Satellite-based optical water classifications in global oceans

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Acknowledgments

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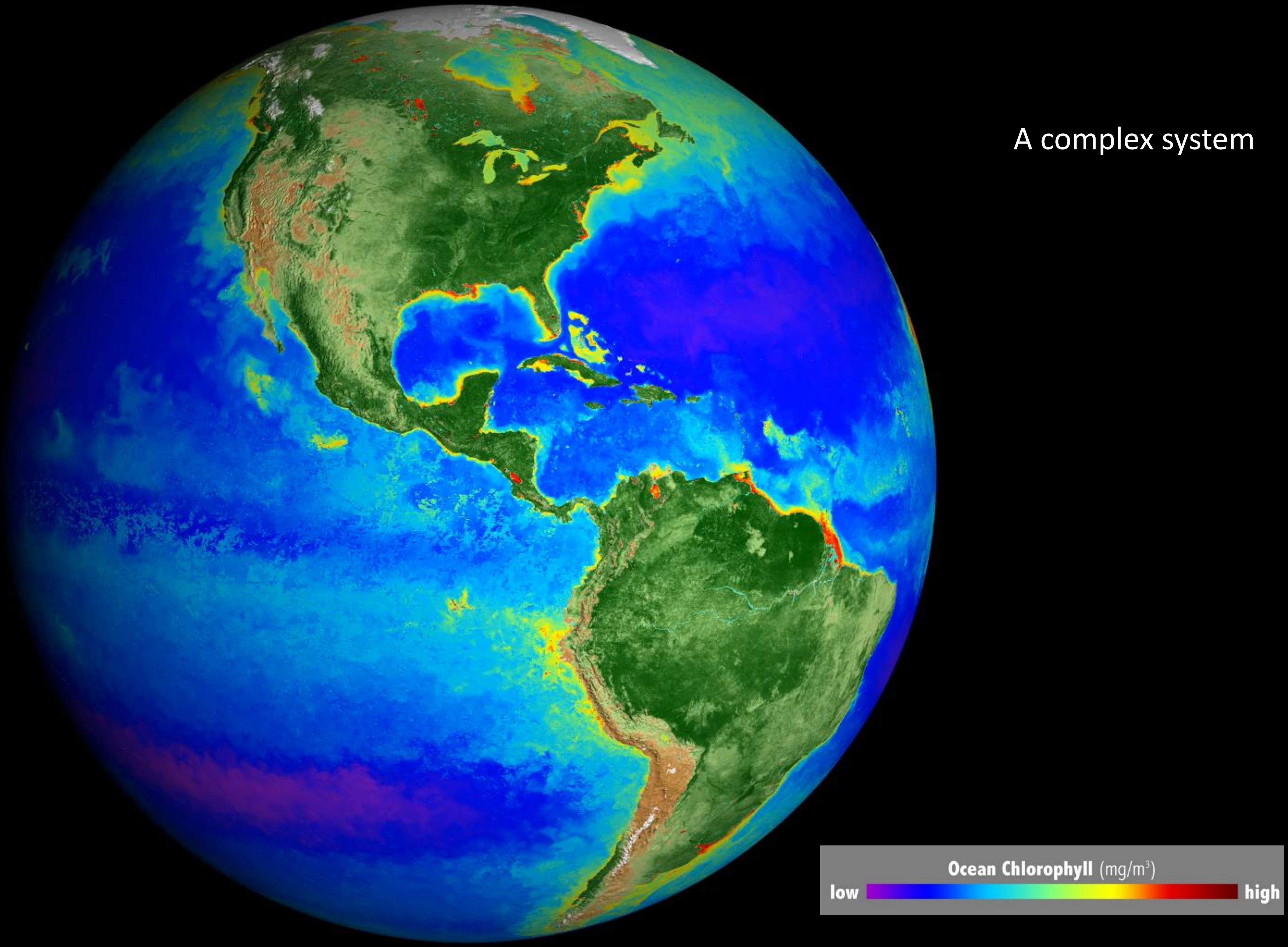
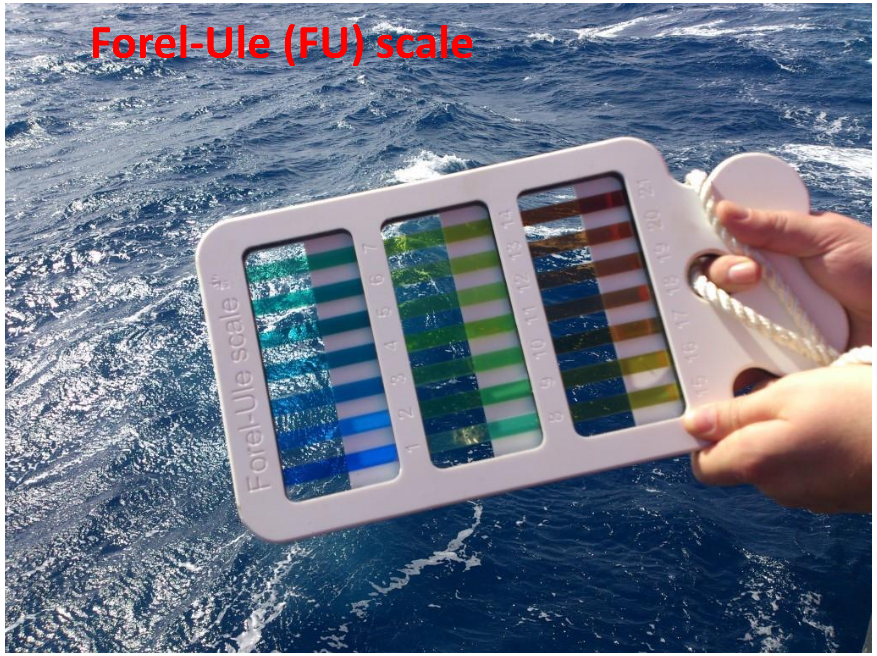
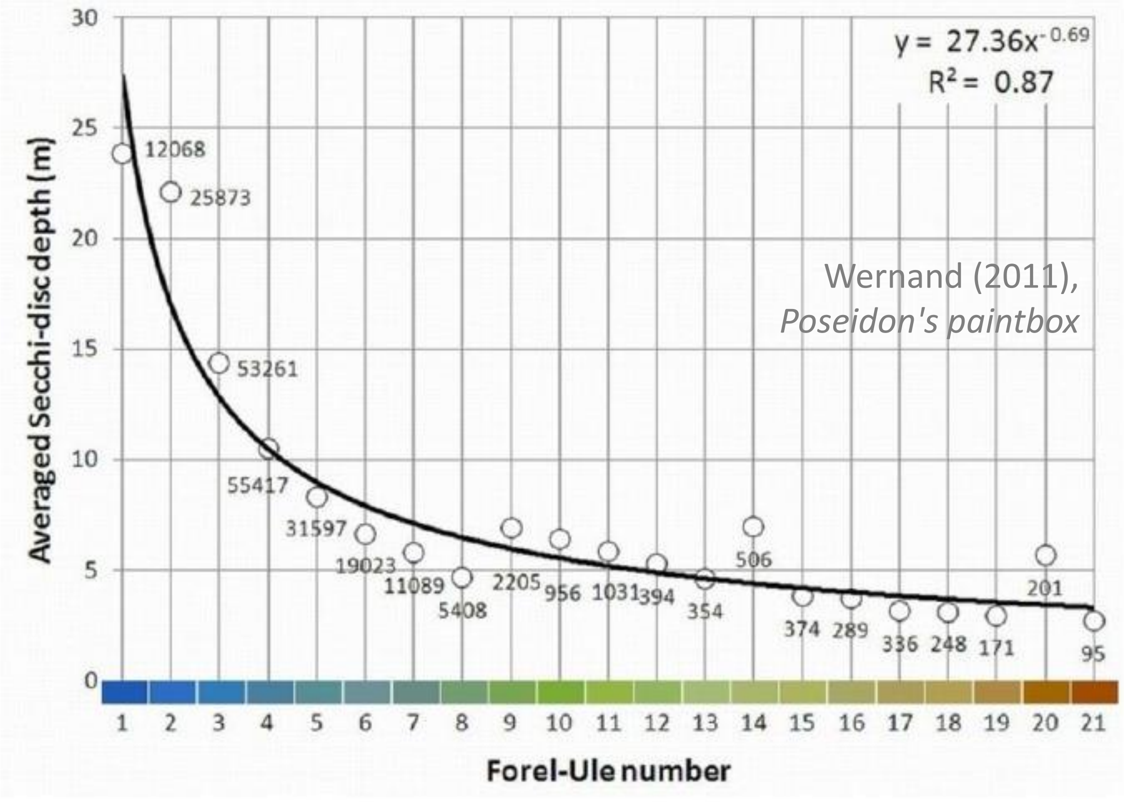
A complex system



Credit: NASA SVS

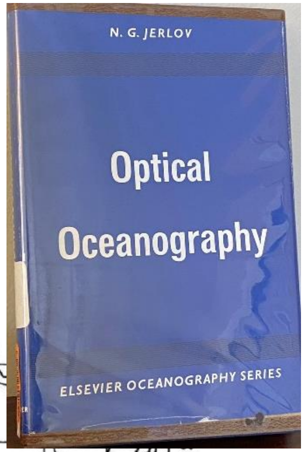
Water classifications started with human-eye observations…

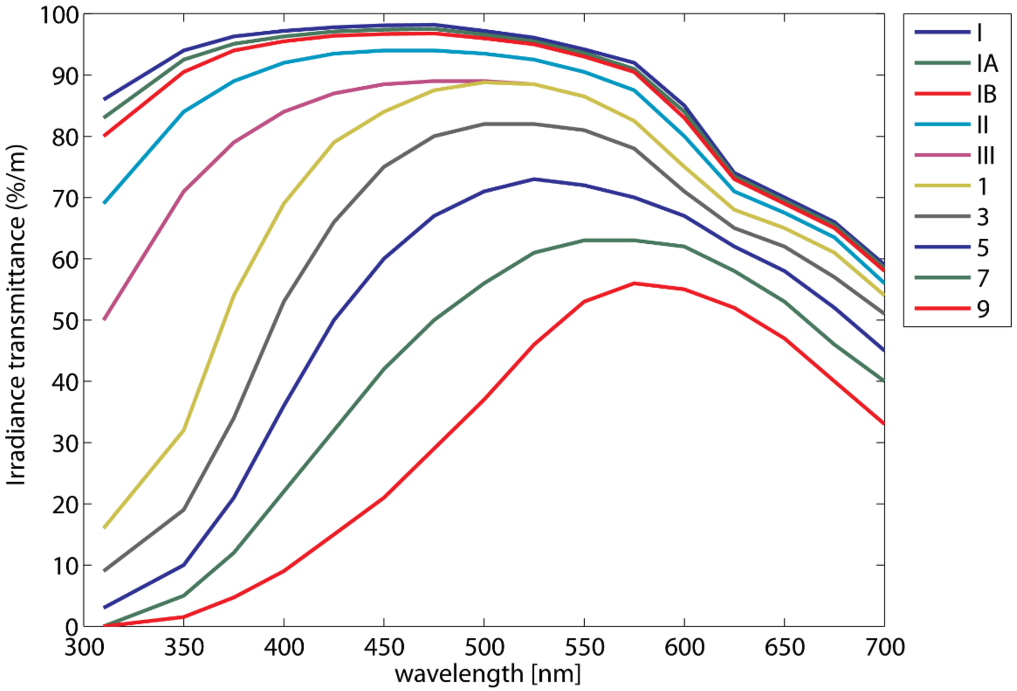


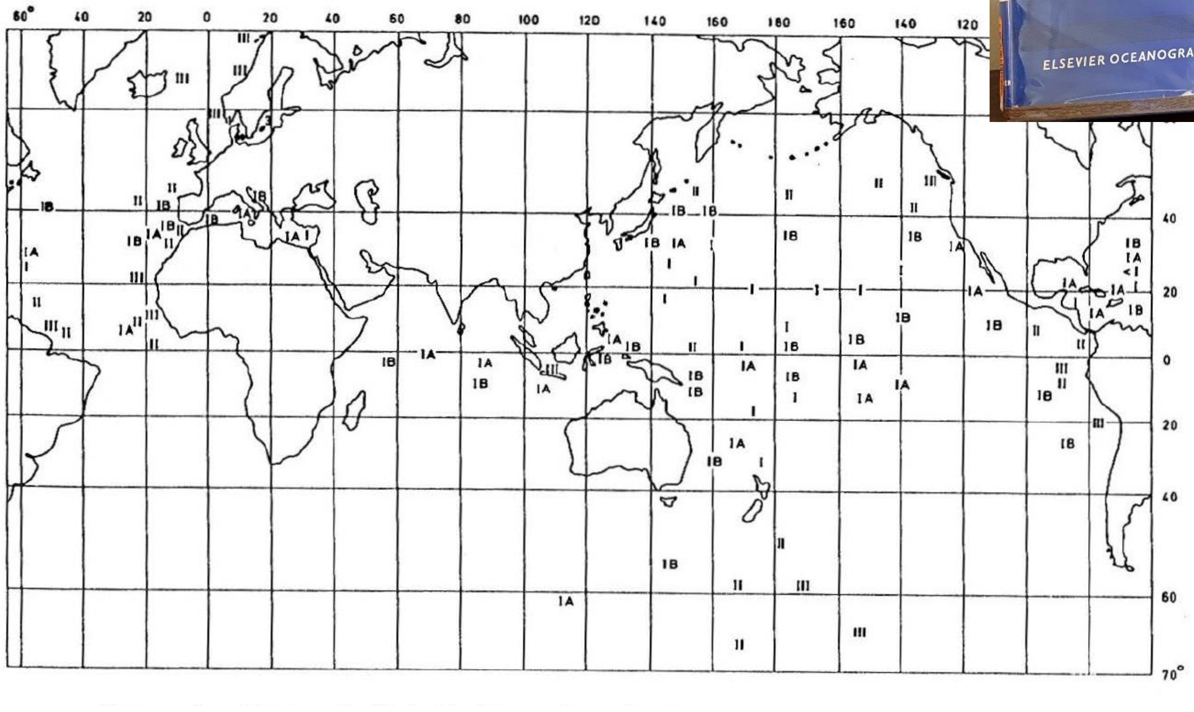


- ✓ It consists of 21 scales designed by Forel (1890) and Ule (1892)
- ✓ It is the first attempt to divide the oceans based on their colors
- ✓ It has accumulated the longest ocean optical records (>100 years)

Jerlov water classifications (1968; 1976)



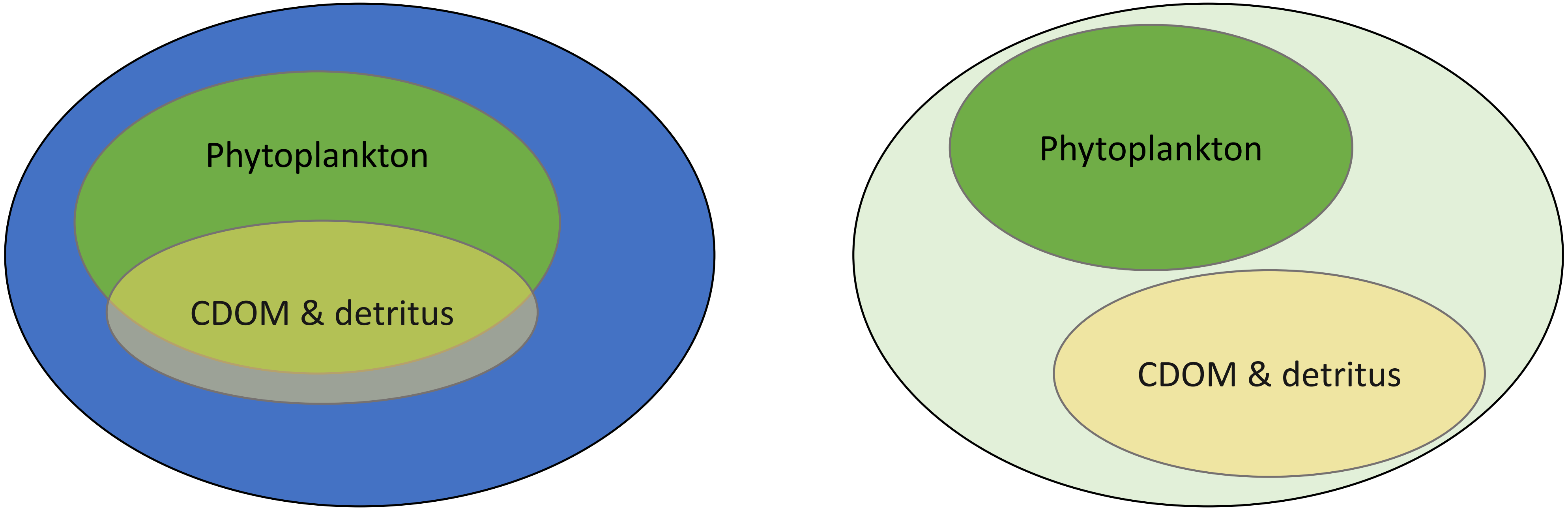




- ✓ First quantitative classifications: I-III for open oceans, 1-9 for coastal oceans
- ✓ Occasionally used in the ocean color remote sensing and ocean modeling systems

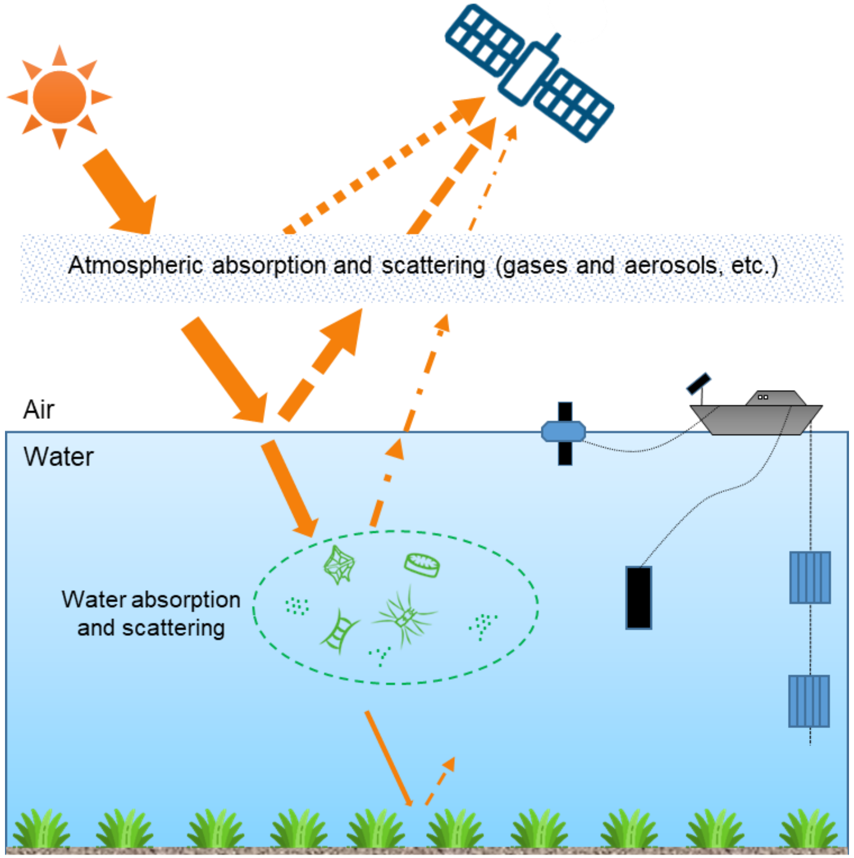
Case 1 & Case 2 classifications

Recommended readings: Morel & Prieur (1977); Mobley (2004)

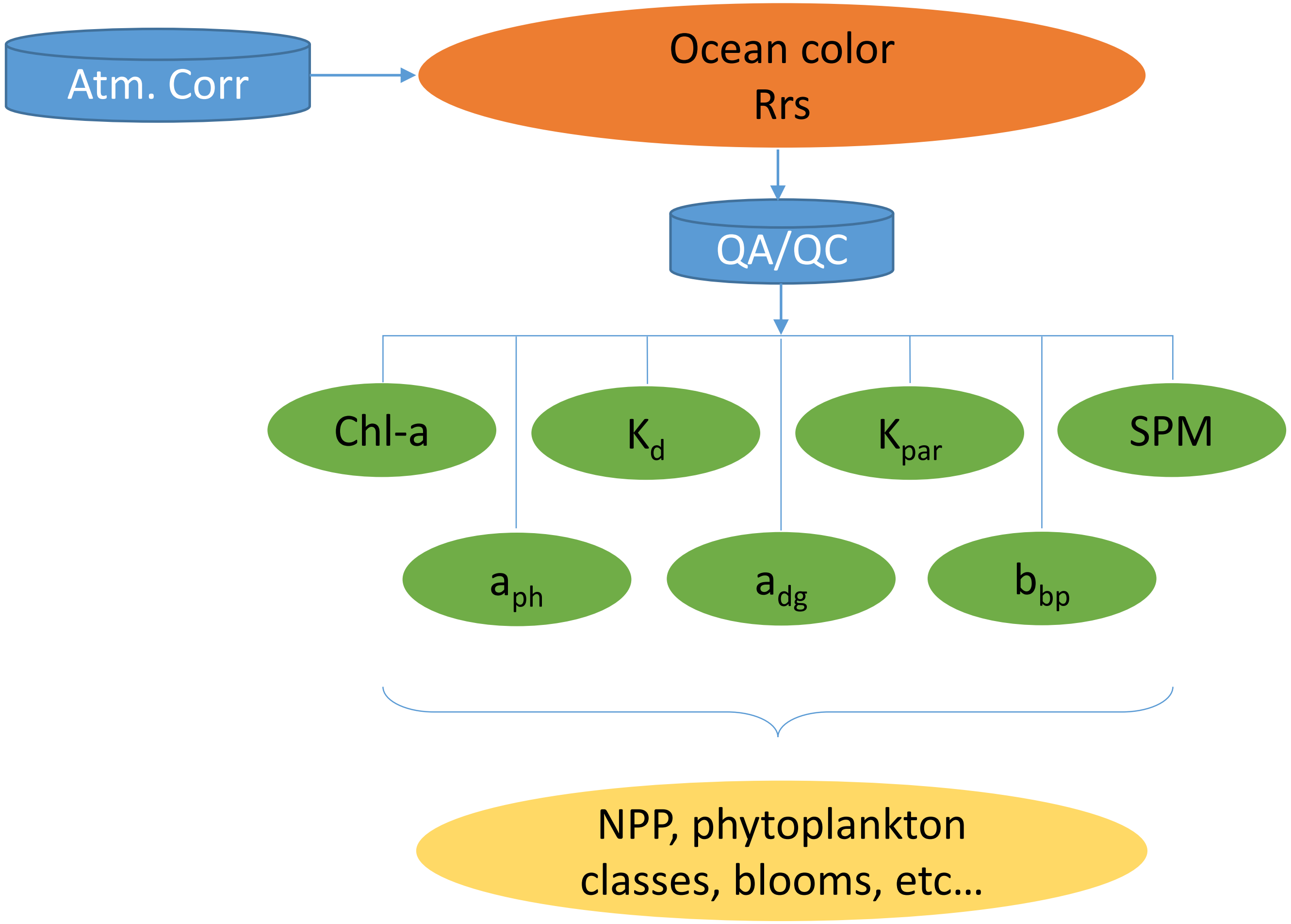


- ✓ It is this classification that has been frequently referred to in various presentations
- ✓ It played an important role for bio-optical modeling and the development of the ocean color satellites
- ✓ No clear demarcation line to separate Case 1 and Case 2 waters

Satellite ocean color data

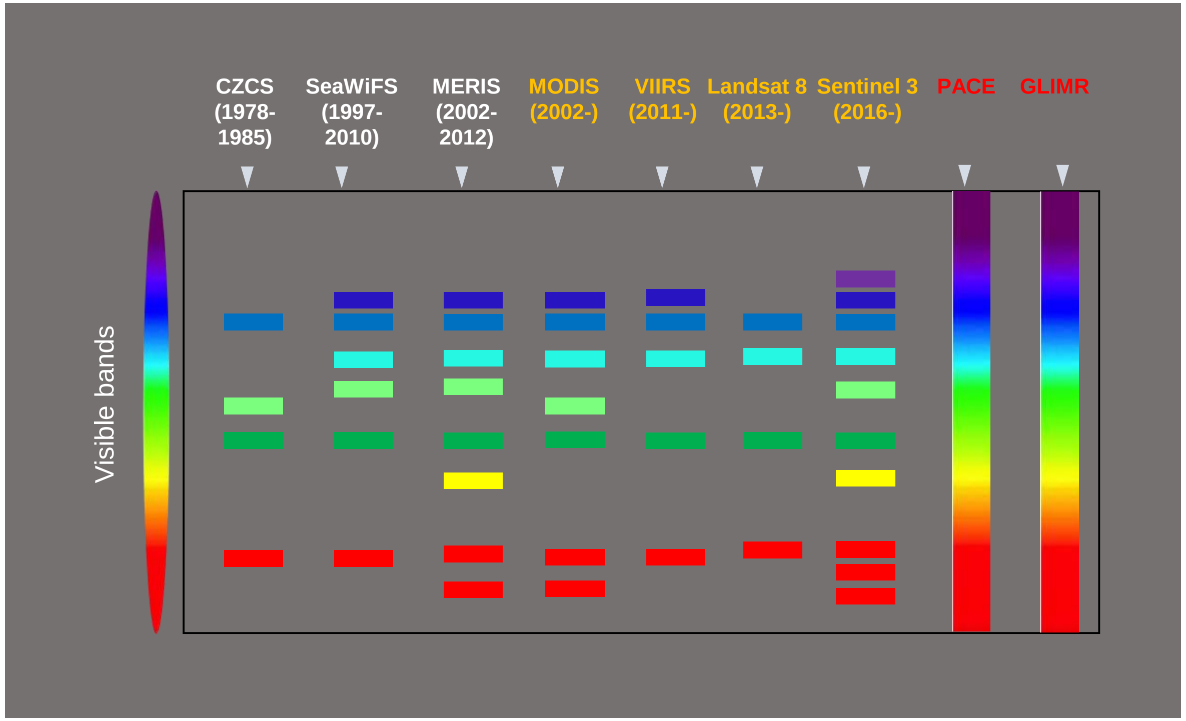


Wei et al. (2023), *Satellite ocean color validation*



Priority problems

✓ **Compatible/applicable**



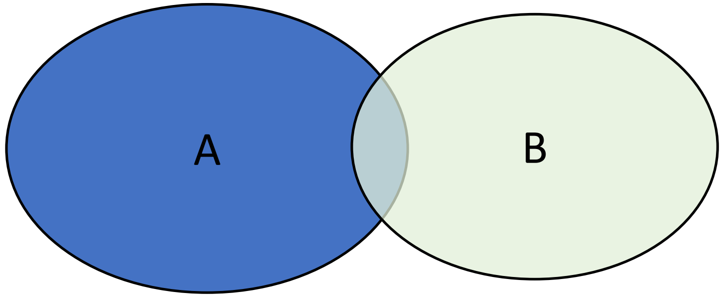
✓ **Reliable**

✓ **Comparable**

This requires the classifications are insensitive to the number of wavelengths of the satellite sensors

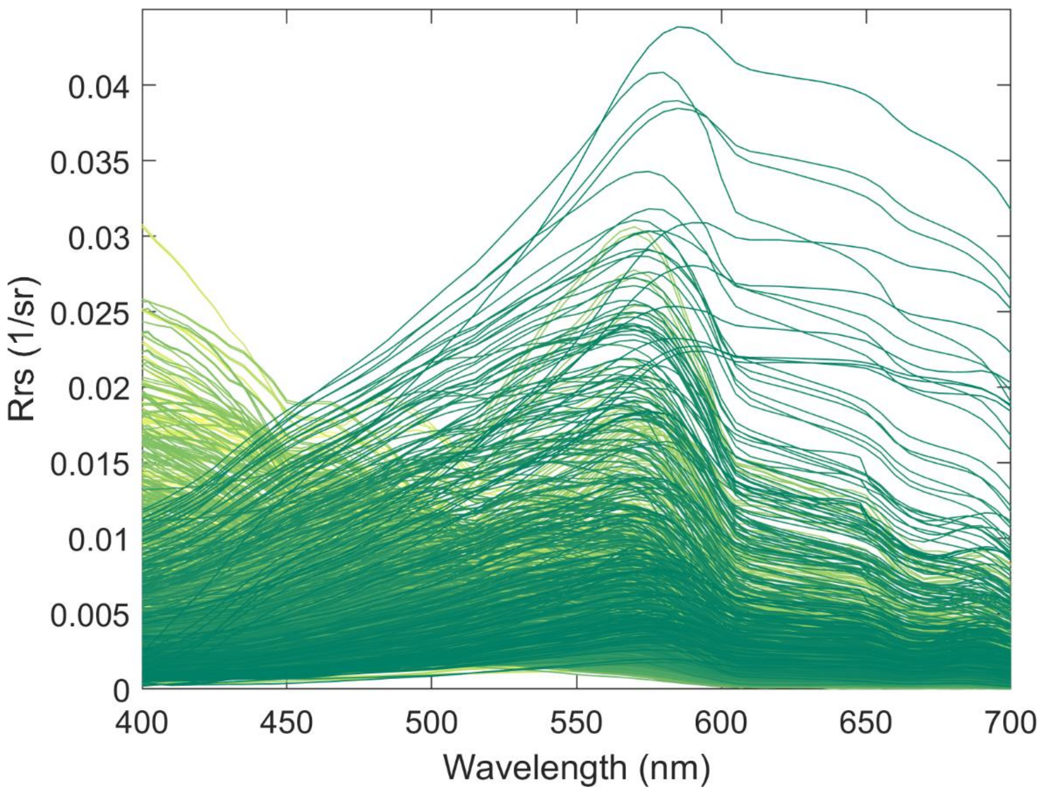
✓ **Distinguishable**

The resultant water classes are ideally distinctive from each other

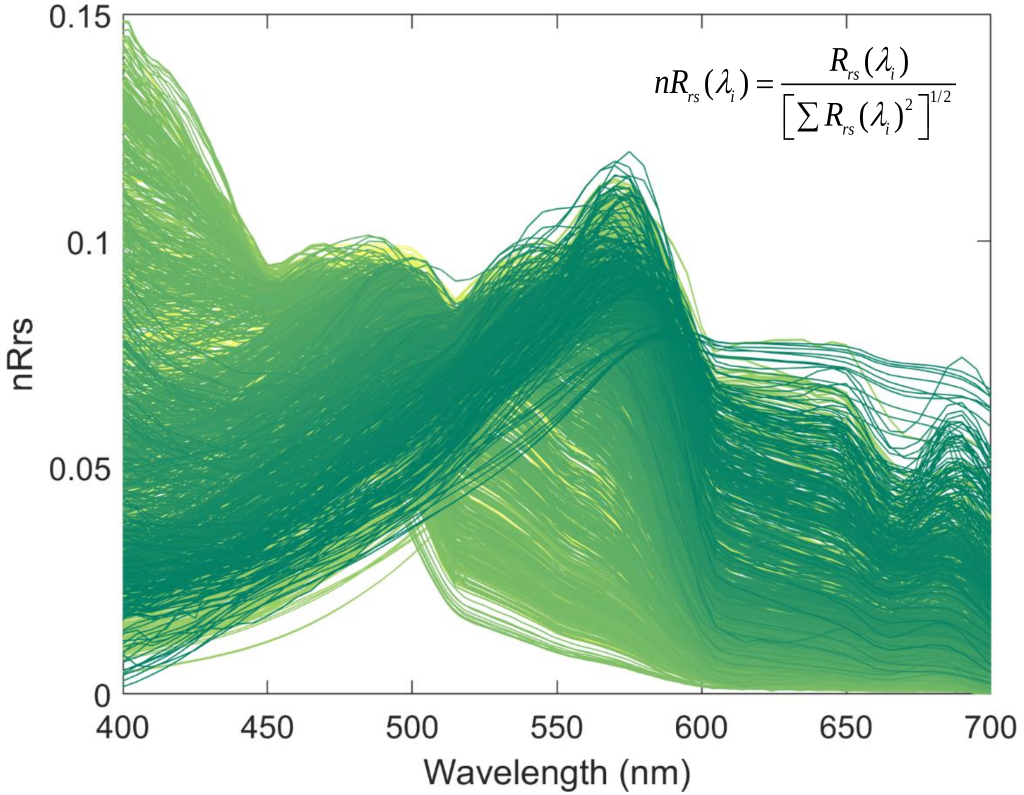


Hyperspectral data

Remote sensing reflectance



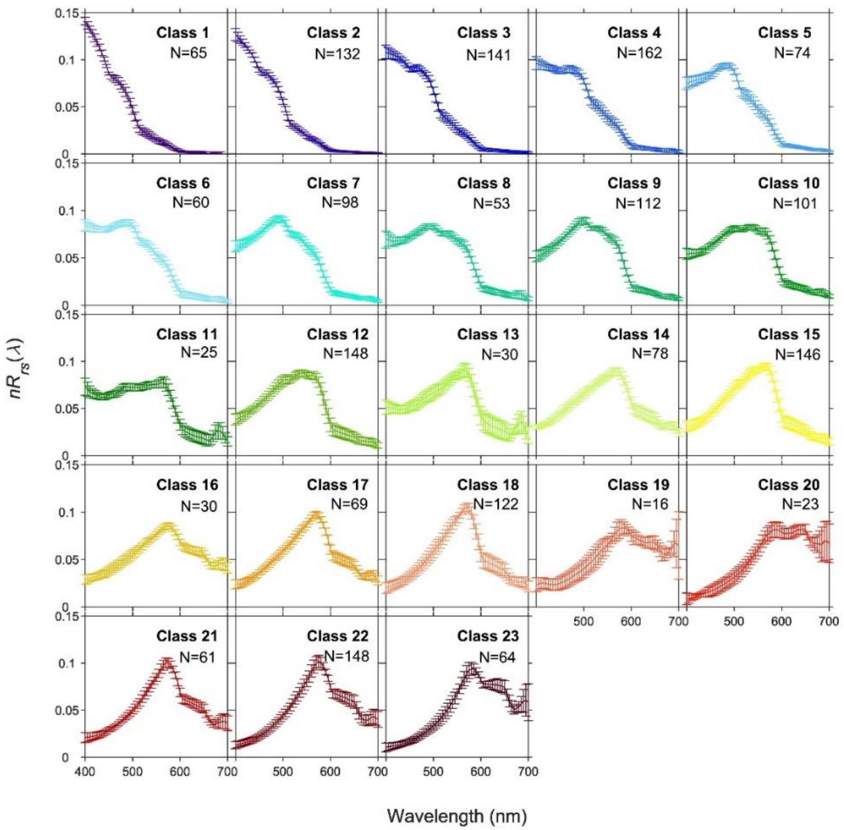
Normalized remote sensing reflectance



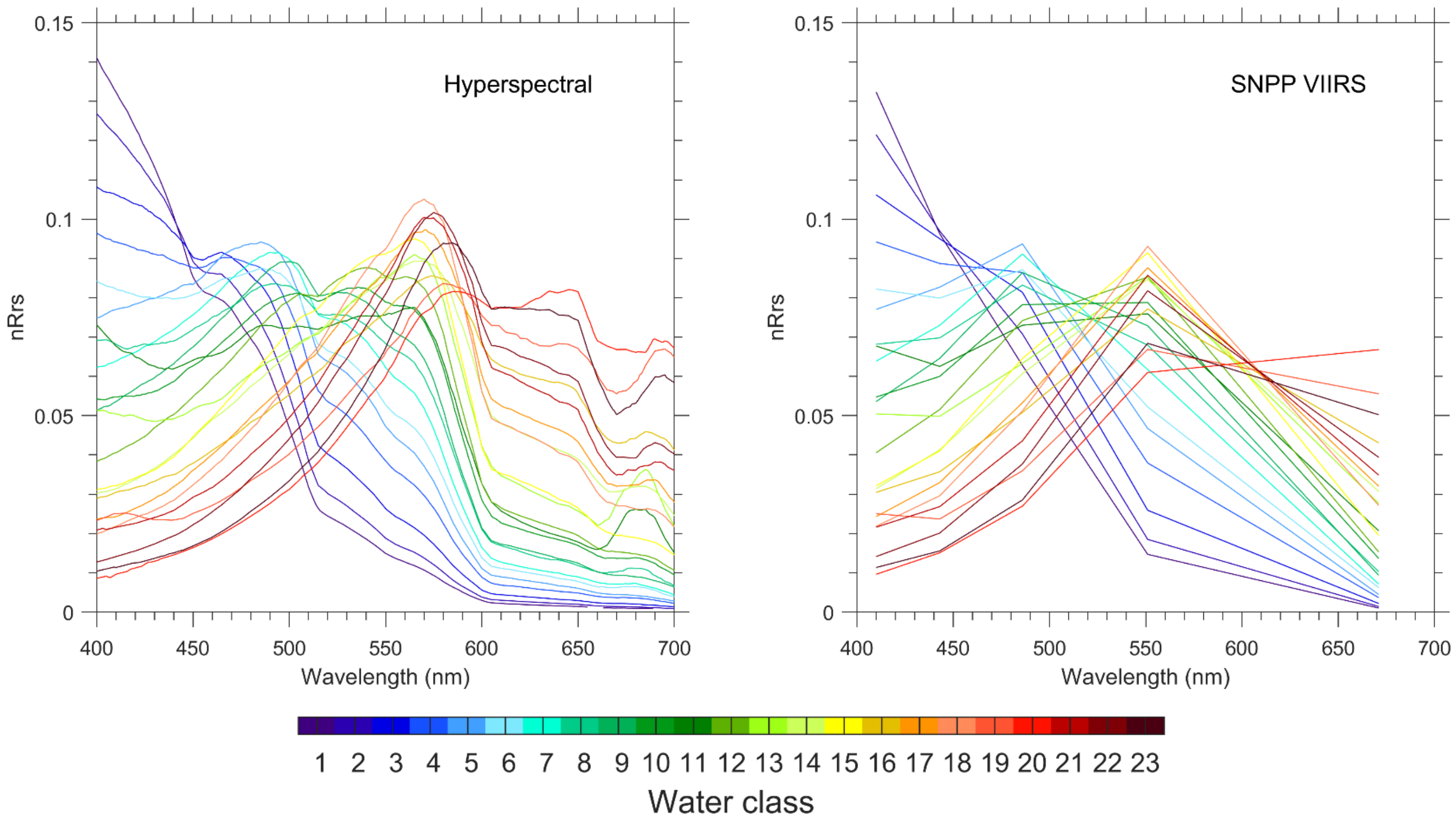
- ✓ Training data consist of in situ measurements and simulations

Hyperspectral clusters (k = 23) based on spectral similarity

- ✓ Cosine distance between two individual nRrs spectra is computed: $d = 1 - \dfrac{\mathbf{A}\cdot\mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|}$.



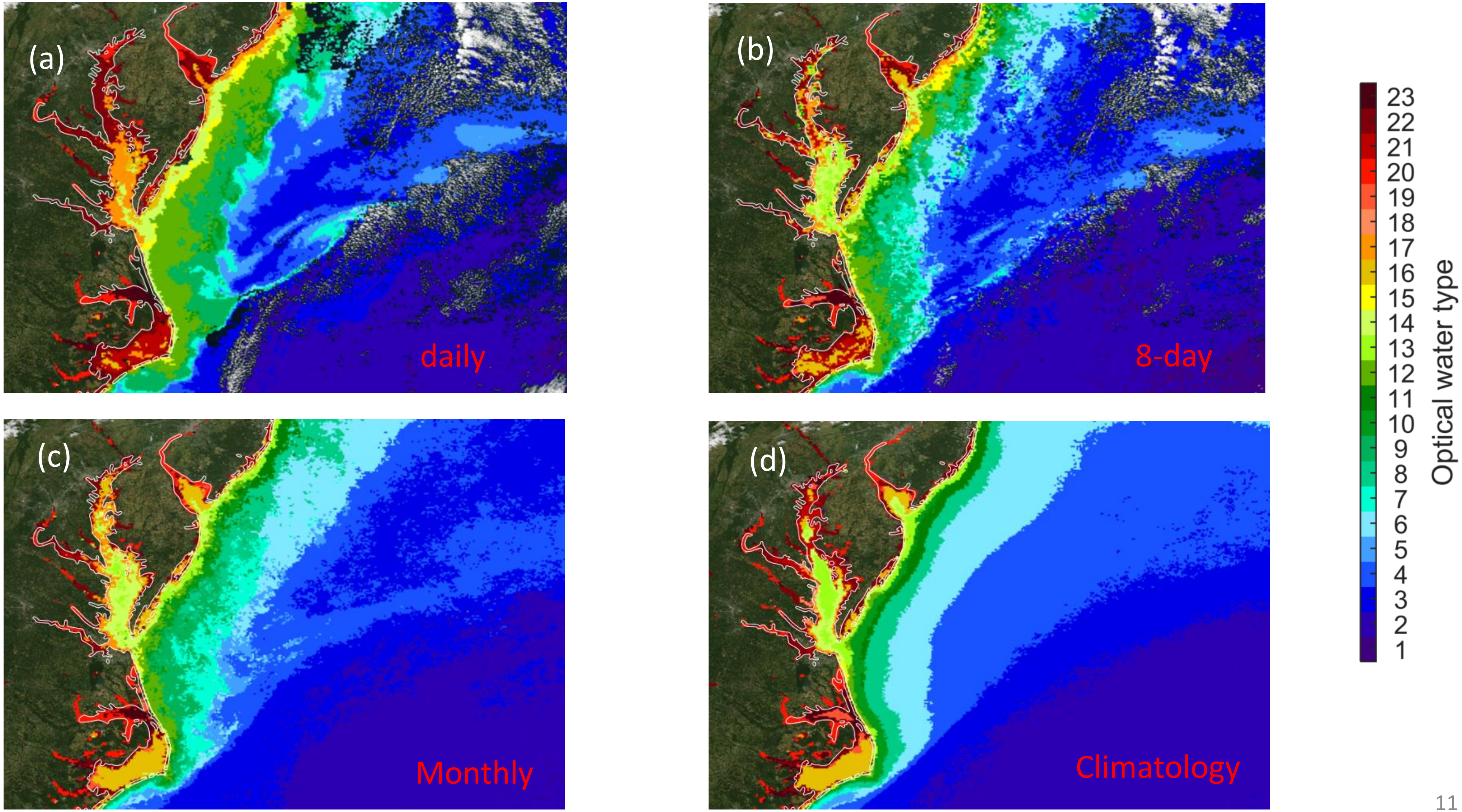
Mean spectra & STD



Hyperspectral

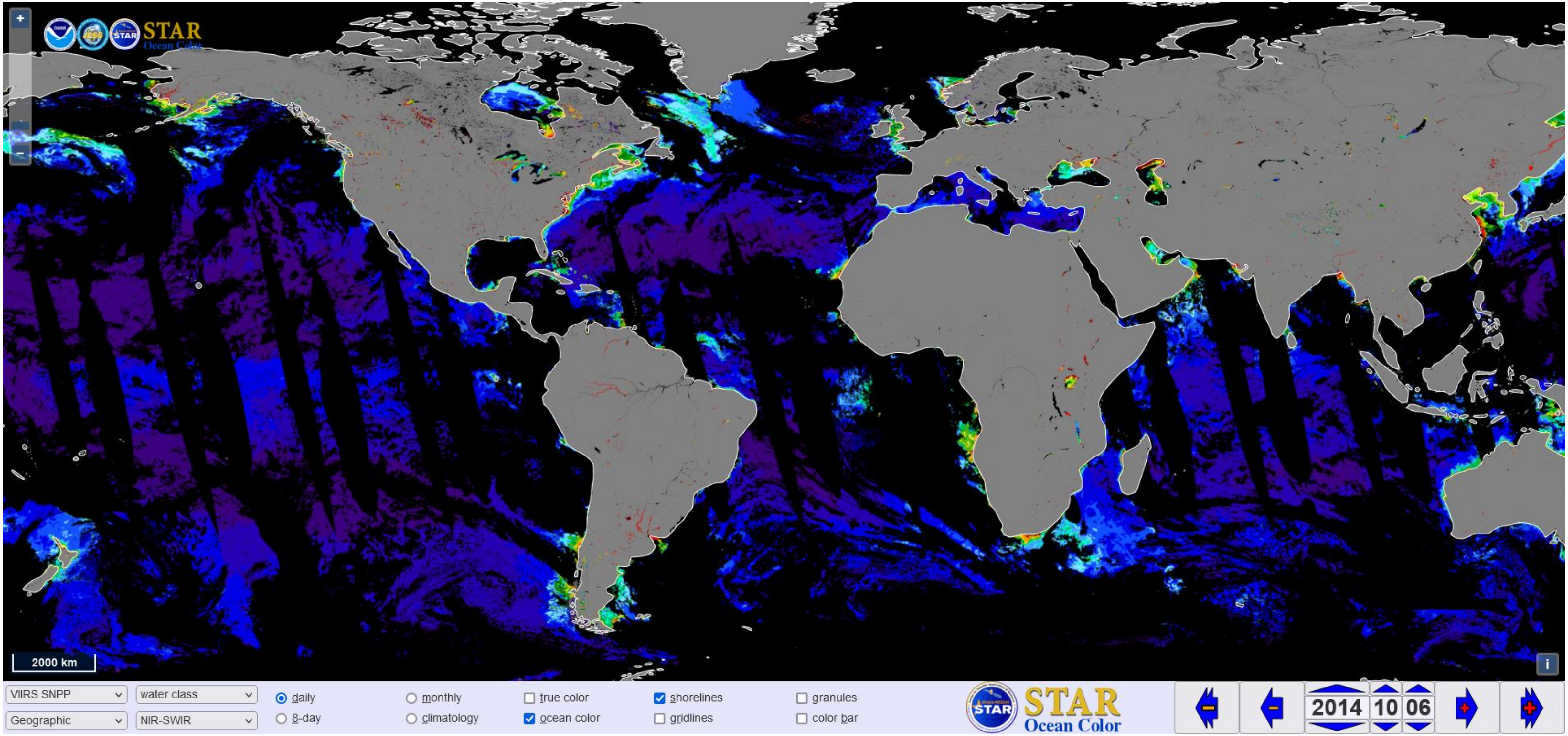
VIIRS bands

Model implementation with SNPP VIIRS

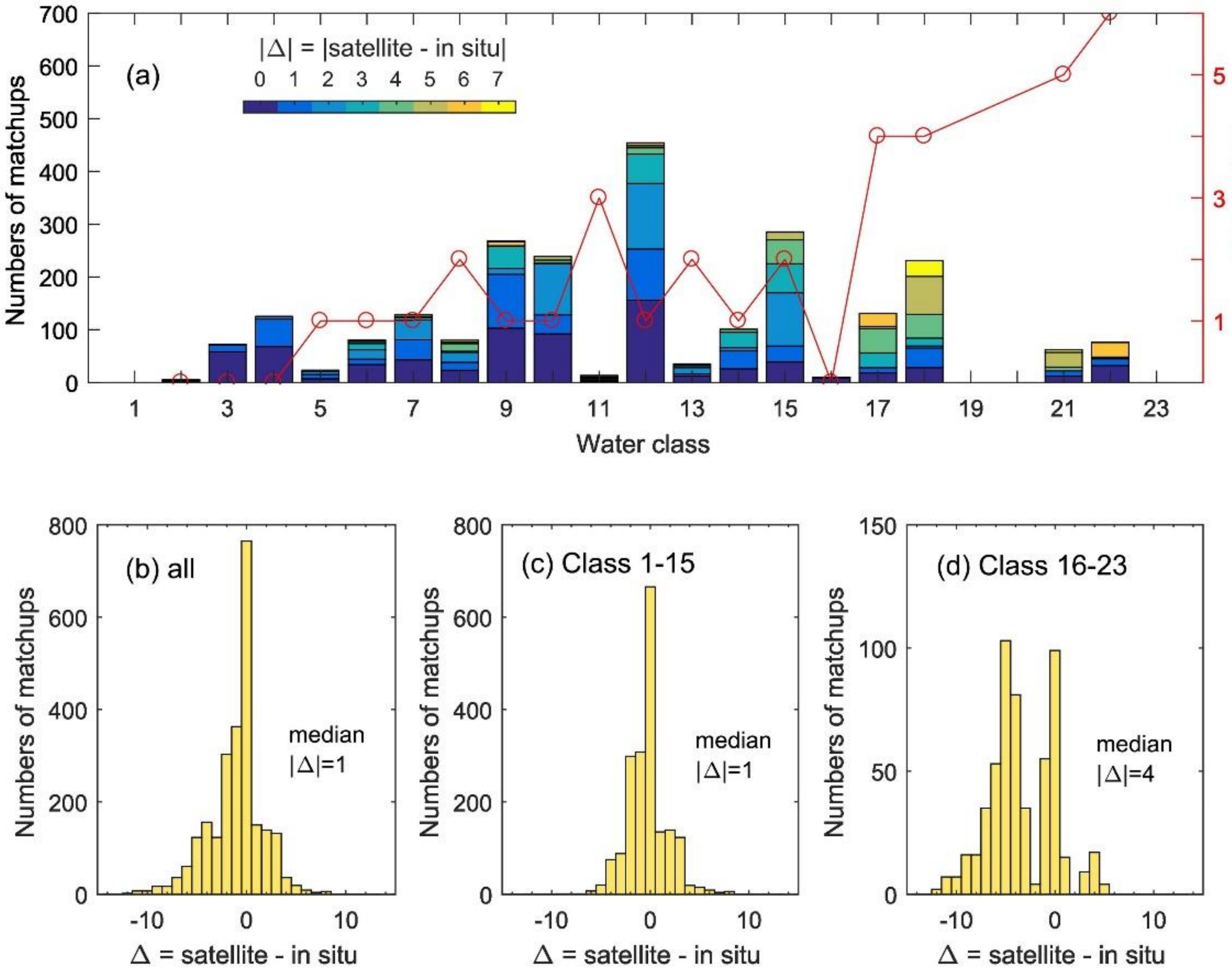


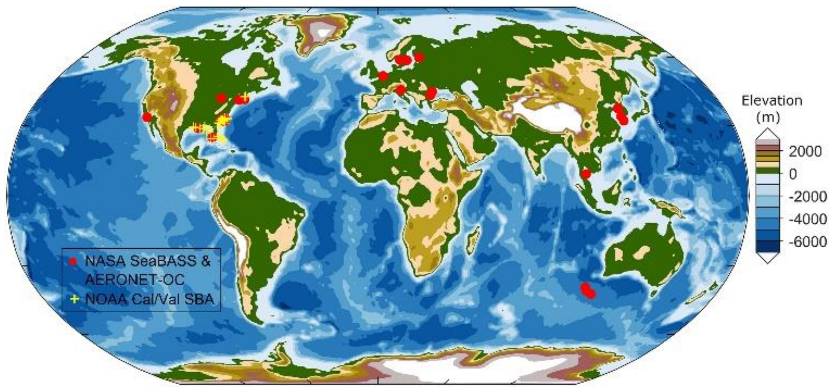
Satellite water classes data are online

https://www.star.nesdis.noaa.gov/socd/mecb/color/ocview/ocview.html



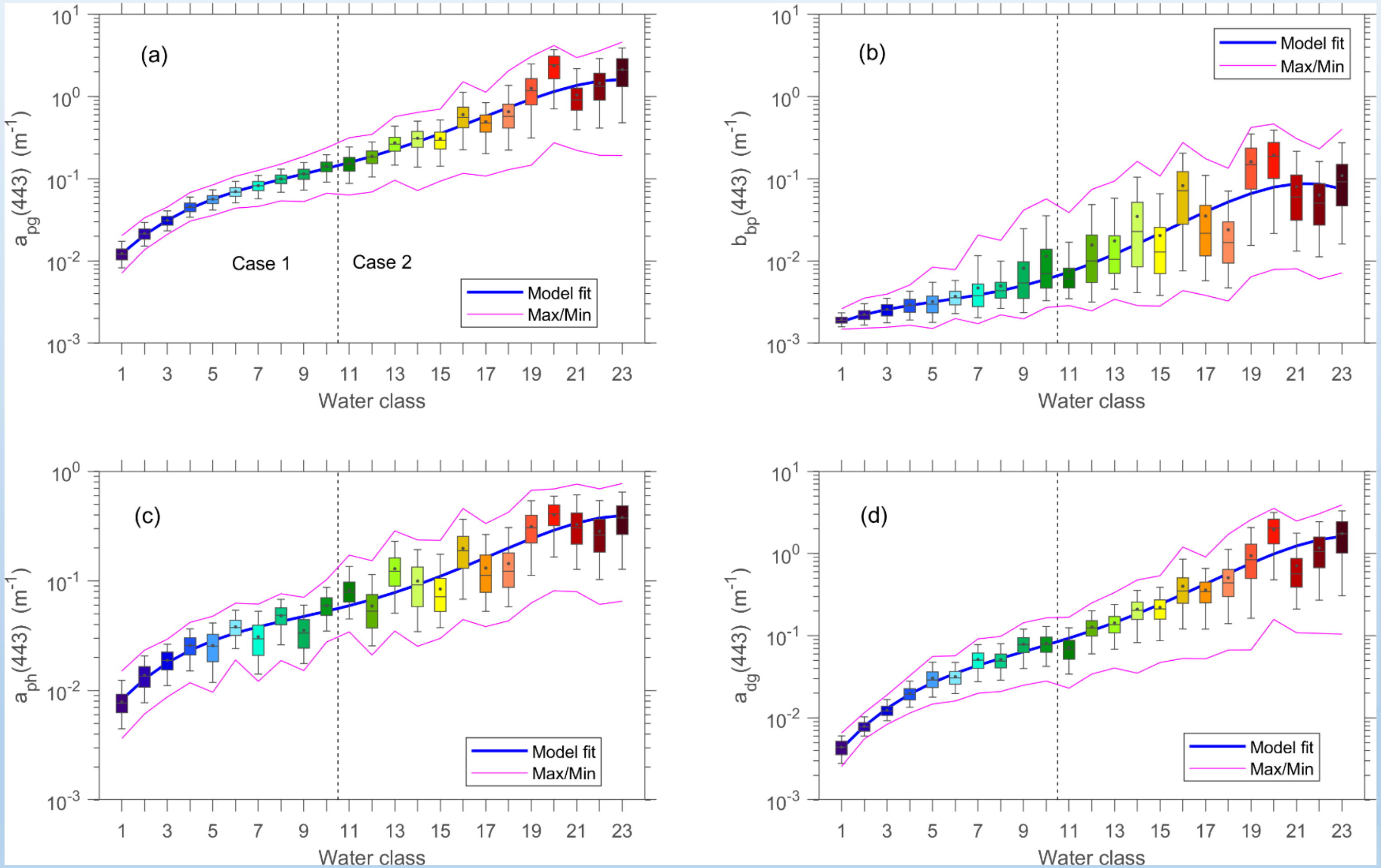
Validations with in situ and satellite matchups





Variation and distinction of bio-optical properties

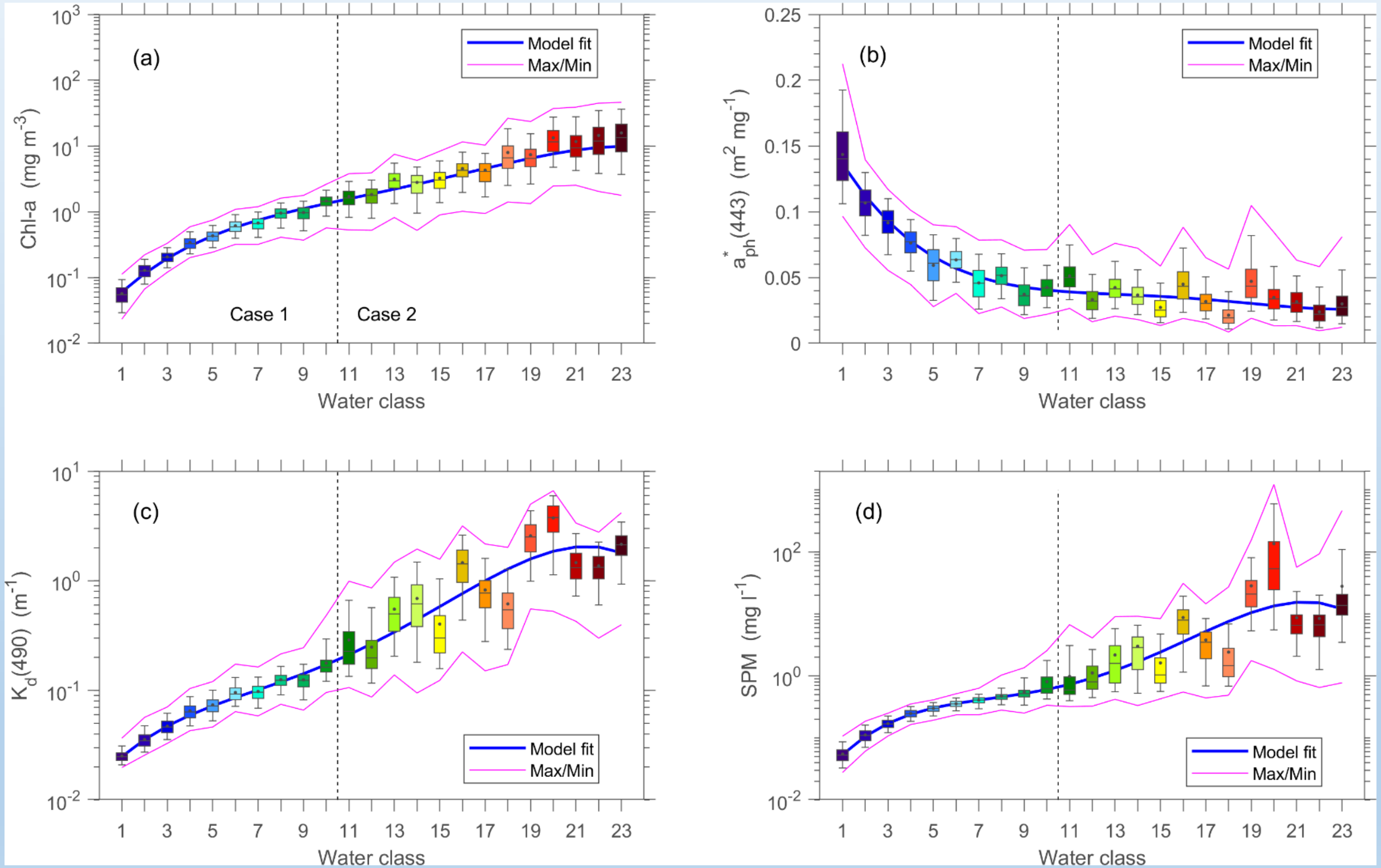
(based on the SNPP VIIRS 2012-2020 data)



a_{pg}: total absorption coefficient b_{bp}: backscattering coefficient of particles a_{ph}: absorption coefficient of phytoplankton a_{dg}: absorption coefficient of CDOM & detritus

Variation and distinction of bio-optical properties

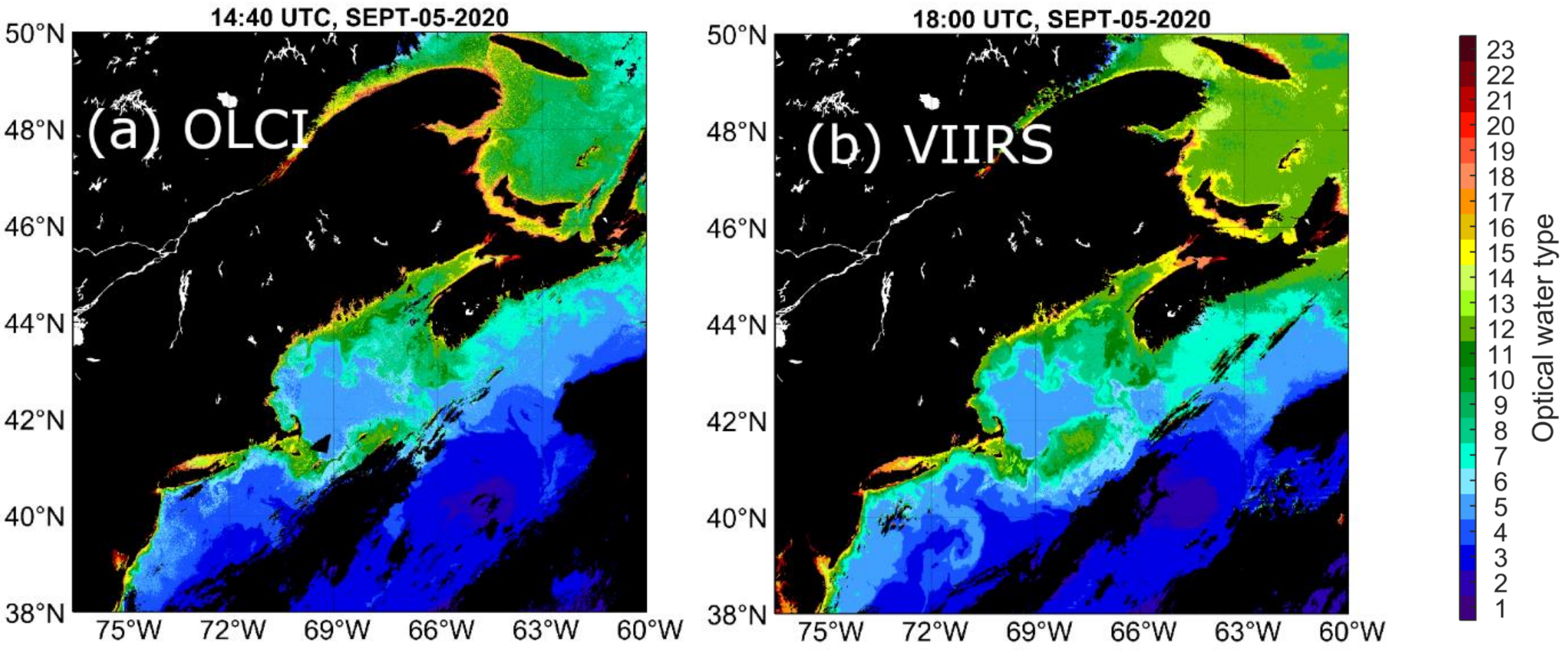
(based on the SNPP VIIRS 2012-2020 data)



Chl-a: chlorophyll-a concentration a_{ph}^{*}: Chl-a specific absorption K_d: diffuse attenuation coefficient   *SPM*: suspended particulate matter

Water classes from multispectral satellites

Northeast coastal oceans of the US and Canada



Wavelength

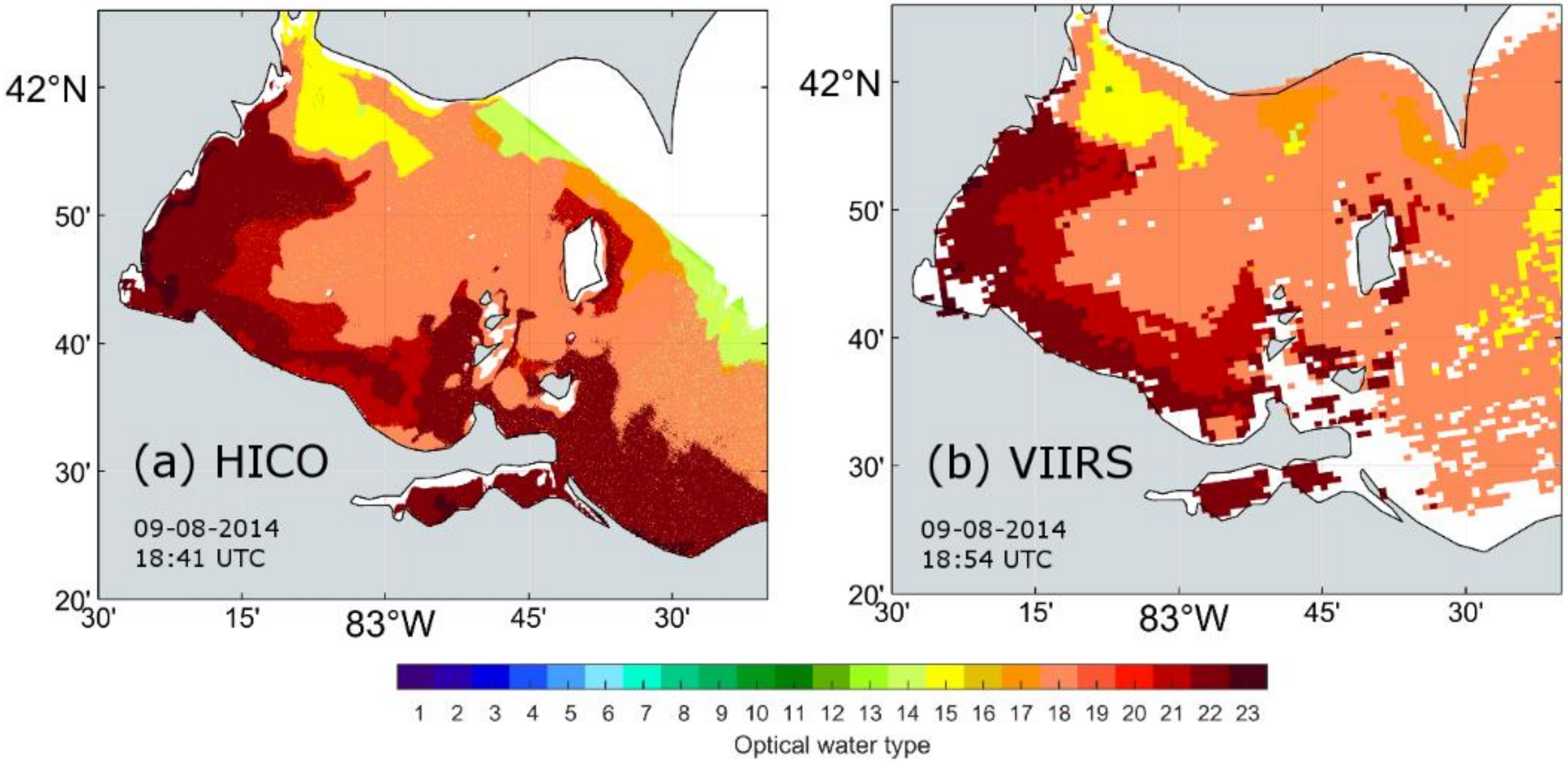
Sentinel 3A OLCI: 400, 413, 443, 490, 510, 560, 620, 665, 674, 681 nm
SNPP VIIRS: 410, 443, 486, 551, 671 nm

Spatial resolution

Sentinel 3A OLCI: 300 m
SNPP VIIRS: 750 m

Water classes from hyperspectral & multispectral satellites

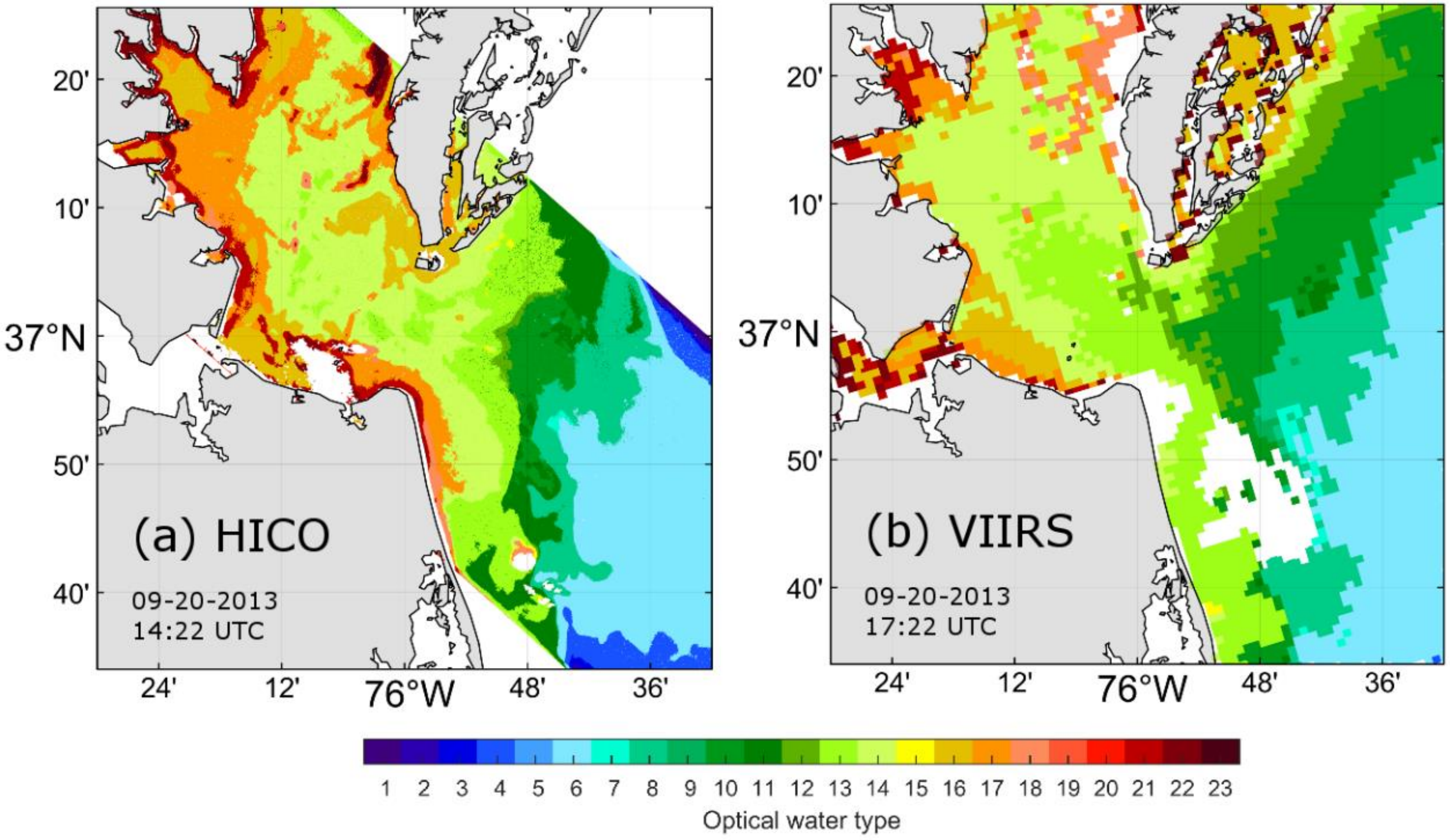
Lake Erie



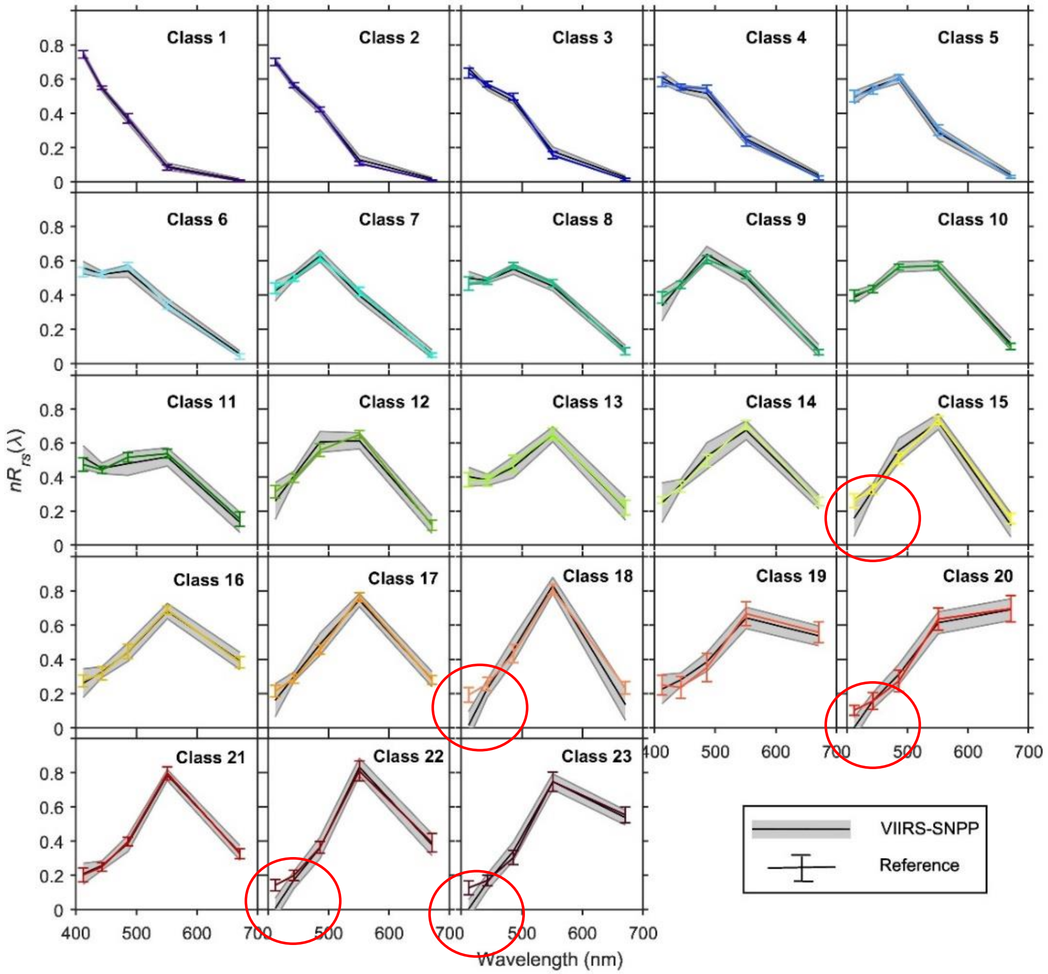
HICO: >50 visible bands; 90 m resolution
VIIRS: 5 visible bands; 750m resolution

Water classes from hyperspectral & multispectral satellites

Chesapeake Bay



Models vs. satellite Rrs spectra

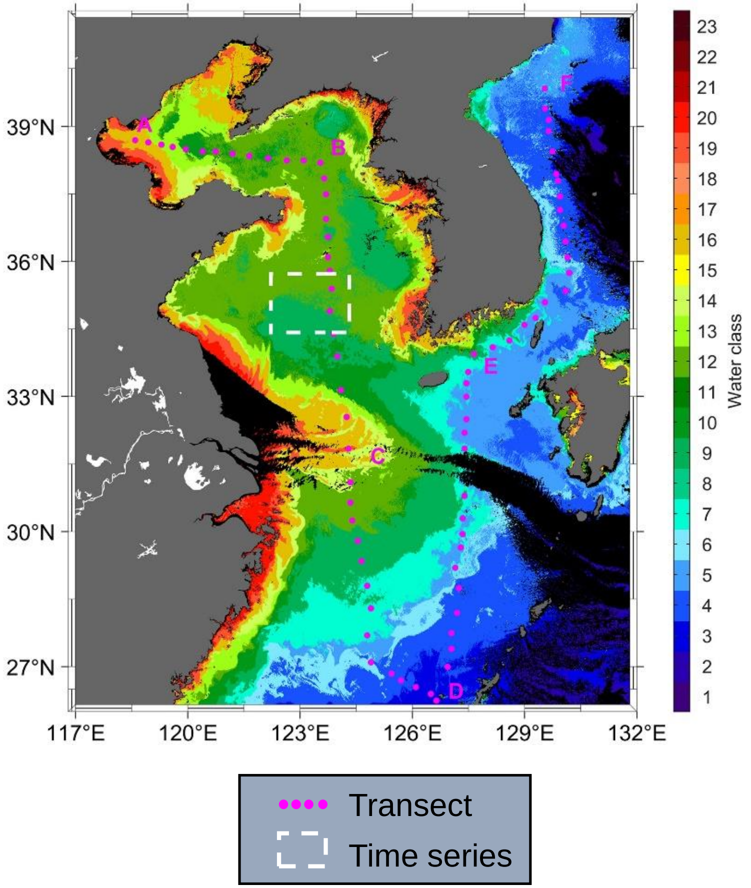


Percentage differences

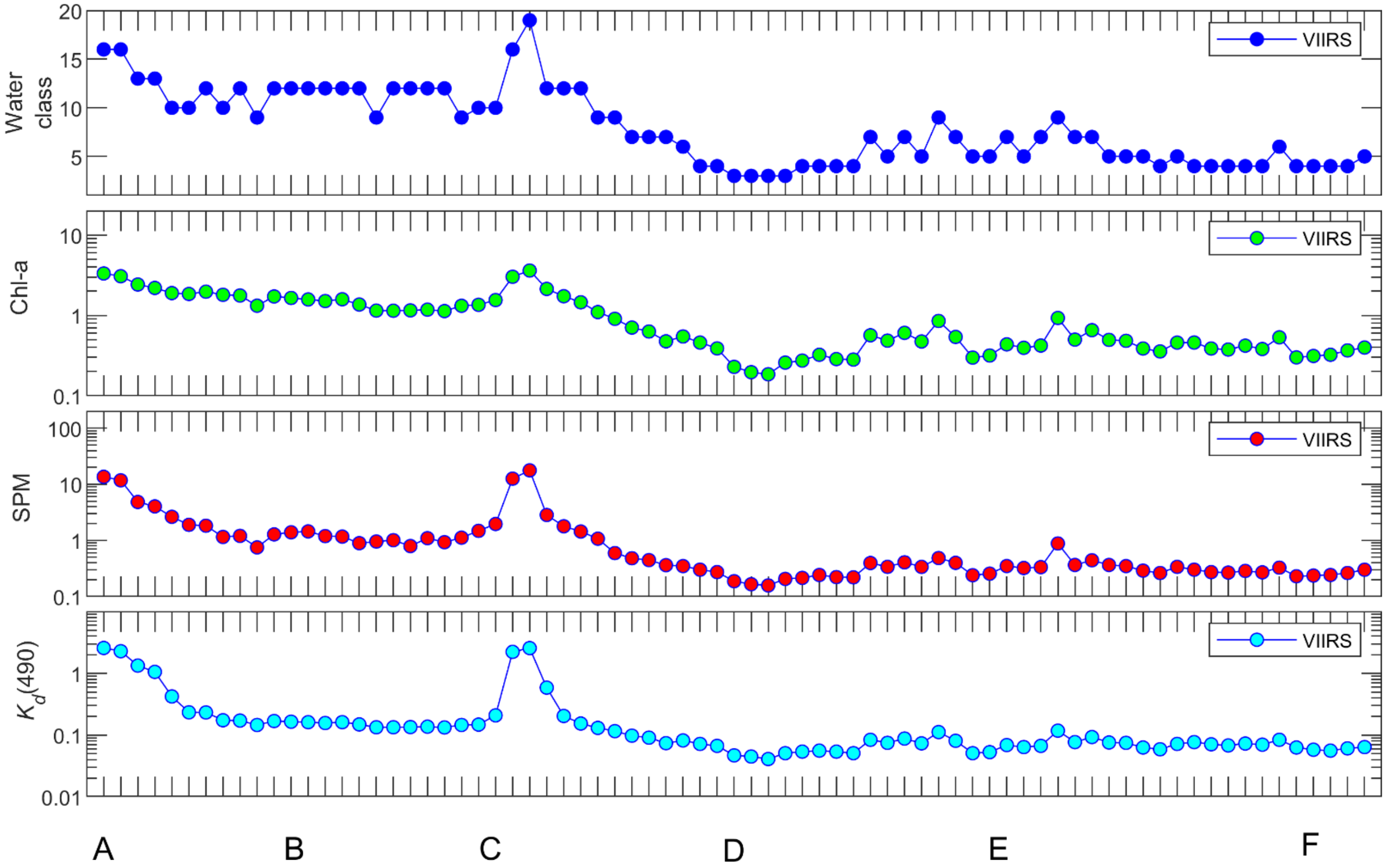
Class	410	443	486	551	670
1	0.5%	−0.9%	−2.1%	7.0%	**103.0%**
2	0.7%	−1.5%	−0.9%	**19.8%**	**121.4%**
3	4.2%	−3.0%	−4.8%	**14.1%**	**99.8%**
4	4.0%	−1.6%	−4.8%	5.8%	**68.2%**
5	−1.4%	3.2%	−1.0%	−4.9%	**34.9%**
6	4.8%	−0.2%	−5.4%	2.1%	**34.3%**
7	−3.7%	2.6%	1.7%	−5.6%	**13.4%**
8	7.0%	0.8%	−3.8%	−3.6%	**14.9%**
9	**−12.5%**	1.5%	5.0%	−3.1%	**13.4%**
10	−2.6%	0.9%	0.1%	0.1%	**15.5%**
11	9.0%	1.9%	−7.2%	−3.5%	**−12.6%**
12	**−17.2%**	3.3%	8.6%	−5.6%	4.1%
13	4.8%	0.3%	−4.5%	−0.3%	−2.7%
14	−6.4%	3.6%	5.2%	−4.2%	−1.0%
15	**−39.6%**	−1.6%	9.4%	−1.1%	**−25.2%**
16	−4.8%	2.2%	−0.9%	−0.9%	1.9%
17	**−24.7%**	4.2%	7.0%	−2.3%	1.5%
18	**−92.1%**	**−10.1%**	5.4%	3.0%	**−41.9%**
19	−9.6%	**18.9%**	9.3%	−3.6%	−3.7%
20	**−98.9%**	1.0%	**14.2%**	−3.3%	−0.8%
21	3.3%	3.2%	−2.9%	−1.3%	1.7%
22	**−95.2%**	−13.0%	−0.7%	2.7%	−3.2%
23	**−97.2%**	−5.3%	12.3%	0.0%	−2.9%

Coherency between water classes & water bio-optical properties

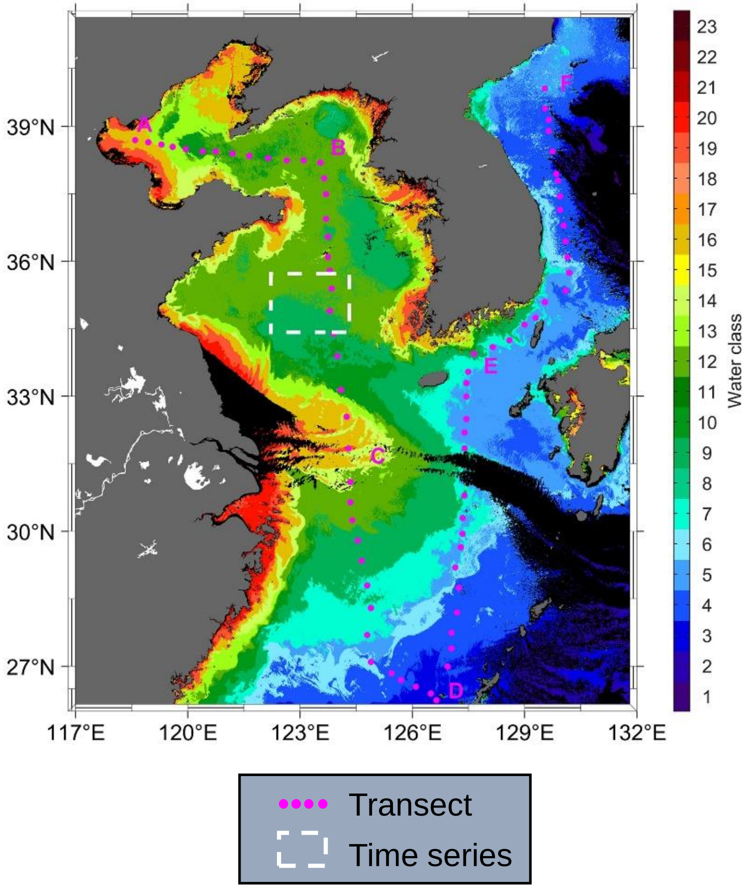
Northwest Pacific coastal ocean



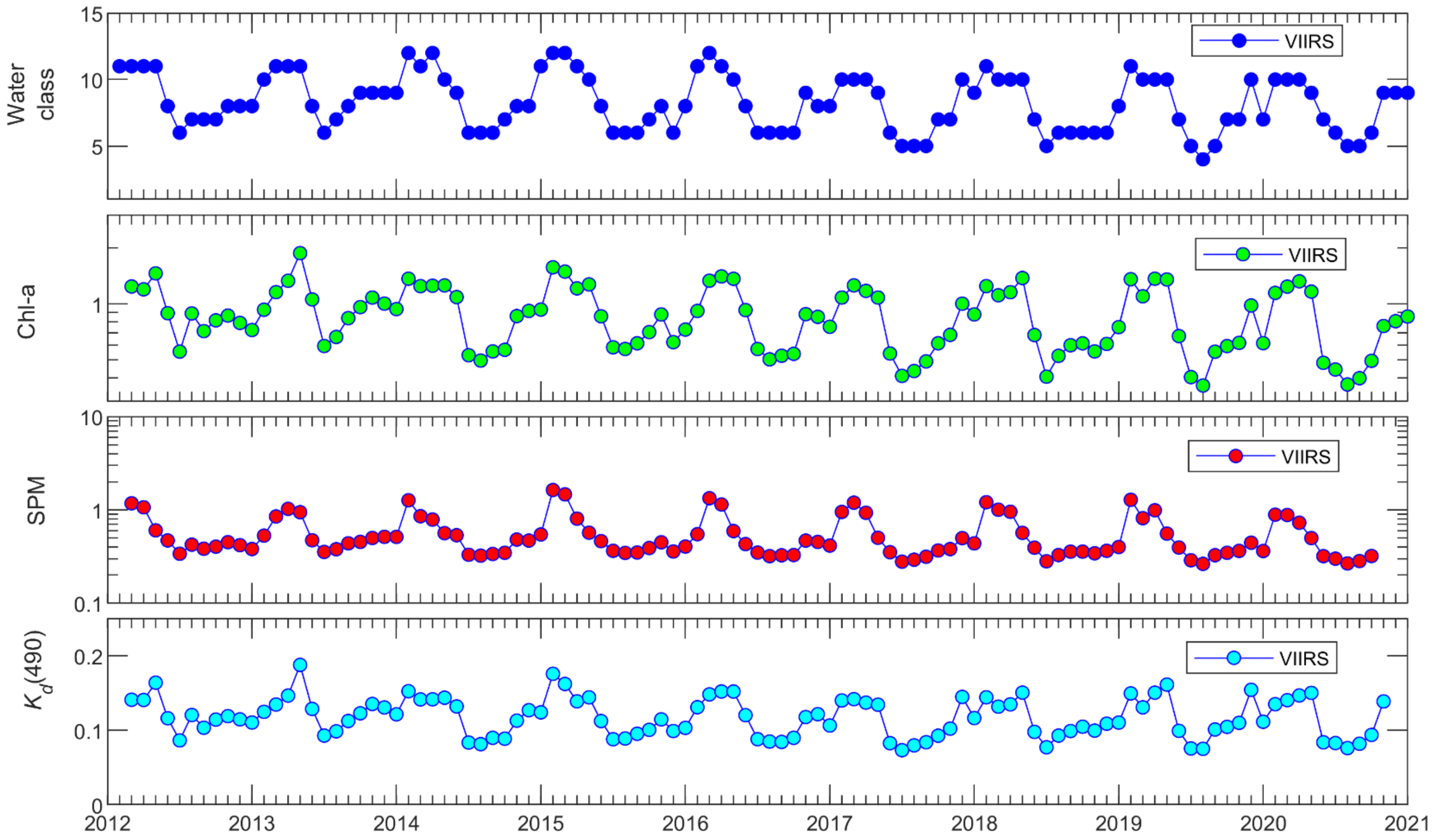
Spatial variation



Northwest Pacific coastal ocean

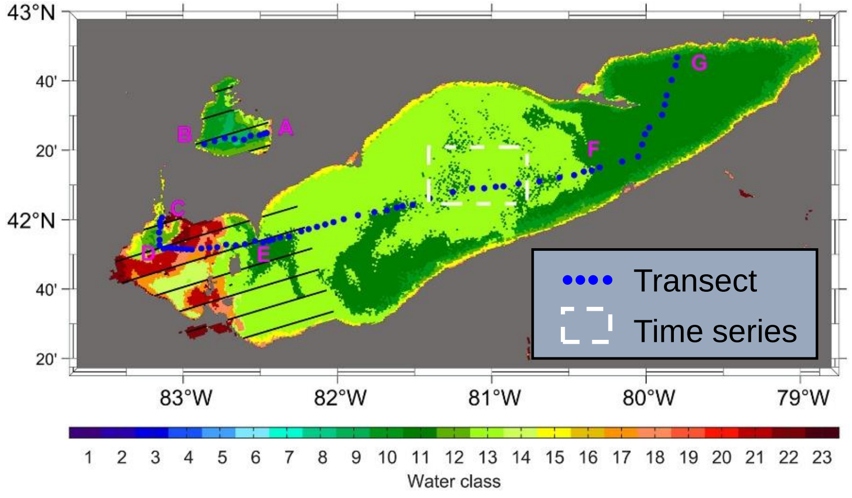


Time series (monthly)

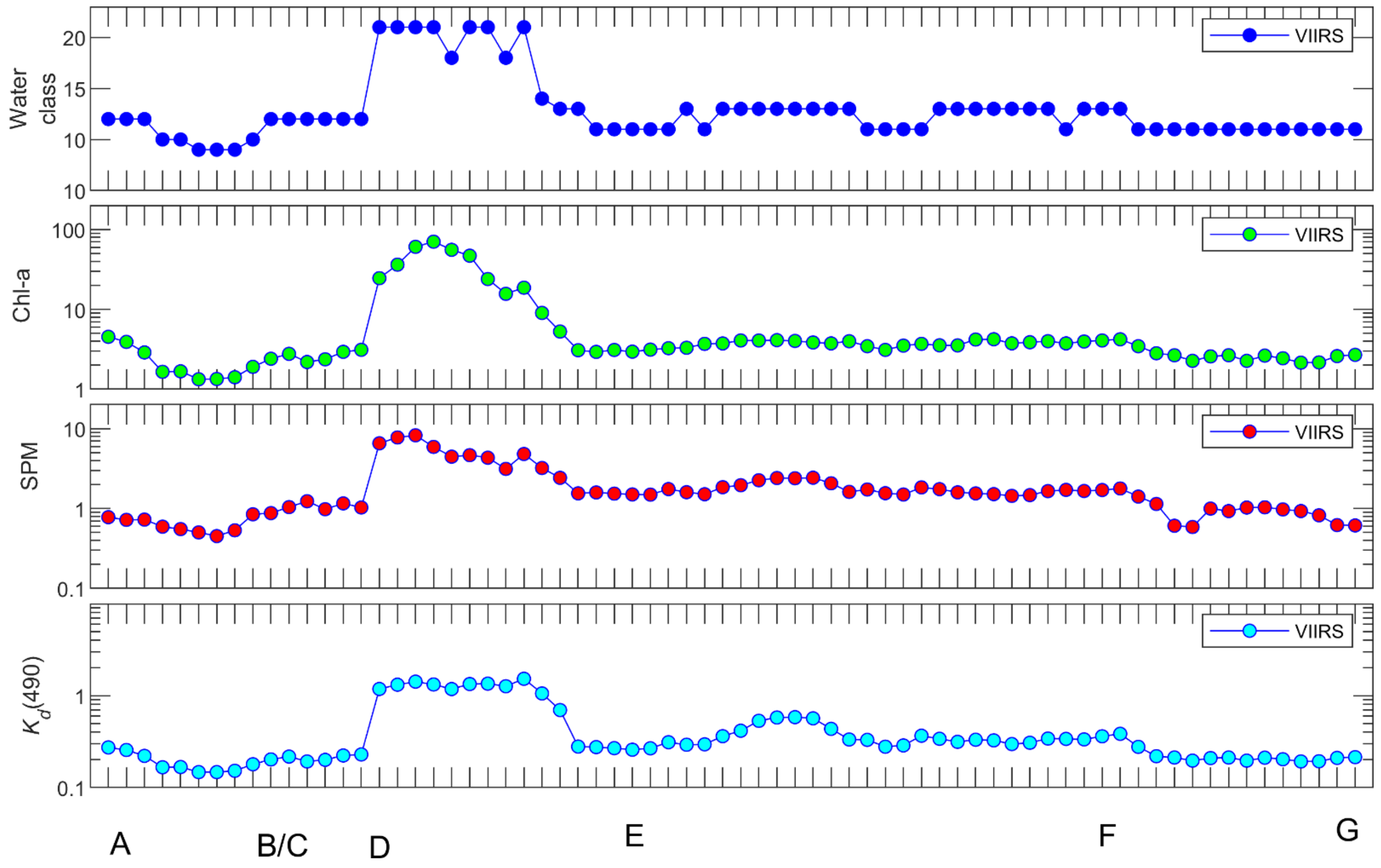


Coherency between water classes & water bio-optical properties

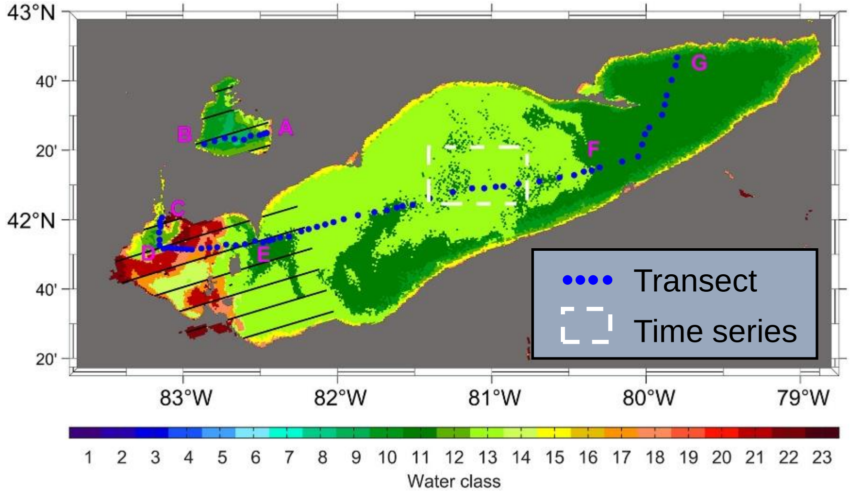
Lake Erie



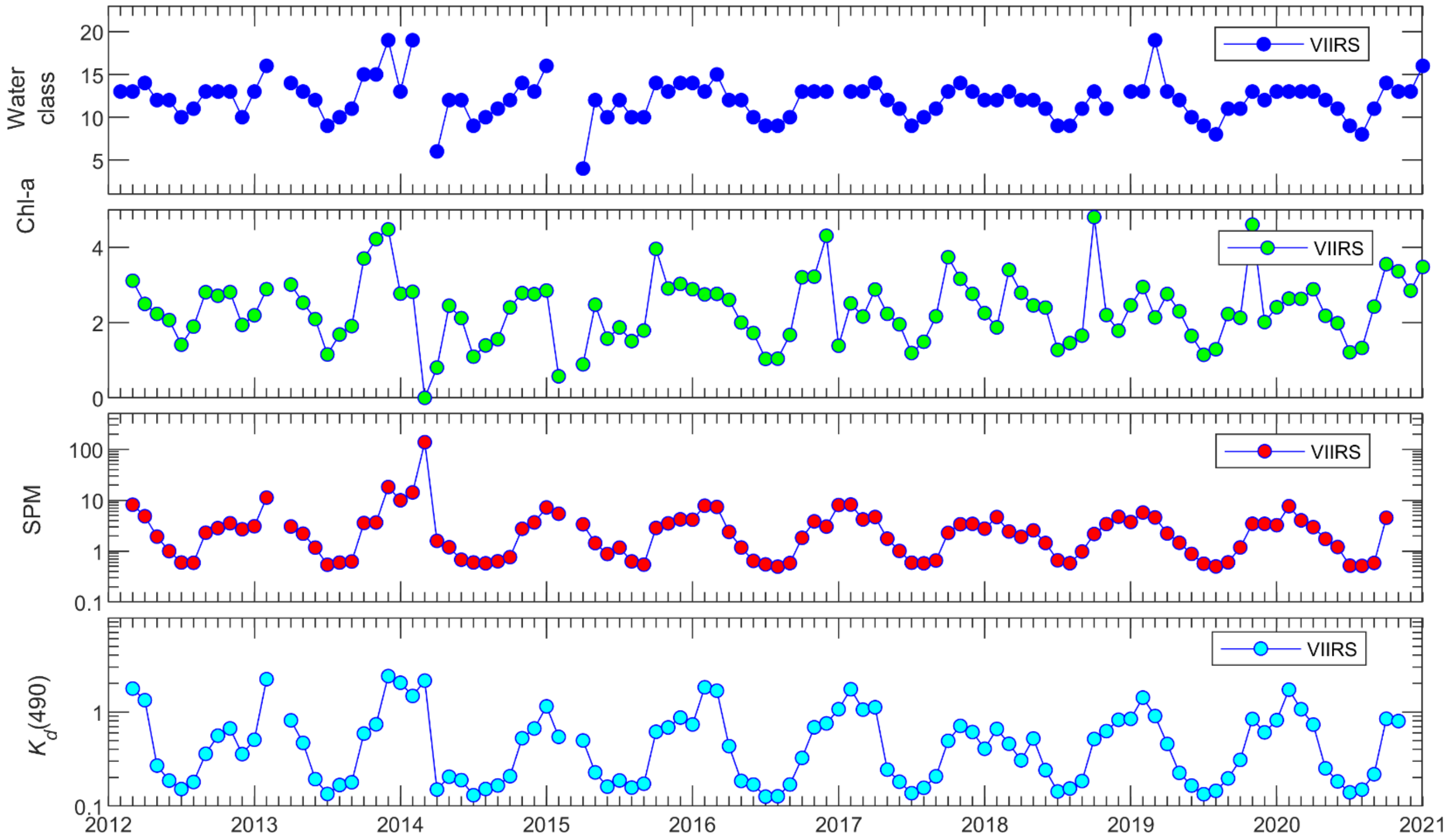
Spatial variation



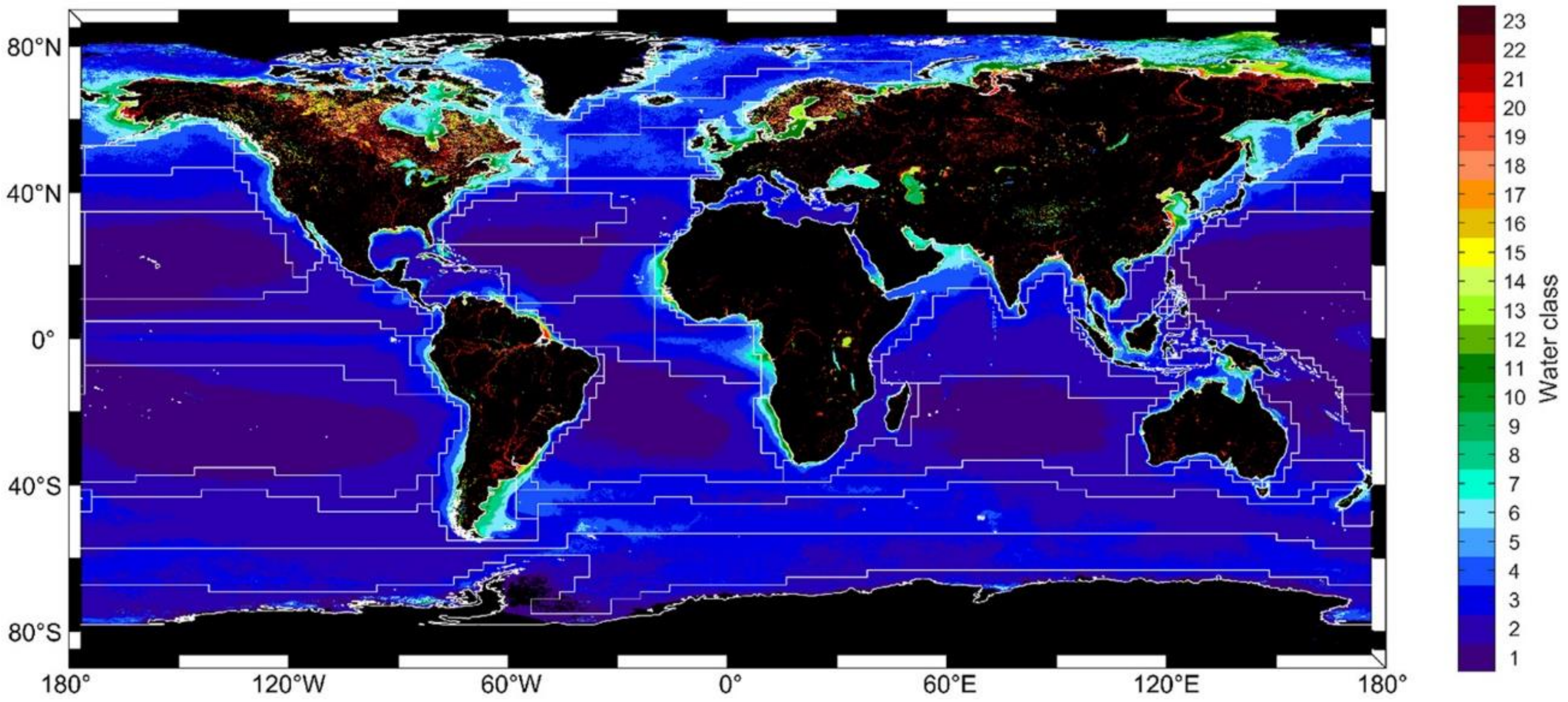
Lake Erie



Time series (monthly)

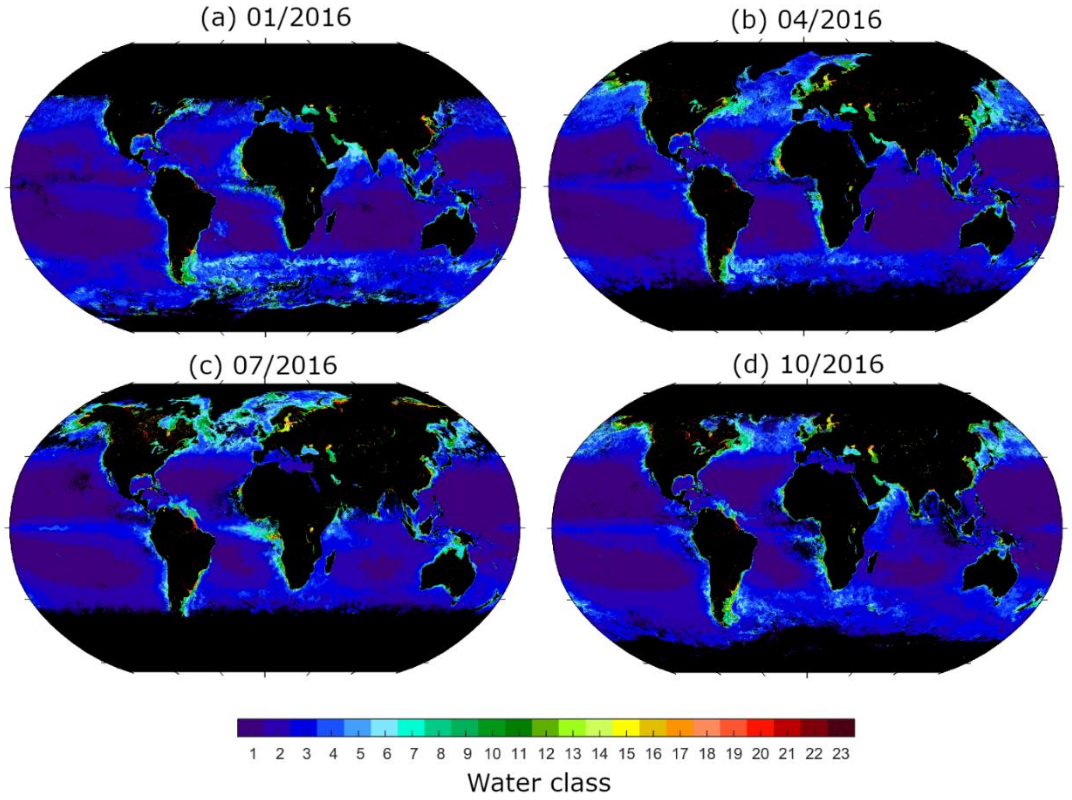


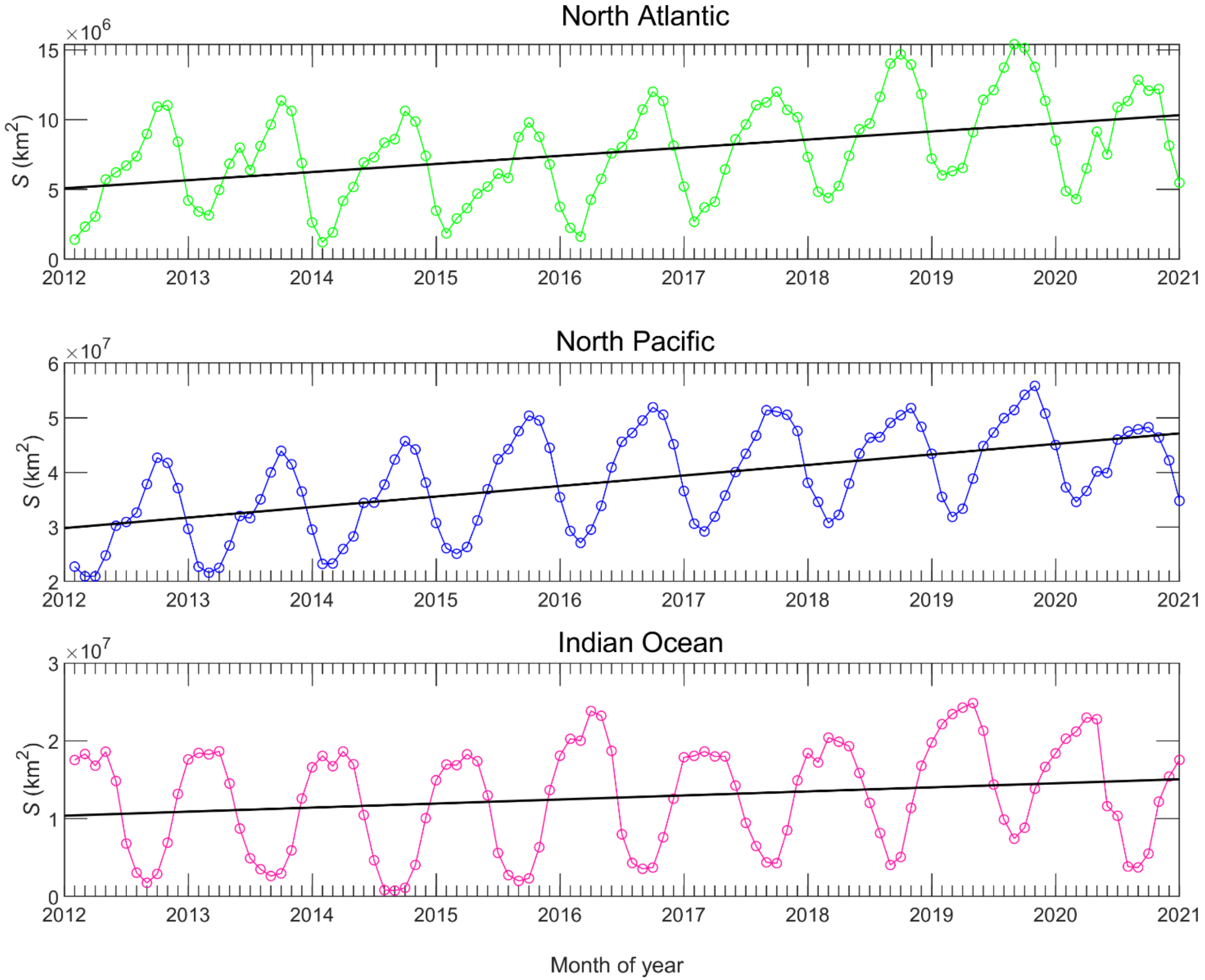
Satellite water classes as ocean ecological provinces



- ✓ Longhurst's ocean provinces are overlaid on top for comparison

Ocean subtropical gyres quantified as "Class 1" waters





Summary

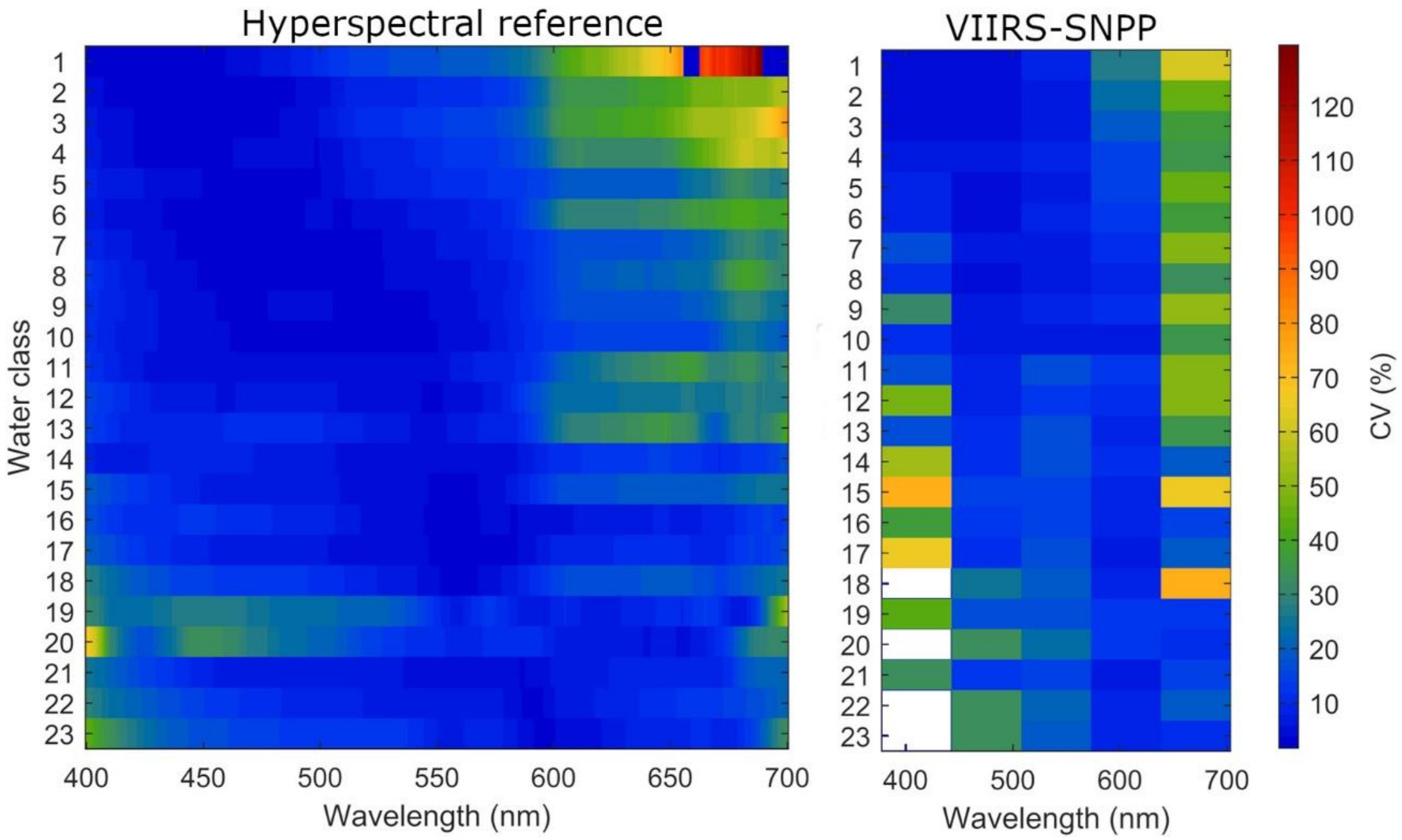
1. Experimental data products of the optical water classes are being routinely generated from VIIRS.
2. The resultant water classes have distinctive bio-optical properties and are reliable.
3. A hyperspectral classification model is developed based on the spectral similarity of Rrs.
4. Decades-long (and consistent) time series of water classes can be created from the suite of satellite missions.
5. Case analyses are demonstrated for potential applications.

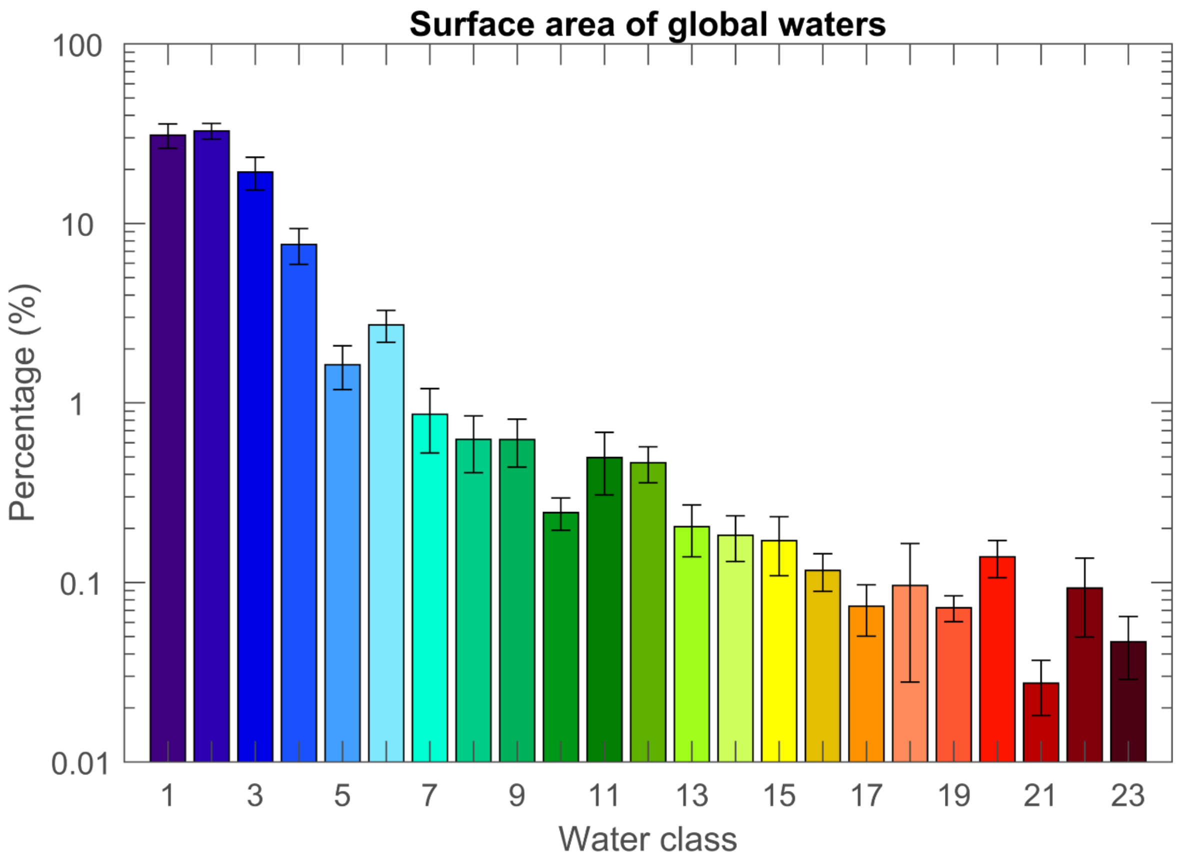
Publication

Wei, J., M. Wang, K. Mikelsons, L. Jiang, S. Kratzer, Z. P. Lee, T. Moore, H. M. Sosik, and D. Van der Zande (2022), Global satellite water classification data products over oceanic, coastal, and inland waters, *Remote Sensing of Environment*, *282*, doi: https://doi.org/10.1016/j.rse.2022.113233.

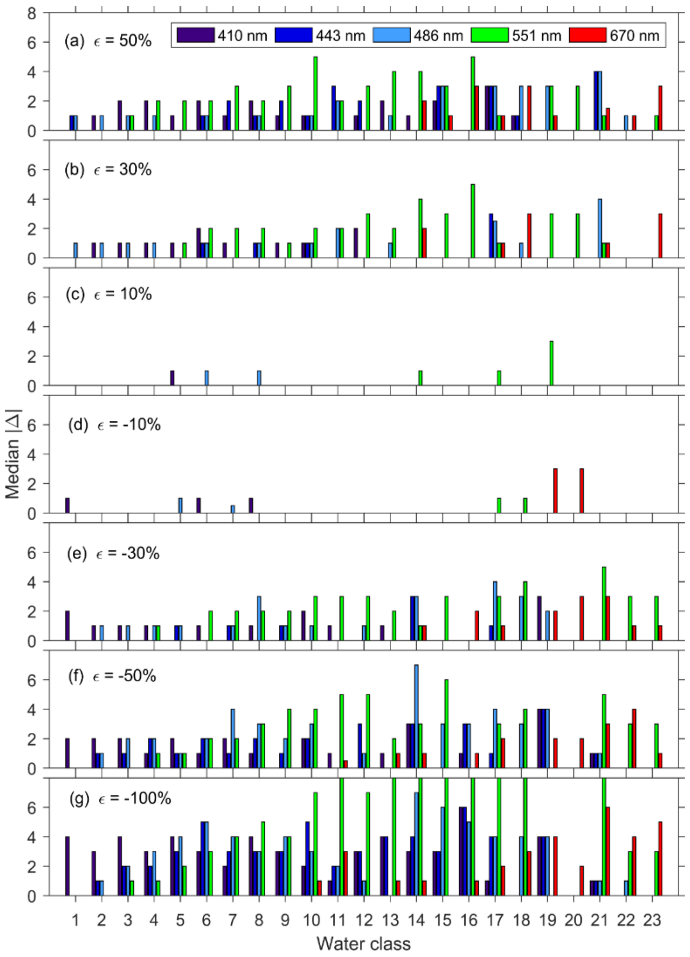
Backup slides

Variances of nRrs




Surface area of global waters
100
10
1
0.1
0.01
Percentage (%)
1
3
5
7
9
11
13
15
17
19
21
23
Water class

Uncertainties associated with atmospheric correction

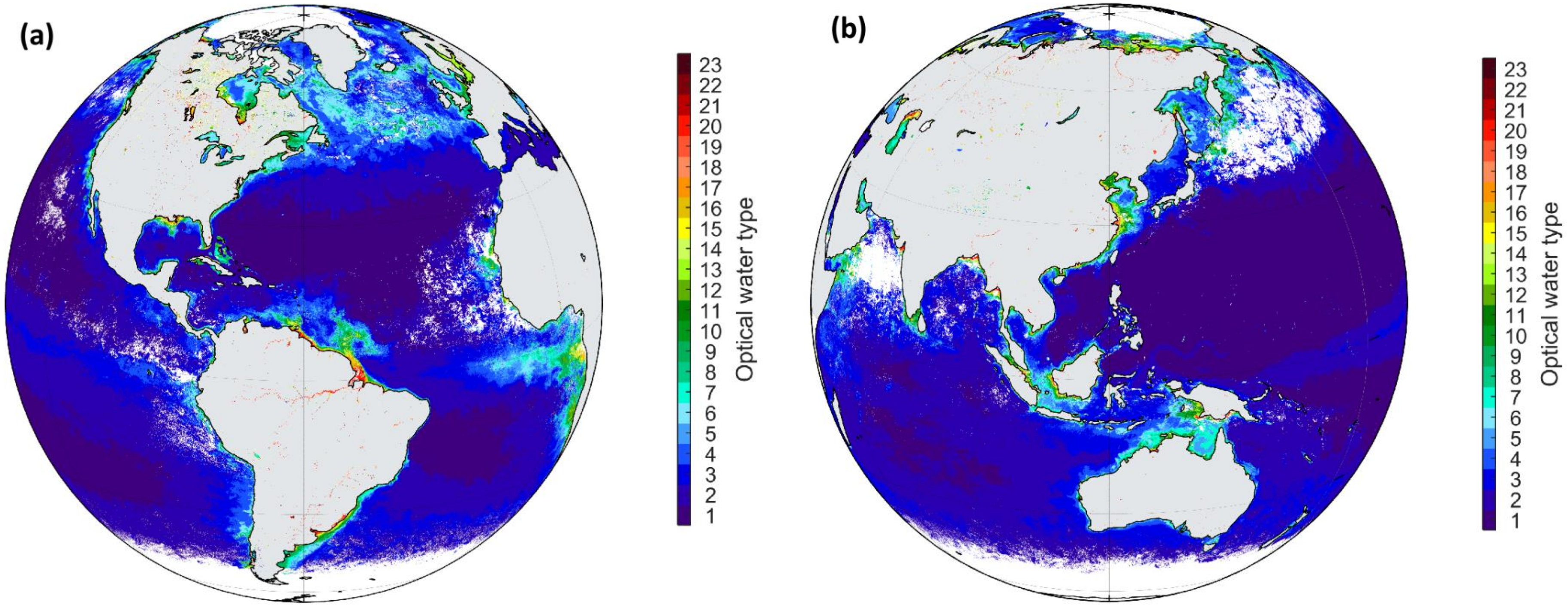


- ❑ An error (ε) was added to $nR_{rs}(\lambda)$ at one wavelength only for each simulation.
- ❑ Minor errors in $nR_{rs}(\lambda)$ (i.e., $\pm$10% in this study) exert minimal influence on the resulting water classes.
- ❑ When errors reach $\pm$30% and $\pm$50%, the uncertainties in the water class products can increase substantially.

- ❑ In extremely clear waters, such as Class 1–3, the blue bands play a major role in the water class uncertainties.
- ❑ In contrast, the green and red bands are relatively more important in the opposite end of the water classes, such as Class 19–23.

- ❑ Subplot "g" shows excessive negative errors –100% added to nRrs. However, error-disturbed $nR_{rs}(410)$ do not significantly increase the water class uncertainty for Class 15, 17, 18, 20-23.

VIIRS-generated water classes



Browse the experimental water classes data at OCView (Ocean Color Viewer):

https://www.star.nesdis.noaa.gov/socd/mecb/color/ocview/ocview.html