Satellite Remote Sensing of Ocean Color

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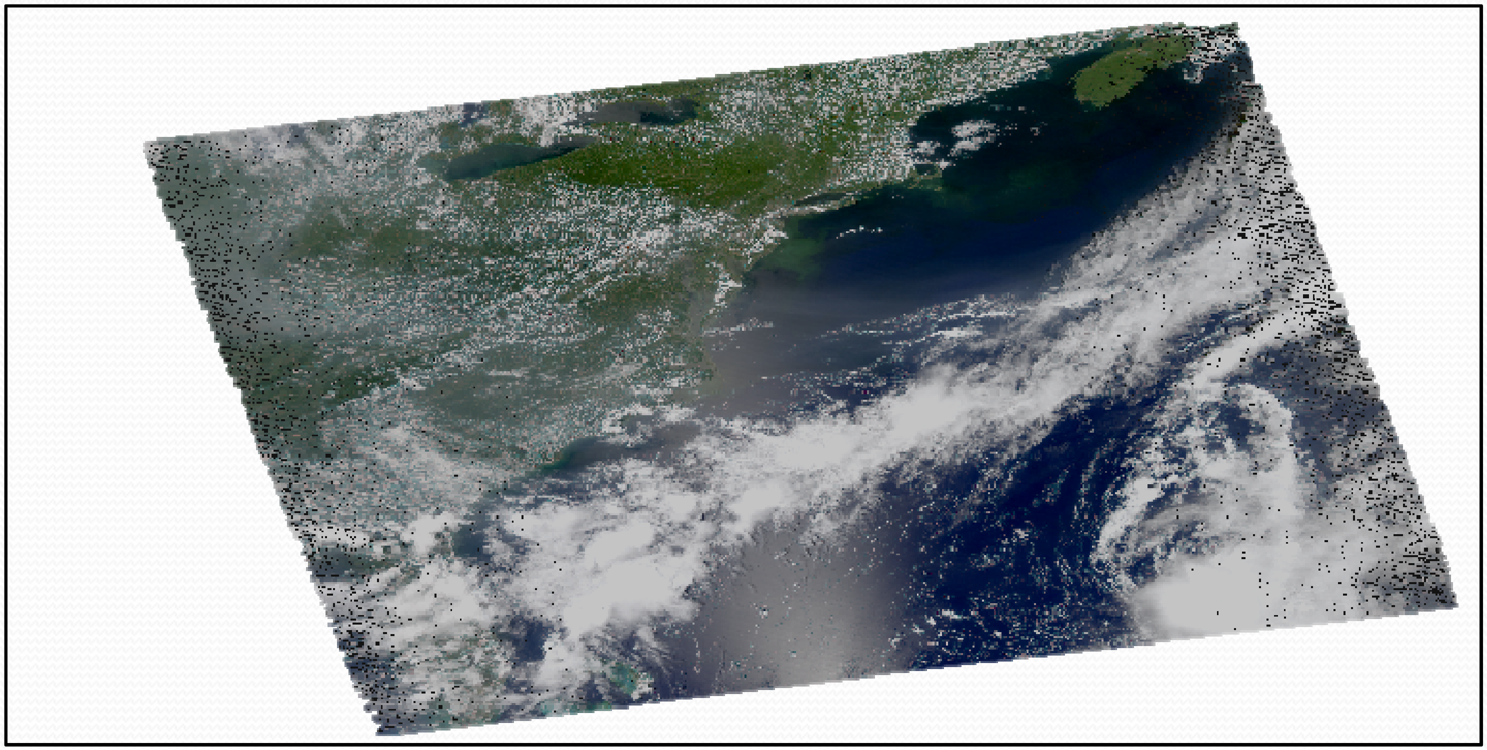
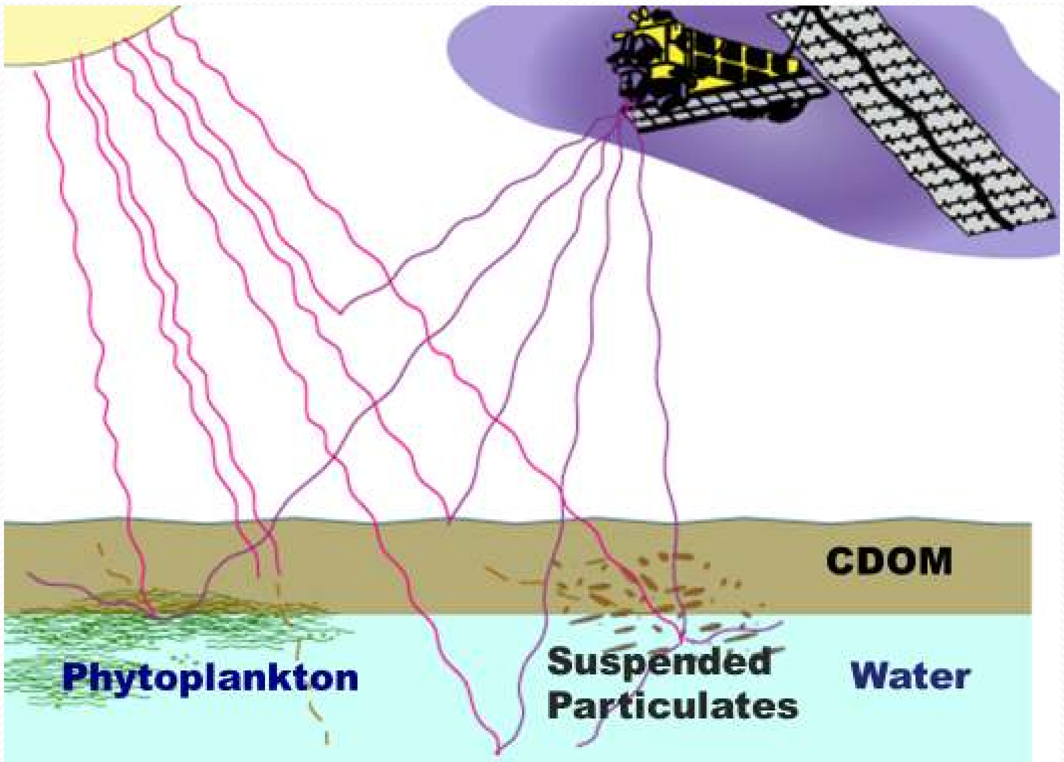
Ocean Color: Spectral Visible Radiometry

- Color of the ocean contains latent information on the water quality(CDOM, Turbidity) and the abundance of the marine microflora (phytoplankton)



CPA -Color Producing Agent

- CPA of natural water: phytoplankton, CDOM, SM, and pure water

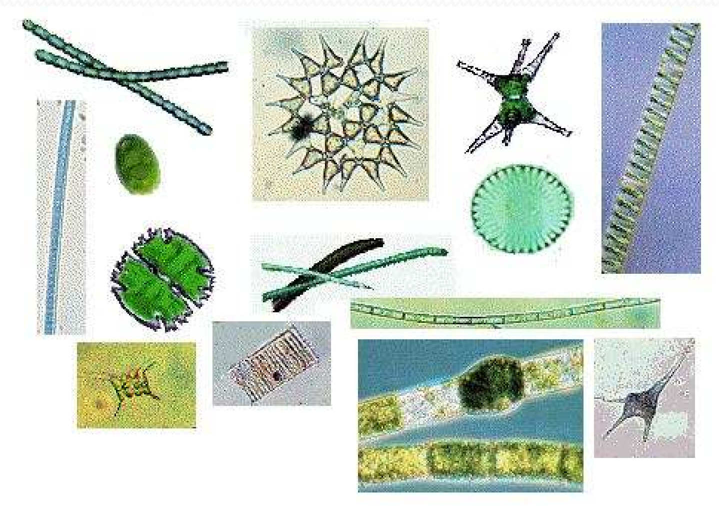


Scatterers: water, algae, particles

Non-scattering: CDOM

Phytoplankton

- Predominantly single-celled and microscopic (0.5 to 250µm) organism
- "Green plants" (chlorophyll pigments, photosynthesis)
- Mostly confined to the surface (illuminated) layer
- Ubiquitous and abundant
- Control color of water (detectable from space)



CDOM

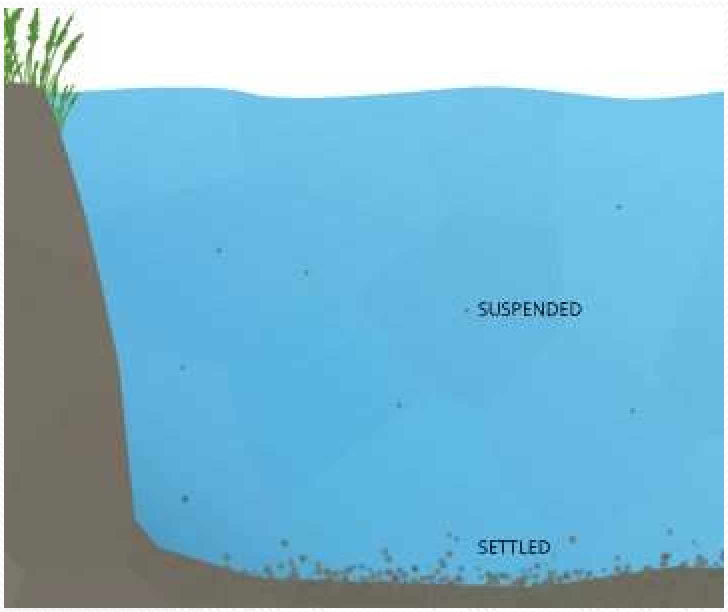
- **C**olored
  Dissolved
  Organic
  Matter

Image Credit: Chris Halaxs

- Plant Decomposition Material, yellow substance
- Terrestrial and Aquatic Sources
- Strongly absorbs short wavelength light ranging from blue to ultraviolet

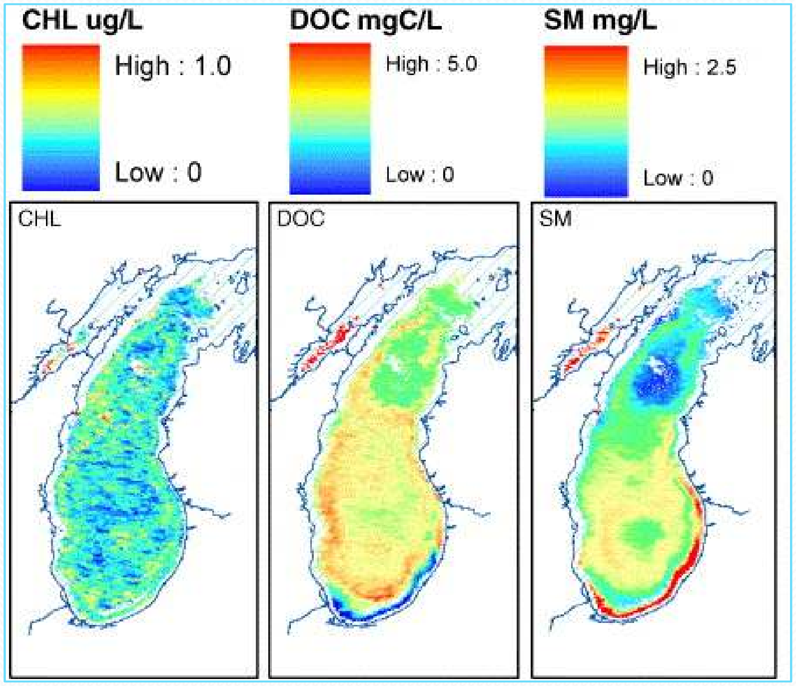
SM-Suspended Minerals

- Mineral Particulates drifting in the water
- From Sediments, inflows
- Made of inorganic materials



Ocean Color Remote Sensing

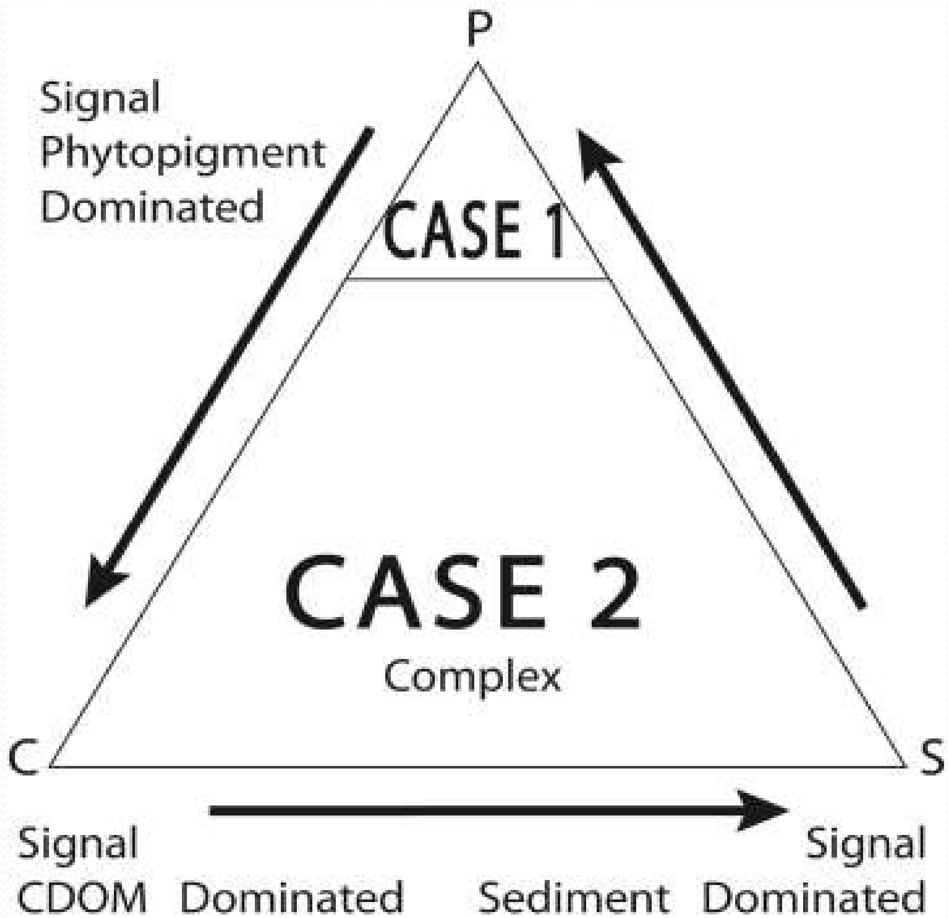
- Ocean-color remote sensing was conceived primarily as a method for producing synoptic inference of the co-extant concentrations from water color of :
  - Phytoplankton Biomass
    - Chlorophyll-a (CHL) as a quantifiable surrogate
  - Inorganic Particulates minerals
    - Suspended minerals (SM) as a quantifiable surrogate
  - Dissolved organic carbon (DOC)
    - CDOM (colored dissolved organic matter) as a quantifiable surrogate



Ocean Color Remote Sensing of Lake Michigan on May 13, 2003 (Pozdnyakov et al. 2005)

Case 1 and case 2 water

- Case I waters are dominated by phytoplankton
- Case II waters have a significant portion of colored dissolved organic matter (CDOM) and suspended material

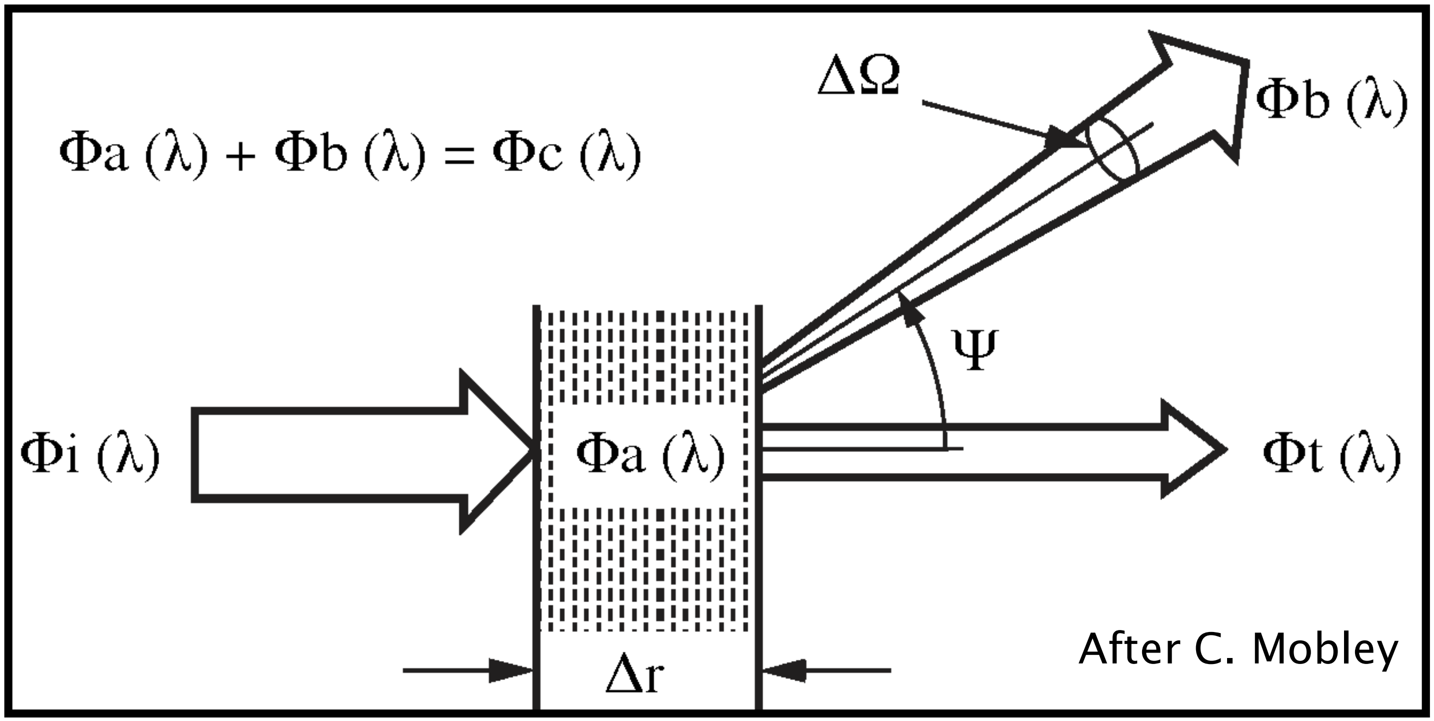


After Janet Trout

Inherent Optical Properties (IOP)

- Attenuation
- Absorption
- Scatterance

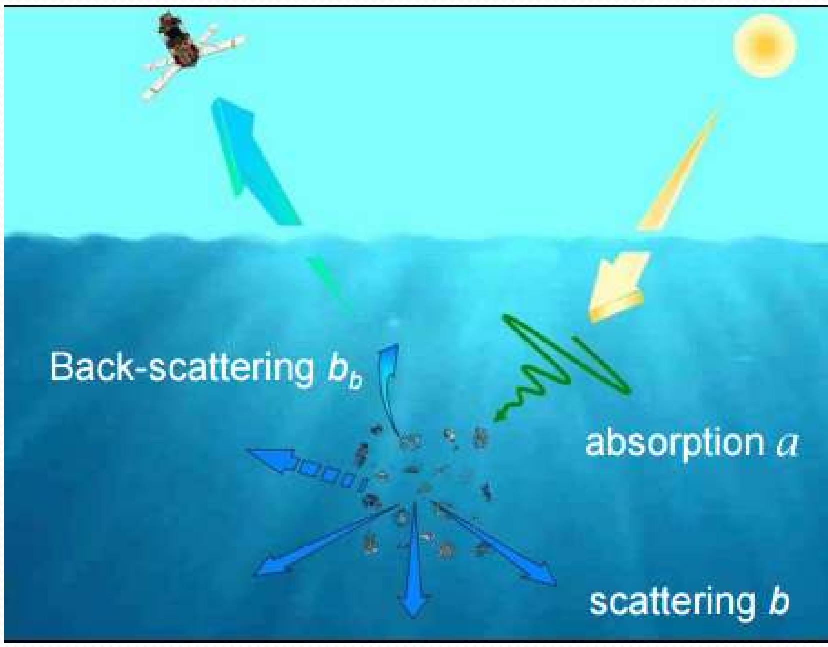
c= a + b



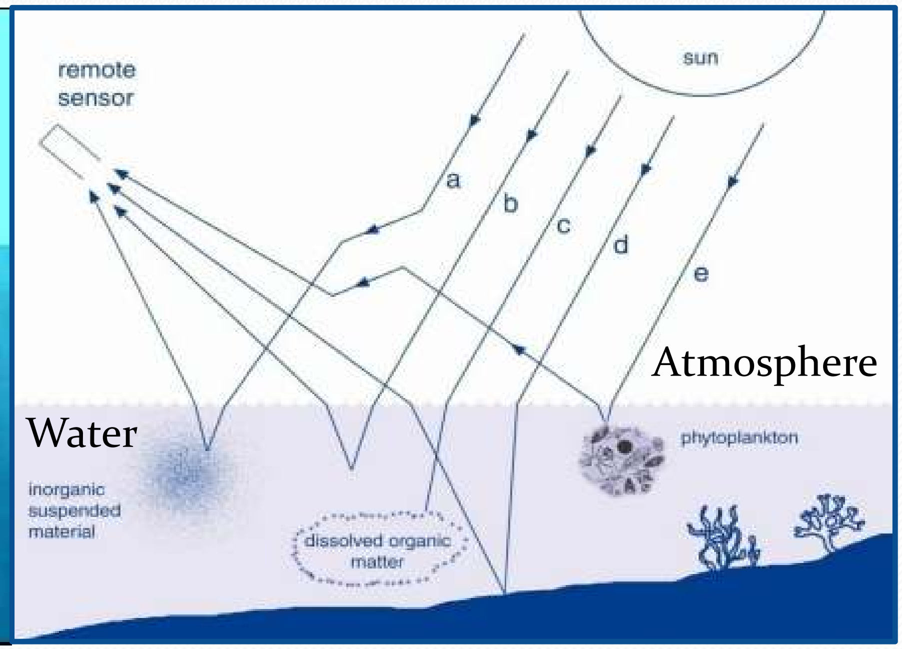
Φ = Photons

AOP-Apparent Optical Properties

- AOP depends both on the medium (the IOPs of the medium) and on the geometric (directional) structure of the radiance distribution.

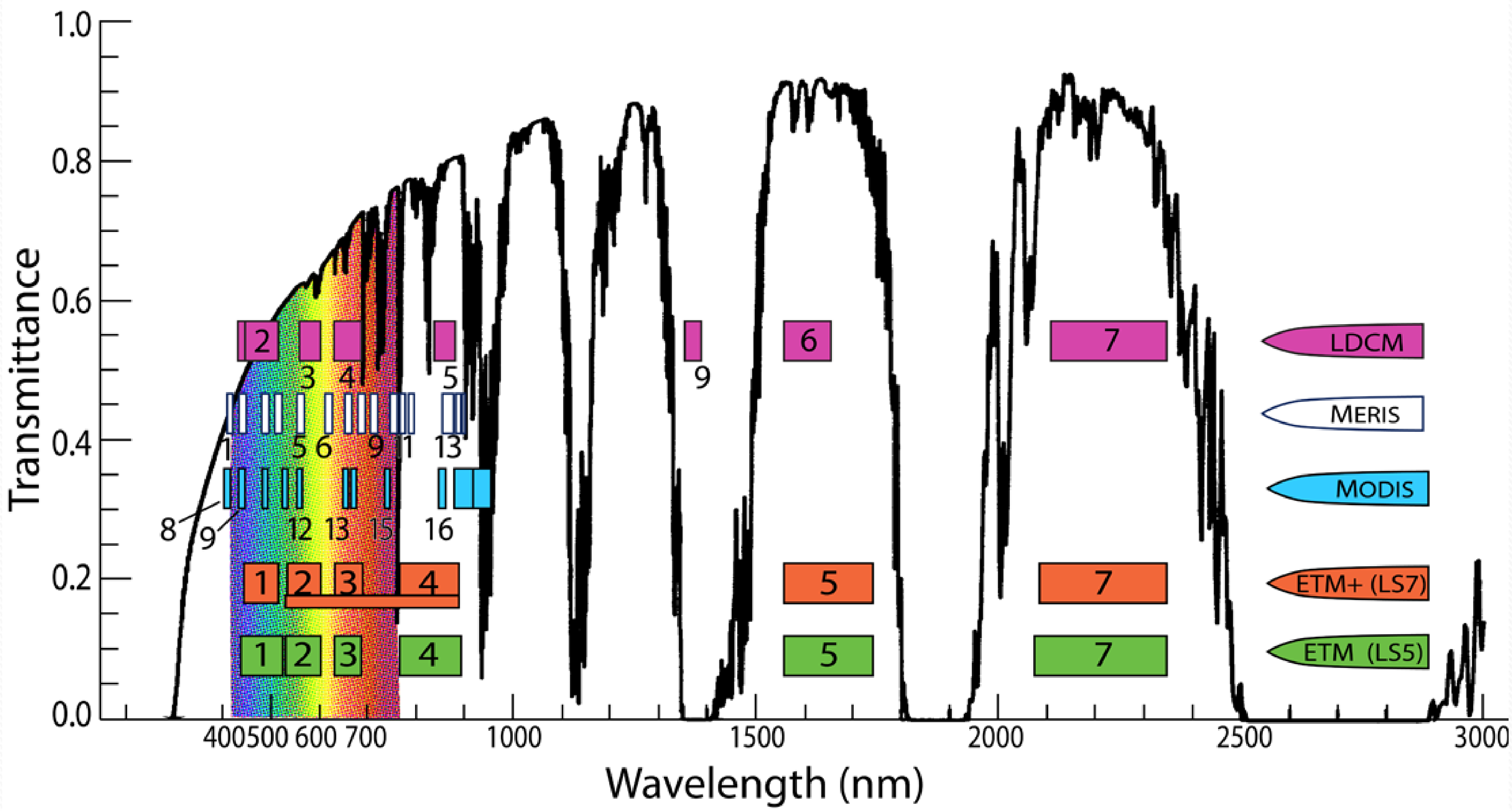


Two optical processes, i.e., : absorption and scattering determine the fate of photons that penetrate into the ocean



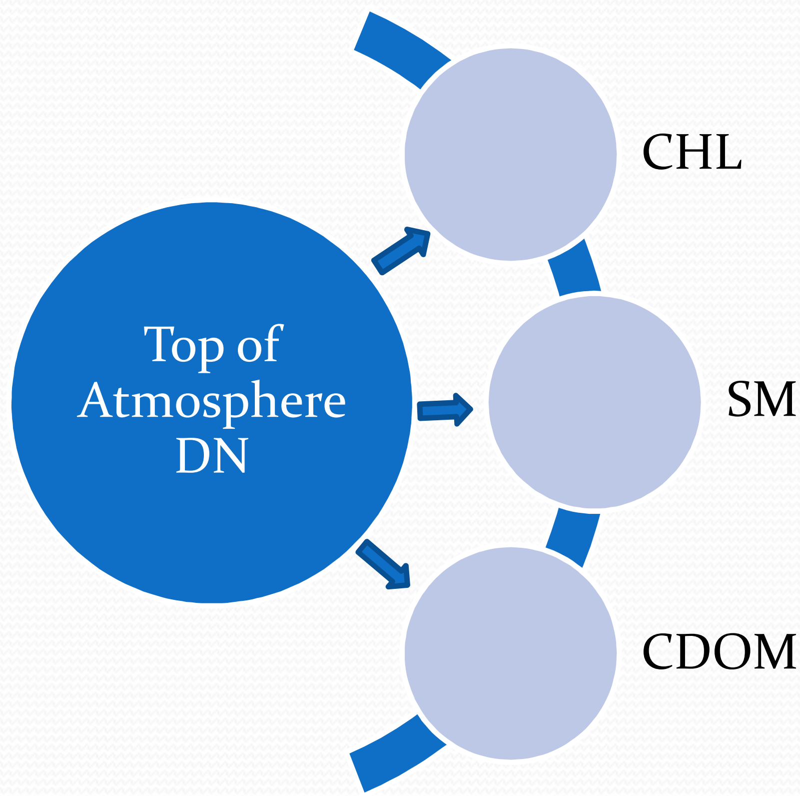
CPA concentration and light direction and strength determines the water-leaving radiance)

Energy Transmittance per Wavelength to Water Surface

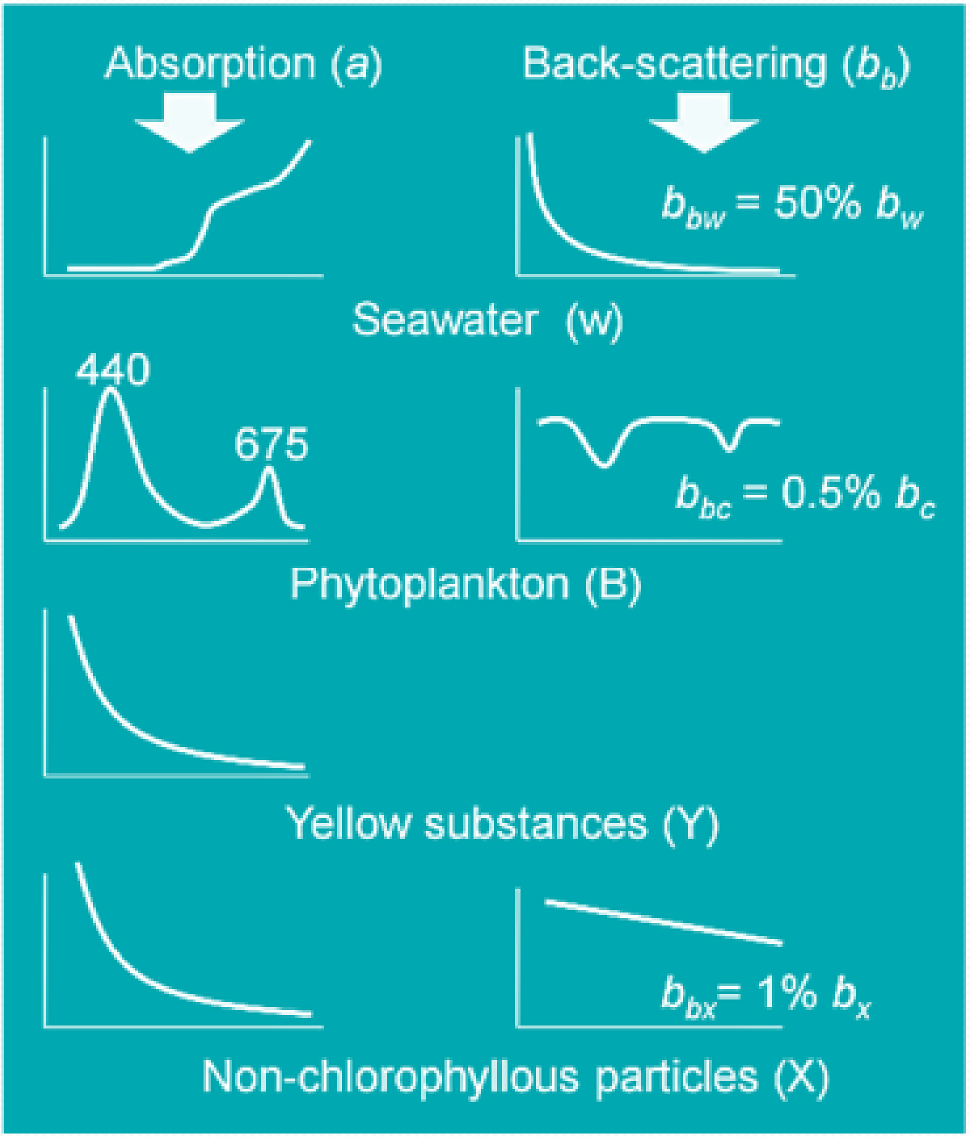


Retrieve algorithms

The numerical process that converts water color (radiometric measurements) recorded by satellites into geophysical values of water quality



Analytical inverse modeling

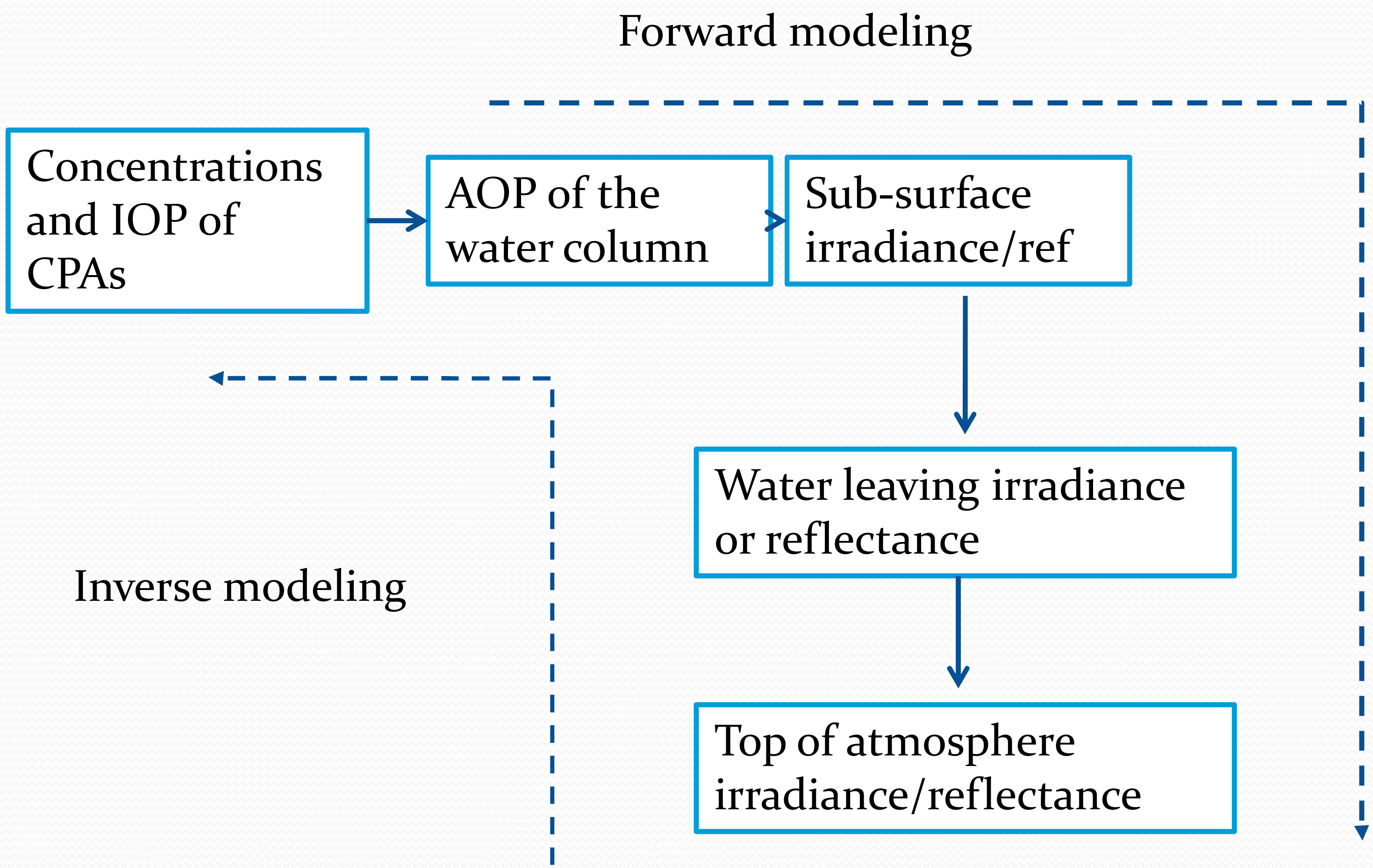


$$a(\lambda) = a_w(\lambda) + a_{chl}(\lambda) + a_{sm}(\lambda) + a_{cdom}(\lambda)$$

$$(b_B)(\lambda) =$$
$$(b_B)_w(\lambda) + (b_B)_{chl}(\lambda) + (b_B)_{sm}(\lambda) + (b_B)a_{cdom}(\lambda)$$

Ocean Color is determined by irradiance leaving the sea surface:

Assume you already know IOP of each CPA



Binding et al. (2012), MODIS-derived algal and mineral turbidity in Lake Erie

Stations for filed sampling

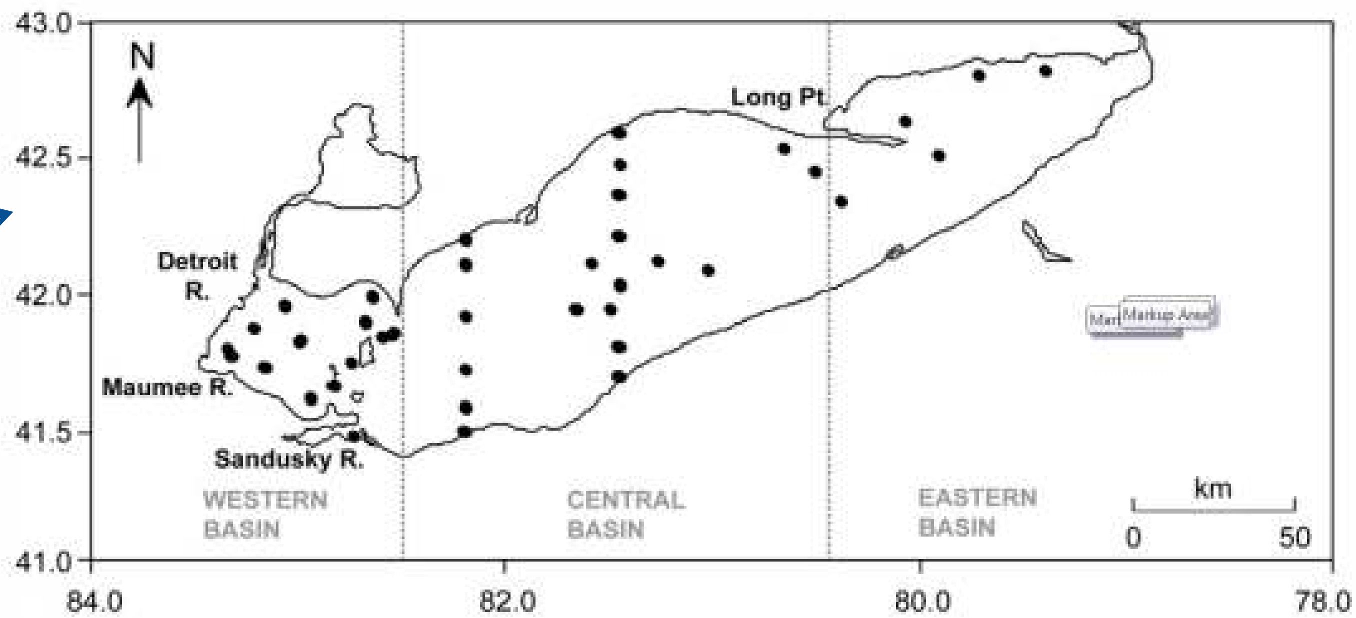


Fig. 1. Map of stations sampled during Lake Erie cruises and delineation of western, central and eastern basins for image analysis.

Algorithm: Invert modeling

$$nLw = F_0 \frac{(1-\rho)(1-\bar{\rho})}{n^2(1-\bar{r}R)} \frac{R}{Q}$$

$$R = f \frac{b_b}{a} = \frac{nLw}{0.54F_0/\pi + 0.48nLw}.$$

$$\frac{b_b}{a}(748) = \frac{b_b{}^*{}_{NAP}[MSPM] + b_b{}^*{}_{Ph}[CHL]}{a_W}$$

$$\frac{b_b}{a}(667) = \frac{b_b{}^*{}_{NAP}[MSPM] + b_b{}^*{}_{Ph}[CHL]}{a_W + a^*{}_{NAP}[MSPM] + a^*{}_{Ph}[CHL]}$$

Results of Binding et al (2012), the seasonal cycles of Chl. a and MSPM(Mineral suspended particulate matter)

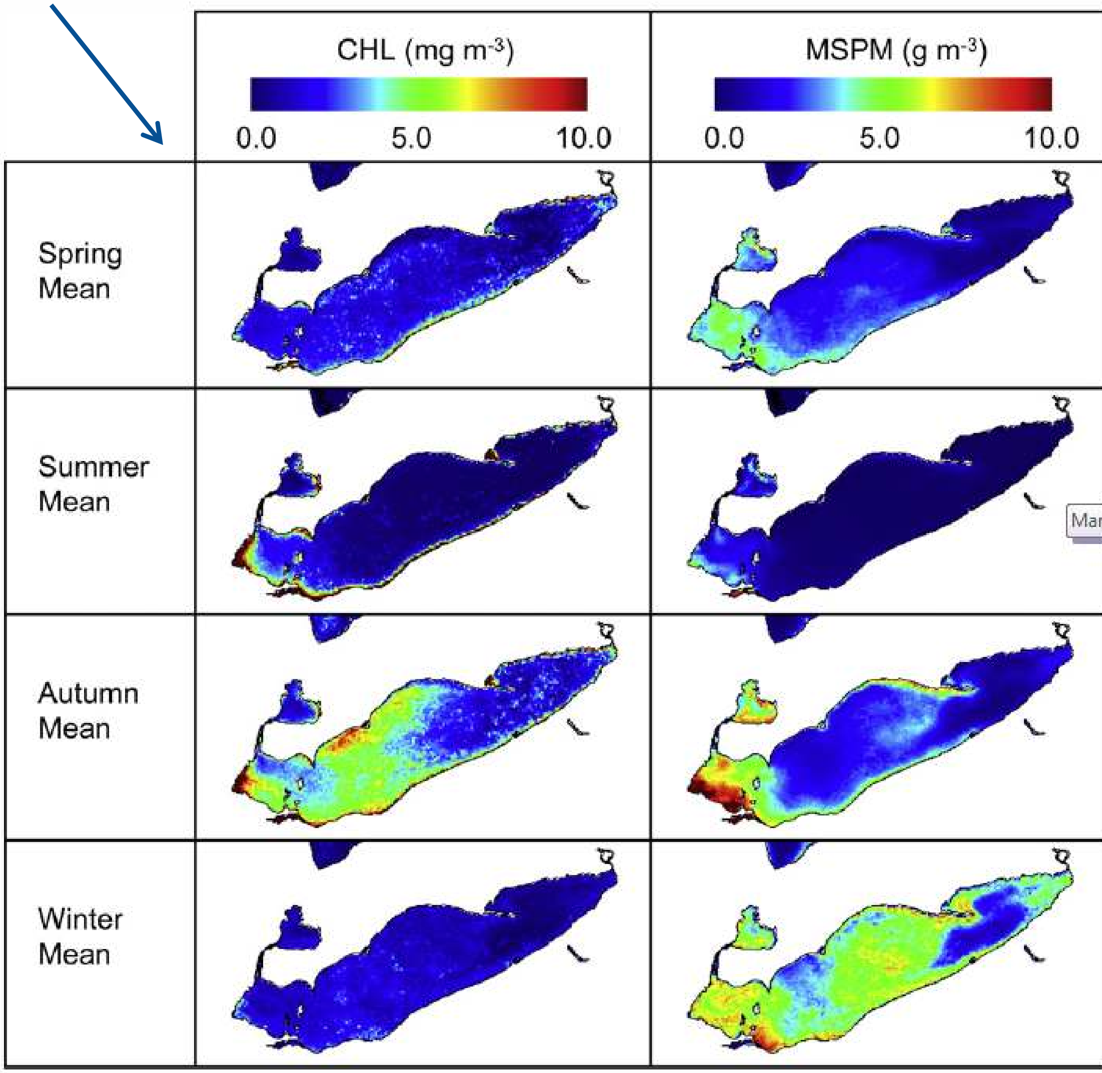
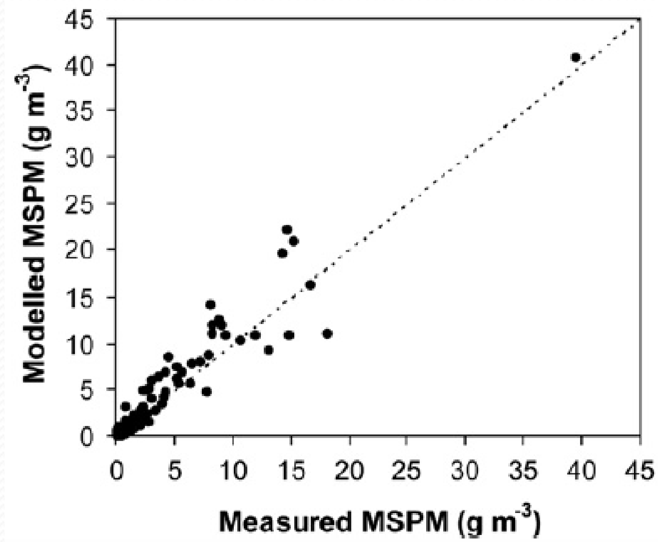
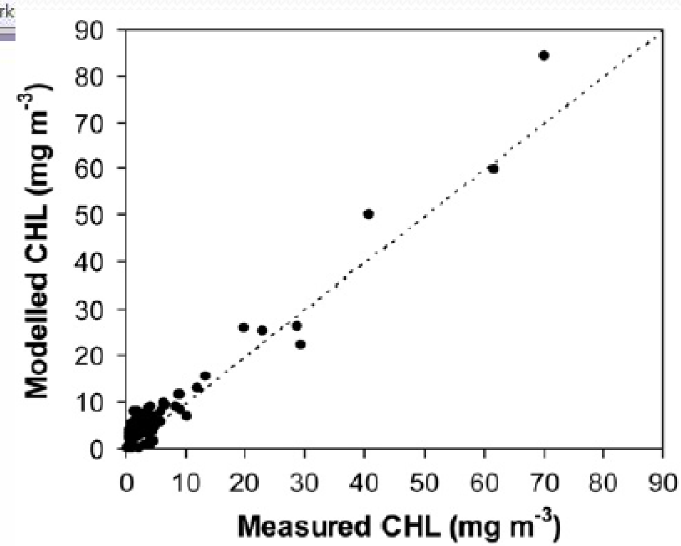
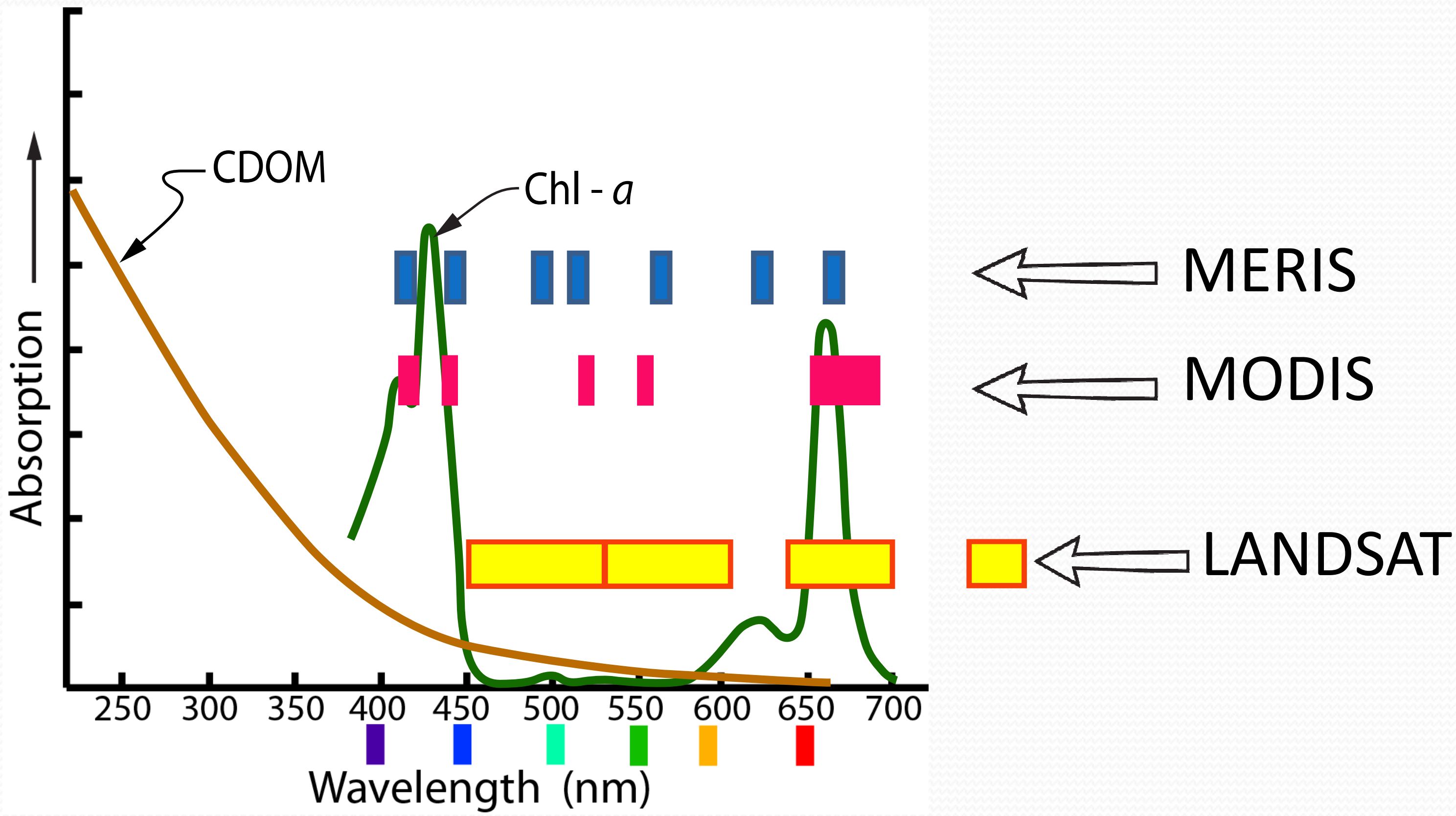


Fig. 6. Seasonal estimated CHL and MSPM concentrations for Spring, Summer, Autumn and Winter, averaged over the years 2003–2008.





Empirical algorithms



Empirical algorithms

$$C_{chl} = f(g(R(\lambda)))$$

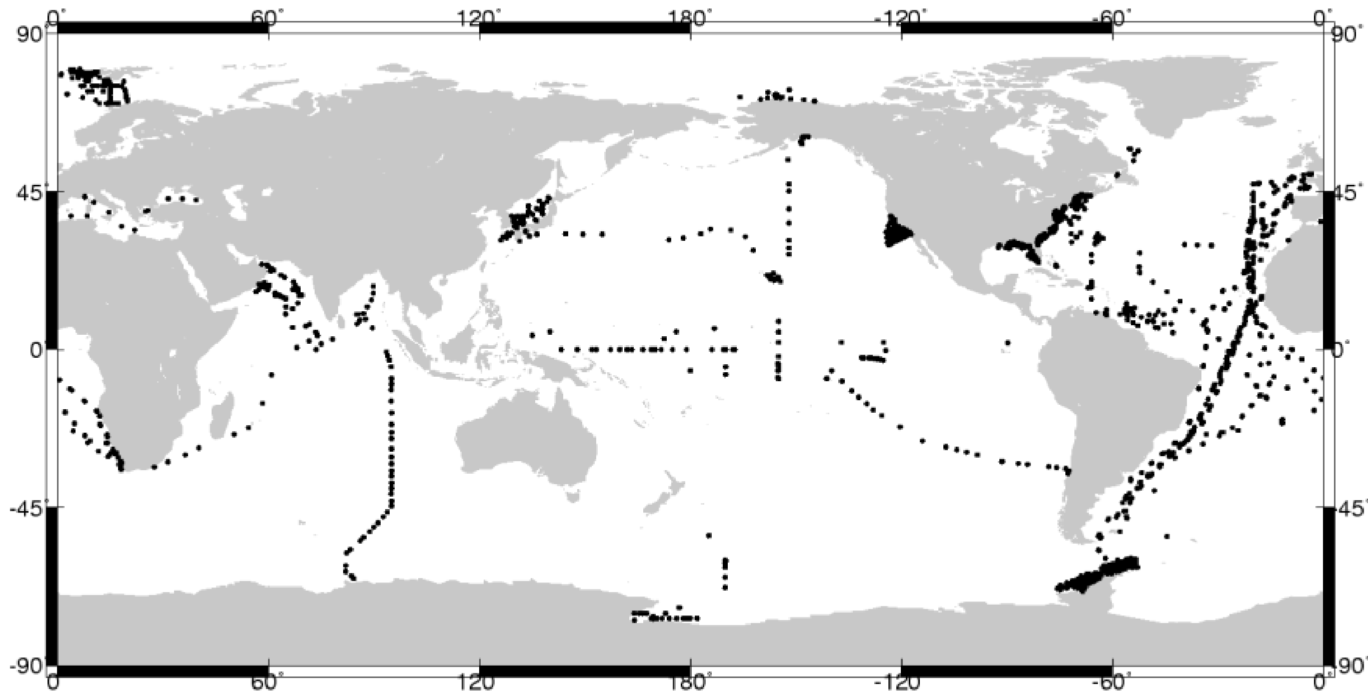
MODIS OC3M

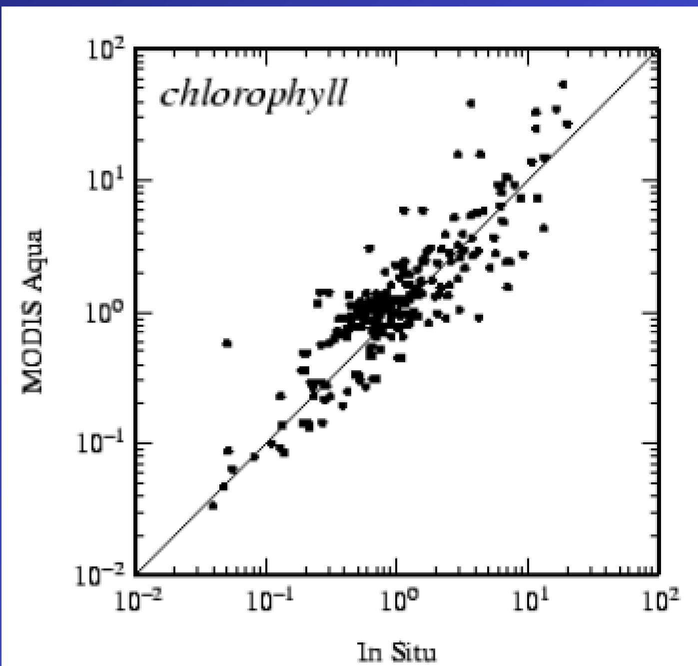
$$C_a = 10^{(a_0 + a_1 R + a_2 R^2 + a_3 R^3 + a_4 R^4)}$$ Where

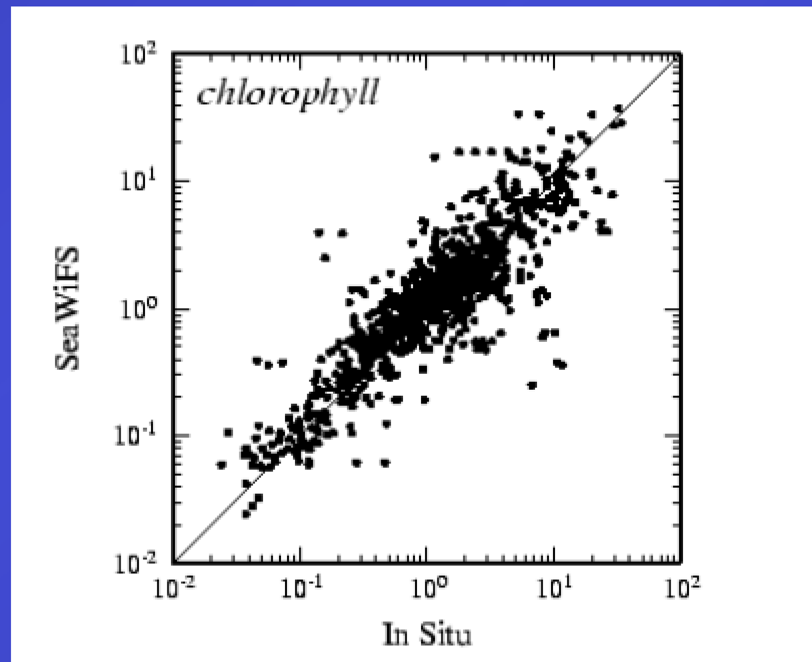
$$R = \log_{10}\left[\frac{\max[R_{rs}(443), R_{rs}(489)]}{R_{rs}(550)}\right]$$

$$a = [0.2424, -2.5828, 1.7057, -0.3415, -0.8818]$$

In Situ validation with NOMAD dataset







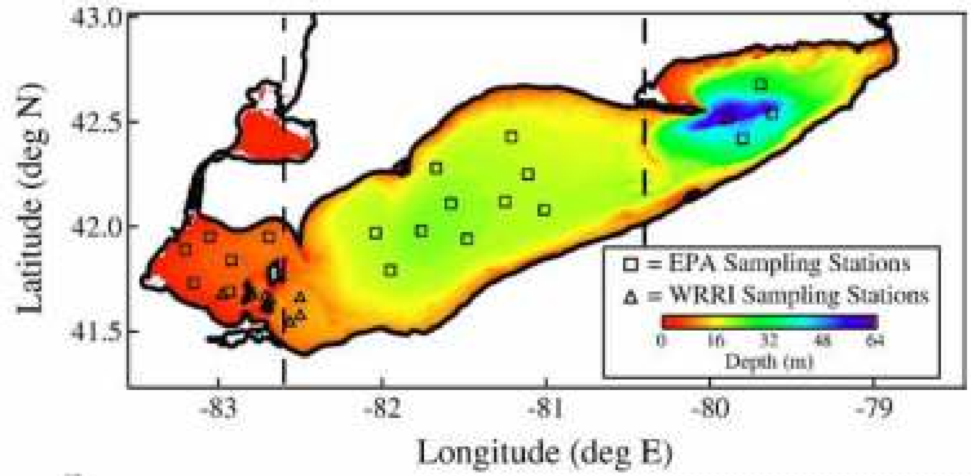
Algorithms used to estimate chlorophyll a concentration (C) or chlorophyll a + phaeophytic concentration $[C+P]$ in μg/L from observations of remote sensing reflectance (R_{rsnnn}) or normalized water-leaving radiance (L_{wnnnn}) at wavelengths nnn nm.

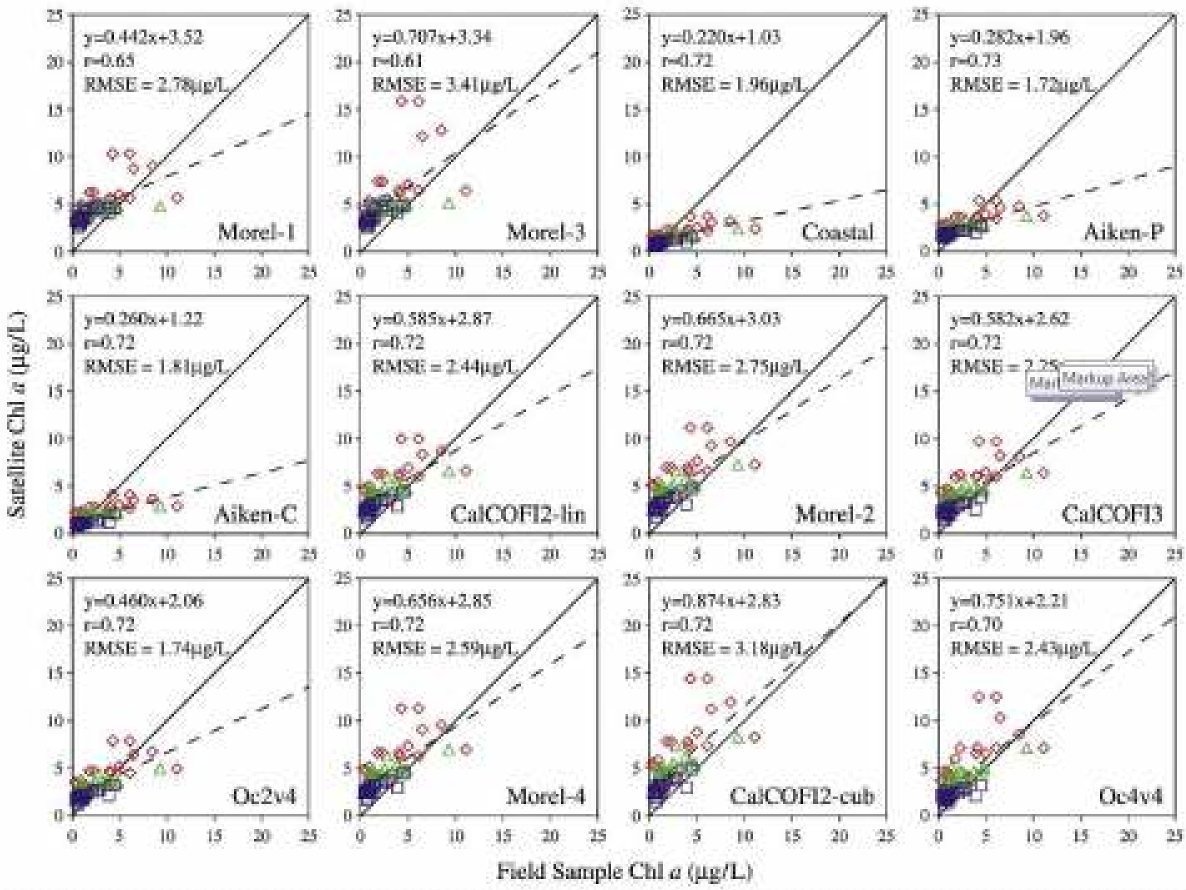
Algorithm	Algorithm equation	Reference
Morel-1	$C = 10^\wedge(0.2492 - 1.768R)$ $R = \log(R_{rs443}/R_{rs555})$	O'Reilly et al. (1998)
Morel-3	$C = 10^\wedge(0.20766 - 1.82878R + 0.75885R^2 - 0.73979R^3)$ $R = \log(R_{rs443}/R_{rs555})$	O'Reilly et al. (1998)
Coastal	$C_{se} = 10^\wedge(-2.5R)$, where $R = \log(R_{rs490}/R_{rs555})$ If $C_{se} \geq 0.5$ then $C = C_{se}$ If $0.1 < C_{se} < 0.5$ then $C = 10^\wedge(\log(C_{se}) * [\log(C_{se}) - \log(0.1)]/[\log(0.5)\ \log(0.1)]$ $+ \log(C_{Oc2v4}) * [\log(0.5) - \log(C_{se})]/[\log(0.5) - \log(0.1)])$ If $C_{se} \leq 0.1$ then $C = C_{Oc2v4}$	Stumpf et al. (2000)
Aiken-P	$C_{22} = \exp(0.696 - 2.085\ \ln(R))$ $C_{24} = (R - 5.29)/(0.592 - 3.48R)$ where $R = L_{wn490}/L_{wn555}$ $[C+P] = C_{22}$; if $[C+P] < 2.0$ μg/L then $[C+P] = C_{24}$	Aiken et al. (1995)
Aiken-C	$C_{21} = \exp(0.464 - 1.989\ \ln(R))$ $C_{23} = (R - 5.29)/(0.719 - 4.23R)$ where $R = L_{wn490}/L_{wn555}$ $C = C_{21}$; if $C < 2.0$ μg/L then $C = C_{23}$	Aiken et al. (1995)
CalCOFI two-band linear	$C = 10^\wedge(0.444 - 2.431R)$ where $R = \log(R_{rs490}/R_{rs555})$	Michell and Kahru (1998)
Morel-2	$C = \exp(1.077835 - 2.542605R)$ $R = \ln(R_{rs490}/R_{rs555})$	O'Reilly et al. (1998)
CalCOFI three-band	$C = \exp(1.025 - 1.622R_1 - 1.238R_2)$ $R_1 = \ln(R_{rs490}/R_{rs555})$ $R_2 = \ln(R_{rs510}/R_{rs555})$	Michell and Kahru (1998)
Oc2v4	$C = 10^\wedge(0.319 - 2.336R + 0.879R^2 - 0.135R^3) - 0.071$ $R = \log(R_{rs490}/R_{rs555})$	O'Reilly et al. (2000)
Morel-4	$C = 10^\wedge(1.03117 - 2.40134R + 0.3219897R^2 - 0.291066R^3)$ $R = \log(R_{rs490}/R_{rs555})$	O'Reilly et al. (1998)
CalCOFI two-band cubic	$C = 10^\wedge(0.450 - 2.860R + 0.996R^2 - 0.367R^3)$ where $R = \log(R_{rs490}/R_{rs555})$	Michell and Kahru (1998)
Oc4v4	$C = 10^\wedge(0.366 - 3.067R + 1.930R^2 + 0.649R^3 - 1.532R^4)$ $R = \log(\max[R_{rs443}, R_{rs490}, R_{rs510}]/R_{rs555})$	O'Reilly et al. (2000)
Baltic	$C = 10^\wedge(0.1520 - 3.0558R)$ where $R = \log(\max[L_{wn443}/L_{wn551}, L_{wn488}/L_{wn551}])$	Darecki and Stramski (2004)

Note that where the maximum operator (max) appears, the largest of the quantities in the square brackets is used.

Witter et al. (2009)

Sampling plots





Assessment results: correlations were between 0.65 and 0.73, however, the slope is biased

Witter et al. (2009)

Performance of ocean color algorithms:

- The absolute accuracy of Chl.a and SM retrieved from satellites signals is questioned
- The spatial and temporal patterns in Chl. a and SM concentrations derived from satellites are sometimes reliable due to good correlations between ground based measures and satellites-based measures
- Empirical algorithms works well for Case 1 water but problematic for Case 2 water
- Analytical inverse modeling potentially can give good results for Case 2 water, but difficulty to develop.

Thank you!

Questions?