

# Sensor Characteristics for Remote Sensing of Inland and Coastal Waters



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# Sensor Characteristics

- Spatial Resolution
- Spectral Resolution
- Signal-to-Noise Ratio
- Temporal Resolution

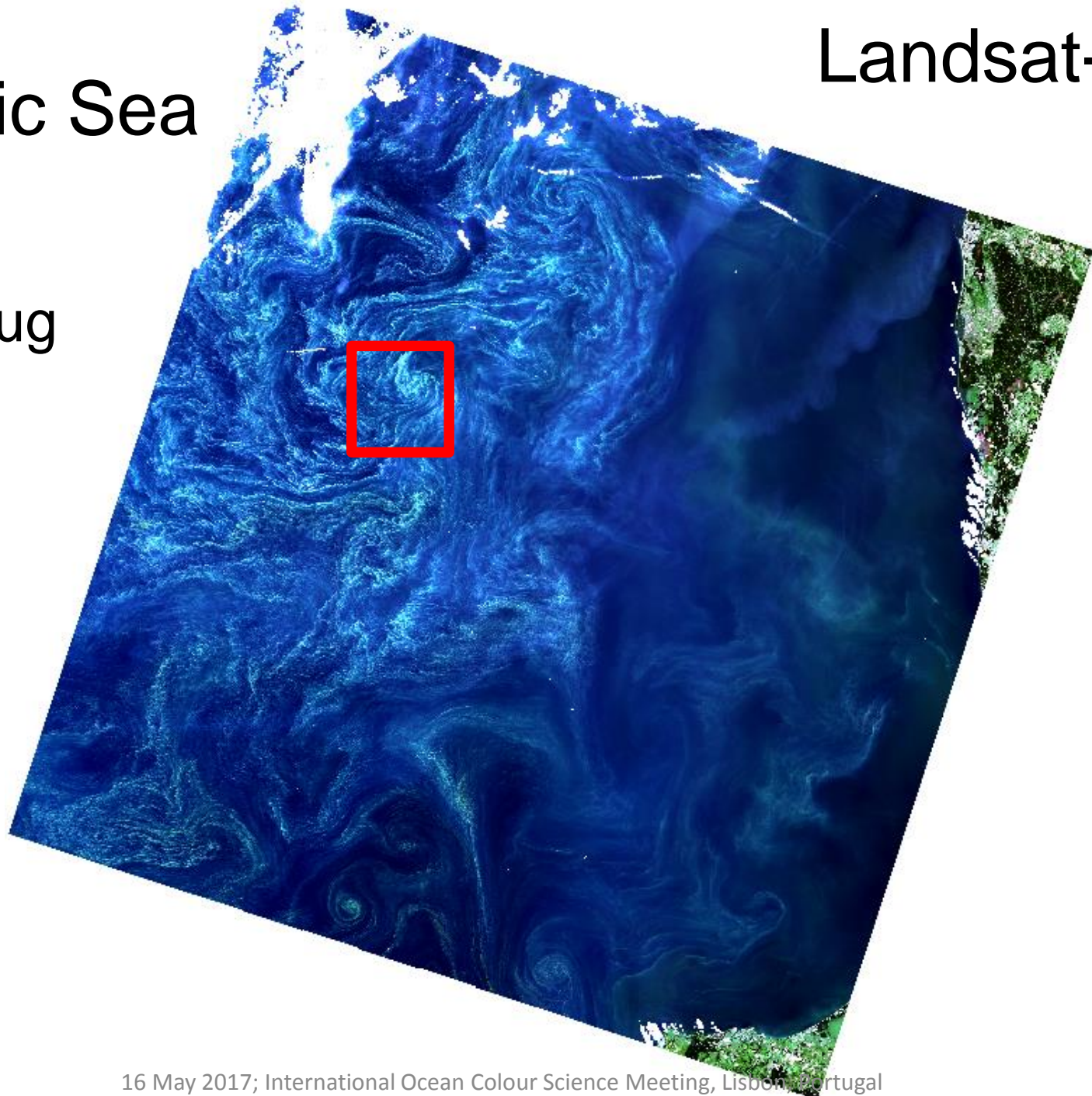
# Spatial Resolution

What is the dominant spatial scale of variability of optically discernible biophysical features in coastal and inland waters?

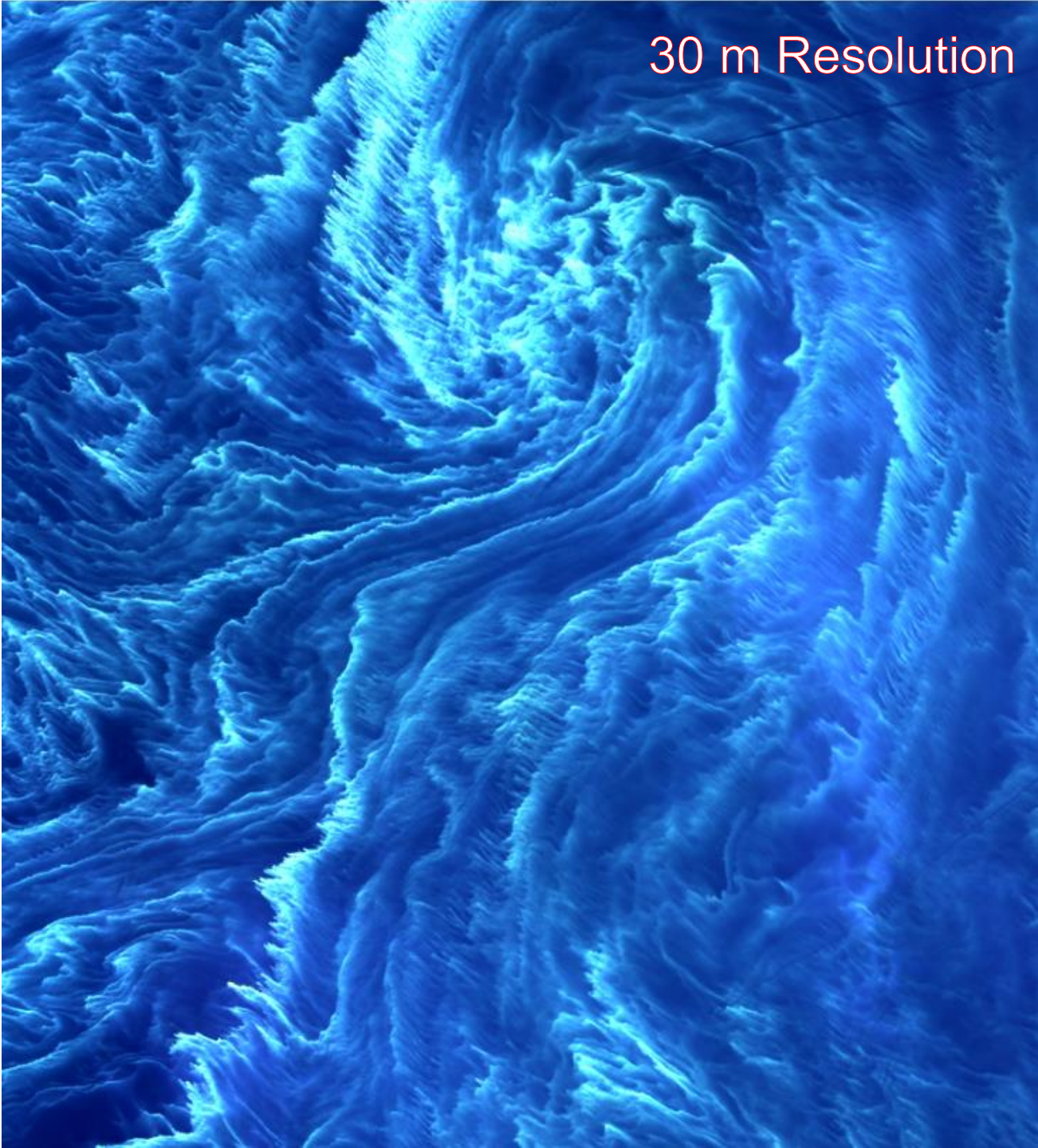
# Baltic Sea

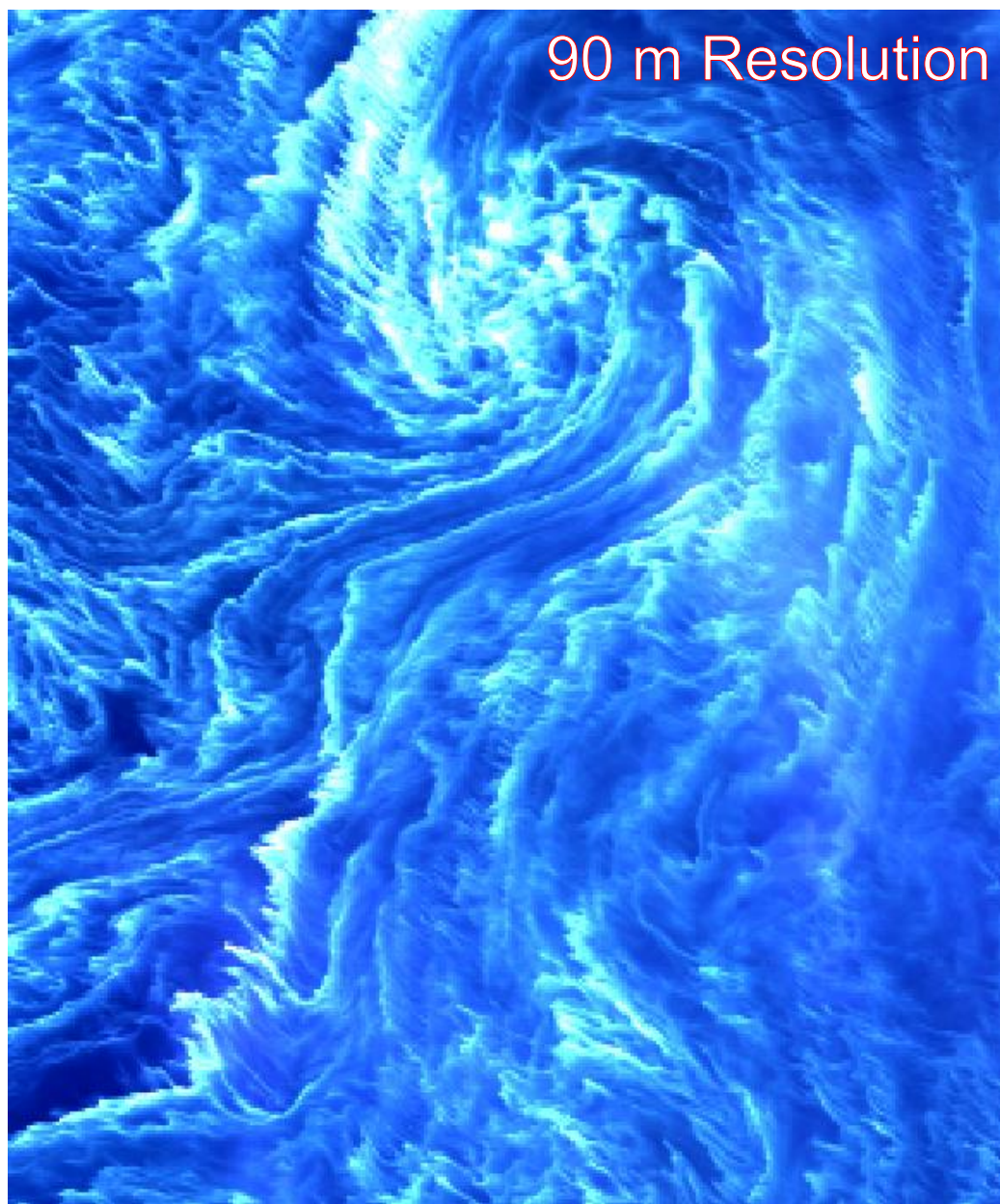
# Landsat-8

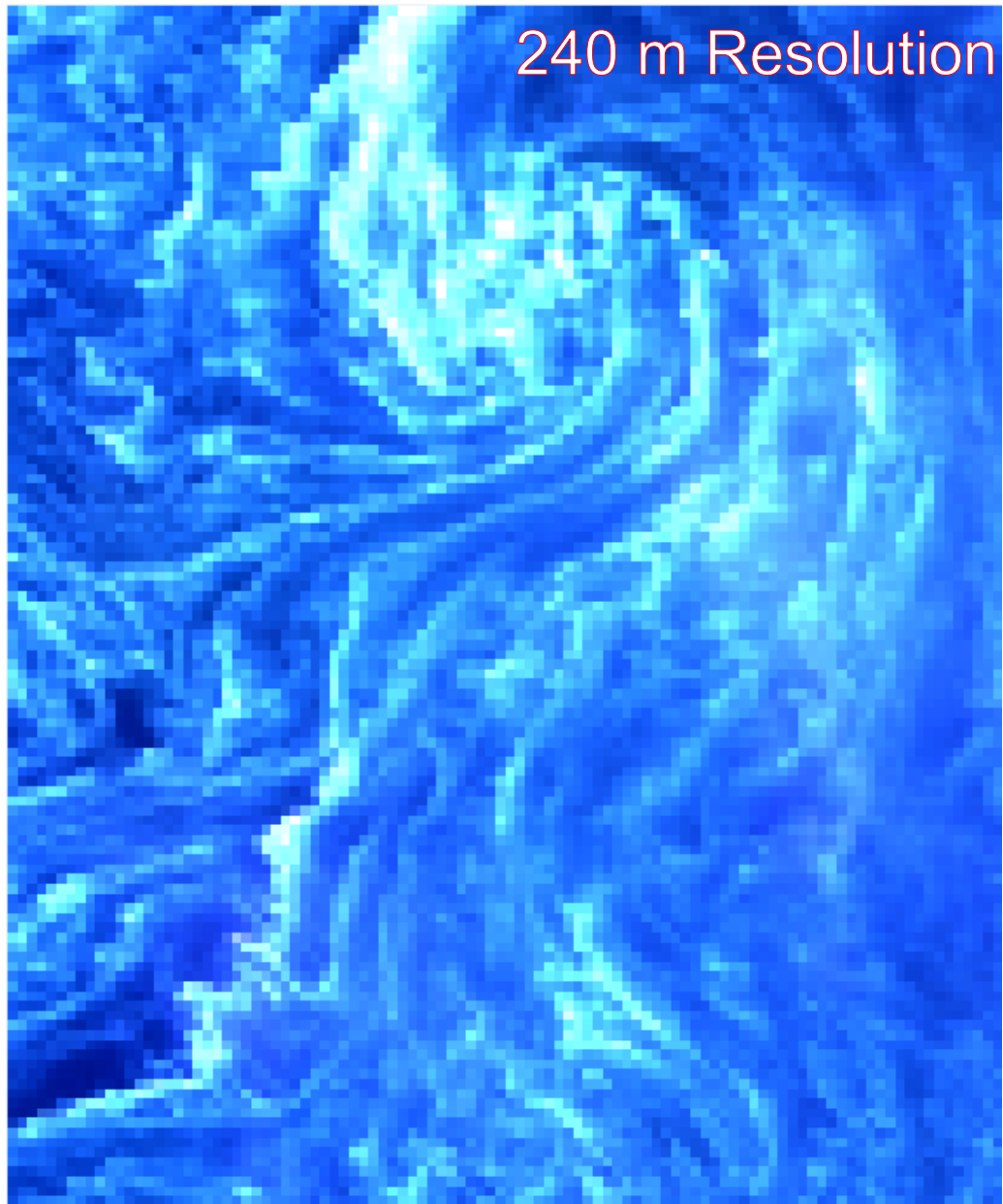
11<sup>th</sup> Aug  
2015

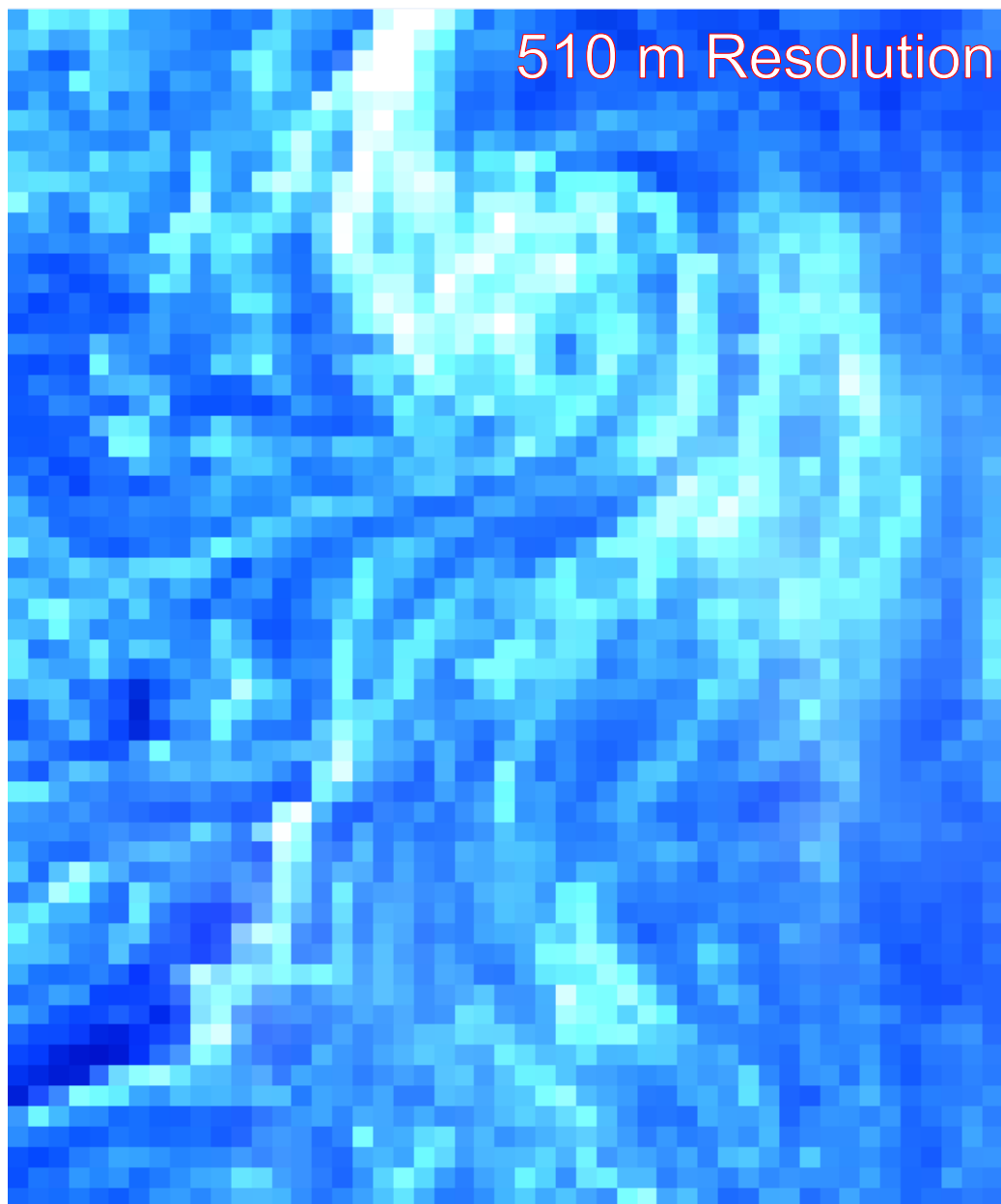


30 m Resolution

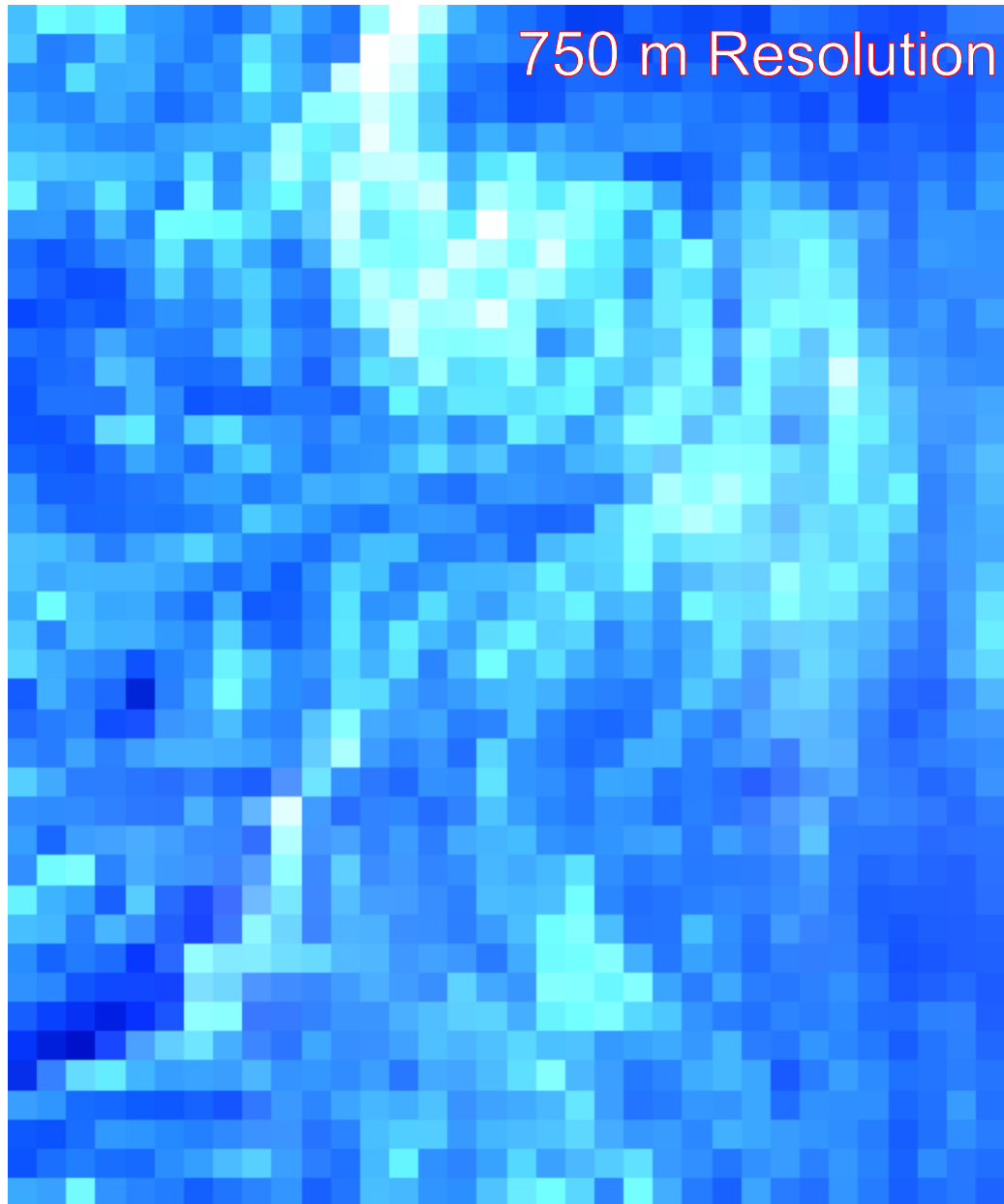


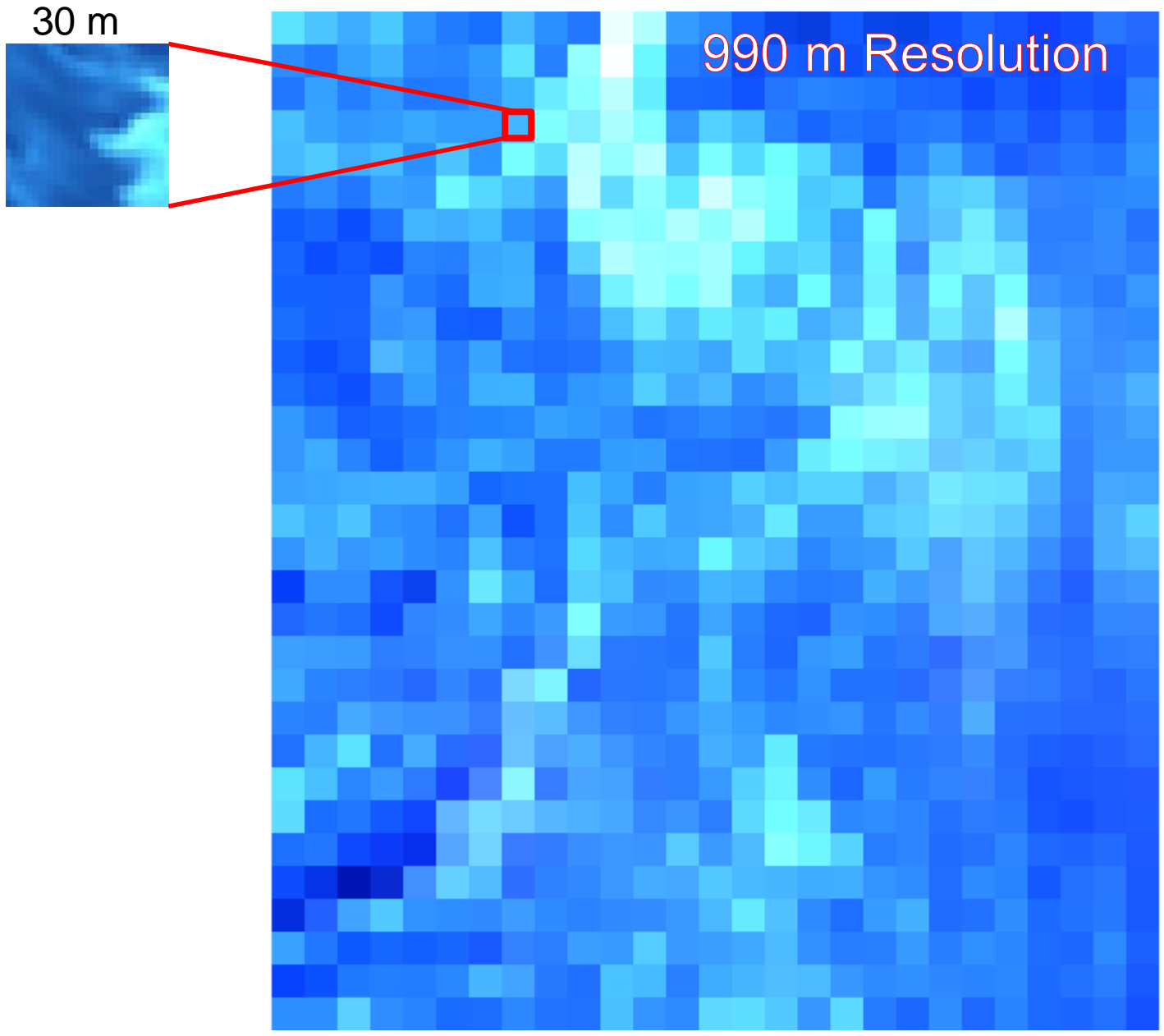










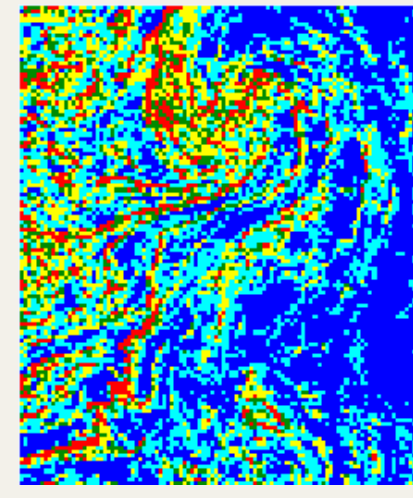
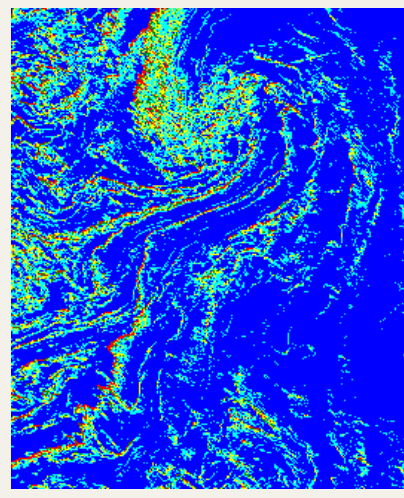
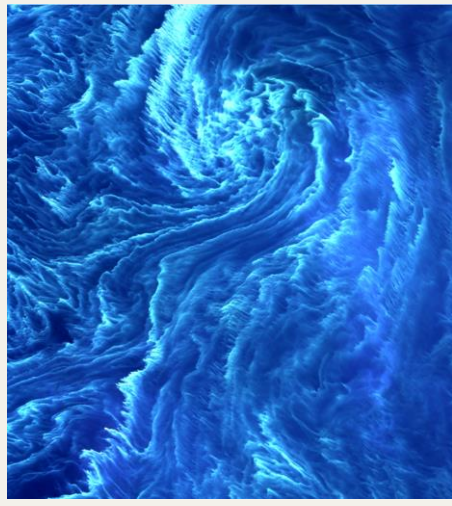


# Sub-pixel Coefficient of Variation

30 m True Color

90 m

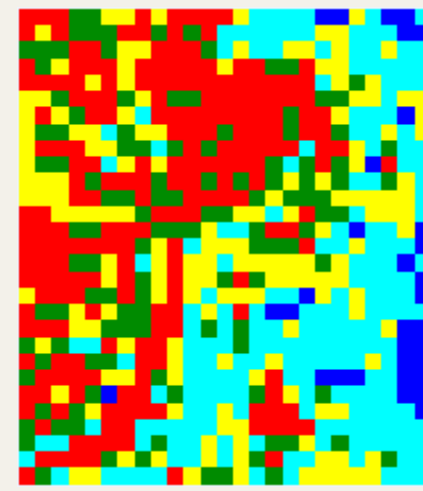
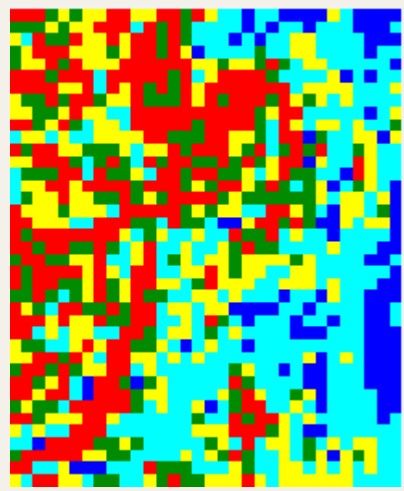
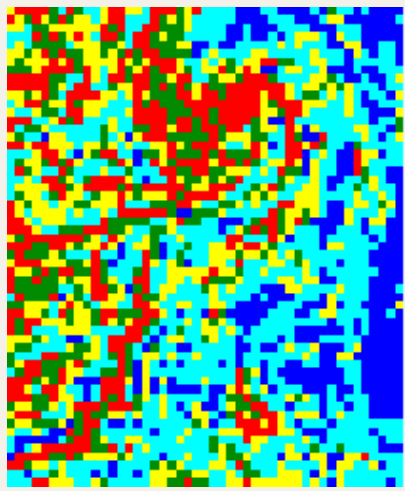
240 m



510 m

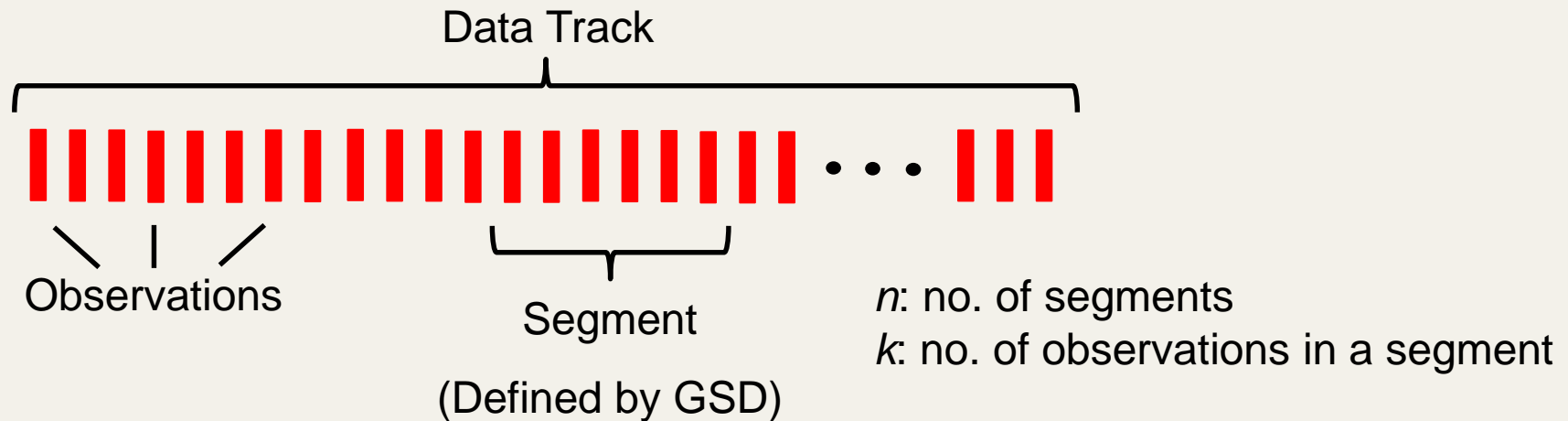
750 m

990 m



# Spatial Variation Study

Along-track data of IOPs and AOPs from **in-water, ship-board, airborne, and spaceborne** platforms

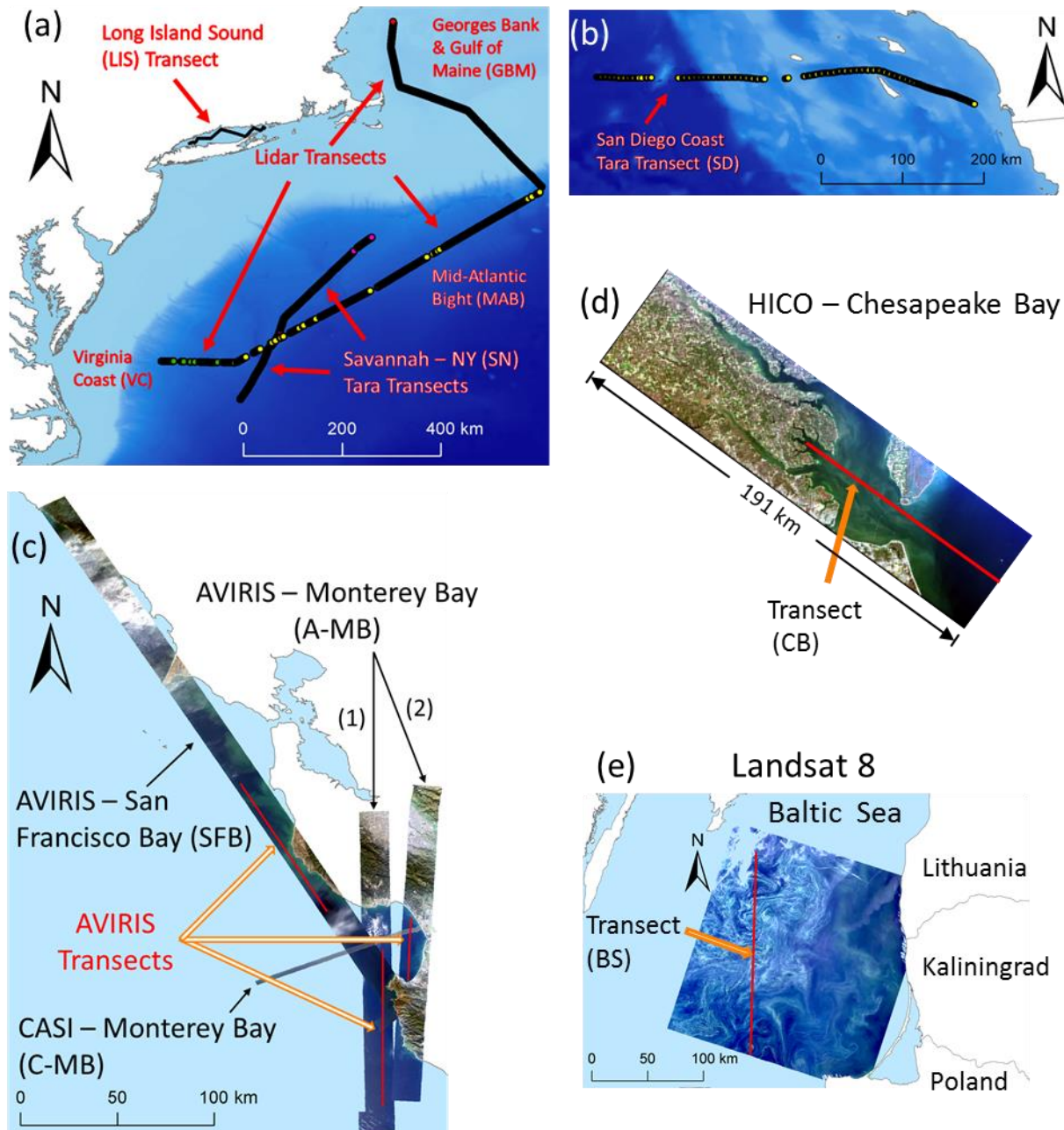


Sub-pixel Variation,  $\overline{CV}_a = \frac{1}{n} \sum_{i=1}^n \left[ \left( 1 + \frac{1}{4k} \right) \frac{\sigma_i}{\bar{x}_i} \right]$

$$2 * [S/I]_{\text{median}} \leq GSD_{\text{min}} \leq 1000 \text{ m}$$

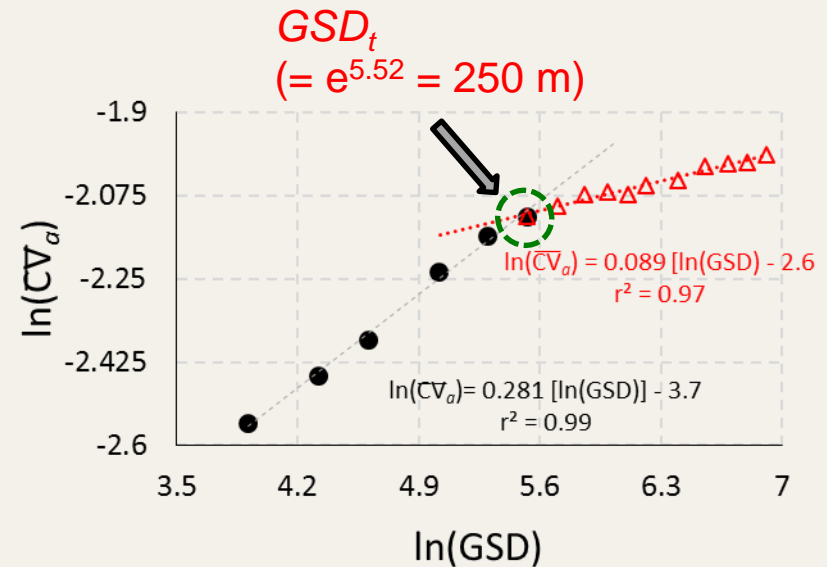
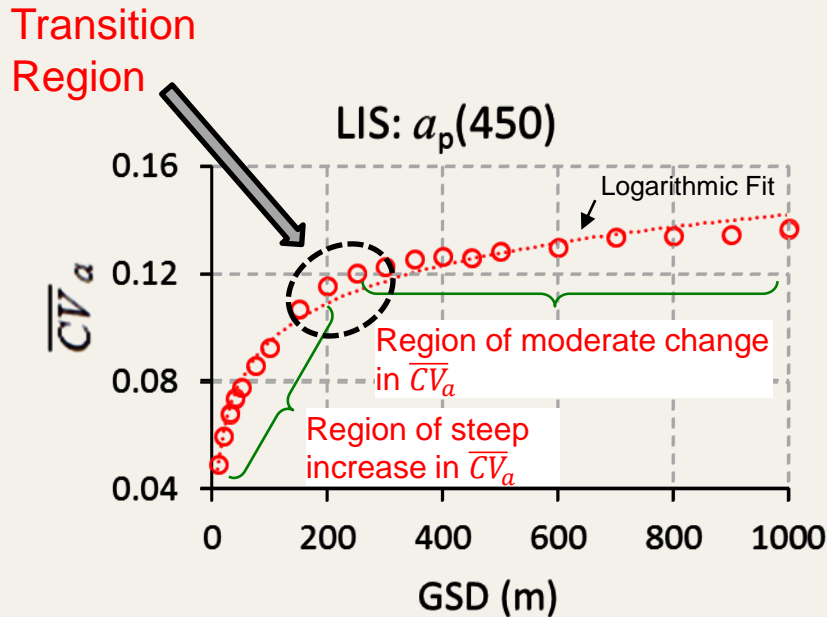
**Bias correction**  
*(Sokal, R. R. and J. F. Rohlf. 1995. Biometry: The Principles and Practice of Statistics in Biological Research)*

# Data



Platform	Instruments	Location	Parameters Analyzed	Transect Length (km)	Spatial Sampling <sup>14</sup>	
					$SI_{med}$	$GSD_{min}$
In-water	<i>ac-s</i>	Long Island Sound (LIS)	$a_p(450), c_p(650)$	LIS: 158	2.8	10
Shipboard	<i>ac-s</i>	Savannah-New York (SN)	$a_p(489), c_p(649)$	SN: 396.8	141	300
		San Diego Coast (SD)	$a_p(488), c_p(650)$	SD: 400	185	400
Airborne	Lidar	Virginia Coast (VC), Mid-Atlantic Bight (MAB), Georges Bank & Gulf of Maine (GBM)	$b_{bp}(532), K_{sys}(532)$	CV: 120	54	150
				MAB: 595	60	150
		San Francisco Bay (SFB)	$R_{rs\_B}, R_{rs\_G}, R_{rs\_R}, R_{rs\_B/G}$	SFB: 74	16.5	40
				AVIRIS	A-MB1: 60	16.2
Monterey Bay (A-MB1, A-MB2)	$R_{rs\_B}, R_{rs\_G}, R_{rs\_R}, R_{rs\_B/G}$	A-MB2: 36	16.1	40		
		CASI	C-MB: 63.5	1.55	5	
Spaceborne	HICO	Chesapeake Bay (CB)	$R_{rs\_B}, R_{rs\_G}, R_{rs\_R}, R_{rs\_B/G}$	CB: 102	97	200
	Landsat-8	Baltic Sea (BS)	$R_{rs\_B}, R_{rs\_G}, R_{rs\_R}, R_{rs\_B/G}$	BS: 175	30	60

# Transition GSD ( $GSD_t$ )

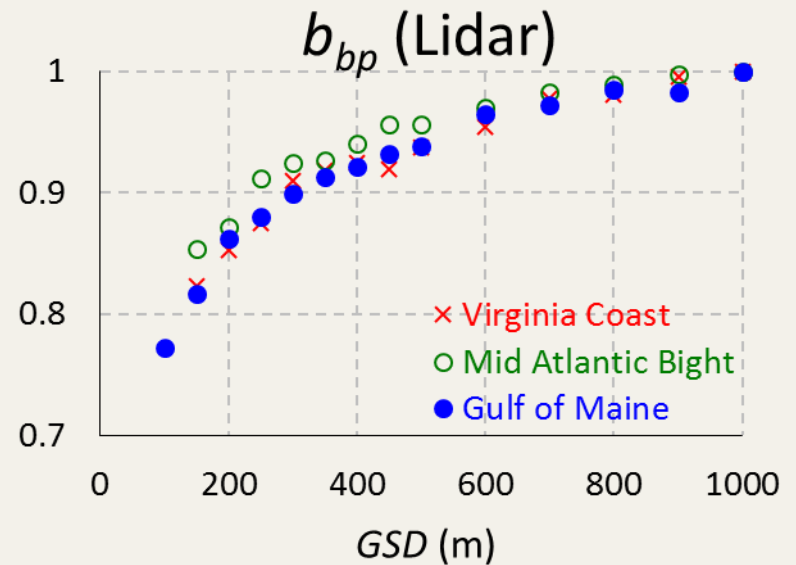
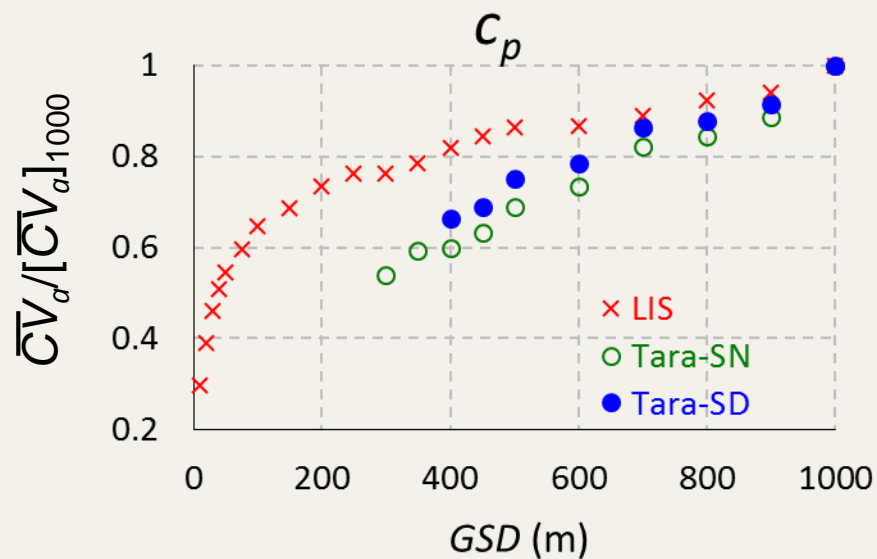
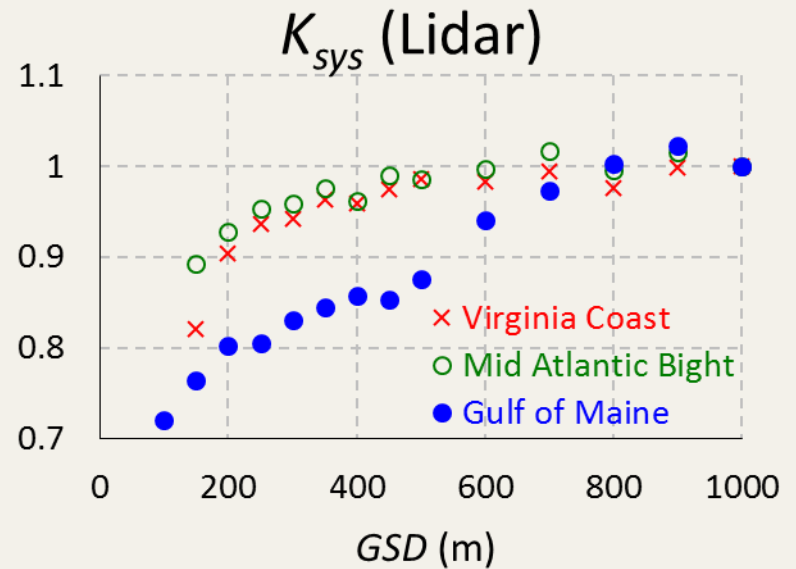
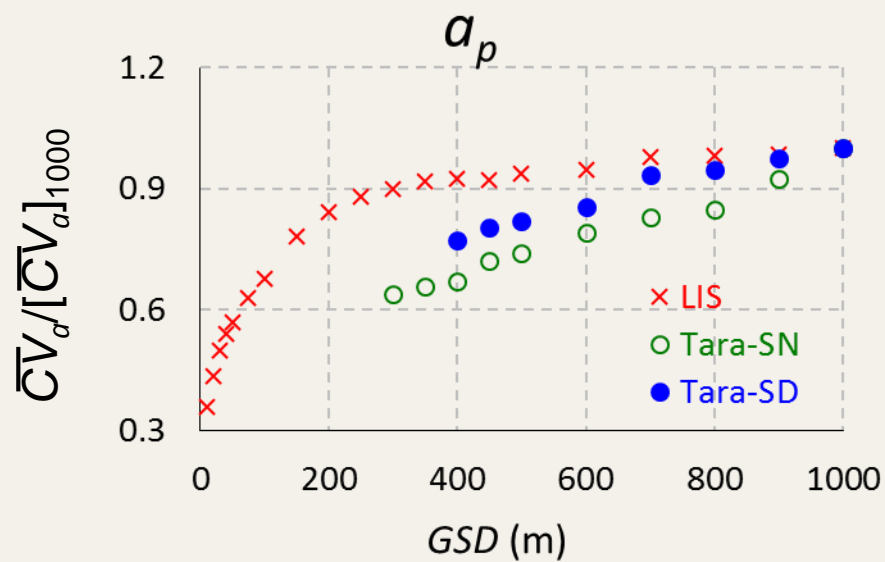


## Methods:

- Log-Log (LL) Method
- Slope Percentile (SP) Method

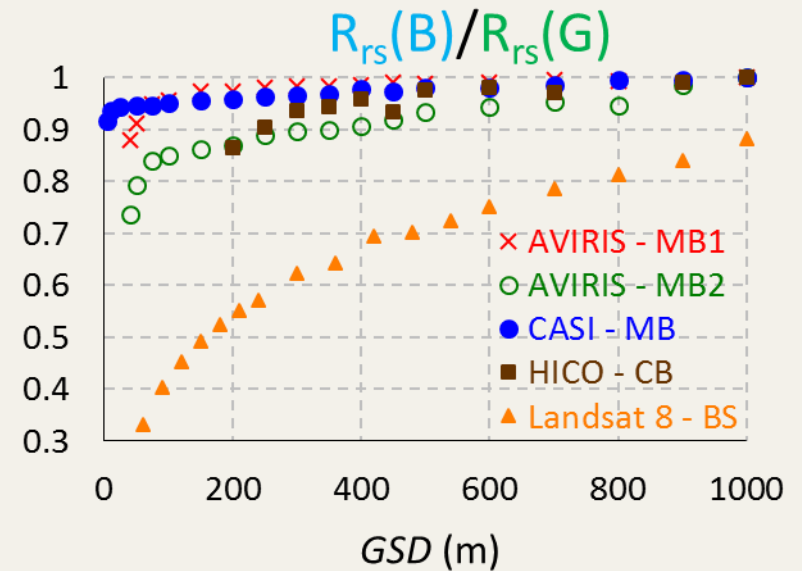
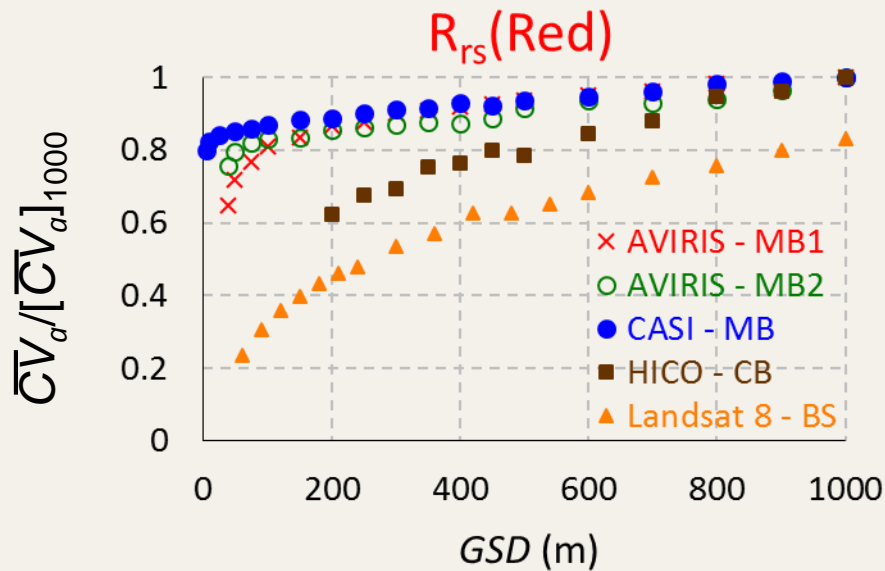
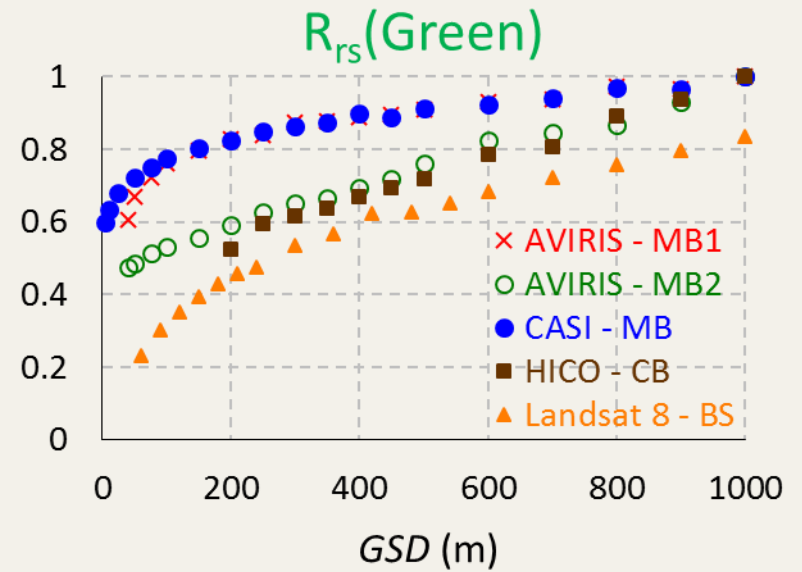
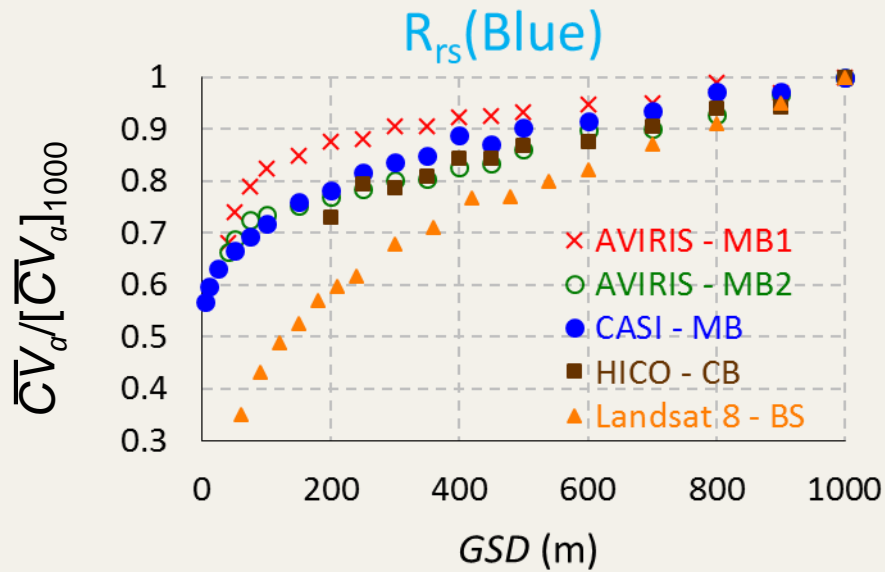
For Details: Moses, W. J., Ackleson, S. G., Hair, J. W., Hostetler, C. A. and Miller, W. D. (2016). *Spatial scales of optical variability in the coastal ocean: Implications for remote sensing and in situ sampling*, *Journal of Geophysical Research: Oceans*, **121**(6): 4194-4208, doi: 10.1002/2016JC011767.

# CV vs. GSD





# CV vs. GSD



Platform & Instrument	Transect	Parameter	$GSD_t$ (m)	
			LL Method	SP Method
In-water; <i>ac-s</i>	Long Island Sound	$[a_p(450)]_{\text{LIS}}$	250	150
		$[c_p(650)]_{\text{LIS}}$	40	100
Shipboard; <i>ac-s</i>	Savannah – New York	$[a_p(450)]_{\text{SN}}, [c_p(650)]_{\text{SN}}$	None	None
	San Diego Coast	$[a_p(450)]_{\text{SD}}, [c_p(650)]_{\text{SD}}$	None	None
Airborne; lidar	Virginia Coast	$[b_b(532)]_{\text{VC}}$	350	300
		$[K_{\text{sys}}(532)]_{\text{VC}}$	350	500
	Mid-Atlantic Bight	$[b_b(532)]_{\text{MAB}}$	300	450
		$[K_{\text{sys}}(532)]_{\text{MAB}}$	600	450
	Georges Bank and Gulf of Maine	$[b_b(532)]_{\text{GBM}}$	200	350
		$[K_{\text{sys}}(532)]_{\text{GBM}}$	200*	200*
Airborne; AVIRIS	San Francisco Bay	$[R_{rs\_B}]_{\text{SFB}}, [R_{rs\_B/G}]_{\text{SFB}}$	75	150
		$[R_{rs\_G}]_{\text{SFB}}$	100	150
		$[R_{rs\_R}]_{\text{SFB}}$	100	200
	Monterey Bay 1	$[R_{rs\_B}]_{\text{A-MB1}}, [R_{rs\_G}]_{\text{A-MB1}}, [R_{rs\_R}]_{\text{A-MB1}}$	100	200
		$[R_{rs\_B/G}]_{\text{A-MB1}}$	75	150
	Monterey Bay 2	$[R_{rs\_B}]_{\text{A-MB2}}$	75	100
$[R_{rs\_G}]_{\text{A-MB2}}$		None	None	
$[R_{rs\_R}]_{\text{A-MB2}}, [R_{rs\_B/G}]_{\text{A-MB2}}$		75	100	
Airborne; CASI	Monterey Bay	$[R_{rs\_B}]_{\text{C-MB}}$	75	100
		$[R_{rs\_G}]_{\text{C-MB}}$	None	150
		$[R_{rs\_R}]_{\text{C-MB}}$	200	150
		$[R_{rs\_B/G}]_{\text{C-MB}}$	None	None
Spaceborne; HICO	Chesapeake Bay	$[R_{rs\_B}]_{\text{CB}}, [R_{rs\_G}]_{\text{CB}}, [R_{rs\_R}]_{\text{CB}}$	None	None
		$[R_{rs\_B/G}]_{\text{CB}}$	300	400
Spaceborne; Landsat-8	Baltic Sea	$[R_{rs\_B}]_{\text{BS}}, [R_{rs\_G}]_{\text{BS}}, [R_{rs\_R}]_{\text{BS}}, [R_{rs\_B/G}]_{\text{BS}}$	None	None

# Results

(for coastal waters)

- Average  $GSD_t(LL)$ : 173 m
  - Average  $GSD_t(SP)$ : 217 m
- } ~ 200 m
- $GSD_t$  generally smaller for regions closer to the shore (dominated by scattering processes)

Does not imply that 200 m is sufficient; it simply means that beyond 200 m there is a significant loss in the ability to capture spatial variability

### Rationale

- Ocean color remote sensors have different spatial resolutions
- Remote-sensing reflectance Rrs: non-linear function of the IOPs
- How pixel size impacts the retrieval of Rrs?
- Which bio-optical model is the less sensitive to sub-pixel variability?
- What is the high frequency of Rrs and IOPs?

### Conclusion and Perspectives

- **Simulated dataset**: no impact of pixel size on estimation of IOPs
- High spatial resolution only necessary for coastal waters highly influenced by river discharge.
- **Dependent of the wavelength**
- **Spatial resolution of 200 meters enough for visualizing most of the coastal changes in the Rrs**
- Use of turbulence method for analysis high frequency changes in the IOPs
- Use of CV (Moses et al., 2016)

# Spatial resolution of ~200 m for capturing most changes in coastal Rrs

- MERIS FR: 300 m over English Channel and French Guiana
- Landsat L8/OLI: 30 m over English Channel and Vietnam processed with Acolite software
- Linear averaging of the spatial resolution

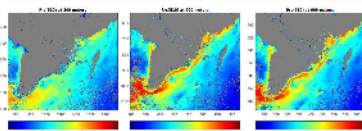


Fig. 2: Comparison of Rrs maps at different resolution of 30, 300, 1000 meters and 1000 meters with the linear averaging of the 3000 meters MERIS data (2003/12/15)

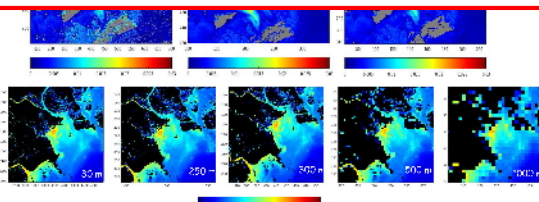


Fig. 3: Co-simulated Rrs maps for different spatial resolutions along the coast of French Guiana (2016/06/22)

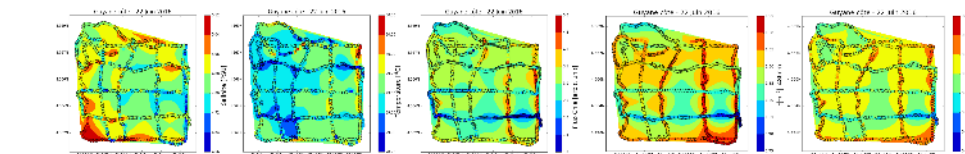
### Field measurements over a pixel and sub-pixel

- Eastern English Channel: 19/01/16; 11/02/16; 14/03/16; 18/03/16; 01/04/16; 19/04/16; 03/05/16; 26/05/16
- French Guiana: 21-22/06/2016
- Continuous measurements of  $a$  and  $bb$  using a bot-wing (WETLABS ac-s or VSF green/red and WETLABB bb-9) + CTD + Fluor chlorophyll



### Simulation of sub-pixel of 250 m over a pixel of 1000 meters along the coasts of French Guiana on June 22, 2016

- Salinity
- Temperature
- Fluor chl
- $a(486)$
- $b_{p}(532)$



### References

Lee, Z. P., C. L. Carter and R. Arango (2002). Deriving inherent optical properties from water color: a multi-band quasi-analytical algorithm for remote sensing. *Appl. Opt.*, 41, 5722-5732.

Lee, Z. P., C. L. Carter and Z. Liu (2002). Impact of sub-pixel variability on ocean color remote sensing products. *Opt. Exp.*, 10, 20844-20851.

Loisel, H., T. S. Andersen, J. W. J. King, C. A. Bretherton and M. D. Miller (2005). Spatial scales of optical variability in the coastal ocean: implications for remote sensing and data averaging. *J. Geophys. Res.*, 110, C02012, doi:10.1029/2004JC001167.

Portman, M. S., Barrow and B. A. Frazer (2006). Uncertainties in coastal ocean productivity indices: a test of spatial sampling. *Remote Sens. Environ.*, 102, 24-35.

Vanhulst, M. and K. Radach (2002). Turbidity associated with offshore wind turbines observed with a Laser-R Remote Sens. *Limnol. Oceanogr.*, 47, 162-170.

Vanhulst, M. and K. Radach (2005). Advantages of high quality SWIR bands for ocean color processing: examples from Landsat-8. *Remote Sens. Environ.*, 96, 89-106.

### Acknowledgments

This work has been supported by the European Space Agency through the MERIS 4th reprocessing project (ARS/003\_025/06/1\_06).

Thanks to the project of ACIS-ST and distribution of the GIS COOC data portal in the frame of the Kallisto, funded by CNRS, using ESA ENVISAT MERIS FR data. Landsat8 data have been downloaded from the USGS website.

Amick B. is thanked for providing the tables for the calculation of  $a$ .

Xavier Mériaux and Arnaud Davin for the help using the bot-wing.

David Jessouly for providing the code to average the satellite data.

# Spectral Resolution

What spectral resolution is required to resolve spectral features in complex inland and coastal waters?

Ryan Vandermeulen, Antonio Mannino, and Aimee Neeley

What are the scales of spectral variability? How does this affect the results?

RESULTS – SPECTRAL VARIABILITY OF PHYTOPLANKTON ABSORPTION

## CONCLUSIONS

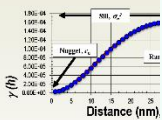
### METHODS

Empirical variograms,  $\gamma(h)$ , are (correlated) with "distance" as

$$\gamma(h)$$

Where:  
 $h$  is spectral distance between bins  
 $N(h)$  is the number of all possible pairs of bins  
 $z_1$  and  $z_2$  are the data values of bins  
 Proceed to calculate  $\gamma(h)$  for 1 nm

In a nutshell: We measure the variance by distance  $h$ , each averaged by the variance measured at diff meaning data structure is no longer range describes the distance it represents the uncertainty, or  $\tau$



Gaussian fit  $\rightarrow g$

### MODIFIER

In this analysis, we are using a variogram, but rather than  $d\gamma(h)/dx$ . This emphasis shows the location of  $h$  words, below this point, of spectral resolution in

### DATA COLLECTION

Hyperspectral data were collected in an open ocean environment (filter pad above water) and in a river environment (above water)

### FILTER PAD ABSORPTIO

Four cultures (see Results) were filtered onto GF/F filters. A spectrophotometer equipped with 0.3125, 0.625, 1.00, and 5.0 absorbance values are normal

### REMOTE SENSING REFLECTANCE

Above-water remote sensing reflectance were taken using Anali Spectroradiometers. These instruments are using un-calibrated radiance or reflectance ( $\rho_r$ ), relative to reflectance of a 10% grey card and is assumed to be a semi-computed as:

$$R_{rs}(\lambda)$$

For this analysis,  $R_{rs}$  is normalized to maximum values and compared. Empirical variograms were individually calculated for each scenario, and results were averaged according to water-type.

Types (PTs) from space, which will require more spectral bands and finer spectral resolution than present ocean color sensors.

nm resolution), with the possibility of subsampling pre-defined regions at a higher spectral resolution, if deemed relevant. This trade study aims to determine the optimal sampling frequency for OCI.

References:  
 Duan, H.T. et al. (2009) "Fluorescence peak shift corresponding to high chlorophyll concentrations in inland water." *Guang pu* 29: 161-4

1

A **MINIMUM** of 5 nm spectral resolution is required to resolve variability across mixed spectrum

2

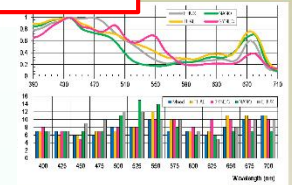
Certain spectral regions may benefit from enhanced spectral subsampling (e.g. fluorescence channel)

3

Results show that even most sensitive regions of the spectrum are resolved at ~4 nm, but does not account for capturing the location of shifting peaks.

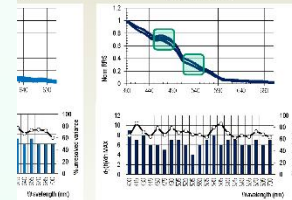
4

At 5 nm spectral resolution, SNR may be ultimate limiting factor for distinguishing fine scale peaks



spectrum of four distinct cultures (top) and the corresponding  $d\gamma(h)/dh$  MAX (below), indicating the spectral resolution at which the most information is gained. Results show most features are resolved at ~6 nm.

### TERRESTRIAL MOUNTAIN OLIGOTROPHIC WATER BAHAMAS



Four spectra obtained from very clear oligotrophic waters in the Bahamas (top), and the corresponding  $d\gamma(h)/dh$  MAX (bottom). Spectral optimization shows that 60-90% of the variance is resolved, with some areas that require 5 nm or less to resolve (475 and 535 nm).

### CONCLUSIONS

A minimum of 5 nm spectral resolution is required to resolve variability across mixed spectrum

Certain spectral regions may benefit from enhanced spectral subsampling (e.g. fluorescence channel)

Results show that even most sensitive regions of the spectrum are resolved at ~4 nm, but does not account for capturing the location of shifting peaks.

At 5 nm spectral resolution, SNR may be ultimate limiting factor for distinguishing fine scale peaks

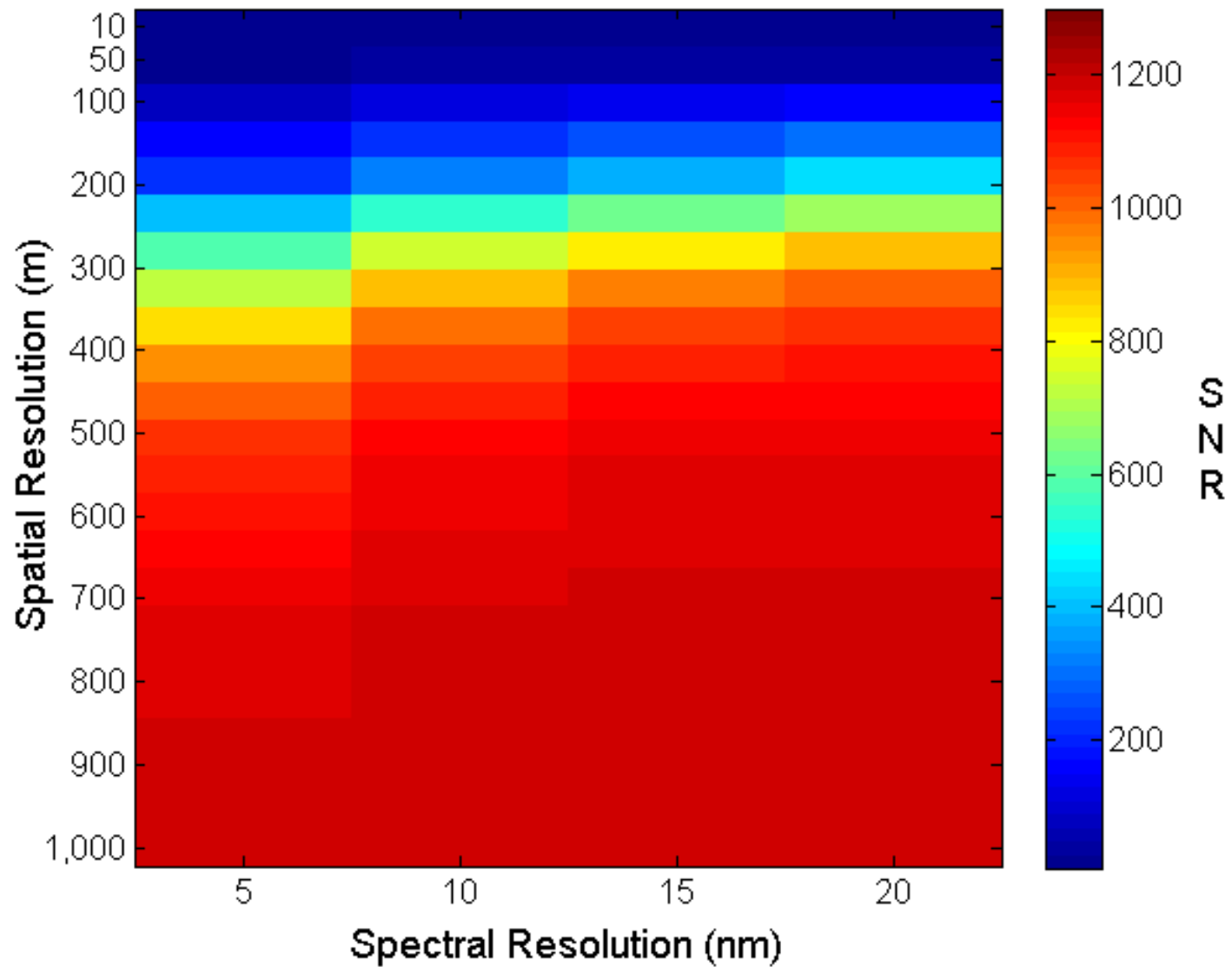
Learning from NASA PACE mission, NOAA JPSS and other satellite sensors for Coastal and River Dominated Ecosystems

# Signal-to-Noise Ratio (SNR)

## Trade-off amongst

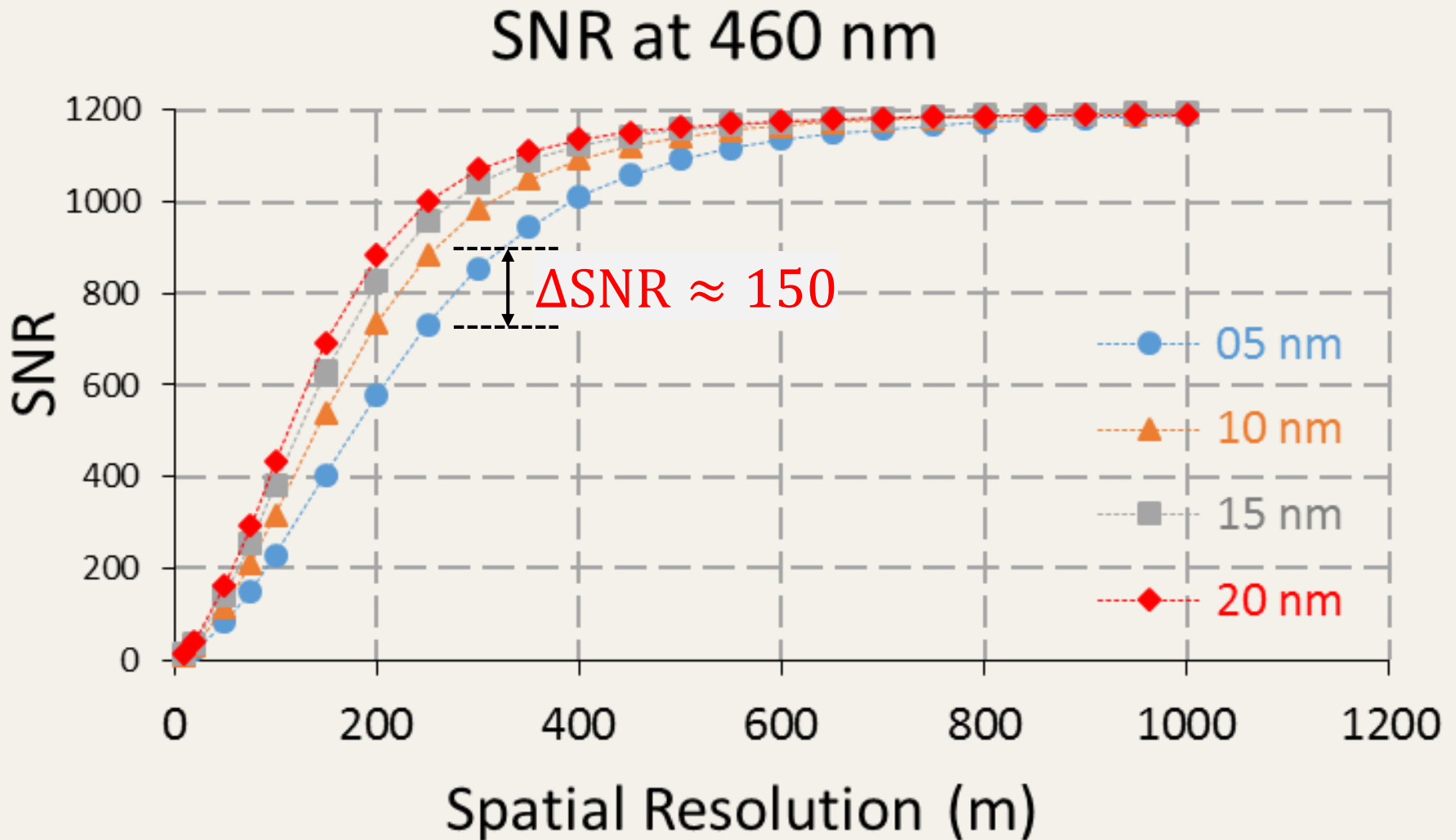
- ❖ Spatial Resolution
- ❖ Spectral Resolution
- ❖ SNR

# Trade-off





# Trade-off



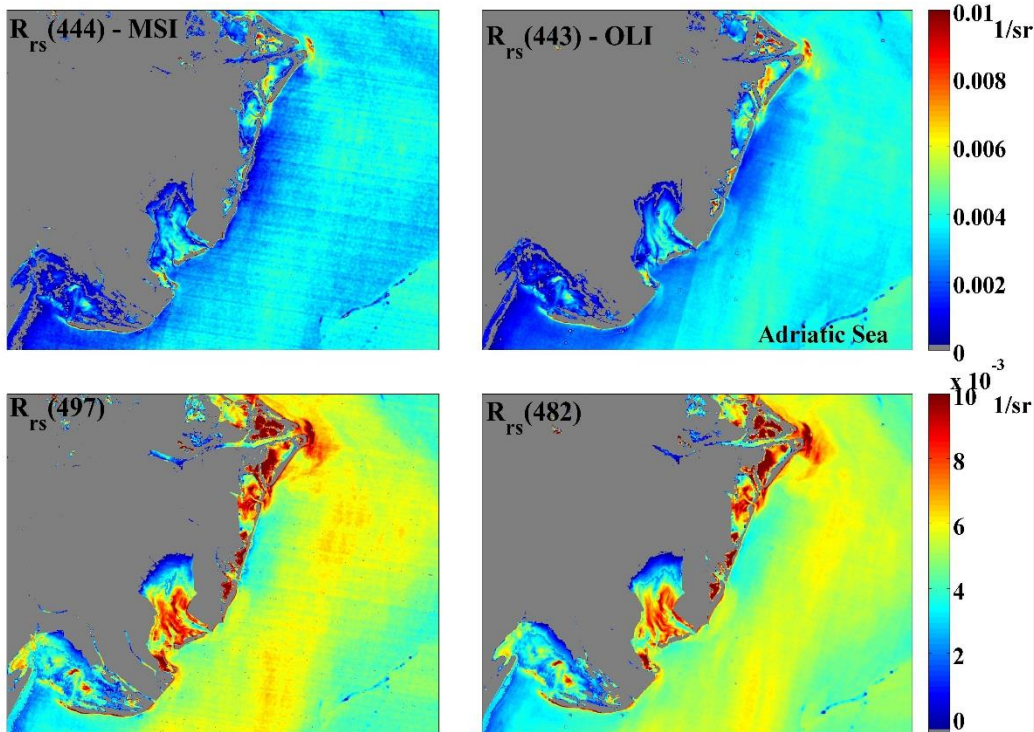
# What does $\Delta\text{SNR} \approx 150$ mean for retrievals?

## A single case study

- Add noise to Rrs spectrum at SNR = 700 and 850
- Estimate chl-*a* for both cases and compare to the estimate from noiseless Rrs spectrum to determine the uncertainty due to noise,  $U_{\text{SNR}}$
- Effects of SNR on atmospheric correction not considered here
- $U_{\text{SNR}=700} = 0.17 \pm 4.5\%$
- $U_{\text{SNR}=850} = 0.15 \pm 3.7\%$

# Impact of spatial aggregation on $R_{rs}$ (blue)

Pahlevan et al. (2017)



Spatial averaging can only qualitatively improve the product quality.

Even after spatial averaging, the OLI-derived products are of higher quality (due to its better SNRs).

Pahlevan, N. , Sarkar, S., Franz, B. A., He, J. “**Sentinel-2 MultiSpectral Instrument (MSI) data processing for aquatic science applications: Demonstrations and preliminary validations**”. Submitted to *Remote Sensing of Environment*

# Signal-to-Noise Ratio (SNR)

- Atmospheric correction is a major contributor of uncertainties in retrievals

 AGU PUBLICATIONS

JGR

Journal of Geophysical Research: Oceans

RESEARCH ARTICLE Requirement of minimal signal-to-noise ratios of ocean color sensors and uncertainties of ocean color products  
10.1002/2016JC012558

Key Points:

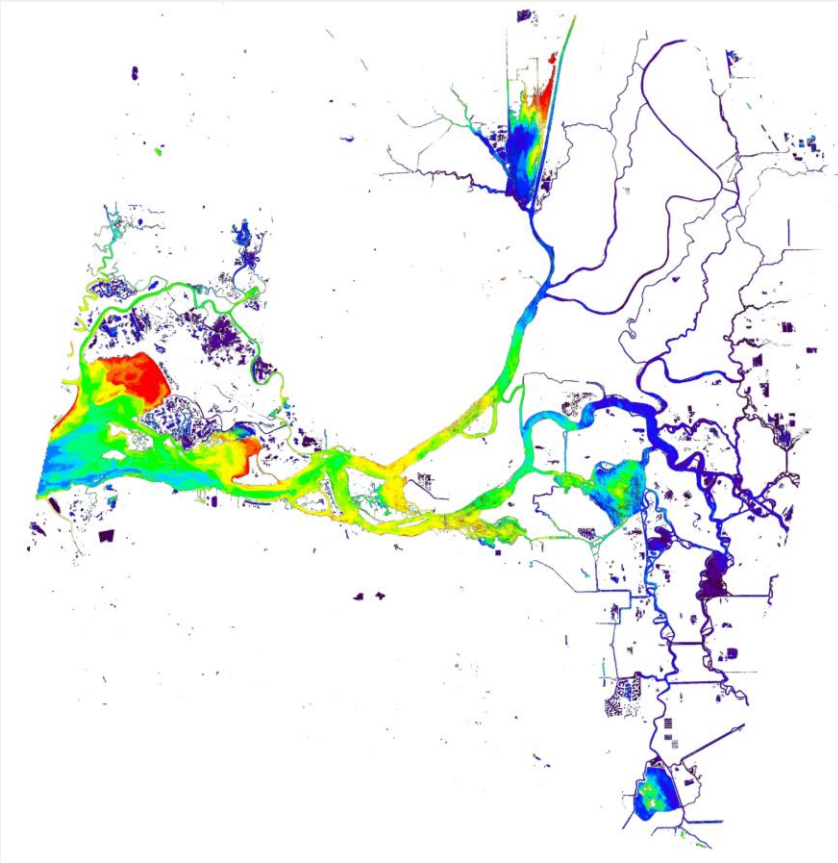
Lin Qi, Zhongping Lee, Chuanmin Hu, and Menghua Wang



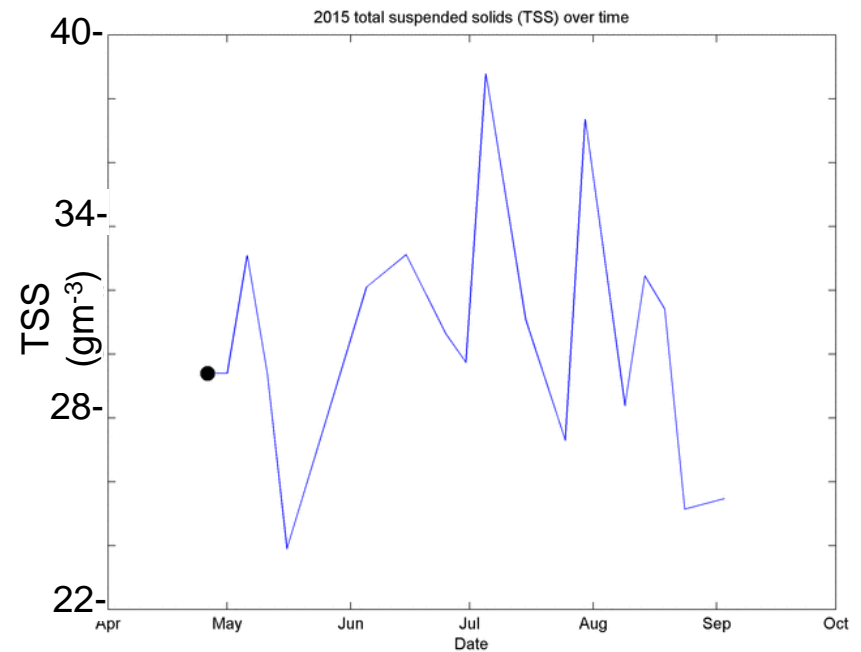
“...once SNR(NIR) is above 600:1, an SNR(vis) better than 400:1 will not make a significant reduction in product uncertainties...”

# Temporal Resolution

## TSS concentration in Sacramento-San Joaquin River – from SPOT Take 5 Data



Christiana Ade et al. (see poster)



# Synergistic Use of Satellite Data

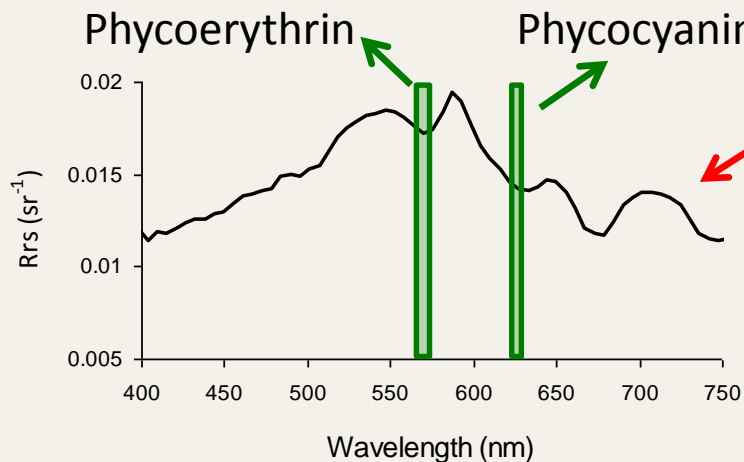
Lake Kinneret (Israel)

HICO Image 11 Mar 2013



14 Mar  
2013

MODIS  
R645



The presence of **phycoerythrin** and **phycocyanin** was confirmed by lab analysis of water samples

# Acknowledgments

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- Dr. Dave Miller (Naval Research Laboratory)
- Dr. Emmanuel Boss (University of Maine)
- Dr. Chris Hostetler (NASA Langley Research Center)
- Dr. Jonathan Hair (NASA Langley Research Center)

# Thank You!

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