

Questions and Answers Specific to the Presentation:

Q. Were there any issues with geolocation accuracy?
A. There was some inaccuracy with the first image (as pointed out by Eric Hochberg, this may have possibly contributed to problems with results from the first image). Other images appeared to be fairly accurately geo-located, based on comparison with Google Earth.

Q. Did you calculate the time savings by initially parsing the data out as opposed to going in every pixel within the image?
A. The parsing of the data into classes took about 45 minutes. Using Hydrolight takes 2 minutes for a single spectrum. A simpler model makes it possible in 5-10 seconds. With the pre-classification approach, OE needs to be applied to only 70 pixels (or however many classes one decides to classify the image into), whereas with the per-pixel approach OE would have to applied to all pixels in the image, which, for a high-resolution image, could be more than a million. Thus, even when using the simpler model, it would take several days to process a single image on a per-pixel basis. The pre-classification approach significantly cuts down the processing time and keeps it within operational limits, with only a marginal reduction in accuracy.

Q. Why do you think the computational time and expense between these two models is so different? Presumably these models should not be so far apart.
A. I agree that the results were surprising. The difference in computational time is simply due to the difference in the time it takes for each model to run once. Hydrolight-Ecolight is more sophisticated than SWRT, takes into account more input parameters, and takes longer to run. The difference in accuracies might have to do with how the parameters were set up. Additional tests are needed to examine the impact of certain default settings in Hydrolight-Ecolight. Measurements of inherent optical properties of the water column would help do a more direct comparison between the results from these two models.

Q. What was the chlorophyll range?
A. Presuming that coral waters were rather clear, I set the range low around 0.02.

Q. How did you parameterize the backscatter in Hydrolight?
A. I chose the calcareous sand as sediment type and start values from Hydrolight.

Dr. Peter Gege – DLR Earth Observation Center, Processing of Hyperspectral PRISM Imagery Data in the Heron Coral Reef Using WASI-2D

The primary goals of this work were to (1) adapt the Water color simulator (WASI-2D) (download: https://ioccg.org/resources/software/, Gege 2004, Gege and Albert 2006) to coral reef environment; (2) derive quantitative information about water quality, water depth and benthic cover from hyperspectral PRISM imagery; and (3) assess and validate the quality of the derived parameters and evaluate the challenges of using these technologies in coral reef environments. CORAL/PRISM hyperspectral images (crops from 3 flight strips covering Heron Reef; provided by Eric Hochberg) were used as data.

About WASI: The water color simulator (WASI[3]) has been developed for the simulation and analysis of spectral parameters in water (a, R_{rs}, E_d, L_u,...). It presents an analytical model of downwelling irradiance and includes a number of bio-optical models for deep water and shallow water. Further, WASI contains an elementary data base of SIOPs, bottom substrates and atmospheric absorbers. WASI is physically traceable and includes transparent calculation steps.

Information on the bio-optical model used:

$$R_{rs}(\lambda) = \frac{\zeta \cdot r_{rs}(\lambda)}{1 - \Gamma \cdot r_{rs}(\lambda)} + R_{rs}^{surf}(\lambda)$$

$R_{rs}(\lambda)$: PRISM spectra

$r_{rs}(\lambda)$: sub-surface remote sensing reflectance

$R_{rs}^{surf}(\lambda)$: Reflections at the water surface

$$r_{rs}(\lambda) = r_{rs}^{deep}(\lambda) \cdot \left[1 - A_{rs,1} \cdot exp\{-(K_d(\lambda) + k_{uW}(\lambda)) \cdot z_B\}\right]$$

$$r_{rs}^{deep}(\lambda) = \sum_{i=0}^{4} g_i \left(\frac{b_b(\lambda)}{a(\lambda) + b_b(\lambda)}\right)^i$$

In order to provide representative input data for bio-optical model of shallow water such as coral reef environments, we set the following aims: (1) avoid spectrally similar albedo as inversion cannot distinguish these; (2) minimize the number of substrates in order to reduce ambiguity issues; and (3) cover the range from 400 – 830 nm for depth below 1 m. We removed spectral similarities and reduced the dataset from 11 mean spectra in the range 400-700 nm to 6 spectra with large differences in spectral shape. Due to the spectral ambiguities, spectra covering an extended range of 400-830 nm were used to get a reliable inversion.

Examination of how spectral range affects fit resulted in the following conclusions: (1) each fit parameter reacts differently to ignoring the near infrared (NIR) spectral range; (2) the induced changes cannot be attributed solely to the spectral range; they are also related to the sensitivity of a parameter on error propagation; (3) CDOM, seagrass, red algae and coral brown react too sensitively to draw clear conclusions on the impact of the spectral range; the scatter plots are quite noisy with related r^2 below 0.62; and (4) sand, water depth and TSM are the most stable parameters with $r^2 > 0.85$.

An examination of how many and which parameters should be fitted by changing the number and type of fit parameters concluded in the selection of 9 parameters: (1) phytoplankton concentration (green algae); (2) total suspended matter concentration; (3) CDOM concentration; (4) water depth; (5) fraction of sand; (6) fraction of seagrass; (7) fraction of red algae; (8) fraction of brown coral; and (9) fraction of sun glint. Phytoplankton fit results (consistent between 3 images) were in good agreement with *in situ* data above 0.5 mg m^{-3} but underestimated chlorophyll concentration inside the reef.

Total suspended matter (TSM) fit results (consistent between 3 images) were in fair agreement with the *in situ* data (their uncertainty was in the order of 100% and their spatial variability was very high) and quite variable inside the reef. CDOM fit results (different between 3 images) were too low inside the reef (frequently zero) and in no correlation with the *in situ* data. Further, the inversion failed in determining CDOM. Unleveled seafloor and variable water level (tide, waves) caused water depth fit results (consistent between 3 images) to be difficult to validate. Nevertheless, they were in reasonable correlation with the *in situ* data considering sea floor topography and tides with the best correlation found for depth below 4 m. Sand fit results (highly consistent between 3 images) were in some correlation with *in situ* data; the fit tends to overestimate at low sand cover (mainly at water depths > 10 m). Seagrass fit results (consistent between 3 images) were locally highly variable and in no correlation with *in situ* data of algae cover (no validation data for seagrass available). It later became clear that there was no seagrass in the area and highlighted the importance of running the algorithm with realistic input spectra, if the environment is not well known. Algal cover fit results (similar between 3 images) were locally highly variable and in minor correlation with *in situ* data of algae. Similarly, coral fit results (consistent between 3 images) were locally highly variable and in some correlation with *in situ* data. See coral validation graph below in Figure 2 and images in Figure 3).

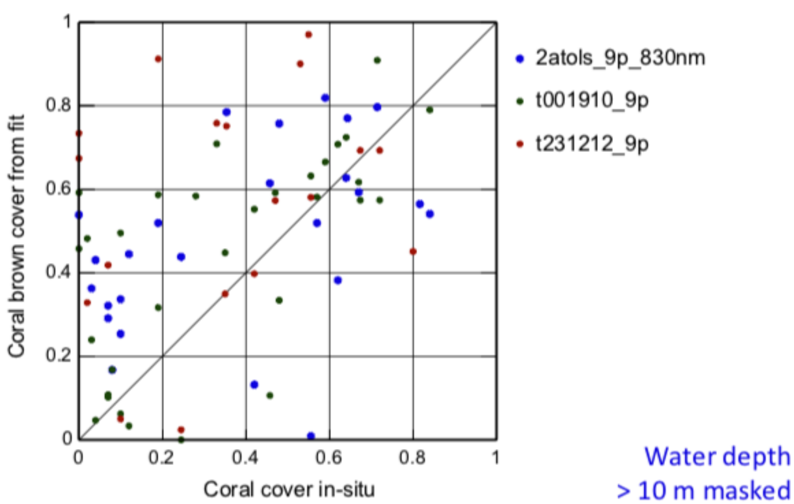

Figure 2. Coral cover *in situ* vs. Coral brown cover from fit.

In summary, we found PRISM data quality to be excellent. It provided a complete data set that was perfect for algorithm development and validation. WASI software was easy to adapt to the new environment. Communication with collaborators Heidi, Eric, Steve and Stefan was timely, smooth and extremely helpful!

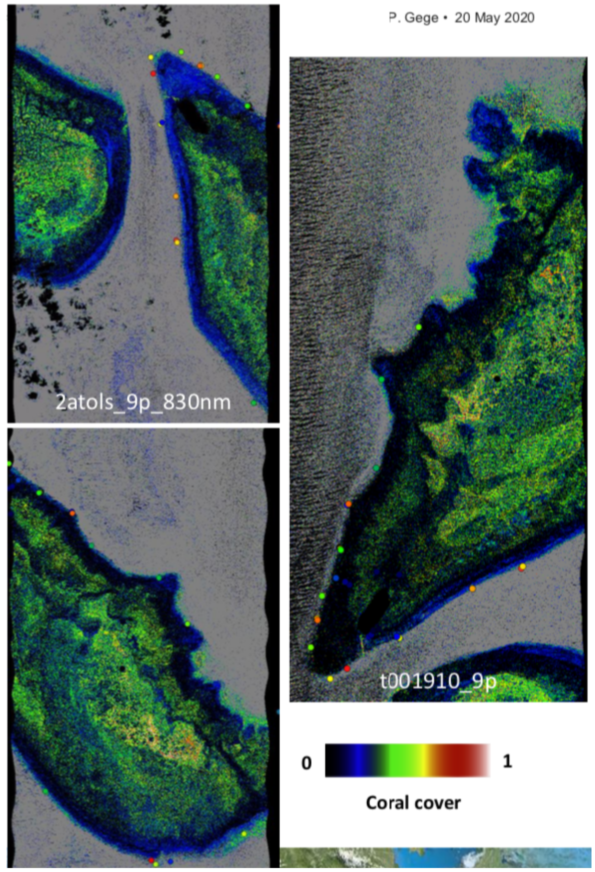

Figure 3. Coral cover.

Some of the challenges and limitations encountered included: (1) The coral reef environment is optically very complex and introduces ambiguities to the reflectance spectra. To overcome this challenge, input database (benthic albedo) and fit settings (spectral range, number and type of fit parameters, initialization, spectral weighting) were optimized. (2) Spectral range of substrate spectra was too narrow. This was solved by, replacing the spectra with similar spectra from other sources. (3) Georeferencing of one image was off by 115–140 meters. To solve this problem, the image was manually moved and rotated in ENVI until reef edges matched the Google Earth image. (4) Tidal effects make bathymetry validation challenging. Water level records of Heron Island, interpolation of data with a cosine function, and correction of PRISM and *in situ* data proved helpful. (5) Computation time of WASI was very long (13-33 hours per cropped scene). Patience and 3 computers were needed.

As a next step, an overview of the available data and project members with information on the data sets that are being analyzed would be useful. For publication, a more detailed data analysis would be necessary including the extension of statistical meta-analysis of fit comparison, the exclusion of deep-water pixels for shallow water parameters, and the consideration of water depth, georeferencing uncertainties and bottom topography in the validation. We would also be happy to contribute to a collaborative community paper.

Questions and Answers Specific to the Presentation:

Q. Have you thought about integration of your model and the classifications with a reduced band set to show the true influence of hyperspectral vs. multispectral capabilities?

A. Running the model with a reduced number of bands does not save too much computation time. The difficulty here is the selection of the best weighted bands:

Coral reef environments hold information at every wavelength. As a result, you unavoidably lose some information when reducing bands. An alternative is to do work with multispectral sensors, but we would have to look at the simulation to understand the exact differences. It would be relatively easy to resemble the PRISM data, run the same inversion on the resembled data and check the differences. It would also be helpful to take PRISM data and construct SPG data to examine if there is any loss in information.

Q. What does the infrared help with other than the sunglint?
A. My approach to correct for the sunglint is to do the inversion simultaneously with the inversion of the water body and the seafloor. That means I need applicable data in the model. It turned out that this sunglint correction works better if you separate it from next steps. Standard approaches also rely on infrared signal. However, if infrared is affected by sea floor in shallow waters (< 1 m depth), the algorithm might assume that the water is black resulting in the signal measured from the surface. For remote sensing of water depth < 1m the infrared and also bottom coverage should be included.

Q. Did you do any confusion matrix to check the performance of your algorithm? Further, you used a lot of categories. Seagrass showing up shows that it is being incorrectly detected when it really was something else (as we know that there is no seagrass there). Did your approach mix categories?
A. I made correlation plots that compare different runs with different fit settings but did not do a confusion matrix. My approach mixed categories. I fitted four bottom substrates simultaneously and included the seagrass spectrum, because I thought there might be seagrass. There is mixing of the classes, otherwise seagrass would have shown 0 (there is no seagrass in the environment). Nevertheless, I got a relatively good fit despite the input spectrum being used.

Q. Do you think some of the benthic absorption went into the water color?
A. It is important to understand the sensitivities of error propagation. I have never used so many fit parameters simultaneously, so it may be a problem of overfitting that causes spectral ambiguities. It is possible to get similar reflectance spectra using very different parameter combinations. Chlorophyll has been underestimated inside the reef. This error then propagates to errors of the other parameters. Wesley Moses used a reduced number of fit parameters (four parameters) making the image less noisy. Possible approaches to minimize parameters are to treat deep and shallow water separately. That would allow reduction of at least one or two parameters and make the retrieval of benthos more robust.

Q. How did you come up with 9 parameters being the best number?
A. I just ran an inversion of the entire image and used the residual and spectral angle maps to look where I got the better correspondences of the fit and measured curve. I used these two parameters to assess the validity of the fit for the entire image. I tried to minimize the differences across the image of the residual and the spectral angle.

Spectral weighting: Spectral weighting means to do an inversion that weights certain bands higher. If you are interested in a certain parameter, you can tune the fit so that it retrieves that parameter better than if you would weigh them equally. This approach was used to derive bathymetry: I weighted channels higher that are more sensitive to water depth than others.

GROUP PRESENTATIONS – ELKHORN SLOUGH DATASET

Hakai Institute, Luba Reshitnyk, MSc.

The primary objective of this work was to apply methodologies for extracting seagrass extent from hyperspectral imagery (AISA Fenix) collected at Sidney Spit, British Columbia, Canada (O'Neill et al. 2013) to hyperspectral imagery (PRISM) collected in Elkhorn Slough, California, USA (Dierssen et al., 2019). These methodologies included (1) land masking, (2) removal of spectral reflection (deglinting), (3) generating image derivatives and (4) testing supervised classification algorithms. In this demonstration we asked – can methods developed for mapping eelgrass extent (in this case, Sidney Spit) translate to other coastal areas (Elkhorn Slough, CA)?

1. **Context for ACT participation**

The Hakai Institute is a non-profit charity research organization based in British Columbia (BC), Canada whose research focus is the study of coastal ecosystems including canopy-forming kelp and seagrass beds. Mapping coastal habitats along the BC coasts using optical remote sensing methods is challenging. The vast coastline is complex and remote, experiences large tidal exchanges (3 – 5 m) and experiences high cloud cover. To overcome these challenges, the Hakai Institute has launched the Airborne Coastal Observatory (ACO) – an aerial platform housing multiple sensors including lidar, high-resolution cameras and an AISA Fenix hyperspectral sensor. Hyperspectral data is a newer realm of research for Hakai and the opportunity to join the ACT algorithm demonstration presented an opportunity to (1) apply established methodologies with existing datasets and (2) collaborate with the larger coastal hyperspectral research community.

For this activity, we took previous analytical approaches developed by O'Neill et al. (2013) to determine the extent of seagrass from data collected at Elkhorn Slough. Prior to analysis, we compared the site and water characteristics between the two study sites to assess whether we could anticipate the O'Neill methods developed at Sidney Spit, BC, performing well for the Elkhorn Slough dataset. The Vierra bed (Elkhorn) showed nearly double the concentration of chlorophyll-a and higher colored dissolved organic material (CDOM) absorption when compared to Sidney Spit; however, total suspended material (TSM) was largely comparable between locations. Overall, concentrations of optical constituents were more comparable than expected. Differences in contrast between eelgrass and sediment presented a potential confounding issue (bright sand at Sidney Spit compared to dark grey sediment at Elkhorn Slough). At Sidney Spit, the conditions (turbidity) on the acquisition day allowed optical separation of eelgrass to a depth of 7.5 m. At Elkhorn, the deepest bed (Vierra) is between 2.0 – 4.5 m depending on the tide. The bed depth during imagery acquisition was approximately 3 m (collected at high slack tide of 1.49 m above MLLW). We anticipated that the shallower depth of the Elkhorn data should increase classification accuracy.

The data we used were atmospherically corrected Elkhorn Slough Vierra Bed PRISM data (July 2013) with 1 m resolution. In addition, we were provided with diver field measurements of *Z. marina* percent cover (Aug. 2011/13) for data validation. O'Neill et al. (2013) achieved the highest level of eelgrass classification through the following image processing and classifications steps: atmospheric correction, surface glint correction, deep water masking and a maximum likelihood classifier using four key bands unique to eelgrass – slope 500 – 530 nm, first derivatives of 556 nm, 580 nm, and 602 nm. For the ACT demonstration, we modified the methods from O'Neill et al. 2013 to suit the parameters of the data provided. Specifically, a deep-water mask was not applied due to the lack of bathymetric data. Given the shallow nature of the site, this step was deemed unnecessary. A flowchart of the image processing steps is presented in Figure 4, and a detailed description is provided in the following text.

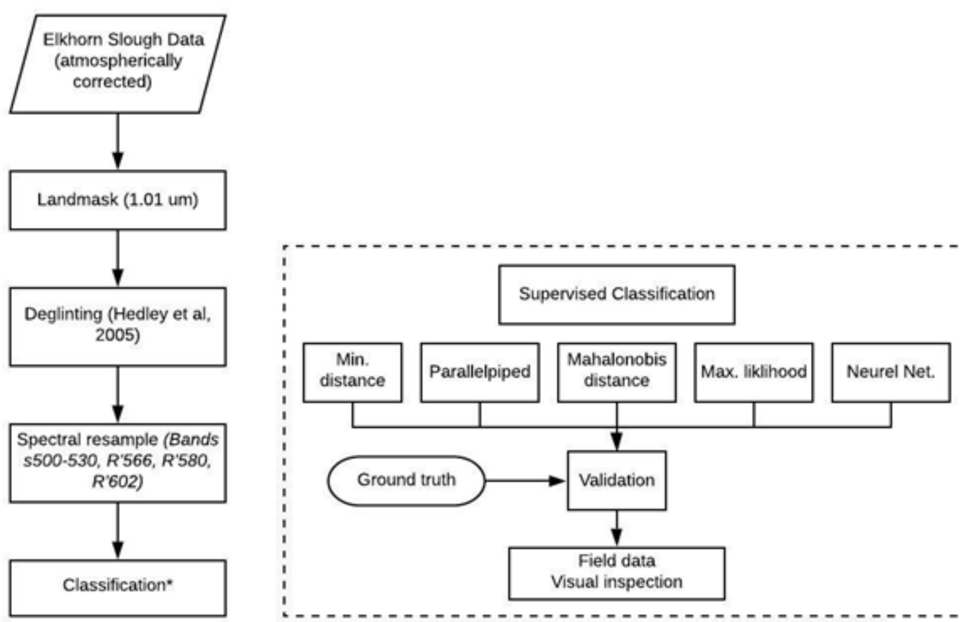

Figure 4. Image processing steps.

Landmasking was conducted based on a threshold (1.01 μm). Deglinting was conducted following Hedley et al. (2005) and performed very well (Figure 5). Image analysis was completed in ENVI, and the reduced variable data set for slope and the four key spectral derivatives (Bands s500-530, R′566, R′580, R′602) were derived (s = slope, R′ = derivative). The derivative at R′602 did show more noise and including it in the classification resulted in degradation of quality. As a result, it was left out to retain the other three primary inputs. In testing different supervised classifications, using the diver data, a 3×3 pixel sampling area was established over each specific point location. A median 3×3 filter was applied to the classification results. The best classification results were achieved with the Mahalanobis Distance and Maximum Likelihood algorithms (Figure 6). Both algorithms detected additional eelgrass in the upper intertidal, potentially indicating the presence of green algae. However, without *in situ* ground validation, that remains unconfirmed. Overall there was good visual agreement between a grayscale band at 550 nm and the results from Dierssen et al. (2019) paper.

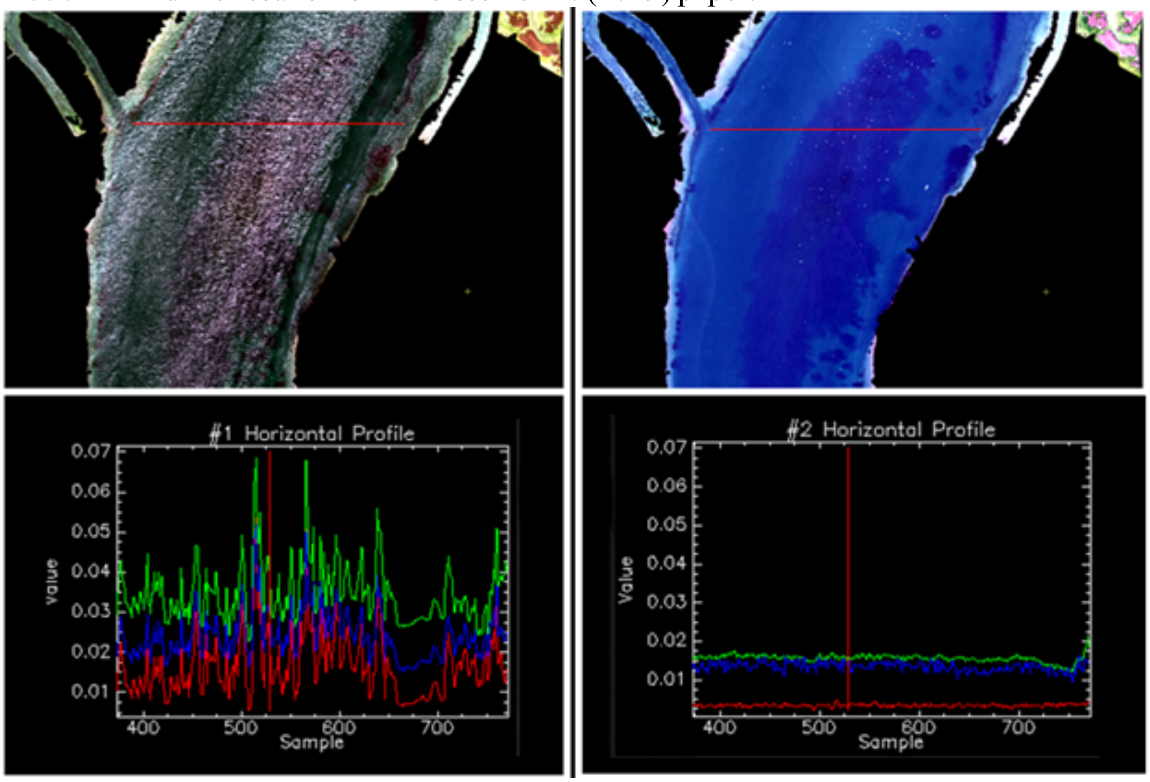

Figure 5. Glint correction example in a portion of heavily glint affected optically deep water in the PRISM image. Top panels: True color PRISM imagery before and after glint correction. Bottom: an image profile showing Rrs at 550 nm (upper blue line), 670 nm (middle green line) and 750 nm (lower red line) before and after glint correction.

We were successful at visually delineating seagrass using this method and found that the methodology adapted from O'Neill et al. (2013) was applicable to mapping the extent of seagrass from Elkhorn Slough. From a participation perspective, the project was manageable in structure and scope and was informative in the application of derivatives for future work. Some of the challenges and limitations included positioning errors and the limited quantification of accuracy.

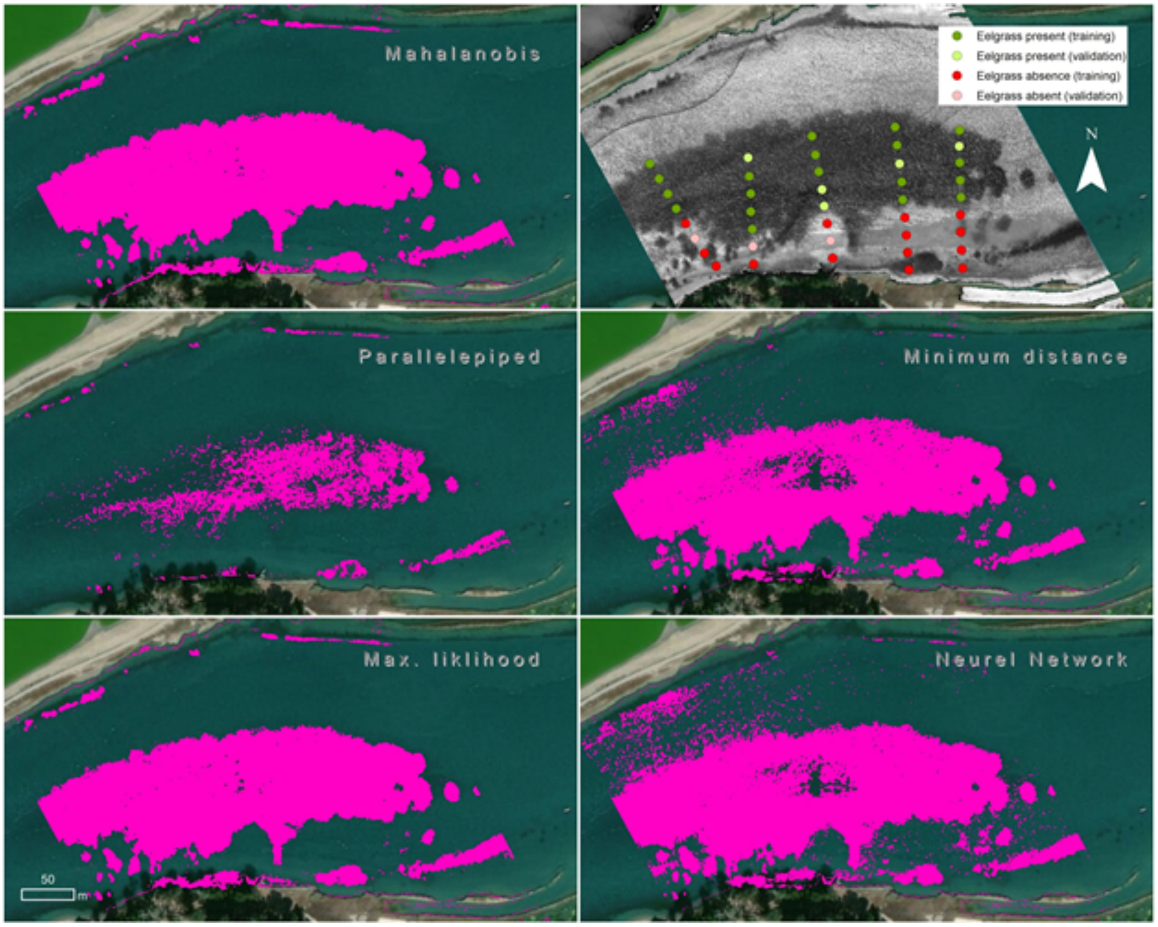

Figure 6. Top right panel: Diver data of eelgrass training and validation data at Vierra Bed. All other panels show classified eelgrass (pink) from supervised classification algorithms.

Next steps could include correcting for the positional ground-truth discrepancy and applying and testing a water correction method on other available datasets (e.g., bathymetry). Further, we have the opportunity to do field work at our field station in British Columbia in summer 2020 and will be planning a low tide hyperspectral overflight. The aim is to develop a method for conducting updated inventories for coastal habitat classes in this area, leveraging hyperspectral systems. We are currently investigating the radiometric calibration methods that we want to apply and are interested to maintain a dialogue with the group about the work done in the past and opportunities to learn. A publication is currently not anticipated from this work. However, if there is any aspect of our work that relates to a community paper, we would be more than happy to contribute. We are looking forward to learning more information about practices for benthic classification. Thank you for the support from the group and especially to Heidi Dierssen.

Questions and Answers Specific to the Presentation:

Q. Are you planning to do water column collection for validation?
A. We are planning to do water column data collection. Generally, we are trying to get as much data as we can while we have the opportunity. We are thinking carefully about what data we are able to collect and how to collect it. We hope that the weather will permit field data collection, while we get the overflight.

Note: British Columbia is a difficult location for mapping. We definitely have the benefit of strong knowledge of this area including high resolution bathymetry. However, we lack spectrally consistent signals across the coast because it is so remote. We are wondering about the best practices when it comes to this? We have thought of flying low and slow to maximize spatial resolution. We anticipate 2-3 m of resolution to target more broader classes rather than specific species by using another remote sensing data set, we are hoping to build a spectral library for these classes.

GROUP PRESENTATIONS – LAKE ERIE HABS DATASET

MTU-MTRI, Dr. Michael Sayers

This work utilized ocean color sensors for bio-optical modeling to examine at annual trends of bulk chlorophyll abundance in Lake Erie. The goal was to explore how we can extend our bio-optical approach (or semi-analytical algorithm) to hyperspectral data and improve components such as community composition and abundance in different pigments, etc. Careful thinking about parameterization of the model and the specific optical properties that we use (spectral shape of our phytoplankton absorption coefficients, CDOM absorption, slopes, etc.) was required. Data limitations in Lake Erie, such as in phytoplankton absorption spectra laboratory a_{ph} partition data, raise the question of how to best parametrize the model with the data available. Particulate Absorption, a_p, data from an *ac*-s spectrophotometer deployed in Lake Erie since 2015 (data collection is continuing at eight stations on a weekly basis) are available. This data set allows—along with CDOM absorption—determination of a_{ph} spectra. The questions that we asked were: Can we use the shape of a_p spectra to parametrize our bio-optical model to retrieve a_{ph}? If we have a_p, how can we decompose useful information out of a_{ph} looking at the spectral space?

The available data set allows us to create a set of optical properties with a given reflectance type profile. I have explored reflectance data, optical water types, assigning reflectances into categories, and the optical properties we have measured in each category, as well as summarizing those statistically (Figure 7). If we can take a pixel from an image and compare it to our optical water type library, we have an accompanying set of optical properties and can parametrize the model. Our approach seems promising: I have looked at all the *in situ* data (2015, 2016) to generate statistical models and have also applied the data to more recent years (2017, 2018) as an independent validation on the *in situ* data. I have managed to retrieve a_{ph} with a robust result on the *in situ* reflectance.

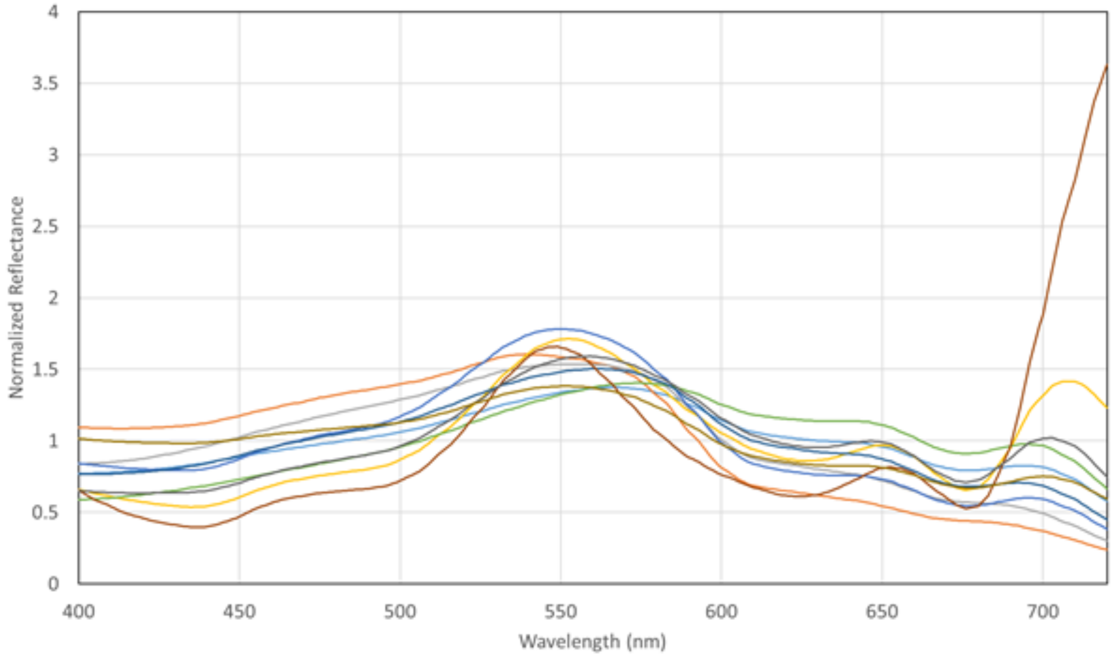

Figure 7. Normalized remote sensing reflectance clusters from *in situ* radiometric measurements made in Lake Erie in 2015 and 2016.

Next steps are to start applying our approach to the imagery. In order to do that, good atmospherically corrected data are crucial. We are planning to investigate using empirical correction methods and radiometry from a very nearby dark parking lot target, which could be corrected for the aircraft model and applied to the model. We are also working on a document with project updates that will be distributed in the near future. We greatly appreciate any technical advisory and feedback from the group. We would be more than happy to contribute to a community paper comparing methodologies and best practices.

Questions and Answers Specific to the Presentation:

Q. Do you have any recommendations around things that you have been doing that might benefit others at the moment?

A. A few things: Dealing with semi-analytical type models, it is very important to be mindful of the collection and making sure that the reflectance data used is clean. It is difficult to entirely remove the surface effects, but we have done a relatively good job here. For aircraft observations, it is important to remove all of the surface contamination from our pixels. An important question to ask is how do we come to a standard on our reflectance product from airborne imagery.

PUBLICATION DISCUSSION

Three categories of publications were discussed:

1. ACT report, comprising a description of the overall program with summaries of presentations from CORAL, Elkhorn Slough, and Lake Erie including objectives, methods, results, challenges, benefits, and recommendations. Further, it was discussed to include a write up that reflects the ACT demonstration process: Was it effective? How did teams benefit from participating? Was this approach useful for advancing new technology? This contribution is that report.

2. Individual team publications

3. Community papers:
   a. Method Consideration for Hyperspectral Remote Sensing of Benthic Habitats
   b. Method Consideration for Hyperspectral Remote Sensing of Water Quality (HABS)
   c. Best Practices for Use of Hyperspectral Imaging in Coastal Environments

Led by Professor Heidi Dierssen (University of Connecticut), a detailed outline for the Benthic Methods community paper was established and discussed (outlined below).

Note: We hope to produce a companion manuscript that reflects the HABS work, as well. We understand that because of COVID-19 some of the HABS work has been delayed.

Methodological Considerations for Hyperspectral Remote Sensing of Benthic Habitats

1. Introduction
   - 1.1. Overview of project
   - 1.2. Approaches
     - 1.2.1. Forward models (Moses)
     - 1.2.2. Inversion models (Gege, Garcia, Hochberg, Dierssen)
     - 1.2.3. Tuned empirical algorithms (Reshitnyk, Dierssen)
2. Image Quality
   - 2.1. Atmospheric correction (similar methods used for Elkhorn and Heron with Thompson model) and comparison plots to field R_{rs}. Empirical secondary correction may be needed and basic steps for that.
   - 2.2. Geocorrection. Challenges and correction by all group with known ground control points
   - 2.3. Tidal corrections
   - 2.4. Residual glint correction
     - i. How it appears in the data and fixes (most did this?)
     - ii. Luba has figures of before and after for Elkhorn using Hedley et al.
     - iii. Dierssen has cross-track algorithm for PRISM
   - 2.5. Spectral smoothing? – which techniques were done if any?

- 2.6. Image artifacts – Reshitnyk showed at 600 nm in Elkhorn Slough

3. Benthic Reflectance Libraries
   - 3.1. Brief mention of benthic classes used (Hochberg and Gege reducing class numbers based on spectral similarity)
   - 3.2. Methods vary from using a mean representative (Moses) to selecting from a probability distribution (Garcia)
   - 3.3. Expanding spectra into NIR
     - 3.3.1. Gege's analysis of expanding 400-700 to 400-830 nm
4. Image Pre-Classification
   - 4.1. Optically deep vs. optically shallow detection
   - 4.2. Supervised classification (Moses)
   - 4.3. OBIA methods?
5. Selection of Endmembers and Fit Parameters
   - 5.1. Fit parameters
     - 5.1.1. Bathymetry and measures of pathlength
     - 5.1.2. Water column (Dierssen)
     - 5.1.3. Benthic habitat (Hochberg)
   - 5.2. Garcia lookup table classification approach to select benthic endmembers
   - 5.3. Number of fit parameters –
     - 5.3.1. Gege analysis on parameter no. (residuals and spectral angles)
     - 5.3.2. Degrees of freedom and non-unique solutions
6. Spectral Range and Weighting
   - 6.1. Impact of NIR in retrievals (Gege)
   - 6.2. Spectral weighting for different habitats
     - 6.2.1. Reshitnyk seagrass weighting 500-530 nm
     - 6.2.2. Garcia weighting for coral?
7. Radiative Transfer Solutions
   - 7.1. Simplified solutions – Gege, Garcia
   - 7.2. Hydrolight-Ecolight – Moses (challenges in parameterization).
8. Inversion Solutions
   - 8.1. Setting initial conditions
   - 8.2. Leven. Marq. Methods
   - 8.3. WASI method
9. Algorithm Performance
   - 9.1. CPU time – all methods from 33 hours to minutes
   - 9.2. Use of ideal endmembers
     - 9.2.1. Seagrass leaf for canopy, coral without 3D
     - 9.2.2. 3D canopies
     - 9.2.3. Detrital matter obscuring benthos
   - 9.3. Common Misclassifications
     - 9.3.1. Classes not present -- Seagrass in Heron Isl.
     - 9.3.2. CDOM vs. glint
     - 9.3.3. Phytoplankton Chl vs. benthic vegetation
     - 9.3.4. Seagrass vs. macroalgae
     - 9.3.5. TSM (bbp) vs. seagrass leaf endmember
   - 9.4. Mixed pixels

        9.4.1. Presence/absence approaches
        9.4.2. Fractional models
    9.5. Propagation of uncertainty
10. Validation of Products
    10.1. Challenges with co-location
        10.1.1. GPS accuracy
        10.1.2. GPS locations underwater (methods)
        10.1.3. Path length effects for bathymetry
        10.1.4. Index of refraction correction
    10.2. Homogeneity of the area being classified
        10.2.1. Percent cover – what do they mean, distribution)
        10.2.2. Assessing homogeneity with a radiometer buoy
    10.3. Environmental influences
        10.3.1. Waves
        10.3.2. Measurement interference
    10.4. Recommendations

Comments made during the discussion:

1. We might want to include parametrization of the bottom as a subsection. Bottom parametrization was a big aspect in the CORAL mission.
2. We might want to include a subsection under image quality addressing sensor noise.
3. A section addressing tradeoffs would be useful: e.g., as we go into deeper water, the information in the water column becomes more apparent and information from the benthic community becomes less apparent. Uncertainty shifts from the water column to the seafloor. As the water becomes shallower, the opposite occurs. Where we are in the shallow water environment can greatly affect the optical properties of the water. As a consequence, if optical properties are coupled and the water is shallow, the information about the water column has high uncertainty compared to the bottom.
4. We could also address analysis based on sensor quality: Which retrievals are reasonable to attempt and which are not feasible due to lack of information in the data.
5. Would this publication address mission planning for airborne campaigns, e.g., how to conduct overall planning, identify important mission aspects, flight line planning, field validation? It is important to discuss best practices in data collection upfront versus trying to apply models with insufficient or inappropriate data.
    a. Likely a second paper to address these Best Practices. This main focus of this paper is on the processing of the datasets/imagery we had.
    b. A Best Practice paper could follow on and be more prescriptive. It could have a tropical and a temperate example. It also may be useful for coming users of remote sensing data who are planning to collect their own data.
6. Lessons learned about validation:

   a. There is a need for meter-level accuracy in georeferenced data. This applies particularly to mixed heterogeneous habitats.
   b. Tides affect airborne imagery and it presents a challenge to correct for tidal effects.
   c. Classification of homogeneity is useful (mean and distribution of percentages; minimize variance help assess homogeneity).
   d. Understanding of the actual target being assessed (seagrass leaves etc.) is important.
   e. 3D influences vertical variability in reef and kelp beds (Heidi publication).
7. Professor Dierssen has a special working group to produce a report specific on benthic reflectance measurements and estimates. This comprises partly basic sciences as well as an overview on measurement theory and methods for estimating benthic reflectance and best practices that could be useful for a community paper.

Note: If applicable, suggestions made during the group discussion were integrated into the revised outline above.

Best Practices for Use of Hyperspectral Imaging in Coastal Environments (leveraging with other groups in a technically reviewed report/document):

Led by Dr. Andrea VanderWoude (NOAA) and Dr. Eric Hochberg (Bermuda Institute of Ocean Sciences), a detailed outline for the Best Practices community paper was established and discussed. The goal was to identify a framework and outline of sections for an overarching Best Practices guide.

1. Introduction
   1.1. Document targeted airborne and drone data
2. Glossary of Key Terms
3. Description of Hyperspectral Processing Flow
4. Person Power Needed to Accomplish Goals
5. Defined Mission Objective (*NEED to emphasize your end goal; split for suborbital and orbital?)
   5.1. Point out differences between suborbital and orbital
   5.2. Decide on a sensor
      5.2.1. Spatial resolution
      5.2.2. Bandwidth, spectral resolution
6. Mission Planning – flight operations
   6.1. Plane installation
   6.2. Computing power and needs
   6.3. Flight line layout
   6.4. Diffuse sky-light consideration
   6.5. Viewing angle
   6.6. Outside of these standards for different environments
7. Radiometric Calibration of Hyperspectral Imager

   7.1. Vicarious calibration
   7.2. Biosphere calibration
8. Geometric Calibration – GPS units
9. Environmental Characterization (sensors needed for calibration and validation for ground truth)
   9.1. Validate radiometry
   9.2. Validate geophysical product
   9.3. Detailed measurements for environmental conditions – how detailed do you need to characterize an environment for your algorithm?
10. Raw to Radiance Image Cubes
11. Georeferencing
12. Corrections
   12.1. Smile correction
   12.2. Striping
   12.3. Spectral smoothing
   12.4. Cloud masking
   12.5. Sun glint correction
   12.6. Atmospheric correction
   12.7. Outside of these standards for different environments
13. Calculating Reflectance
14. Guidance for Data Management Structure and Organization – need a data manager
   14.1. Consistent filename construct
   14.2. Good metadata and version control
   14.3. Making data easily discoverable outside of your organization (i.e. realm of big data, how to find useful data)
   14.4. Cloud computing vs. desktop computing (data to algorithms or algorithms to data)
   14.5. Data-sharing and open source movement for processing code and data
      14.5.1. I.e. NOAA to NCEI and GitHUB NOAA groups
      14.5.2. Coordinated sampling – multiplicative efficiencies
15. Sources of Uncertainty
   15.1. Homogeneous vs. heterogeneity
   15.2. Outside of these standards for different environments
16. Algorithm Considerations
   16.1. What to parameterize? What are the parameters?
17. Summary
   17.1. Same concerns for orbital data

ACT IN THE NEXT 1-2 YEARS

Lead: Dr. Mario Tamburri, ACT, University of Maryland Center for Environmental

Planning for Winter/Spring 2021 Hawaii Workshop

We think that the work ACT has been doing presents a highly productive area and exciting new approach to understanding coastal systems and we would love to continue the work. Our limitation is the uncertainty of funding availability. On June 1, 2020, we are entering the 5th year of cooperative agreement with NOAA. As we cannot rely on further funding at this point, we have decided to focus our efforts on completing two tasks:

1. Best practices publication (discussed previously)
2. Formal technology demonstration and verification. We envision a combination of technology demonstration and workshop with service providers demonstrating their technology imaging systems. We can contribute our expertise in conversations around how to best use these technologies. Lake Erie presents a good location as there is a lot of good background data on water quality characterization available.

SUMMARY AND NEXT STEPS

The recommendations emerging from this workshop include a list of next steps ACT will undertake:

1. MANUSCRIPT: Methodological Considerations for Hyperspectral Remote Sensing of Benthic Habitats. The outline for the manuscript is included above.

2. ACT's hope is that a similar manuscript will be developed for HABS. ACT members will work with the participants who are working on HABS who were unable to join us during the workshop.

3. BEST PRACTICES MANUSCRIPT: The outline for the manuscript is included in previous pages. ACT members, TAC members and participants can work on fleshing out the Best Practices manuscript outline over the next few months.

4. VENDOR DEMONSTRATION: We will plan for a vendor demonstration of drone or airplane mounted, individual-user, hyperspectral imagers in the Great Lakes in summer 2021.

5. WORKSHOP: We will plan for an in-person workshop in Hawaii winter 2021, should our world situation stabilize by that time.

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REPORT REFERENCE

McManus MA, S Ackleson, C Anderson, T Bell, K Cavanaugh, H Dierssen, P Gege, M Gierach, E Hochberg, J Kok, S Lohrenz, P Moehlenkamp, W Moses, N Pahlevan, S Plattner, LY Reshitnyk, M Sayers, B Schaeffer, D Schar, A VanderWoude, T Johengen, H Purcell and MN Tamburri 2020. Coastal Hyperspectral Algorithm Demonstration Workshop. pp. 36.