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Satellite for Estimating Aquatic Salinity and Temperature (SEASALT) – A Scientific Overview

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ABSTRACT

SEASALT is a small satellite mission designed to explore the estimation of salinity in coastal environments using ocean color. A SEASALT constellation would fill the coastal gap by providing coastal SSS observations with much higher spatial resolution (30m) and much shorter revisit times (less than 1 day) on a global scale.

Planet's nanosatellites currently provide daily monitoring of the earth's surface, as well as coastal locations, at 3-meter resolution. However, they do not have the required bands needed in the near infrared (NIR) for atmospheric correction (they only possess 1 NIR band), thus making atmospheric correction over water very challenging. Accurate atmospheric corrections are fundamental to reliably retrieving salinity from ocean color. SEASALT has these required bands by design. Planet's nanosatellites also do not have a 412nm band to monitor CDOM and create optimized salinity products. SEASALT has bands centered at 412nm, 470nm, 540nm, 625nm, 746nm, 865nm, and 12013nm. A SEASALT constellation has the potential to monitor coastal regions consistently on a global scale as locally-optimized salinity retrieval algorithms can be developed. Besides retrieving SSS with a high temporal and spatial resolution, SEASALT will retrieve concurrent sea surface temperature (SST).

INTRODUCTION

Earth remote sensing typically involves satellites built and launched by government agencies such as NASA, NOAA, ESA, JAXA, etc. Currently operational polar-orbiting ocean color sensors include NASA's MODerate Resolution Imaging Spectroradiometer (MODIS), NOAA's Visible Infrared Imaging Spectroradiometer Suite (VIIRS), and the Sentinel-3 Ocean and Land Colour Instrument (OLCI), which provide multi-spectral band sets with a roughly daily revisit rate at a fairly coarse spatial resolution (greater than 750 meters). Challenges arise when using these sensors for analyzing complex coastal waters where proximity to land introduces additional spectral complexity in critical optical properties key to water color, such as suspended sediments, bottom reflection, and colored dissolved organic material (CDOM).

The Satellite for Estimating Aquatic Salinity and Temperature (SEASALT)'s primary mission objective is to obtain optical and thermal coastal ocean measurements to estimate SSS and SST. SEASALT will be equipped with bands for color, NIR bands for atmospheric correction, and the Long Wave Infrared (LWIR) band for surface temperature (Table 1).

Table 1: SEASALT Bandset

Wavelength (nm)	Purpose
412	Deep blue, CDOM
470, 540, 625	Visible RGB
746, 865	NIR – atmospheric correction (Gordon/Wang)
12013	LWIR – surface temperature

Literature from the past 40 years shows that in river-dominated coastal zones, sea surface salinity (SSS) can be estimated from optical measurements. Freshwater sources such as rivers are richer in CDOM than salty oceanic water. As these two water masses mix in coastal areas, the CDOM concentration declines, and the salinity increases. There is an inverse linear relationship between CDOM and salinity if conservative mixing is assumed. This relationship, in principle, can be used to estimate SSS from CDOM, which in turn can be derived from satellite ocean color measurements (Figure 1). Based on these ideas of mixing, additional studies also show how remote sensing reflectance (Rrs) throughout the visible spectrum can be used to empirically develop regionalized salinity algorithms. Current microwave (e.g. SMAP) and spectroradiometer satellites (e.g. MODIS and VIIRS) typically cannot retrieve accurate SSS in coastal zones due to spatial and temporal resolution limitations, among other factors. A SEASALT constellation with spatial (30m) and temporal (less than 1 day) resolution resolves these issues.

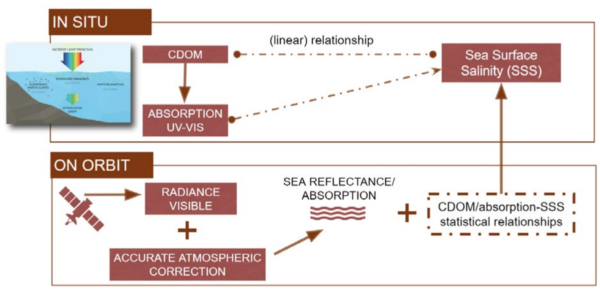


Figure 1: Relationship between Rrs, CDOM, and SSS

To create optical salinity products from ocean color satellite imagery, the spectral top-of-atmosphere (TOA) radiances recorded by the satellite must be atmospherically corrected. However, ocean color atmospheric correction of small satellites typically presents a challenge. The atmospheric signal, which generally represents about 90% of the total TOA signal recorded by the satellite, must be removed prior to calculating water-leaving radiances, and ultimately the water bio-optical properties. The atmospheric signal consists of Rayleigh scattering (scattering by molecules, calculated from sensor viewing geometry) and aerosol scattering (modeled from radiances in two NIR bands). Typical coarse-resolution ocean color sensors such as MODIS, VIIRS, and Sentinel-3 OLCI have 9, 11, and 21 bands, respectively. Two or more of those bands are at near/mid infrared wavelengths needed to select aerosol models for atmospheric correction of the visible bands. The presence of a second NIR band separates SEASALT from other small satellites (e.g. Planet's nanosatellites), by allowing for SEASALT ocean color imagery to be atmospherically corrected using traditional/standard atmospheric correction methods [1-3].

Coastal regions with an in situ CDOM-SSS linear relationship are normally regions where the Evaporation minus Precipitation (E-P) atmospheric forcing is much less than the river runoff. Also, the CDOM is not much affected by bio-optical processes for the relationship to hold. In these regions, both SSS and CDOM (or its absorption of visible light, especially ultra violet to deep blue) can be seen as a water mass tracer.

Recent observations support a near-linear trend in CDOM versus salinity in terrestrially affected waters, as CDOM and/or CDOM proxies decrease to nearly undetectable levels as salinity approaches oceanic values [4-15]. If the mixing of offshore and terrestrial end-member water masses is the only process affecting CDOM, CDOM signals decrease linearly with increasing salinity. Importantly, a number of studies demonstrate that the statistics for the linear fits between CDOM and salinity appear to vary temporally (or at least seasonally) and regionally [15]. Figure 2 depicts regional variability between absorption at 443nm, which is related to CDOM, and SSS.

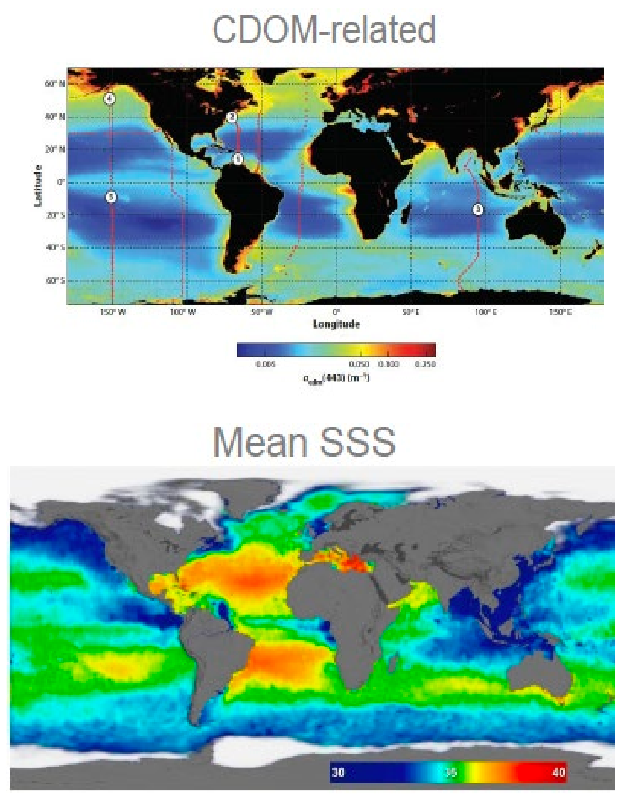


Figure 2: Regional variation of global absorption at 443nm (top image), which is related to CDOM, and global SSS (PSU, bottom image)

In summary, for estimating SSS from satellite optical sensors, we need to retrieve the sea-related part of the radiance that arrives in the satellite. Therefore, an accurate atmospheric correction is fundamental. An empirical algorithm relating CDOM/Rrs to the SSS can then be developed. The relationship between these variables is not well established on a global scale, primarily due to the scarcity of in situ observations. Several studies indicate the relationships are regionally dependent, but it is likely they are related to water types (Jerlov classification: 9 water types for coastal waters; 3 water types for open ocean). To better understand these relationships, more coordinated in situ and remote measurements are necessary.

METHODOLOGY

Required in situ Observations

In situ measurements will be vital for developing optical salinity algorithms, as well as validating products such as SST. Potential instruments used for collecting in situ data consist of Autonomous Surface Vehicles (ASV), such as wave gliders or saildrones. Wave gliders are easy to mobilize and deploy on a global scale and have the capability to be a mission-oriented robust technology with near real-time satellite communications capabilities. They can traverse large areas (in particular frontal zones) with high spatial resolution. Due to their modular design, other bio-optical, chemical, and spectral sensors can be added. Figure 3 shows a wave glider located at Woods Hole Oceanographic Institution, which is currently being prepped for deployment (as of May 2022).

Figure 3: Wave glider being prepped for deployment at WHOI. The sensors on the deck left to right include an Acoustic Doppler anemometer, RH – Air temp, a secondary winds sensor, and part of the downward facing Acoustic Doppler Current Profiler.

Additionally, we will use ASVs and other in situ stations currently available to us, such as the Aerosol Robotic Network Ocean Color (AERONET-OC) platforms and the Marine Optical Buoy (MOBY) mooring, which provide water-leaving radiance measurements to calibrate and validate SEASALT's optical products. AERONET-OC platforms are typically located in more turbid, coastal water environments, where ocean dynamics are sometimes changing on hourly time scales. MOBY is an autonomous optical buoy, which is moored off the island of Lanai, in Hawaii. It is the standard calibration and validation site for the ocean color community. Table 2 summarizes the instruments planned for this mission.

Table 2: Required Instruments for In Situ Measurements

Variables	Essential Variable	Algorithm Development	Validation
SSS	Yes	Yes	Yes
CDOM	No	Yes	No
Reflectance /Radiance	Yes	Yes	Yes
Chlorophyll (Chl-A)	No	Yes	No
SST	No	Yes	No
Physical Environment (winds, currents, freshwater fluxes, river runoff	No	No	No

Variables	Study – Regional SSS Dynamics	Temporal Frequency/Spatial Resolution/Domain	Potential Instrumentation
SSS	Yes	Hourly, covering all seasons, multiple regions, ideal: crossing frontal zones	ASV, mooring, shipboard (Thermosalinograph), drifters
CDOM	No		Mooring, ASV, shipboard
Reflectance /Radiance	No	Hourly, covering all seasons, multiple regions	Spectroradiometer (e.g. Spectral Evolution 1100f), AERONET-OC, MOBY

Chlorophyll (Chl-A)	No		Mooring, ASV, shipboard
SST	No		Mooring, drifters, ASV, AUV, shipboard
Physical Environment (winds, currents, freshwater fluxes, river runoff	Yes	Hourly to daily, targeted regions, period depending on the science objective (month to year)	Mooring, ASV, shipboard – with CTD, ADCP, and met and air-sea flux measurements

SEASALT's potential regions of interest are depicted in Figure 4. These are river-dominated regions in which SSS-CDOM linear relationships have been shown to exist in previously published literature.

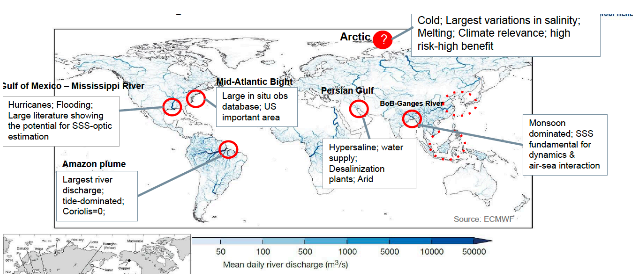


Figure 4: SEASALT Potential Regions of Interest

Salinity Retrieval Algorithms

This study discusses efforts conducted throughout the SEASALT design phase to create an empirical optical salinity algorithm based on in situ cruise data to be later tuned with orbital data. One method for developing a salinity algorithm is to use in situ bio-optical measurements, such as absorption and backscattering inherent optical properties, turbidity, or CDOM measurements. For example, the algorithm could be developed using time-series data and tested using vertical profile data. However, our main focus is to use in situ hyperspectral Rrs measurements to develop our optical salinity algorithm. Here, we establish trends between SSS and Rrs and use those trends to develop algorithms for estimation of SSS (Figure 5).

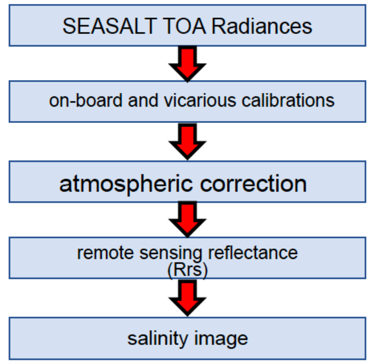


Figure 5: Example Optical Salinity Algorithm Using Rrs

One such method utilizes in situ salinity and Rrs measurements from a cruise the Naval Research Laboratory conducted in the northern Gulf of Mexico from March 24 thru April 17, 2018 (Figure 6). During this cruise, there were 8 mooring locations collecting bio-optical, CDOM, turbidity, and salinity data. However, only one location had coincident bio-optical and salinity data, as well as spectral Rrs.

Figure 6: Study Area (Mississippi Bight) for Optical Salinity Algorithm Generation

Rrs was measured with an ASD HandHeld Field Spectroradiometer. The in situ hyperspectral Rrs was convolved to Planet's PlanetScope nanosatellite band-specific spectral response functions. We empirically developed a salinity algorithm from the convolved Rrs in situ measurements and their corresponding in situ salinity values. The results show that given an accurate atmospheric correction, optical Rrs in the visible spectrum can be used to produce accurate salinity retrievals (Figure 7). The next steps would be to convolve the in situ Rrs to SEASALT bands when the spectral response functions become available, revise the reflectance salinity algorithms for SEASALT, and continue testing salinity algorithms with additional data sets from other geographical areas.

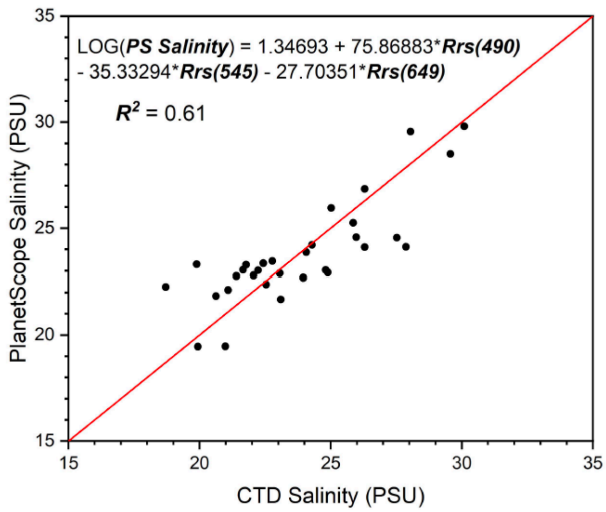


Figure 7: In Situ Salinity (from CTD) Compared to In Situ Rrs Convolved to PlanetScope Relative Spectral Response Functions

There has been other literature published that discuss deriving a regionalized optical salinity product. Fu et. al. discuss two ways to retrieve SSS optically: 1. Using CDOM as an intermediate agent due to its significant correlation with SSS; 2. Directly connecting Rrs with SSS, since SSS can be expressed directly as a function of remotely sensed ocean color bands since CDOM can be estimated by Rrs [16]. Both of these methods are based on the inverse relationship between SSS and CDOM concentration, which performs well in coastal regions, but salinity may be highly variable in coastal and estuarine ecosystems due to unique geographical locations. Therefore, there is no great global salinity algorithm – all require training and tuning. They also discuss the importance of analyzing the temporal and spatial heterogeneity of salinity in coastal areas on the basis of model zoning, and they were able to divide their Gulf of Mexico study area based on variable differences (mostly depth) rather than geographical locations. We will look at conducting a similar analysis with SEASALT, where we must validate and calibrate with in situ measurements.

Vandermeulen et. al. determined that the highest correlations were found in the difference between the Quasi Analytical Algorithm (QAA) absorption products at 486nm and 551nm [17,18]. They also noted that one regression model will not describe the seasonal dynamics optimally, since the baseline (optical properties of freshwater at the mouth of the Mobile river) is changing throughout the year relative to the test parameters. To account for this, they used bi-monthly regression slopes of salinity compared to optical signatures, specifically QAA absorption(486nm) minus QAA absorption(551nm). Vandermeulen et. al. demonstrate that 90% of their satellite data points were within 5 PSU of the in situ measurements. We will look to generate similar QAA products but SEASALT's design is missing the 443nm band that QAA requires. We will look at uncertainties associated with this, as well as possibly using other algorithms for inherent optical product (IOP) generation. One such algorithm is the Linear Matrix IOP algorithm (LMI), which uses wavelengths (410nm, 490nm, and 551nm) and may have better applications for SEASALT than the QAA.

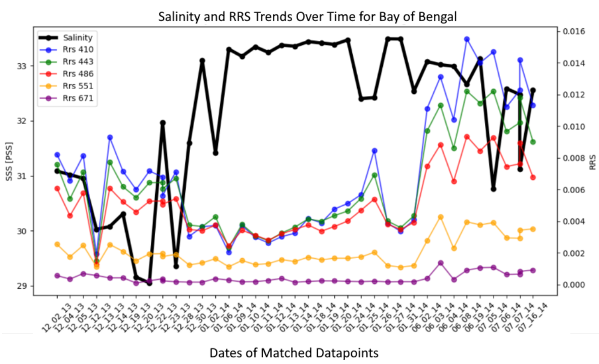
There are optical salinity algorithmic concerns. When an empirical approach is used to generate an algorithm, the coefficients with that algorithm must be tuned and validated for other temporal and spatial domains. Previous analysis by Vazquez-Cuervo et. al. describes this proxy performance function distance from the coast and Qing et. al. show the ability, using passive optical data, to determine an in situ salinity estimate derived from satellite measured reflectance data with a RMSE of 0.8333 PSU (R-squared = 0.64). We expect to achieve similar performance with SEASALT, provided proper calibration can be performed. As a result of experiencing the rigors of the space environment, integral periodic calibrations are essential to meet this standard.

The Impact of Signal-To-Noise (SNR) Ratio

One of the most important differences between SEASALT (and similar small satellites) and the satellites typically used for ocean color studies is the difference in signal-to-noise ratio (SNR). We have performed a preliminary analysis of the impact of SNR on accurate ocean optics and downstream salinity retrievals by observing systematic factors, turbidity, and transient environmental factors.

To perform this analysis, in situ SSS data from cruises and buoys was collected for different areas where coincident VIIRS data was available. Any SSS data was coordinated temporally and spatially to optical Rrs data from VIIRS, which was atmospherically corrected within NRL's Automated Processing System (APS), which is based on the NASA SEADAS code set [19]. Data was only matched if the observations were taken within 2 hours of each other. Following the procedure in Qing et. al., we performed a multi-linear regression on the 410, 486, and 551 bands, which most closely correlate to the bands on SEASALT. For this regression, we used 75% of the data for training and 25% for testing. This produced a baseline regression for the VIIRS satellite. To simulate the SEASALT SNR, noise was added to the Rrs data to effectively change the SNR from that of VIIRS (25.47, 22.99, and 25,31) to that of SEASALT (16.34, 20.72, and 20.44). This noise was simulated using a Gaussian distribution over the center of the data, scattering it to simulate a lower SNR.

This study was performed for the coast of the Amazon River, to examine a location with high monthly and daily variation in SSS, and the Bay of Bengal, which has a low monthly variation. The matched SSS and Rrs data for each of these can be found in Figure 8. More Rrs data than was used in the regression is plotted for completeness. The salinity (black) generally follows the trend of the bands of interest (410, 486, and 551), but relatively few data points make achieving an accurate regression difficult.



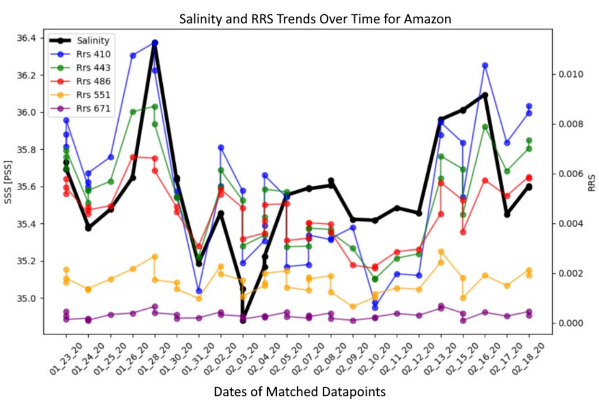
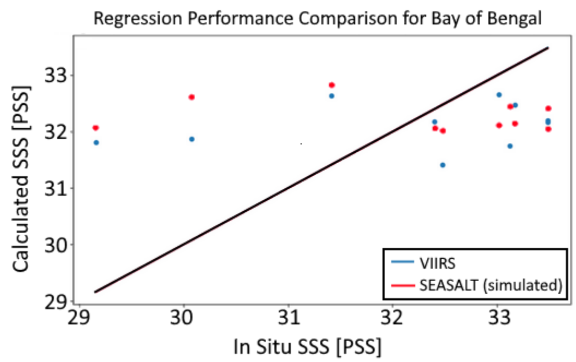


Figure 8: Coincident in situ and Rrs data for the Bay of Bengal (top image) and Amazon (bottom image)

The regression was then performed for both the VIIRS and SEASALT SNR. These results are depicted in Figure 9, which compare the measured SSS to the estimated SSS. The regression for the Amazon is accurate within 0.7 Practical Salinity Units (PSU) for all estimates, and within 2 PSU for the Bay of Bengal. With the additional noise to simulate the SEASALT SNR, there is little difference in each of the calculated points, indicating that the SEASALT SNR is sufficient to perform the types of regressions described in this paper. However, the relatively low number of data points in this regression and the lower performance of the Bay of Bengal study reiterates the importance of a satellite (or constellation of satellites) with a higher revisit rate than VIIRS. Because the salinity variation for the Bay of Bengal was very low, it was difficult to find an accurate regression for the data compared to the higher variation for the Amazon. Future work will be performed to verify these results by expanding the VIIRS data by considering points that are spread more spatially and temporally.



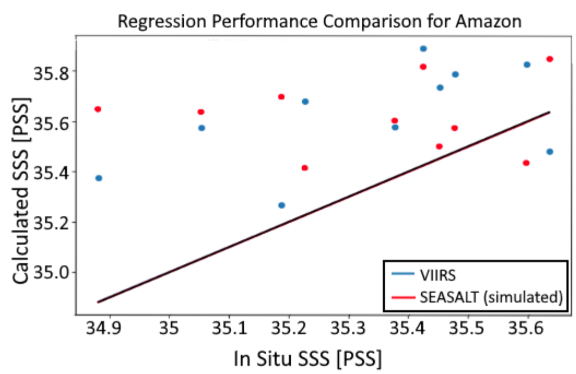


Figure 9: Comparison between the regression for the VIIRS SNR and the SEASALT SNR for the Bay of Bengal (top image) and Amazon (bottom image)

SEASALT Team

Massachusetts Institute of Technology (MIT)

Kerri Cahoy, Mary Dahl, Albert Thieu, Cadence Payne, Charles Lindsay, and Shreeyam Kacker from MIT's STAR Lab have extensive experience with small satellite design, assembly, and operation. They have worked with satellites in the realm of ocean sciences with the BeaverCube satellite [20], which was designed to image the ocean to study changes in ocean color over time.

Woods Hole Oceanographic Institution (WHOI)

Viviane Menezes and Paul Fucile are members of the Physical Oceanography Department at WHOI. Both have considerable experience with remote sensing and physical oceanography, specifically related to salinity variability, air-sea interaction, and ocean circulation. They have strong experience recording in situ measurements with using moorings, floats, drifters, shipboard, and autonomous surface vehicles.

Naval Research Laboratory (NRL)

Sean McCarthy from Code 7331: The Bio-Optical Physical Processes and Remote Sensing Section, has vast experience in processing, analyzing, and ocean color bio-optical algorithmic development for remote sensing data from a multitude of sensors that are viable in complex coastal waters. Specifically, our section has demonstrated this experience over the last twenty-five years with the continued development of the Automated Processing System (APS). APS is used to ingest multi- and hyper-spectral remote sensing data from continuously imaging ocean color sensors to automatically produce numerous products of interest to Navy operations and inputs to bio-optical forecasting models. These Navy support products are derived from optical properties, including but not limited to vertical and horizontal visibility products from Apparent Optical Properties (AOPs) and IOPs, and Electro Optical (EO) system performance products for cameras, lasers, and divers.

Conclusion

Estimating SSS in coastal environments is a difficult problem that a SEASALT constellation would help resolve. SEASALT's relatively high spatial resolution (30m) combined with the revisit rate that a constellation could provide would help answer oceanographic questions pertaining to SSS in Case 2 coastal waters. SEASALT's band set was selected specifically for these operations, which includes two NIR bands needed for conventional ocean color atmospheric correction methods. The research conducted during the design phase demonstrates that optical salinity is achievable; however, calibrations must be applied to optimize the sensor where regional trends and biases exist. Additionally, SEASALT will be capable of deriving SST. SEASALT has concluded its Phase 1 Design Level funding, and we are currently seeking Phase 2 funding for future implementation, testing, and launching.

Acknowledgments

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References

1. Wang, M. and Gordon, H. A simple, moderately accurate, atmospheric correction algorithm for SeaWiFS. Remote Sensing of Environment. Volume 50, Issue 3. December 1994. Pages 231-239.
2. Gordon, H. and Wang, M. Retrieval of water-leaving radiance and aerosol optical thickness over the oceans with SeaWiFS: a preliminary algorithm. Applied Optics. Vol. 33, Issue 3, pp. 443-452 (1994).
3. Ahmad, Z., Franz, B., McClain, C., Kwiatkowska, E., Werdell, J., Shettle, E., and Holben, B. New aerosol models for the retrieval of aerosol optical thickness and normalized water-leaving radiances from SeaWiFS and MODIS sensors over coastal regions and open oceans. Applied Optics. Vol. 49, Issue 29, pp. 5545-5560 (2010).
4. Nelson and Siege 2013. The global distribution and dynamics of chromophoric dissolved organic matter. Annu. Rev. Mar. Sci. 5, 447-767.
5. Blough, N. V., Zafiriou, O. C. and Bonilla, J. (199)3. Optical absorption spectra of waters from the Orinoco River outflow: Terrestrial input of colored organic matter to the Caribbean. J. Geophys. Res., v. 98, C2, 2271-2278. doi: 10.1029/92JC02763
6. Vodacek, A., Hoge, F.E., Swift, R.N., Yungel, J.K., Peltrer, E.T. and Blough, N.V. (1995). The use of in situ airborne fluorescence measurements to determine UV absorption coefficient and DOC concentration in surface waters. Limnol. Oceanogr., v. 4, 411-415. doi: 10.4319/lo.1995.40.2.0411
7. Vodacek, A., Blough, N. V., DeGrandpre, M. D., Peltzer, E. T. and Nelson, R. K. (1997), Seasonal variation of CDOM and DOC in the Middle Atlantic Bight: Terrestrial inputs and photooxidation, Limnol. Oceanogr., 42, 674–686, doi:10.4319/lo.1997.42.4.0674.
8. DeGrandpre, M. D., A. Vodacek, R. K. Nelson, E. J. Bruce, and N. V. Blough (1996), Seasonal seawater optical properties of the U.S. Middle Atlantic Bight, J. Geophys. Res., 101, 22,727– 22,736.
9. Del Castillo, C. E. D., Coble, P., Morell, J., Lopez, J., and Corredor, J. (1999), Analysis of the optical properties of the Orinoco River Plume by absorption and fluorescence spectroscopy, Mar. Chem., 66, 35–51, doi:10.1016/S0304-4203(99)00023-7.
10. Del Vecchio, R., and N. V. Blough (2004), Spatial and seasonal distribution of chromophoric dissolved organic matter and dissolved organic carbon in the Middle Atlantic Bight, Mar. Chem., 89, 169– 187.
11. Del Vecchio R, Blough NV. 2006. Influence of ultraviolet radiation on the chromophoric dissolved organic matter in natural waters. In Environmental UV Radiation: Impact on

Ecosystems and Human Health and Predictive Models, ed. F Ghetti, G Checcucci, JF Bornman, pp. 203–16. Dordrecht: Springer

12. Del Vecchio, R., and A. Subramaniam (2004), Influence of the Amazon River on the surface optical properties of thewestern tropical North Atlantic Ocean,J. Geophys. Res.,109, C11001, doi:10.1029/2004JC002503
13. Hu, C., Montgomery, E. T., Schmitt, R. W., Muller-Karger, F. E. 2004 The dispersal of the Amazon and Orinoco River water in the tropical Atlantic and Caribbean Sea: Observation from space and S-PALACE floats. Deep Sea Research Part II, v. 51, 1151- 1171. doi: 10.1016/j.dsr2.2004.04.001
14. Del Castillo and Miller 2008 On the use of ocean color remote sensing to measure the transport of dissolved organic carbon by the Mississippi River Plume. Remote Sensing of Environment, v. 112, 836-844. doi: 10.1016/j.rse.2007.06.015
15. Palacios, SL, TD Peterson, & RM Kudela (2009) Development of Synthetic Salinity from Remote Sensing for the Columbia River Plume. Journal of Geophysical Research vol. 114. C00B05. doi:10.1029/2008JC004895
16. Fu, Z.; Wu, F.; Zhang, Z.; Hu, L.; Zhang, F.; Hu, B.; Du, Z.; Shi, Z.; Liu, R. Sea Surface Salinity Estimation and Spatial-Temporal Heterogeneity Analysis in the Gulf of Mexico. *Remote Sens.* **2021**, *13*, 881. https://doi.org/10.3390/rs13050881
17. Vandermeulen, R., Arnone, R., Ladner, S., and Martinolich, P. (2014). Estimating sea surface salinity in coastal waters of the Gulf of Mexico using visible channels on SNPP-VIIRS. Proceedings of SPIE - The International Society for Optical Engineering. 9111. 911109. 10.1117/12.2053417.
18. Lee, Z., Carder, K., and Arnone, R. (2002). Deriving Inherent Optical Properties from Water Color: a Multiband Quasi-Analytical Algorithm for Optically Deep Waters. Applied optics. 41. 5755-72. 10.1364/AO.41.005755.
19. Ladner, S.; Crout, R.; Lawson, A.; Martinolich, P.M.; Bowers, J.; Arnone, R.A. Validation Test Report for the Automated Optical Processing System (AOPS) Version 20; U.S. Naval Research Laboratory, 2021
20. Pereira, P., Garcia, M., et. al. BeaverCube: Coastal Imaging with VIS/LWIR CubeSats. Small Satellite Conference Proceedings. 2020. Technical Session V: Next on the Pad.