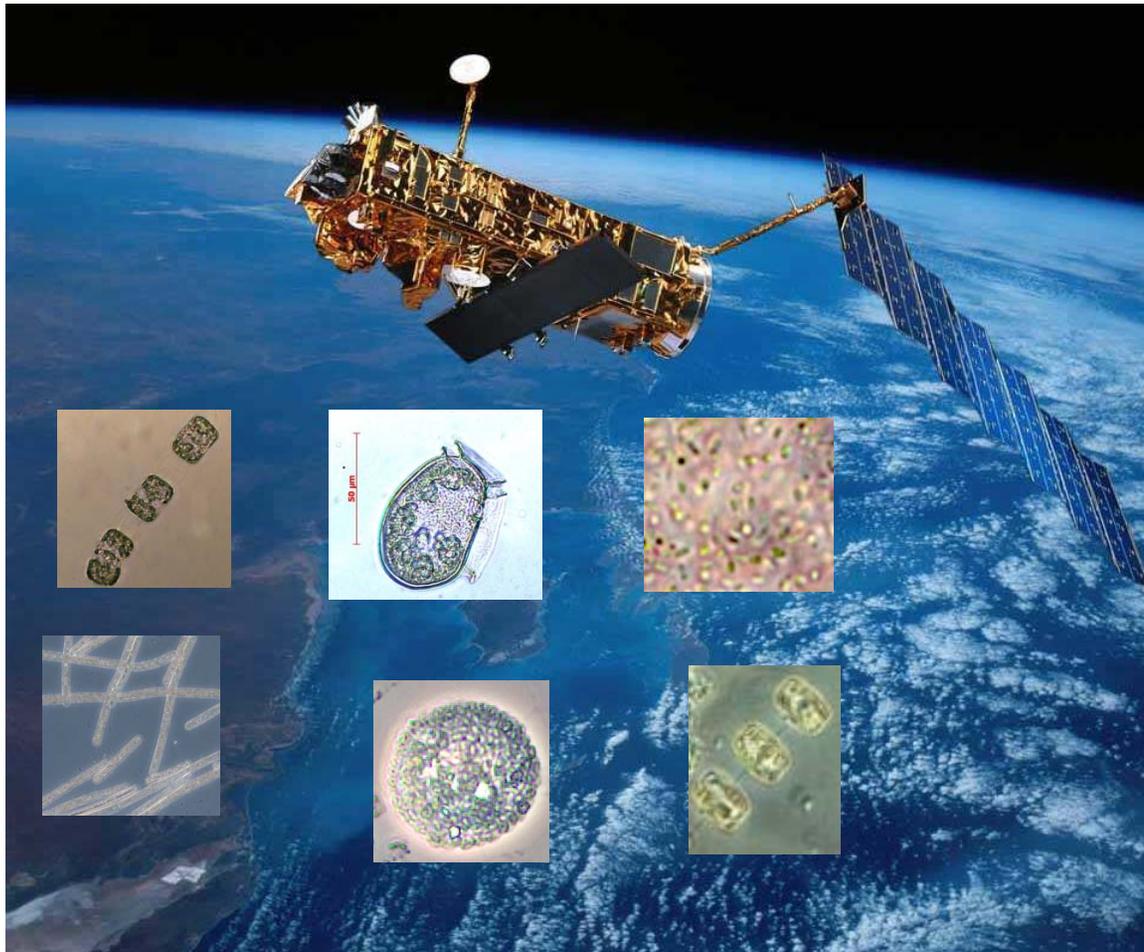


Phytoplankton group products from ocean colour satellite data



Astrid Bracher, Nick Hardman-Mountford



Contributions from: Robert Brewin (PML), Astrid Bracher (AWI), Annick Bricaud (LOV) & Aurea Ciotti (INPE), Cecile Dupouy (IRD), Taka Hirata (HU), Toru Hirawake (HU), Tiho Kostadinov (UR), Emmanuelle Organelli (LOV), Dave Siegel (ERI), Shuba Sathyendranath (PML), Emmanuel Devred (UL)

Overview

Main principles of different phytoplankton groups - basics of different algorithms' approaches

Short overview of current (not complete!!!) multiple phytoplankton functional types (PFT) or size class (PSC) algorithms and satellite products:

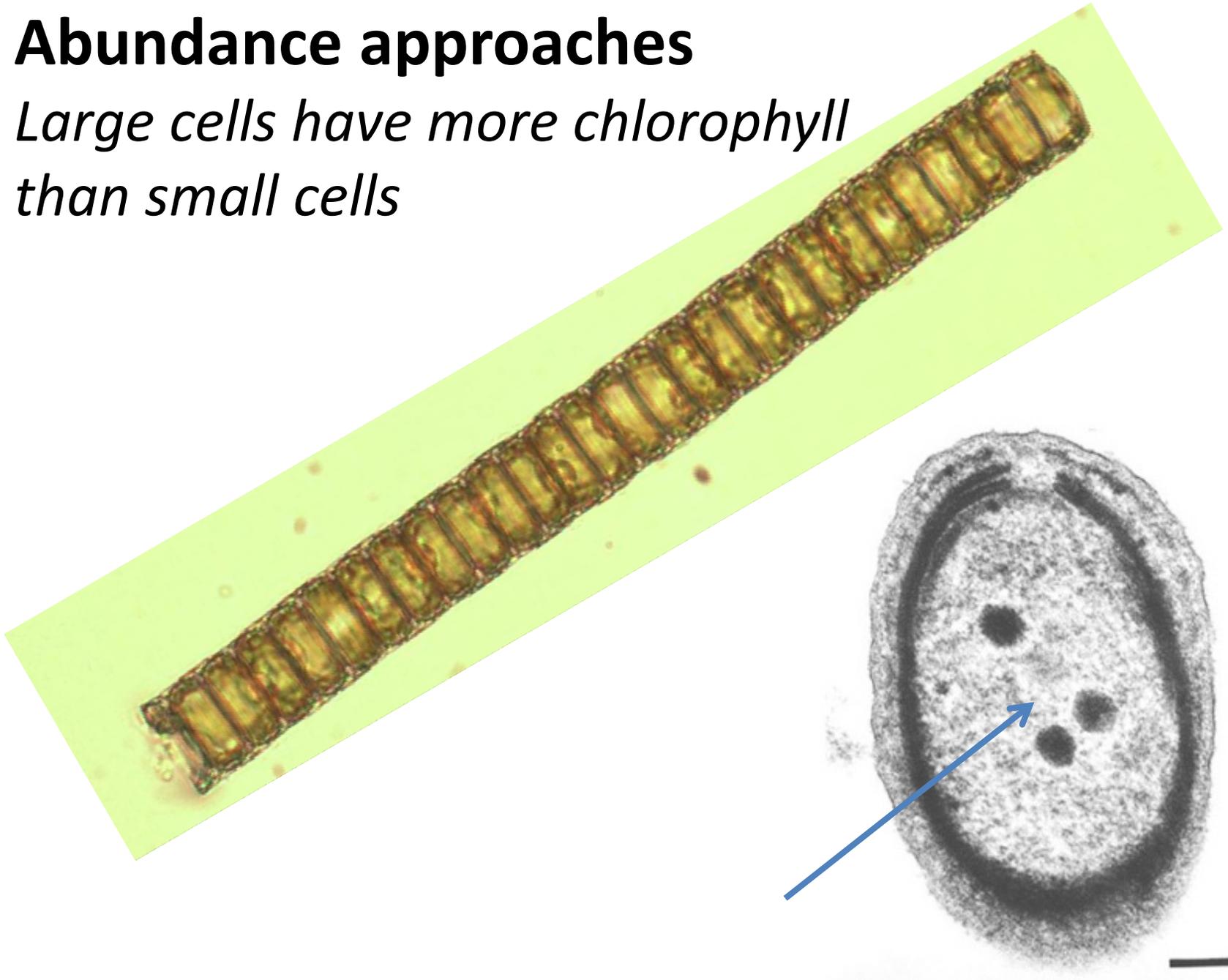
- a) Abundance based - biomass/dominance of different PSC/PFT:**
 - using chl only
 - combined with a443 or bb
 - empirical reflectance ratios (via marker pigments conc.)

- b) Spectral**
 - reflectance anomalies - dominant PFT)
 - phytoplankton absorption (and bbp) - PSC conc.
 - PFT absorption spectra (hyperspectral!) - PFT conc.
 - particle backscatter to infer particle size distribution

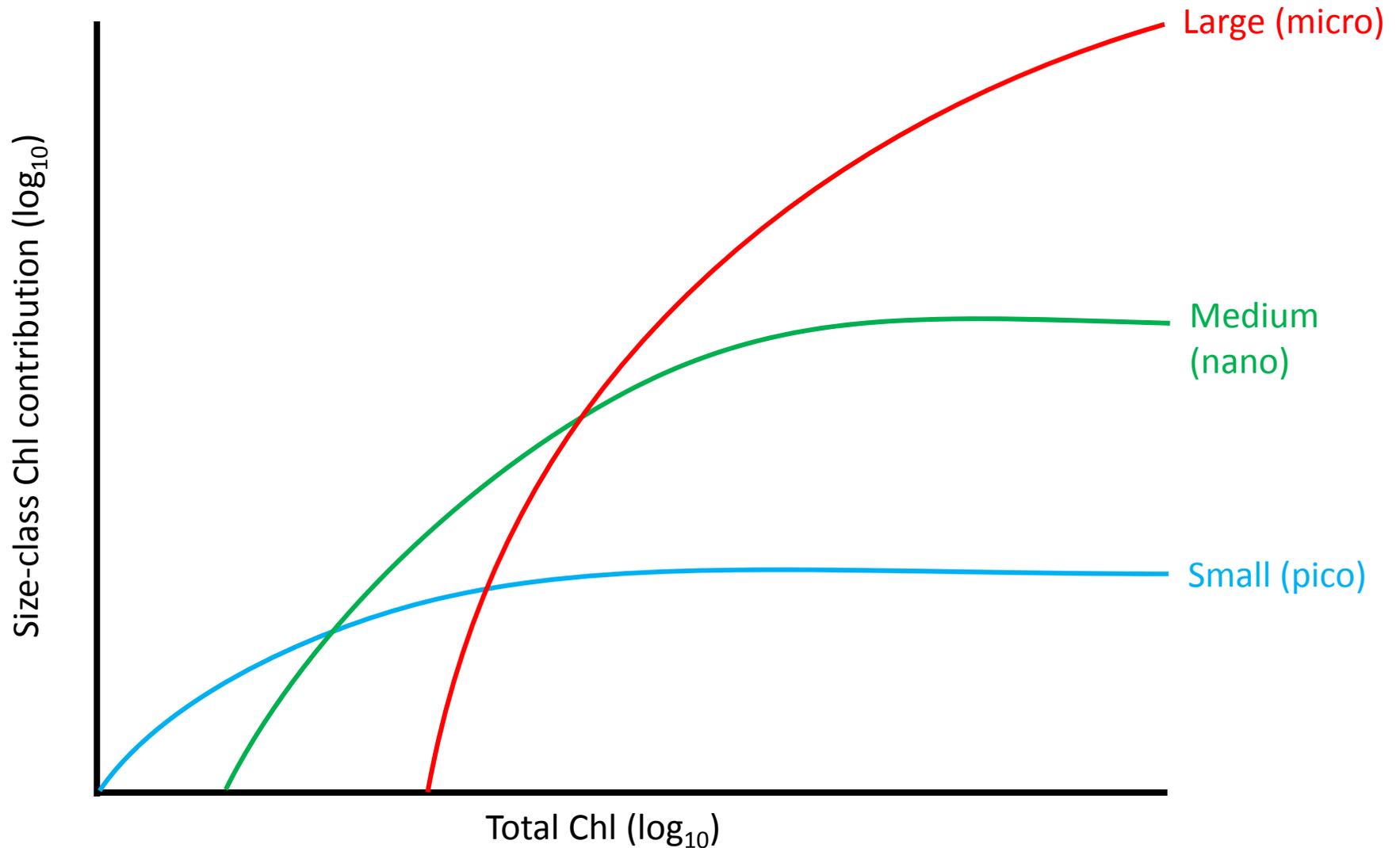
Summary

Abundance approaches

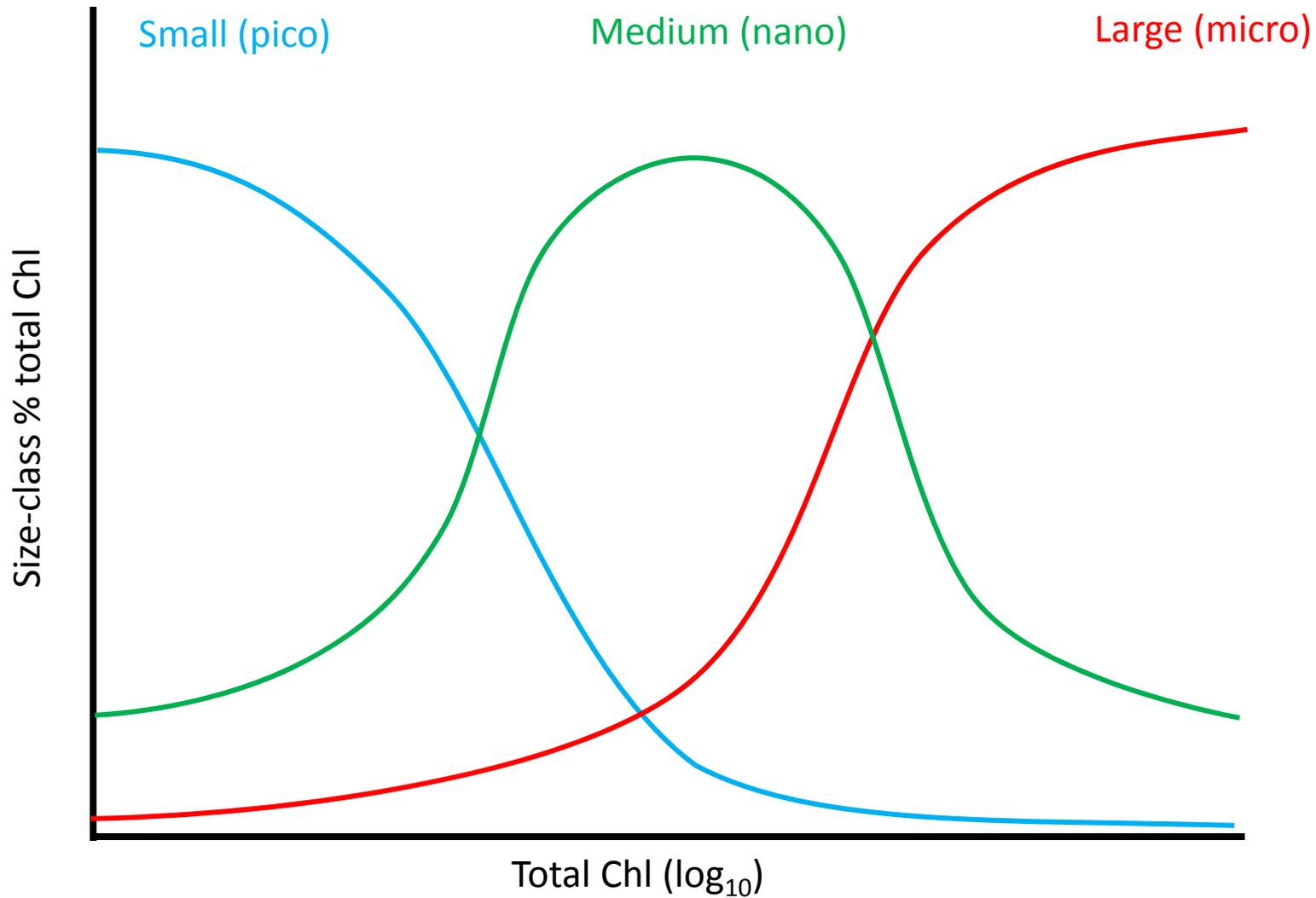
Large cells have more chlorophyll than small cells



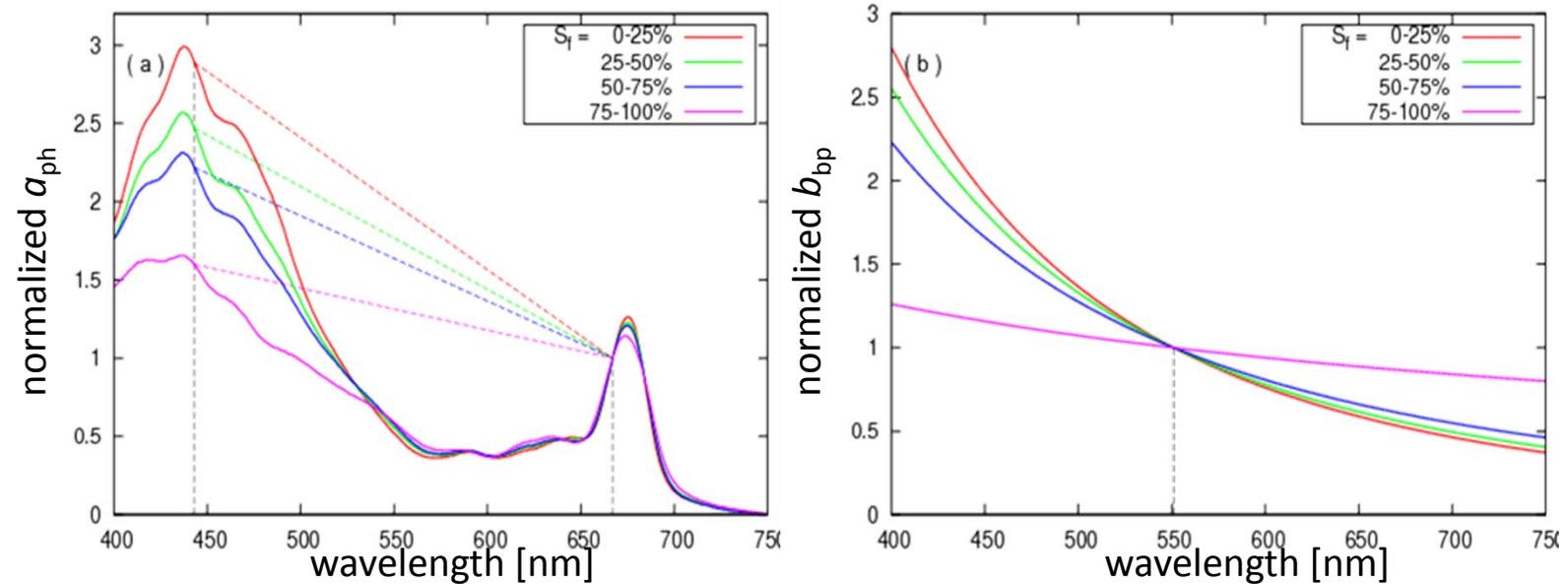
Larger size classes add chlorophyll



Larger size classes add chlorophyll



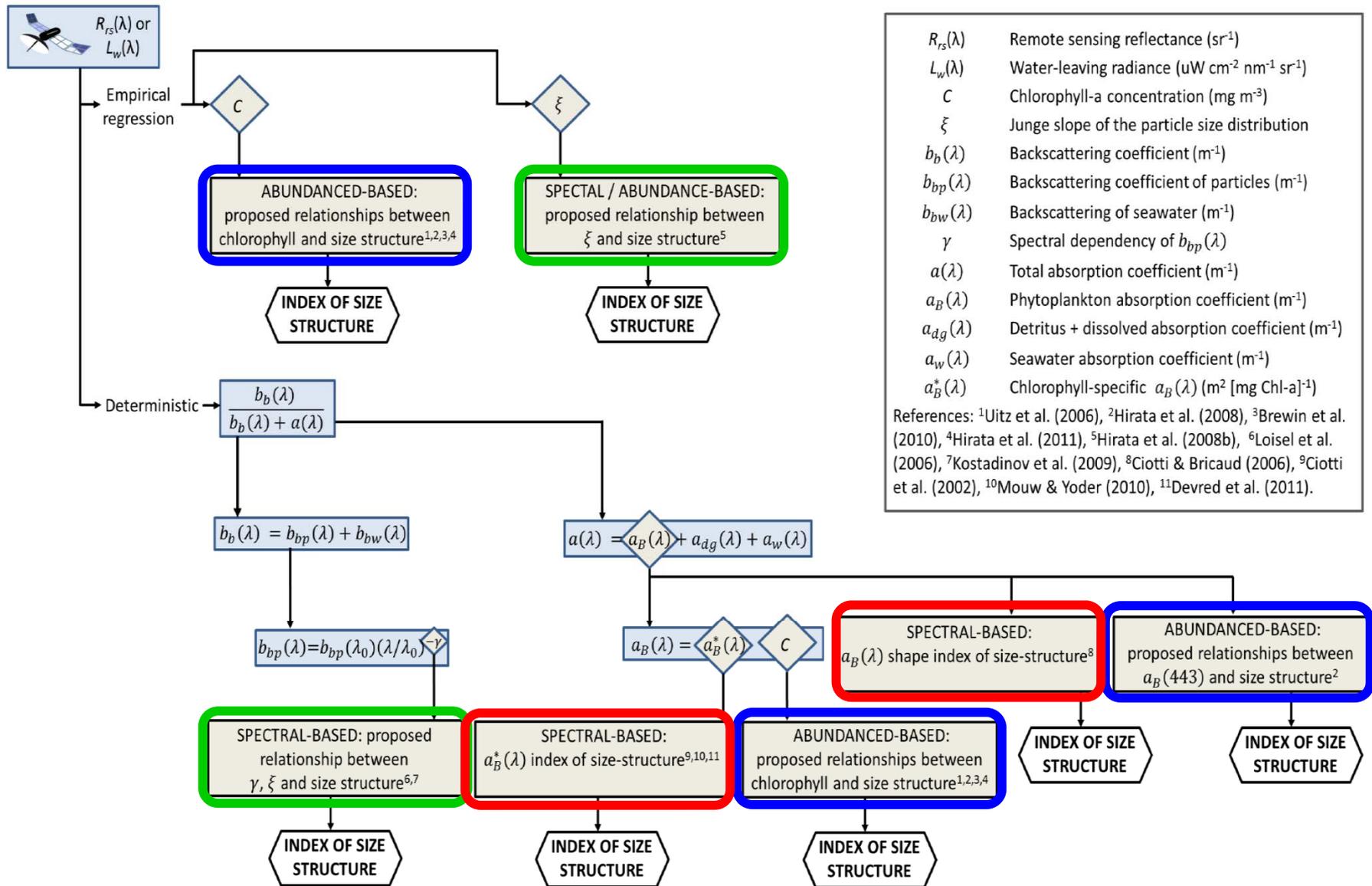
Spectral approaches



Plots courtesy of Toru Hirawake

Based on changes in shape and slope

Size-structure *and* PFT approaches



$R_{rs}(\lambda)$	Remote sensing reflectance (sr^{-1})
$L_w(\lambda)$	Water-leaving radiance ($uW\ cm^{-2}\ nm^{-1}\ sr^{-1}$)
C	Chlorophyll-a concentration ($mg\ m^{-3}$)
ξ	Junge slope of the particle size distribution
$b_b(\lambda)$	Backscattering coefficient (m^{-1})
$b_{bp}(\lambda)$	Backscattering coefficient of particles (m^{-1})
$b_{bw}(\lambda)$	Backscattering of seawater (m^{-1})
γ	Spectral dependency of $b_{bp}(\lambda)$
$a(\lambda)$	Total absorption coefficient (m^{-1})
$a_B(\lambda)$	Phytoplankton absorption coefficient (m^{-1})
$a_{dg}(\lambda)$	Detritus + dissolved absorption coefficient (m^{-1})
$a_w(\lambda)$	Seawater absorption coefficient (m^{-1})
$a_B^*(\lambda)$	Chlorophyll-specific $a_B(\lambda)$ ($m^2\ [mg\ Chl-a]^{-1}$)

References: ¹Uitz et al. (2006), ²Hirata et al. (2008), ³Brewin et al. (2010), ⁴Hirata et al. (2011), ⁵Hirata et al. (2008b), ⁶Loisel et al. (2006), ⁷Kostadinov et al. (2009), ⁸Ciotti & Bricaud (2006), ⁹Ciotti et al. (2002), ¹⁰Mouw & Yoder (2010), ¹¹Devred et al. (2011).

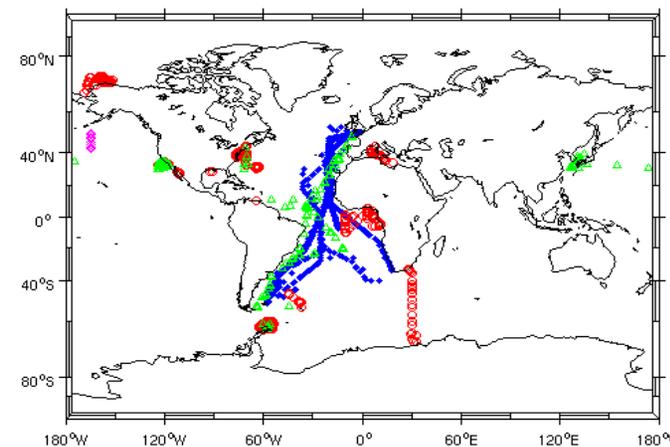
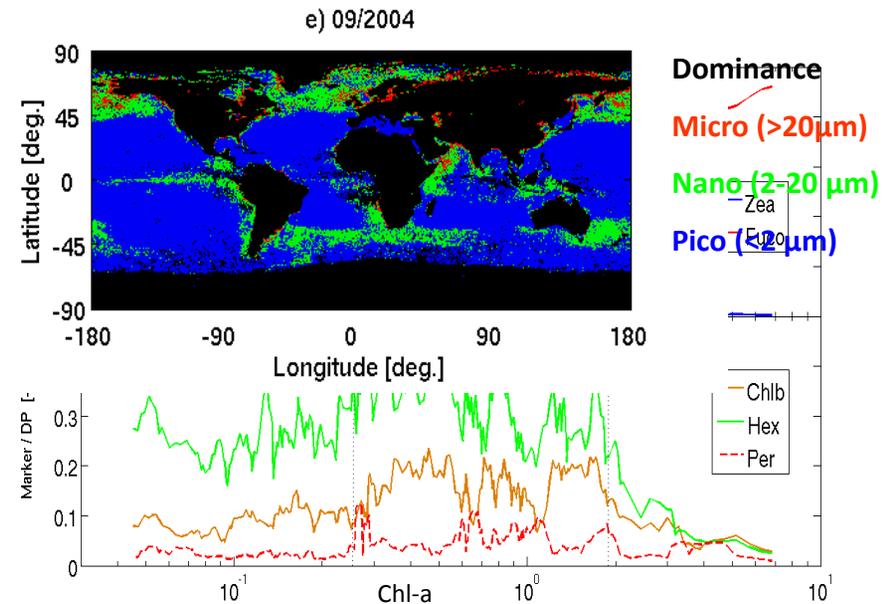
From Brewin *et al.* Chapter 4: Detection of Phytoplankton Size Structure by Remote Sensing. In Sathyendranath *et al.* Phytoplankton Functional Types from Space. IOCCG Report 14, in prep.

Chlorophyll or absorption abundance-based approaches to size and PFT fractionation

Hirata et al. 2008. Dominant size class

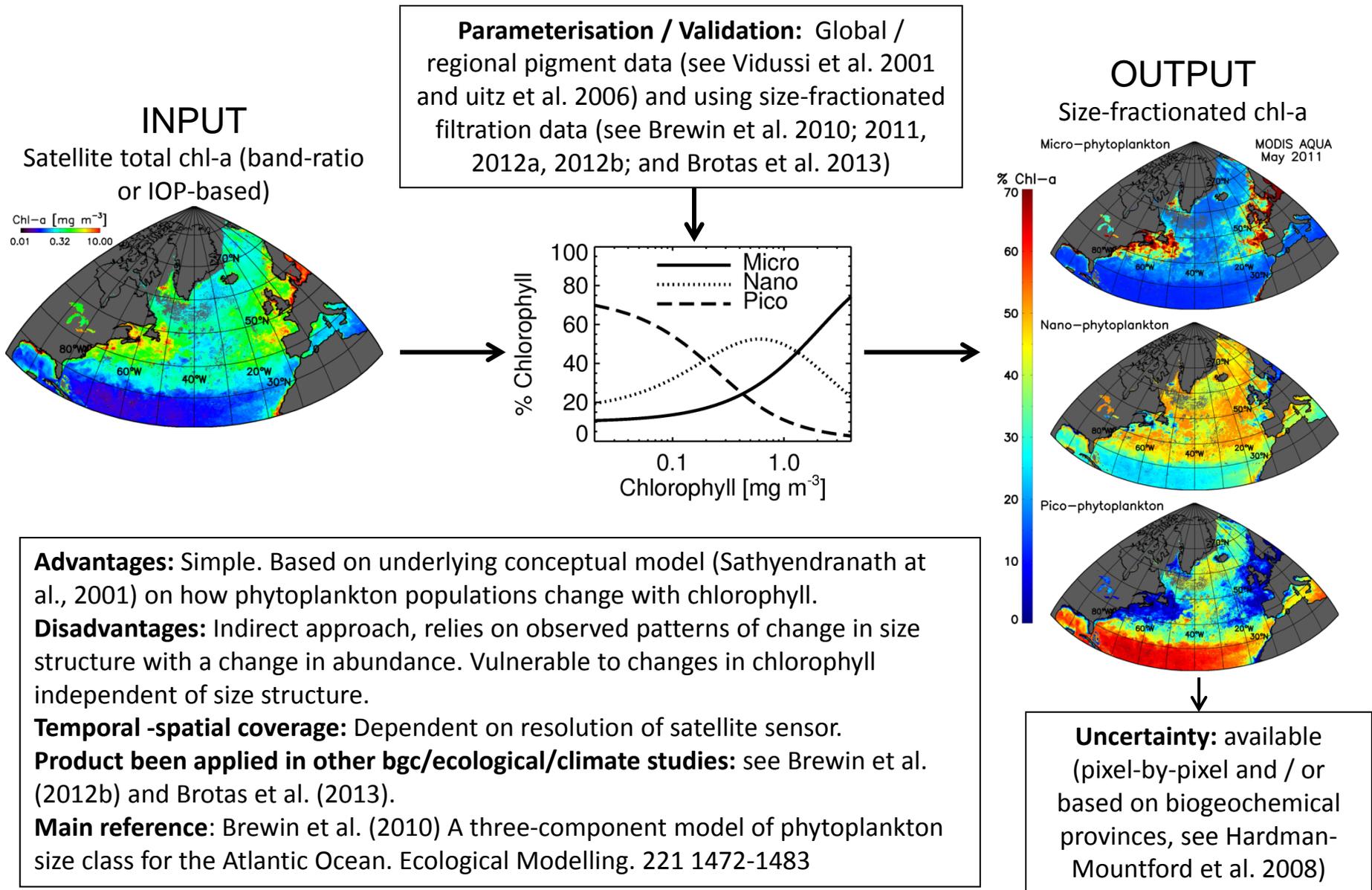
- Phytoplankton pigment composition related to Chl
- Detect size class from Chl biomass
- Also holds for optical absorption

Global Pigment/Optics Data Set
AMT (PML)
SeaBass (NASA, various contributors)
Oshoro (Hokkaido Univ, NOAA)
NOMAD (NASA, various contributors)
(N=5570)



Hirata et al.,
2008 Rem.
Sens. Env.

Brewin et al.: Relationship between total chlorophyll and phytoplankton size structure based on conceptual model of Sathyendranath et al. (2001)



Hirata et al. (2011). Phytoplankton Functional Types for model comparisons

Input: Only Chla or $a_{ph}(443nm)$ derived from OC (L2/L3)

OC-PFT ver. 1.0/1.1

Output: Chla [mg/m^3] and percentage [%] of Microplankton, Nanoplankton, Picoplankton, Diatoms, Haptophytes (Prymnesiophytes), Green Algae, Pico-Eukaryotes, Prokaryotes, Prochlorococcus sp.

Estimated uncertainties: $< \sim 30\%$

Advantage:

- a. many groups of phytoplankton groups to be retrieved (3 size classes + 5 groups).
- b. Quantified outputs (pigment biomass in [mg/m^3] or relative abundance in [%]).

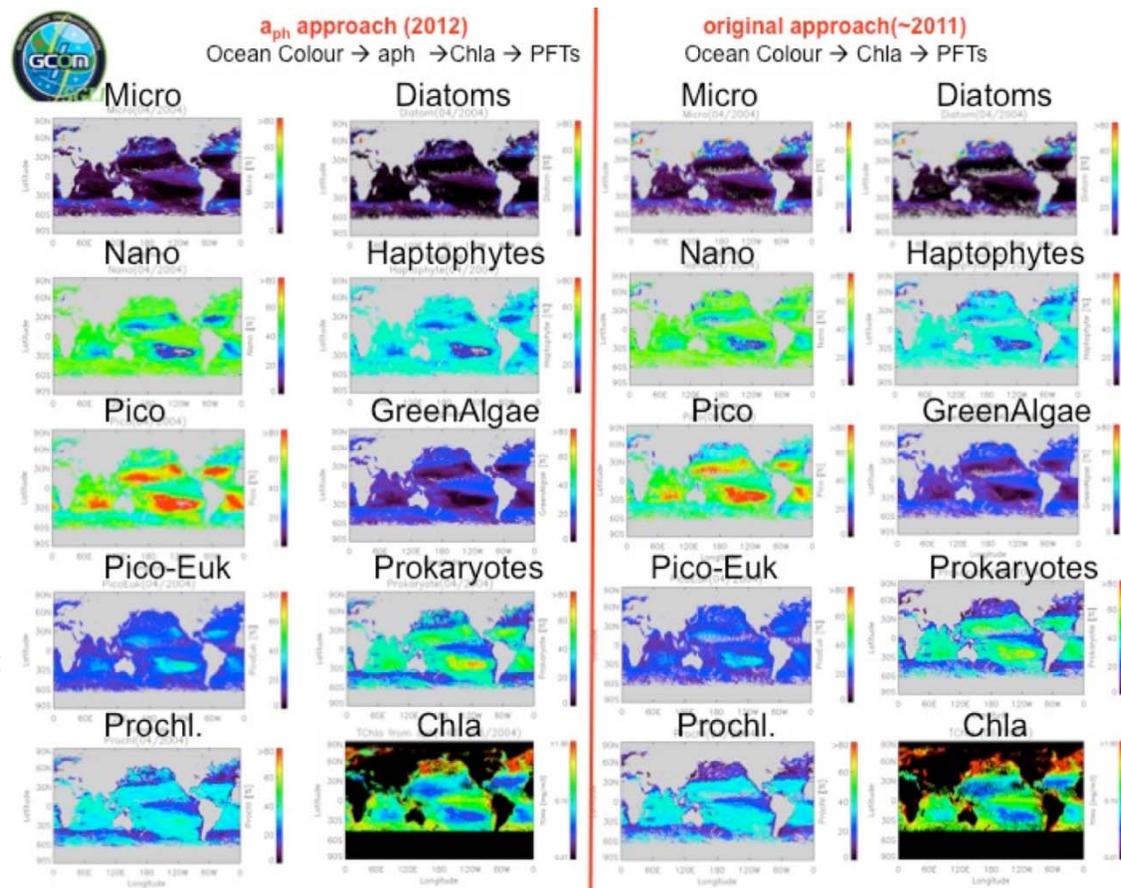
Disadvantage(?):

- a. Empirical relationships involved
- b. May not be applied to shelf- and coastal waters

Spatio-Temporal coverage: Sensor resolution dependent

Main Reference:

Hirata, T., N.J. Hardman-Mountford, R.J.W. Brewin, J. Aiken, R. Barlow, K. Suzuki, T. Isada, E. Howell, T. Hashioka, M. Aita-Noguchi, Y. Yamanaka, Biogeosciences, 8, 311-327, 2011



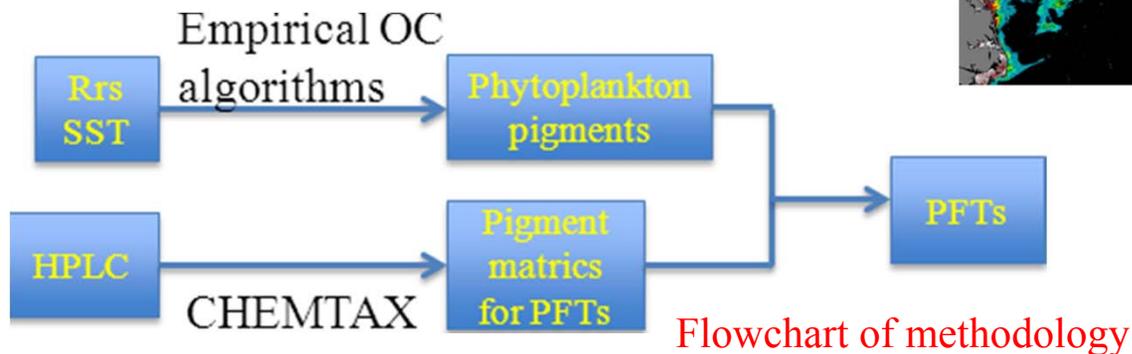
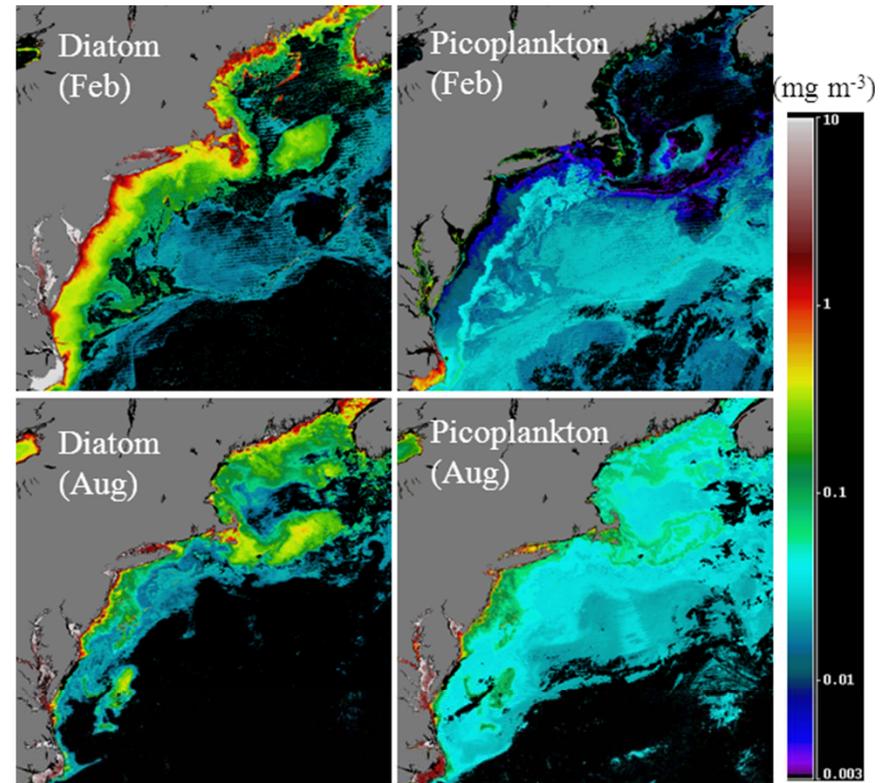
Quantification of many phytoplankton groups

Applications:

- a. Rousseaux et al. Satellite views of global phytoplankton community distributions using an empirical algorithm and a numerical model, Biogeosciences Discuss., 10, 1083-1109, 2013
- b. Hashioka et al. Phytoplankton competition during the spring bloom in four phytoplankton functional type models (submitted)
- c. Palacz et al. Distribution of phytoplankton functional types in high-nitrate low-chlorophyll waters in a new diagnostic ecological indicator model (submitting)

PFTs from space in the U.S. northeast coast

- Empirical ocean color algorithms were developed for pigments (Chl *a*, *b*, *c*, fucoxanthin, zeaxanthin, etc.) in the U.S. northeast coast.
- Field HPLC pigments were related to PFTs by chemotaxonomy (CHEMTAX).
- Combining the above two approaches to determine PFTs from space.
- The distributional patterns in PFTs are oceanographically reasonable, and agree well with previous works by cell counts.



Examples: Abundances (in TChl *a*) of diatoms and picoplankton in the U.S. northeast coast in Feb and Aug.

Spectral approaches: Reflectance Anomalies

The PHYSAT approach

Inter Deposit Digital Number (License APP) : IDDN.FR.001.330003.000.S.P.2012.000.30300.

-> Based on Radiances anomalies : Removed the first order Chl a effect on the signal :

$$Ra(\lambda) = nLw(\lambda) / nLw_{ref}(\lambda, \text{Chl } a) + \text{In situ observations (pigments, counts, cytometry...)}$$

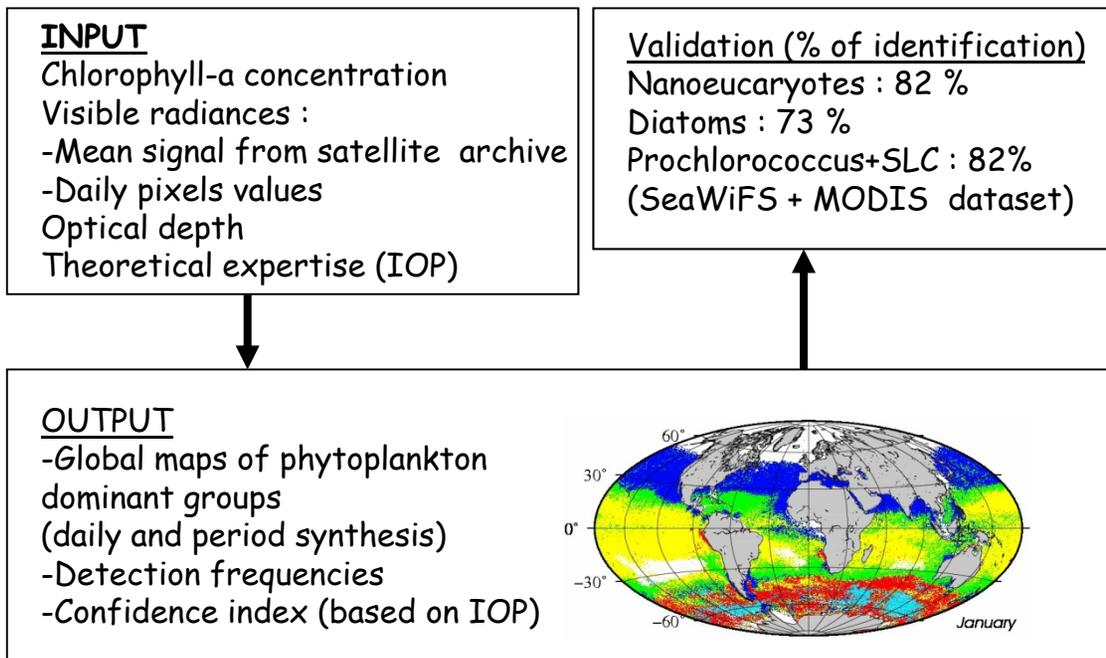
-> Main publications (methodology) :

Alvain S., et al. Moulin C., Dandonneau Y., and Breon F.M, *Remote sensing of phytoplankton groups in case 1 waters from global SeaWiFS imagery*. DSR I- 52, (2005).

Alvain S., Moulin C., Dandonneau Y., Loisel H., *Seasonal distribution and succession of dominant phytoplankton groups in the global ocean: A satellite view*, Global Biogeochemical Cycles, 22, GB3001, (2008)

Alvain S., Loisel H. and D. Dessailly, *Theoretical analysis of ocean color radiances anomalies and implications for phytoplankton groups detection in case 1 waters*, Optics Express Vol. 20, N°2, (2012).

DATA AVAILABLE HERE : <http://log.univ-littoral.fr/Physat>



-> Some Applications :

-Alvain S. et al. *Rapid climatic driven shifts of diatoms at high latitudes*, Remote Sensing of Environment, (2013).

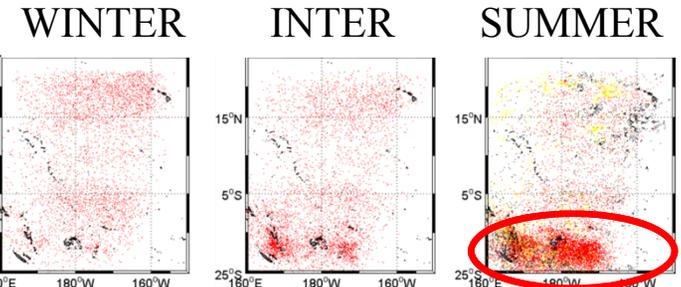
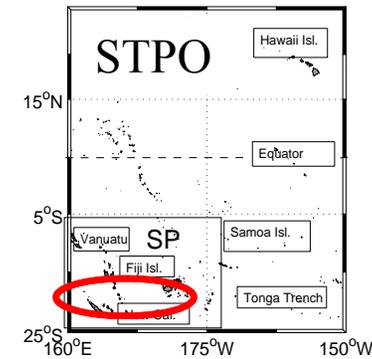
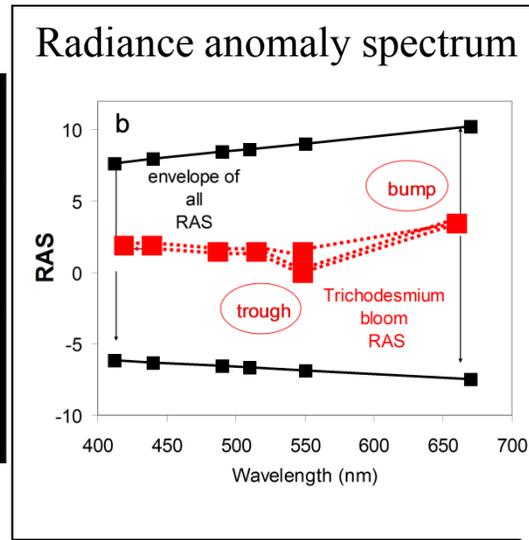
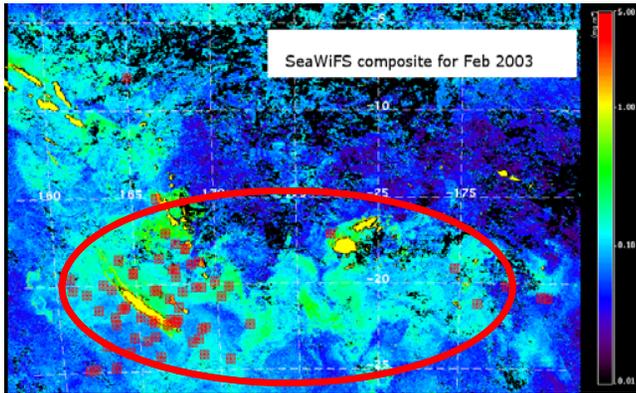
-Demarcq H. et al. (2011) ; *Monitoring marine phytoplankton seasonality from space*, Remote Sensing of Environment RSE-08090

-D'Ovidio F, et al., *Fluid dynamical niches of phytoplankton types* PNAS, Volume : 107 Issue : 43 Pages : 18366-18370 (2010)

-Alvain S. et al. *A species-dependent bio-optical model of case I waters* for global ocean color processing. Deep Sea Res. I, 53, 917-925, (2006).

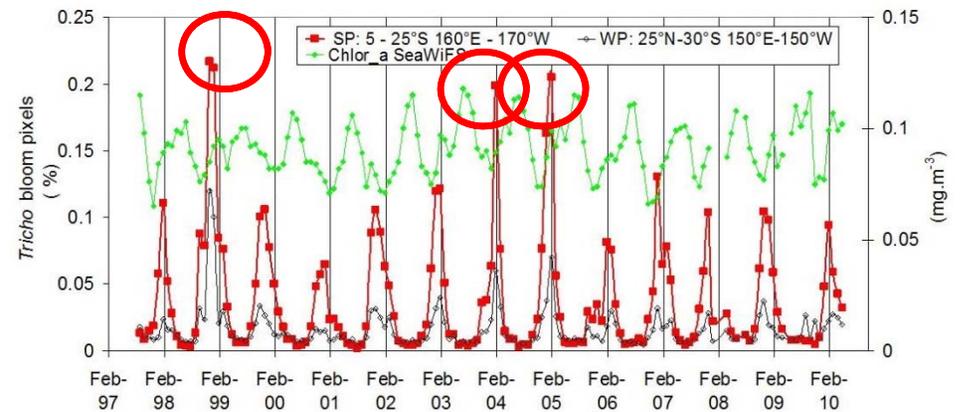
TRICHOSAT: *Trichodesmium* blooms in the STPO

Seawifs image & Tricho obs



- Selection around New Caledonia and Vanuatu : 15°S-25°S
- Selection in SUMMER (max in February 1999, 2003, 2004)
- Complementary of the PHYSAT approach !
- Weakness: detects only surface blooms, low number of pixels (0.1%), works in the South Tropical Pacific Ocean

1997-2010 SeaWiFS series



Dupouy et al., *Biogeosciences*, 8, 1-17 (2011).

Spectral approaches: Absorption-based

Deriving a phytoplankton size factor from satellite reflectances

Reference:

CIOTTI, A.M. and A. BRICAUD. 2006. Retrievals of a size parameter for phytoplankton and spectral light absorption by Colored Detrital Matter from water-leaving radiances at SeaWiFS channels in a continental shelf region off Brazil. *L&O-Methods*, 4: 237 - 253.

INPUTS

Satellite reflectances at
412, 443, 490, 510 nm
(SeaWiFS channels)



OUTPUTS

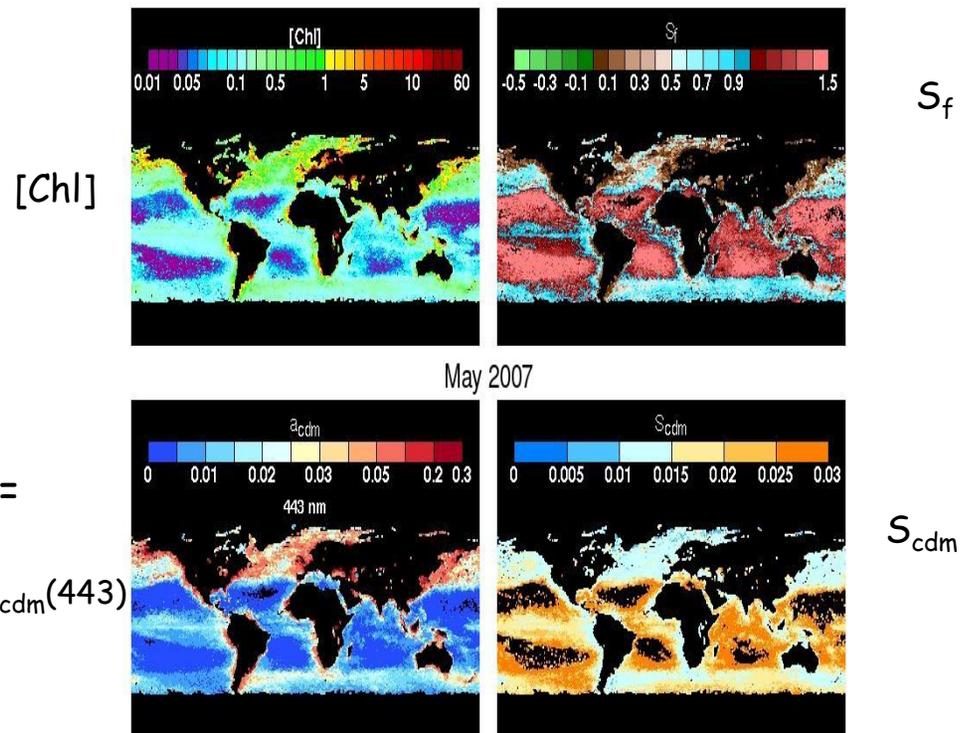
- Dimensionless size factor S_f , varying between 0 (100% micro) and 1 (100% pico)
- Absorption coefficient of CDM ($a_{\text{cdm}}(443)$)
- Spectral slope of CDM absorption (S_{cdm})

General principle:

S_f is estimated from the spectral shape of norm. phytoplankton absorption (according to the package effect)
Satellite reflectances inverted into total absorption coefficients $a_{\text{tot}}(\lambda)$ & chl
Then 3 output variables derived from $a_{\text{tot}}(\lambda)$ by non-linear optimization using a_{ph} ratios which are derived from chl

Validation on shelf waters off Brazil : RMSE = 17% between S_f values estimated from SeaWiFS data and from hyperspectral absorption measured in the field.

Intercomparison with other methods: see Brewin et al. 2011



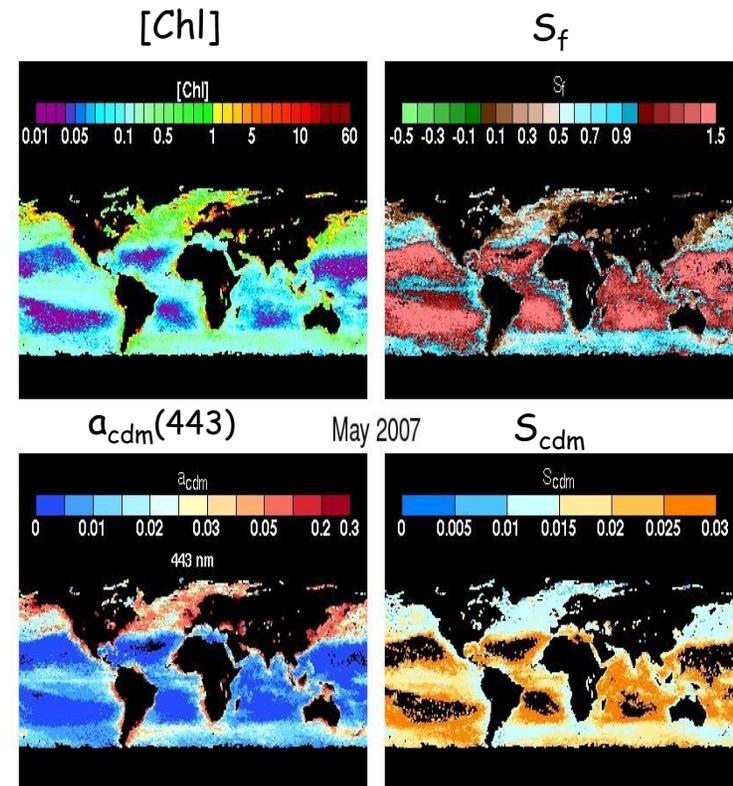
Deriving a phytoplankton size factor from satellite reflectances

Reference:

CIOTTI, A.M. and A. BRICAUD. 2006. *L&O-Methods*, 4: 237 - 253.

Advantages / disadvantages:

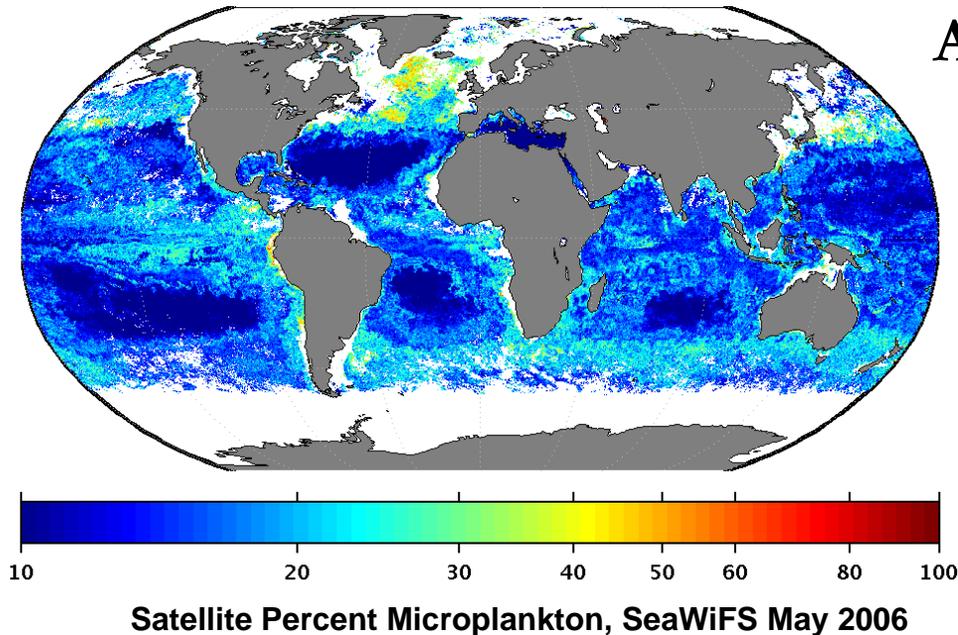
- Spectral-based method: changes in size structure can be detected independently of [Chl] changes
- S_f estimates a continuum of differences in light absorption efficiency, not size fractions *per se*; ranges of sizes can be assumed, but validation is still in progress
- The spectral shape of algal absorption is ruled not only by cell size but also by photoacclimation → source of uncertainty - we are looking for trends in time and space using S_f residuals
- The inversion of reflectances into non-water absorption coefficients, and therefore S_f estimates, are difficult in very clear waters (S_f overestimated)



Application: BRICAUD, A., A.M. CIOTTI and B. GENTILI. 2012. *Global Biogeochemical Cycles*, 26, GB1010, doi :10.1029 /2010GB003952.

Phytoplankton Cell Size: An Absorption Approach Through Look-up Tables

Colleen. B. Mouw and James. A. Yoder (2010)
Optical determination of phytoplankton size
composition from global SeaWiFS imagery.
JGR 115, C12018, doi: 10.1029/2010JC006337.



- **Inputs:** RRS, [Chl] and $a_{\text{CDM}}(443)$
- **Output:** Percent Microplankton
- **Advantages:** Does not assume a direct relationship with chlorophyll. Considers thresholds of sensitivity and the presence of other optically active constituents.
- **Disadvantages:** Retrieves only percent microplankton.
- **Temporal spatial coverage:** Dependent on resolution of sensor.

Validation:

84% within 1 standard deviation,
12%, 2 std. dev., 4%, 3 std. dev.

All data: $r^2 = 0.6$, RMSE=12.64,
1 Std. Dev.: $r^2 = 0.84$,
RMSE=6.35

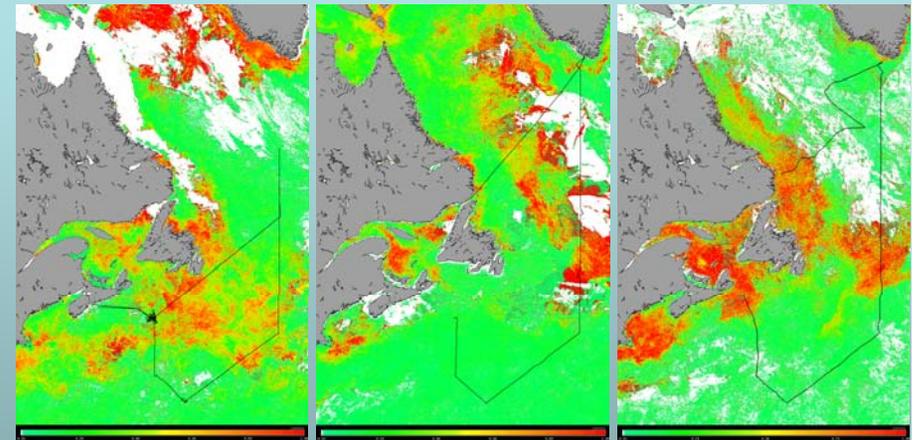
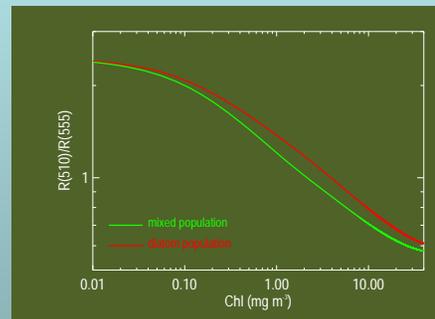
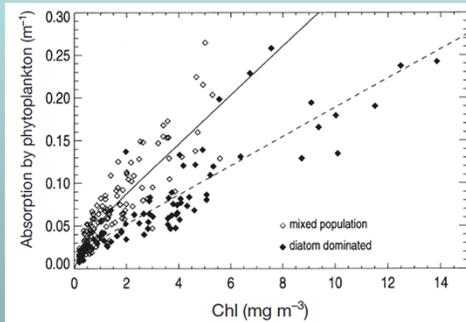
Sensitivity:

SeaWiFS has the sensitivity to retrieve S_{fm}
when: [Chl] 0.05 - 1.75 mg m^{-3} and
 $a_{\text{CDM}}(443) < 0.17 \text{ m}^{-1}$

Of decadal mean imagery,
84% of [Chl] and 99.7% of $a_{\text{CDM}}(443)$
fall within thresholds

Spectrally-resolved approach, from phytoplankton absorption to Diatom (Sathyendranath et al. 2004) and size classes (Sathyendranath et al. 2001, Devred et al. 2006, 2011)

Pixel-based diatom discrimination using spectral information on absorption of diatoms and other phytoplankton populations

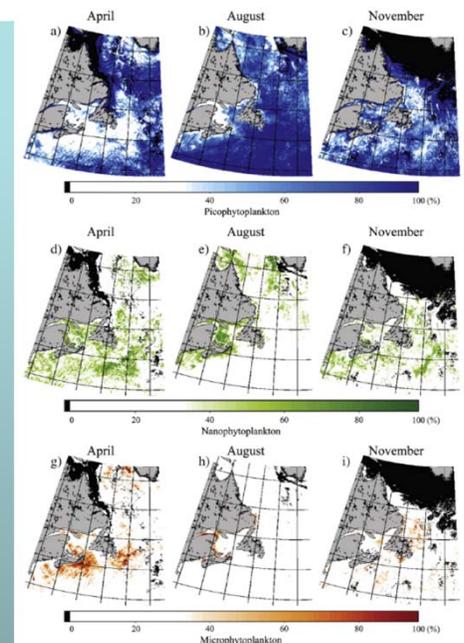
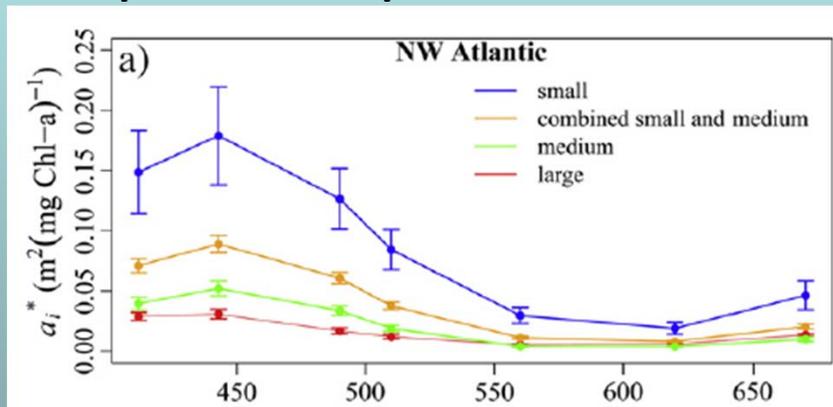


Spring

Summer

Fall

Two-step inversion scheme using linear combination of specific absorption spectra of pico-, nano and microphytoplankton derived from three-component absorption model

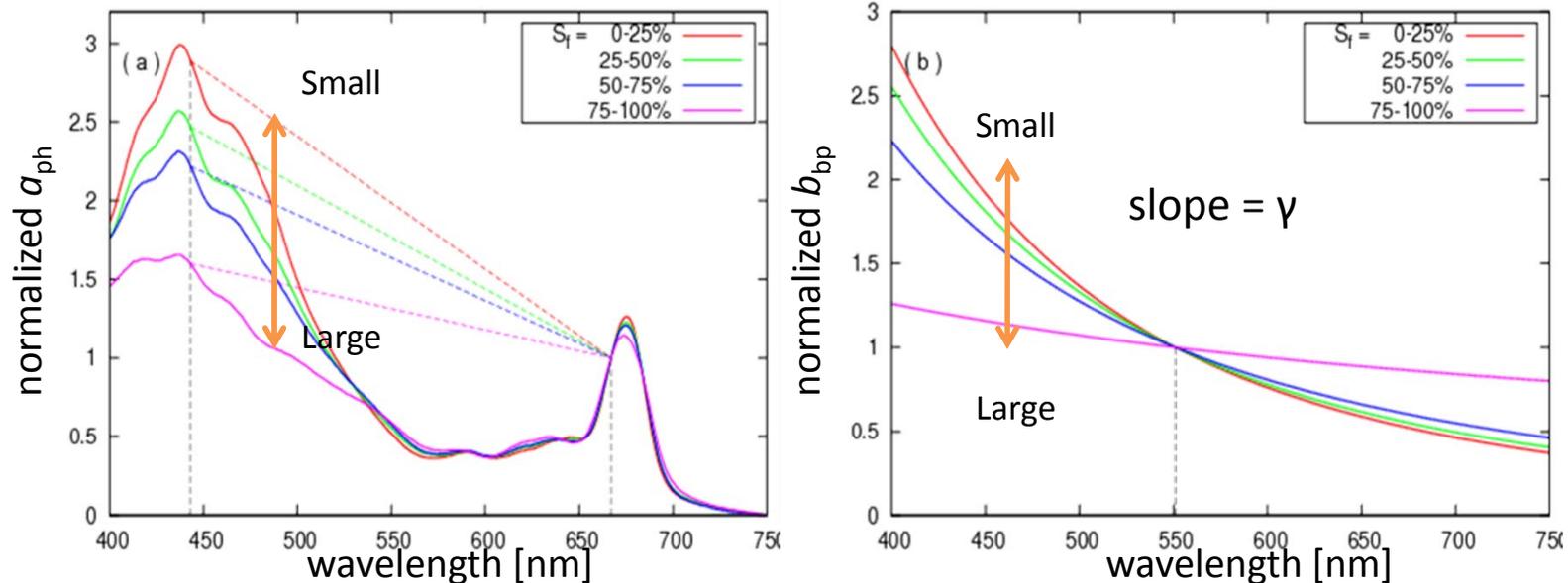


Phytoplankton Size Discrimination Model

Toru Hirawake et al.

Size Index: $F_L = [\text{Chla}_{>5\mu\text{m}} / \text{totalChla}] \times 100 [\%]$

spectral shape of absorption and backscattering coefficients



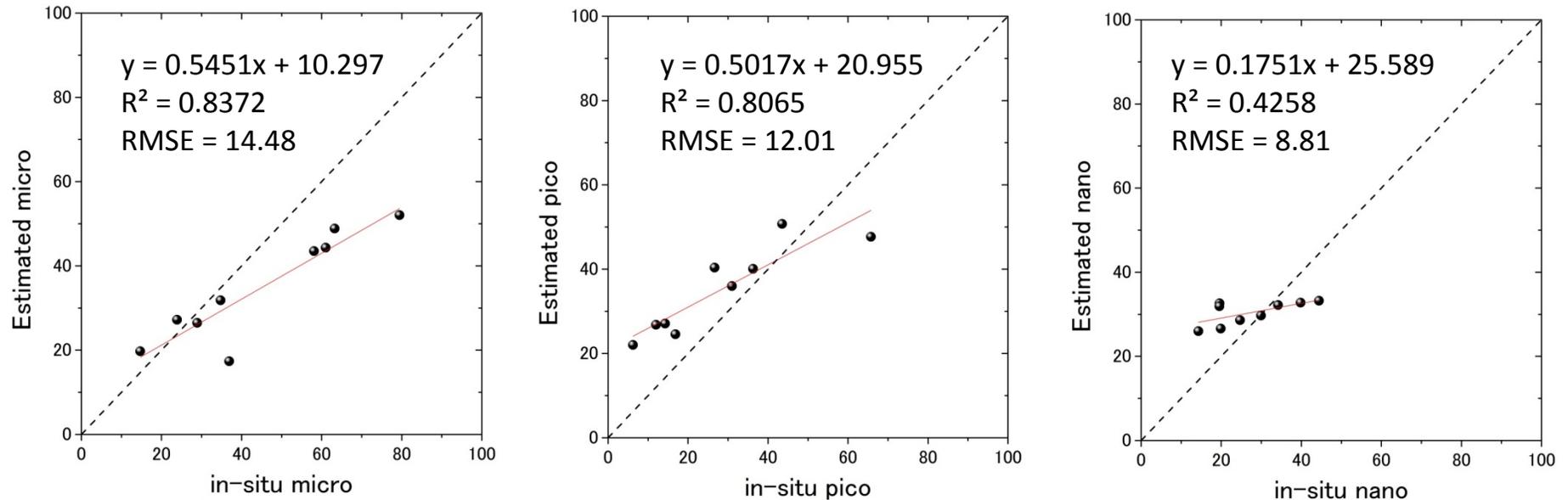
parameterized F_L with a light absorption ratio, $a_{ph}(443)/a_{ph}(667)$, and spectral slope of backscattering spectrum, γ :

$$F_L = \frac{100}{1 + \exp[-(p \times a_{ph}(443)/a_{ph}(667) + q \times \gamma + r)]} [\%]$$

Rrs \rightarrow Optical model
 $\rightarrow a_{ph}, b_{bp}$

Size Discrimination Model (SDM)
 Fujiwara et al. 2011, BG

Validation of the algorithm with *in situ* IOP



$$\text{Microplankton (\%)} = \frac{1}{1 + \exp\left(-\left(-1.34 \times \gamma - 2.41 \times \frac{a_{ph}(490)}{a_{ph}(510)} + 5.54\right)\right)} \times 100$$

$$\text{Picoplankton (\%)} = \frac{1}{1 + \exp\left(-\left(1.08 \times \gamma + 1.67 \times \frac{a_{ph}(490)}{a_{ph}(510)} - 5.23\right)\right)} \times 100$$

Toru Hirawake et al.

$$\text{Nanoplankton (\%)} = 100 - (\text{Microplankton}) - (\text{Picoplankton})$$

The Partial Least Squares regression (PLS) approach

Reference: Organelli E., Bricaud A., Antoine D., Uitz J. (2013). Multivariate approach for the retrieval of phytoplankton size structure from measured light absorption spectra in the Mediterranean Sea (BOUSSOLE site). *Applied Optics*, 52(11), 2257-2273.

INPUT

Fourth-derivative spectra of
PARTICLE or PHYTOPLANKTON
light absorption (400-700 nm)



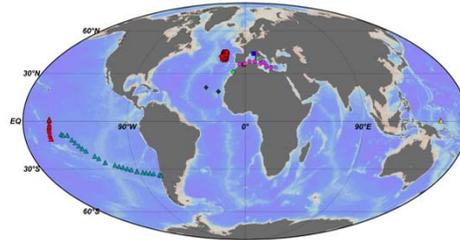
OUTPUT (in mg m^{-3})

[TChl *a*]
[DP] ([Micro]+[Nano]+[Pico])
[Micro] ($1.41 \cdot [\text{Fuco}] + 1.41 \cdot [\text{Perid}]$)
[Nano] ($1.27 \cdot [19'\text{-HF}] + 0.35 \cdot [19'\text{-BF}] + 0.60 \cdot [\text{Allo}]$)
[Pico] ($1.01 \cdot [\text{TChl } b] + 0.86 \cdot [\text{Zea}]$)

PLS-MODELS development:

TRAINING (data from First Optical Depth)

1. GLOBAL data set (n=716): data from various locations of the world's oceans;
2. MedCAL data set (n=239): data from the Mediterranean Sea only.

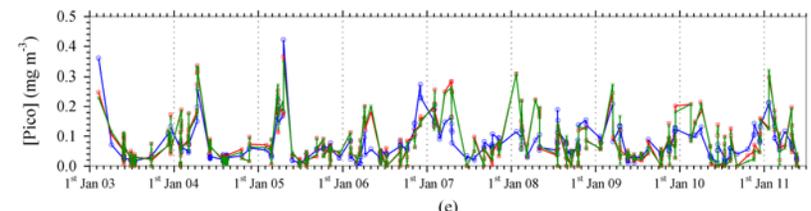
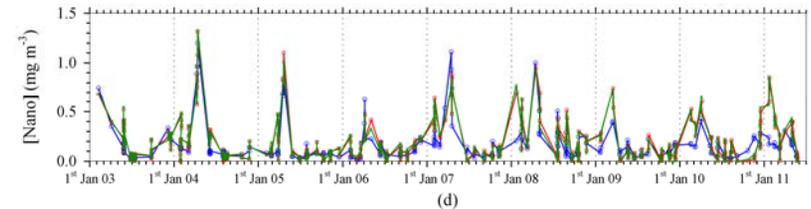
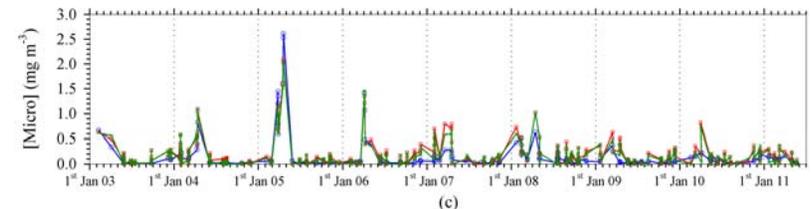
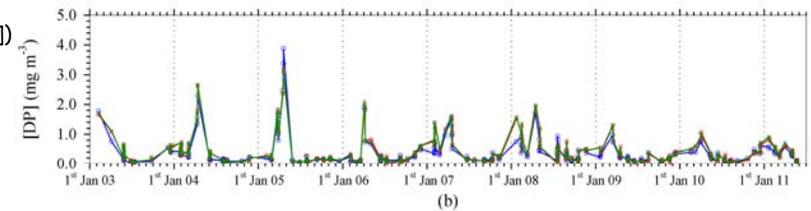
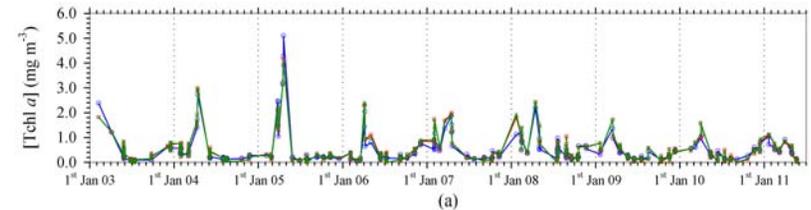


TEST (data from First Optical Depth)

BOUSSOLE time series (2003-2011; n=484)

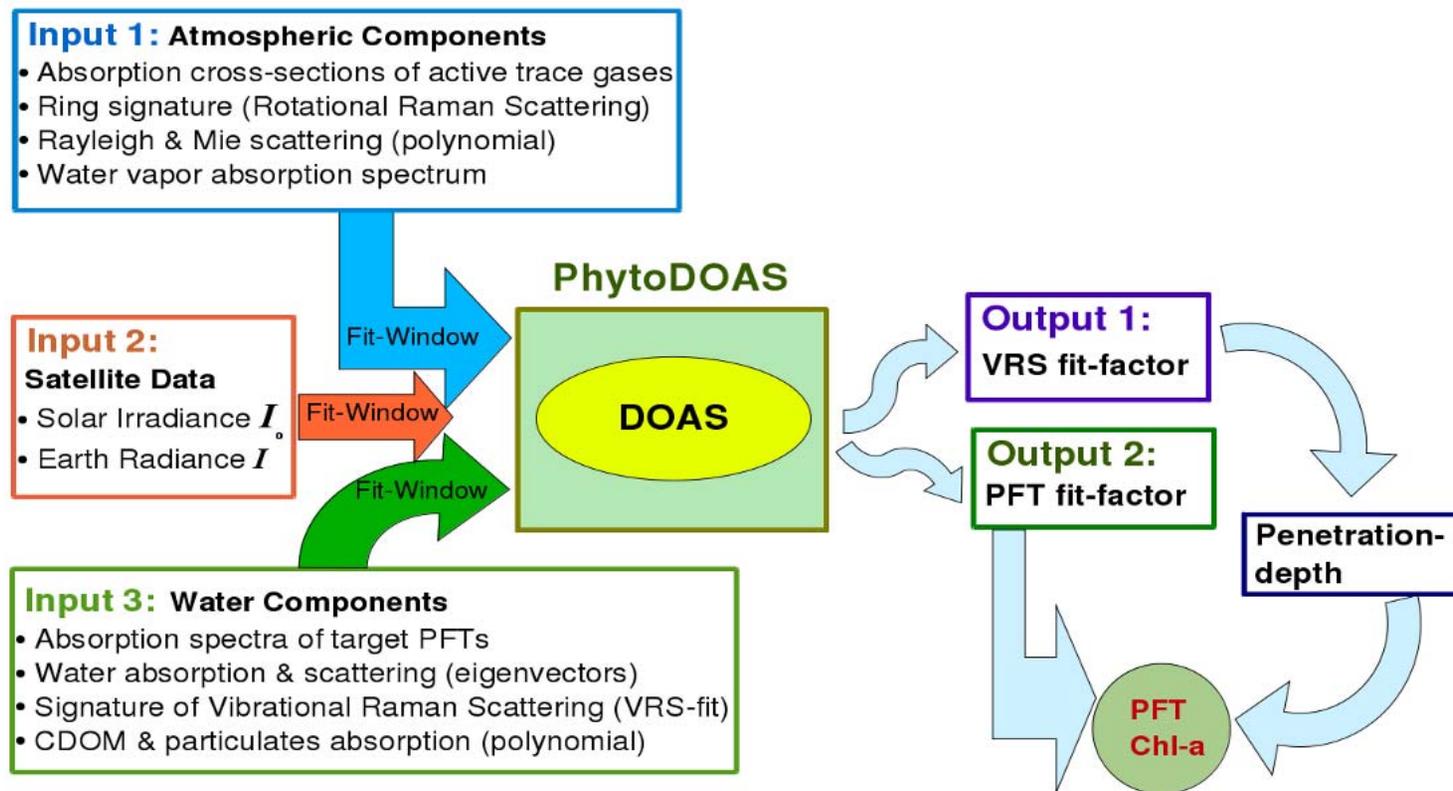
Results, advantages and disadvantages:

1. Accurate TChl *a* and size structure retrievals over the BOUSSOLE time series (analysis of seasonal dynamics!);
2. Insensitivity to NAP and CDOM absorption (it could be extended to reflectance-derived products!);
3. High prediction accuracy of the regional data set (MedCAL).



— HPLC — $a_p(\lambda)$ PLS model — $a_{phy}(\lambda)$ PLS model

Hyperspectral **SCIAMACHY/ENVISAT** data: 240-2400 nm, <1 nm resol, 30km x 60km
Differential Optical Absorption Spectroscopy (DOAS) at 430-530 nm:



PFT SCIAMACHY data 2002-2012

Now: application to GOME-2 (2007-, 2012-, 2018-)

Future: OMI (2004-), Sentinel-5-P, S-4, S-5 (2015-, 2019-, 2020-): daily – 7 km x 7 km pixel

Biomass of Four Phytoplankton Groups with PhytoDOAS

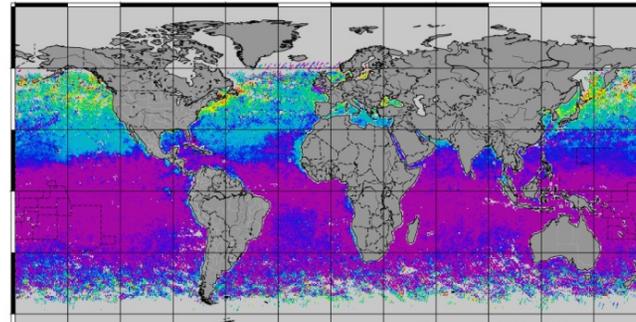
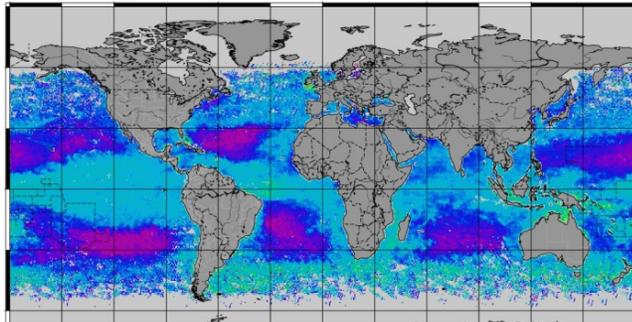
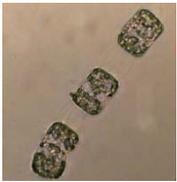


Bracher et al. BG 2009; Sadeghi et al. OS 2012



Mean Chl-a Mar 2007

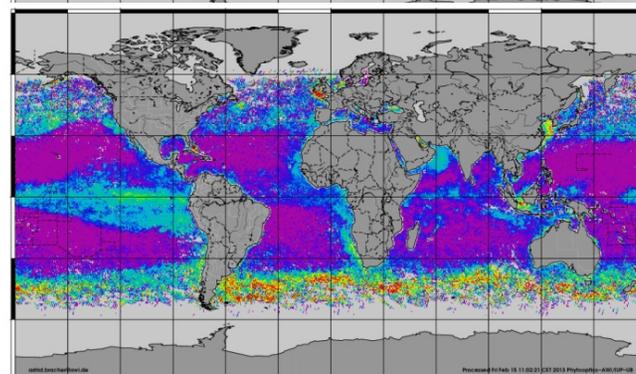
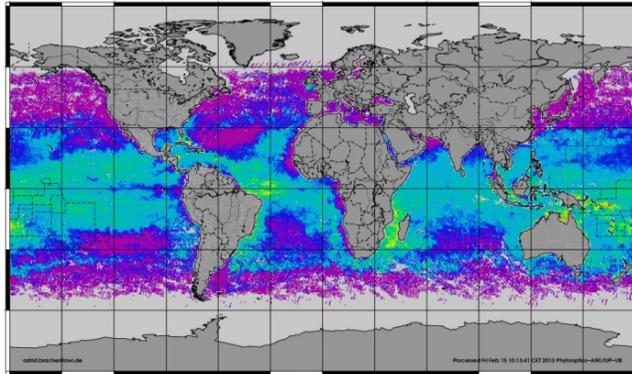
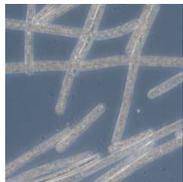
Diatoms



Dinoflagellates



Cyano-
bacteria



Coccolitho-
phores



0.005 0.010 0.050 0.100 0.200 0.300 0.400 0.500 0.600 0.700 1.000 chl-a conc. [mg/m³]

Sensitivity tested with RTM SCIATRAN simulations: at 0.1-30 mg/m³ chl-a within 15%

In-situ validation diatoms and cyanos: within 30%

Coccolithophore products agree well with MODIS PIC, ok with NOBM PFT, good with RGB bloom detection

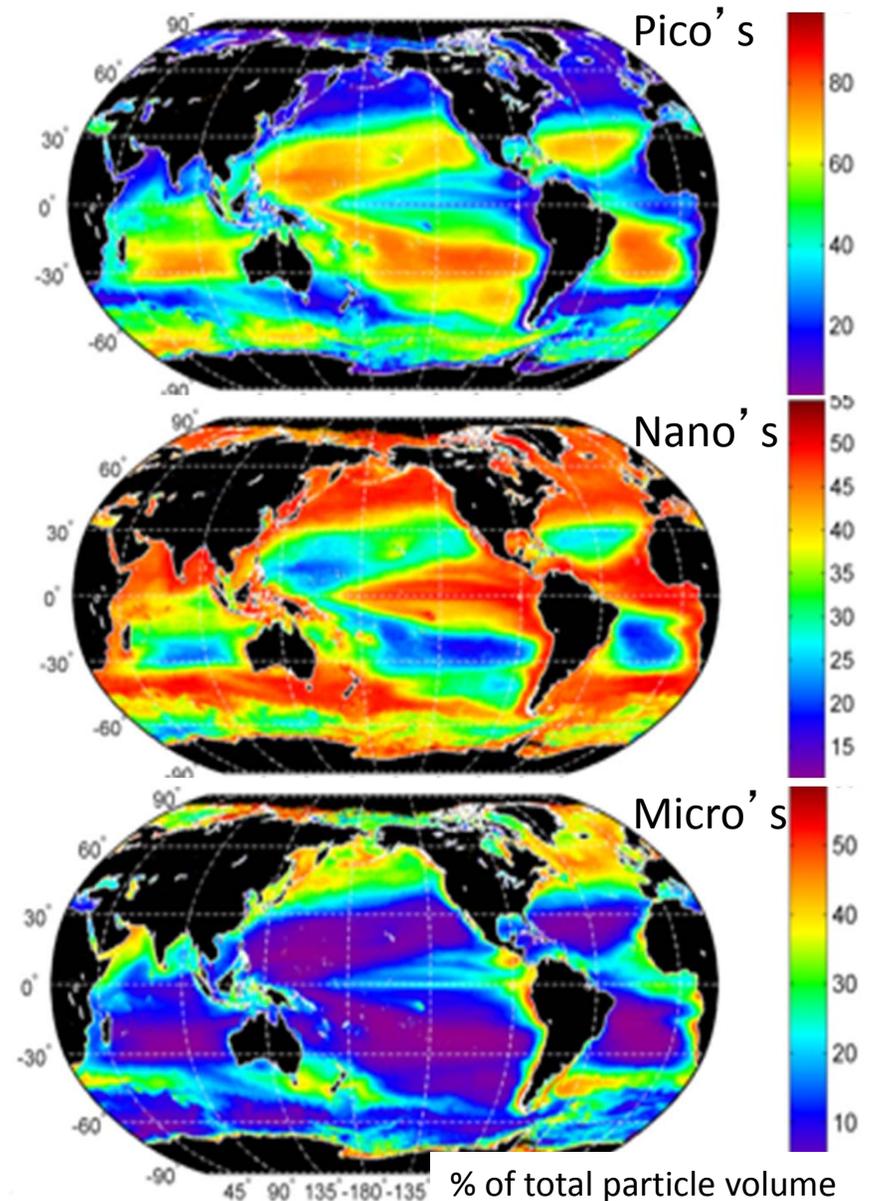
Application: coccolithophores (Sadeghi et al. BG 2012); cyanobacteria (Ye et al. 2012)

Spectral approach using backscatter: Particle (not phytoplankton only) size distribution

Particle Size Distribution (PSD) from Satellite

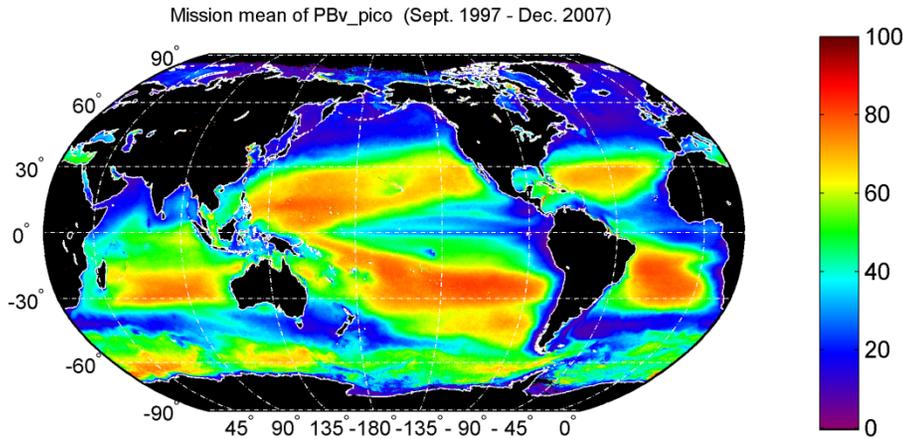
Kostadinov, Siegel & Maritorena [2009] JGR

- Mie theory is used to model PSD as a function of spectral backscatter
- The parameters of a power-law PSD are retrieved
- Particle volumes can be partitioned into pico-, nano- & micro-sizes
 - Pico's dominate oligotrophic regions
 - Micro's are found only in high latitudes & upwelling regions
- Size based approach for assessing plankton functional type

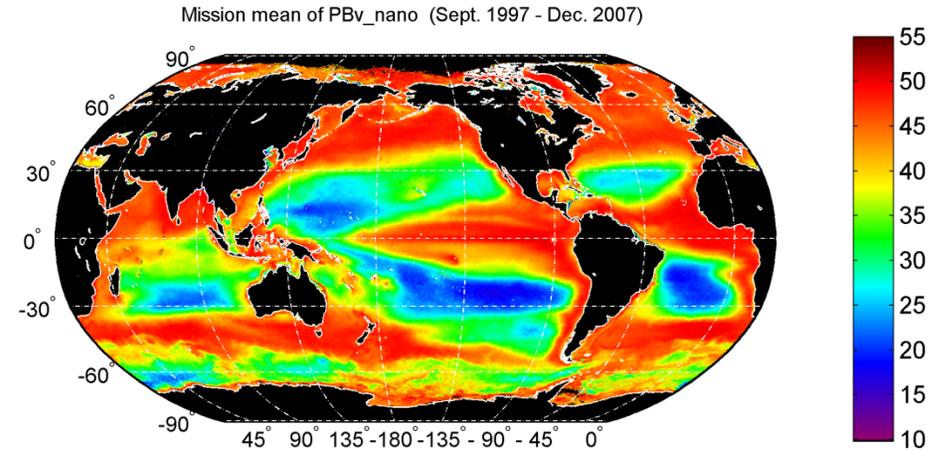


SeaWiFS PFT's = f(PSD slope)

Picoplankton % (0.5 μm to 2 μm)



Nanoplankton % (2 μm to 20 μm)

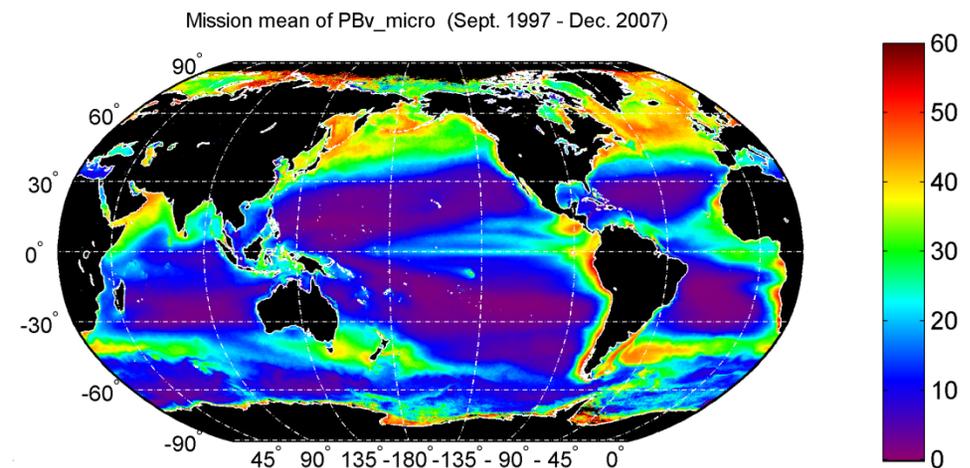


Pico's dominate oligotrophic ocean (>90%)

Nano's in transition regions (~50%)

Micro's only found in upwelling zones & high latitudes (<60%)

Microplankton % (20 μm to 50 μm)



Summary

Variety of approaches shown to get multiple phytoplankton size class (PSC) or functional type (PFT)

Techniques to retrieve the abundance or spectral differences of PSC or PFTS range from

- fast and simple (abundance) versus getting direct physiological interpretation via spectral variations**
- purely empirically to physical (accounting for imprints of PSC or PFTs on radiative transfer)**

Most techniques shown were global

Applications of using these satellite PFTs have started, mostly for evaluation of biogeochemical/ecosystem models, also inferring atmospheric emissions

In order to become operational, these algorithms have to be validated, intercompared and adapted to new sensors in a concise way