Phytoplankton Biodiversity in the Coastal Zone using Hyperspectral Sensing

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IOCS 2015, San Francisco





Hyper- vs Multispectral: What advantages for phytoplankton diversity applications?

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Hyperspectral radiometry contains considerable potential information on phytoplankton community characteristics, above the first order signal variability typically determined by gross constituent concentrations. Such information has significant value across a broad range of applications, ranging from water quality to long term understanding of ecosystem variability

We anticipate the launch of several hyperspectral sensors in the next five – seven years, with high quality radiometry and useable repeat cycles. Such sensors require complex compromises between user needs, increased spectral information, quality of radiometry, swath width/revisit times and other engineering/cost constraints….

Arguably, the community needs a clear and quantitative case outlining the advantages (and disadvantages) of hyperspectral missions across a wide range of water types; typical assemblage variability/succession types and targeted phytoplankton groups, biogeochemistry etc; and the ability to meet user needs and demonstrate impacts of achieving an innovative sensing capability….

Hyper- vs Multispectral: What advantages for phytoplankton diversity applications?

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Main advantages of hyperspectral radiometry:

- Increased number of spectral bands, i.e. equivalent of additional multi-spectral bands, allowing the targeting of new phenomena e.g. phycoerythrin and phycocyanin absorption and fluorescence, longer wavelength scattering related features….

- High spectral resolution allows new techniques such as derivative analyses, similarity indices, and targeting the precise wavelength location of shifting spectral peaks….

- High spectral resolution allows new atmospheric correction/reflectance processing techniques targeting removal of gaseous absorption related features in the water leaving radiance….

Hyperspectral Sensors: Emerging Opportunities…

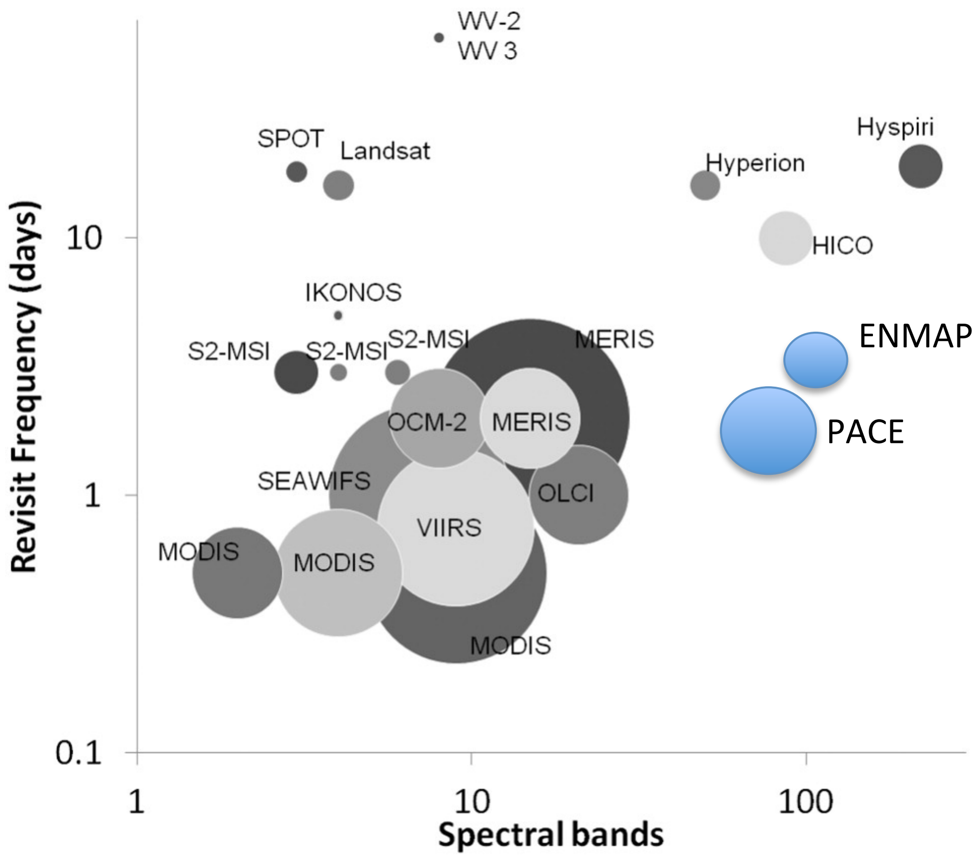

Fig. 5. The spectral (x-axis), temporal (y-axis), and spatial (size of the bubble) characteristics of satellite sensors commonly used for freshwater ecosystem measurements. Note: sensors that provide different spatial resolutions are plotted separately, and sensors with overlapping resolution characteristics are slightly jittered for graphing purposes.

Hestir, E.L., et al., Measuring freshwater aquatic ecosystems: The need for a hyperspectral global mapping satellite mission, Remote Sensing of Environment (2015), http://dx.doi.org/10.1016/j.rse.2015.05.023

Hyperspectral Sensors: Need for High Quality Radiometry

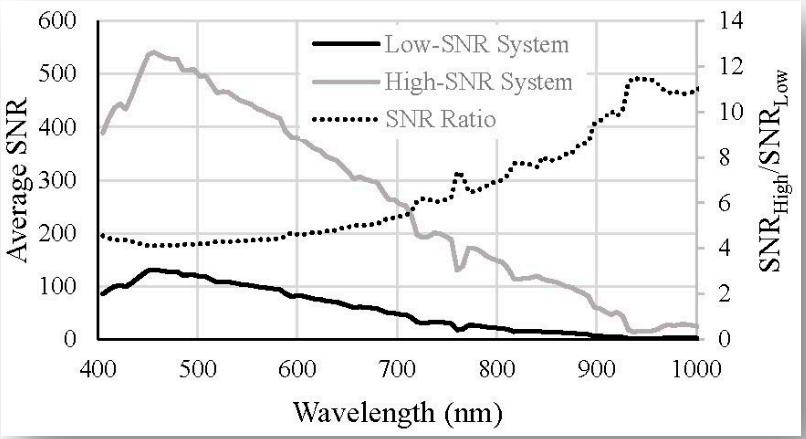

Figure 2. The average SNR calculated from the at-sensor radiances (of all 490 images) for the low- and high-SNR systems. The ratio of the average SNR for the high-SNR system to that for the low-SNR system is plotted on the secondary axis.

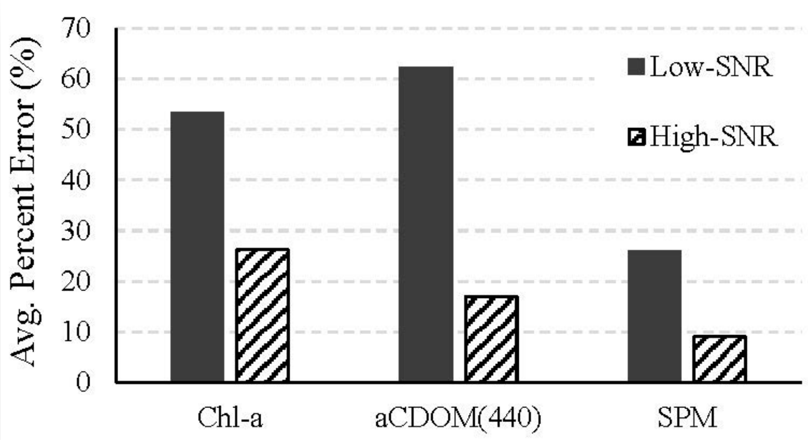

Figure 9. The average percent errors for the low- and high-SNR systems in the concentrations of chl-*a* and SPM and $a_{CDOM}(440)$ retrieved from the 20 atmospherically corrected noisy images using the non-linear least squares error minimization approach

Moses, W.J.; Bowles, J.H.; Corson, M.R. Expected Improvements in the Quantitative Remote Sensing of Optically Complex Waters with the Use of an Optically Fast Hyperspectral Spectrometer—A Modeling Study. Sensors 2015, 15, 6152-6173.

In Situ Measurements: Need for Improved Capability

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HPLC & CHEMTAX ≠ necessary biophysical phytoplankton assemblage data

We cannot use satellites to determine phytoplankton diversity if we do not routinely make sufficiently detailed measurements of that diversity. There needs to be a community and agency push towards broader adoption, further development and standardised protocols for emerging sensors such as imaging flow cytometers, holographic microscopes and other technologies allowing routine measurements of detailed cellular information such as size and taxonomy.

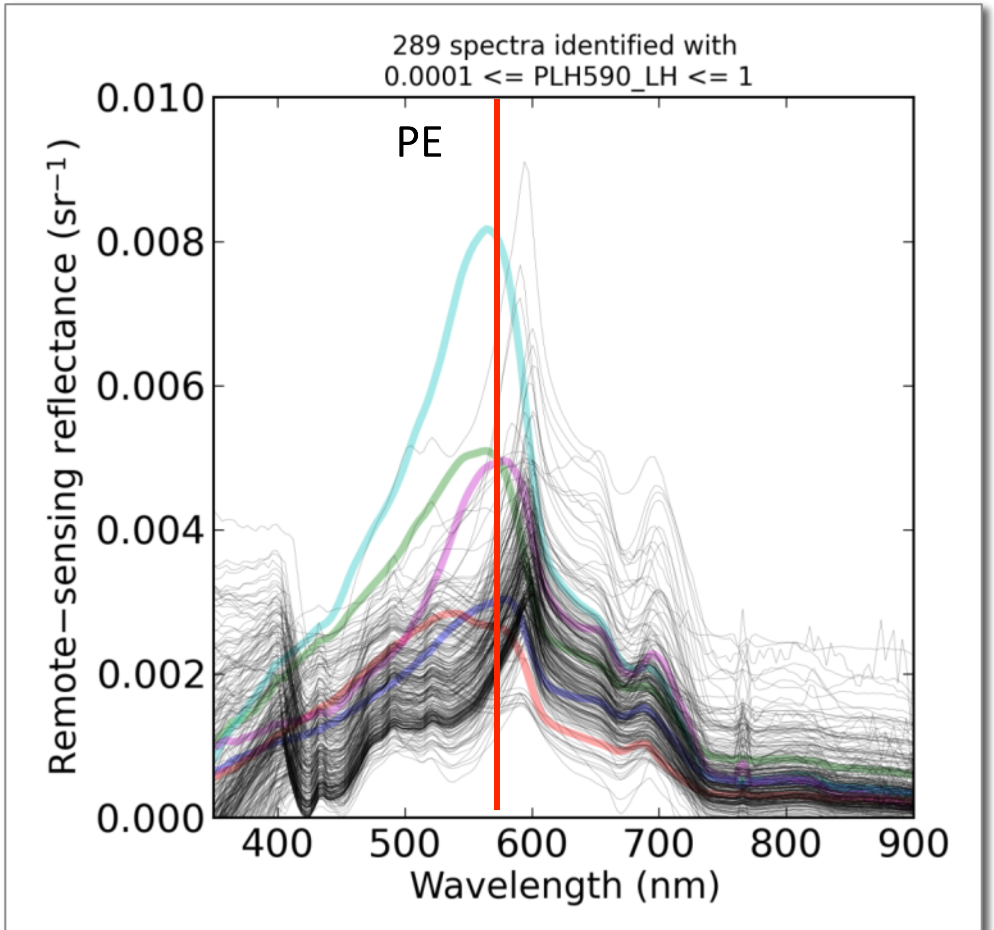
Report on IOCCG workshop: "Phytoplankton Composition from Space: towards a validation strategy for satellite algorithms", October 2014

Consideration of the measurements required for validating PFT algorithms produced the following list.

- Size-fractionated measurements of both HPLC pigments and particulate light absorption.
- Measurements of phycobilin concentrations, equally in size fractions, to the suite of pigments (for Synechococcus, cryptophytes, Trichodesmium)
- FlowCytobot/FlowCAM/flow cytometry (both traditional and imaging)
- Radiometry, both above water and in-water, hyperspectral
- Inherent optical properties (absorption, backscattering, VSF)
- Particle size distribution (PSD, e.g. via LISST)
- Size-fractionated measurements
- Genetics/-omics

Hyperspectral Approaches: Examples of Additional Spectral Information

From 100963 spectra collected in the Baltic Sea…



…289 (0.29%) show extreme phycoerythrin absorption and a distinct orange peak at 590-600 nm

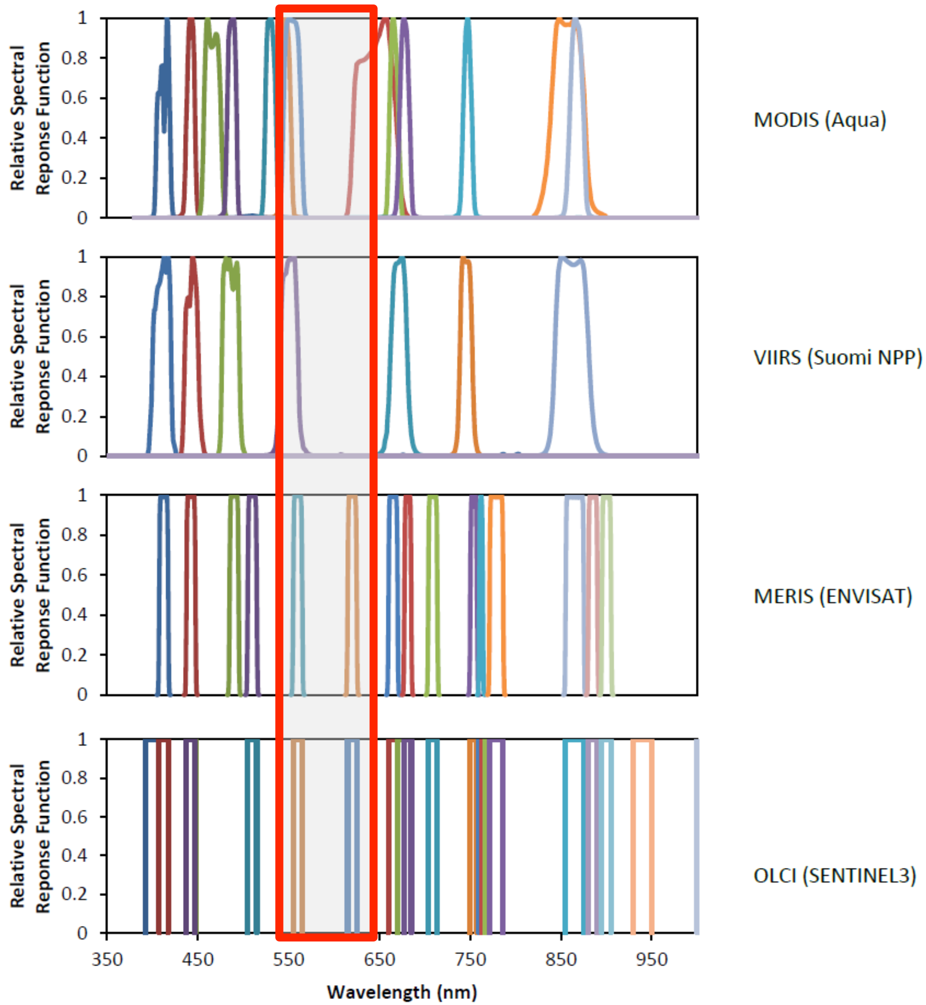
Possibly fluorescence by PE

FerryScope
www.ferryscope.org

Simis et al. *in prep*

Hyperspectral Approaches: Examples of Additional Spectral Information

No 590 nm band from current sensors



Hyperspectral Approaches: Examples of Additional Spectral Information

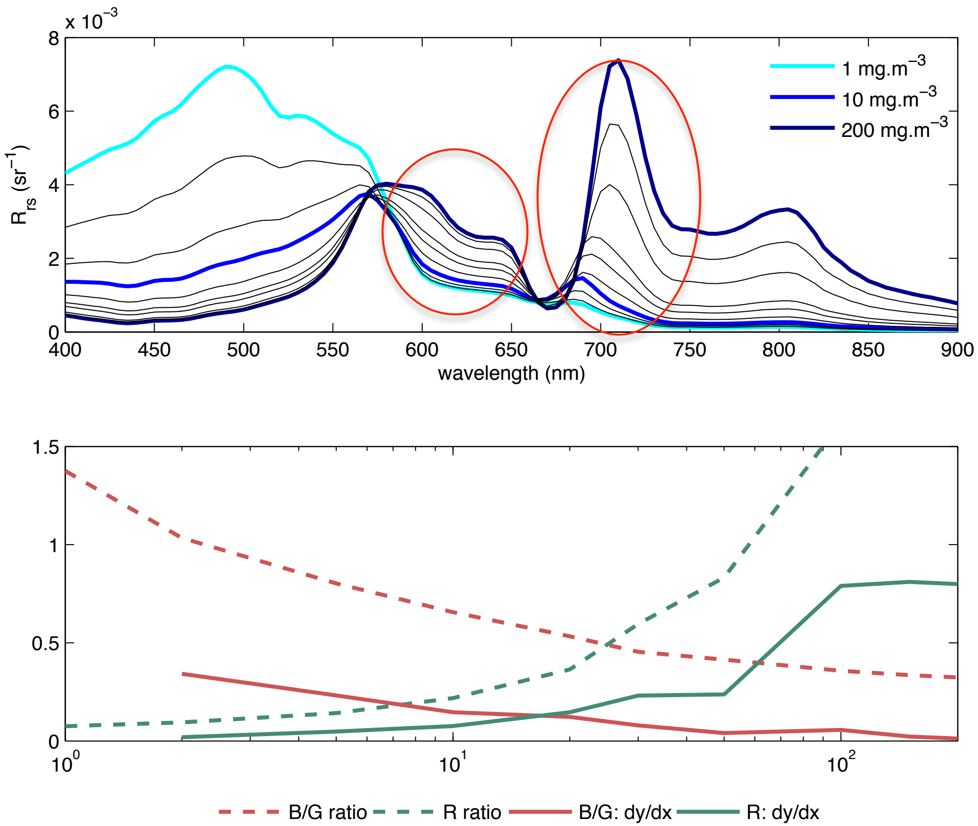


Fig. 6. Modelled EAP R_{rs} (above) for typical dinoflagellate assemblage with effective diameter of 16 μm. Chl a concentrations are 1, 2, 5, 10, 20, 30, 50, 100, 150, 200 mg.m^{-3}. Below the shift from maximum peak reflectance height in the blue/green to the red is shown (dotted lines), for increasing Chl a. The first derivatives of these slopes (solid lines) cross at a Chl a of around 15 mg.m^{-3}, the point at which the red features of high biomass reflectance spectra start to dominate.

Eutrophic and hypertrophic waters contain considerable phytoplankton scattering related signal in the 570 – 650 nm and above 680 nm. Additional hyperspectral related signal in these regions would be very valuable….

Robertson Lain, L., Bernard, S., and Evers-King, H. (2014) Biophysical modelling of phytoplankton communities from first principles using two-layered spheres: Equivalent Algal Populations (EAP) model. Optics Express, 22(14), 16745–16758..

Hyperspectral Approaches: Examples of Phytoplankton Diversity Applications….Multiple Groups

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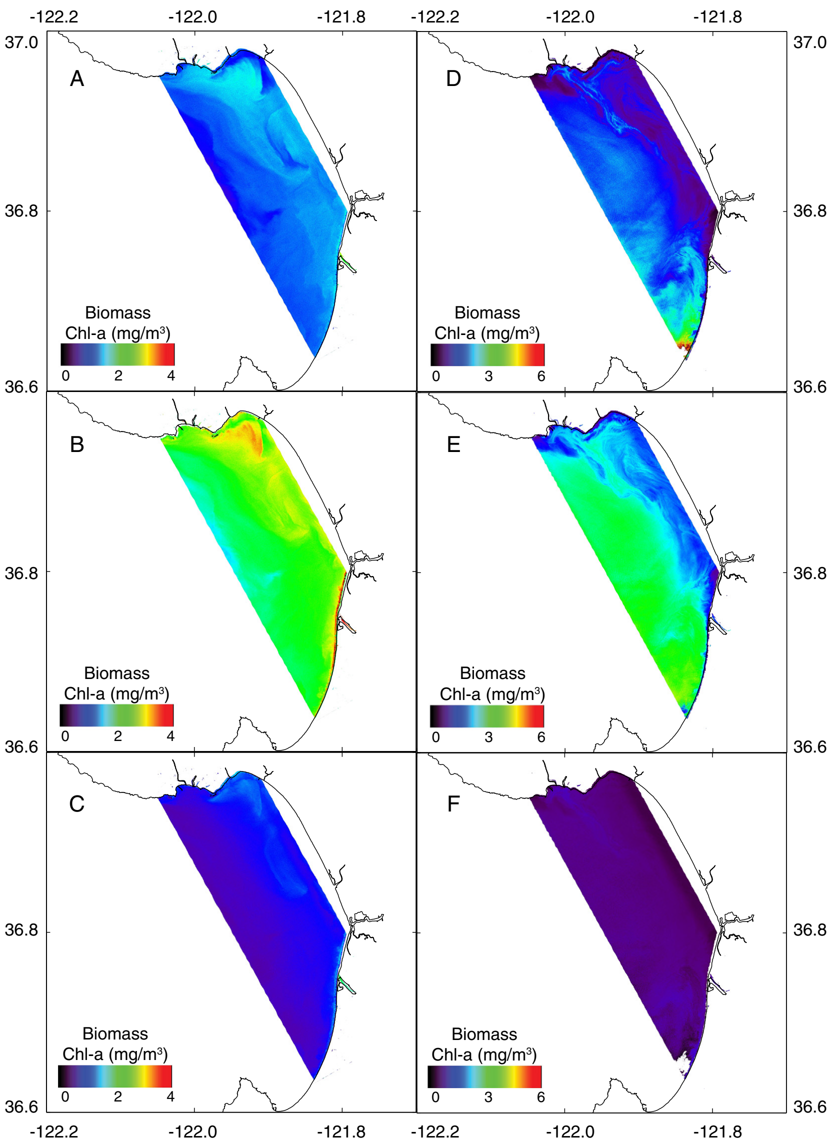

HyspIRI simulations from airborne data using the PHYDOTax spectral library/inversion approach

Fig. 5. Phytoplankton biodiversity — PHYDOTax estimates. Taxon-specific biomass estimated for dinoflagellates, diatoms, and cyanobacteria using PHYDOTax applied to the ATREM+ at- mospheric corrected imagery. 10 Apr 2013: A) dinoflagellates, B) diatoms, C) cyanobacteria, D) dinoflagellates, E) diatoms, F) cyanobacteria.

Palacios, S.L., et al., Remote sensing of phytoplankton functional types in the coastal ocean from the HyspIRI Preparatory Flight Campaign, Remote Sensing of Environment (2015), http://dx.doi.org/10.1016/j.rse.2015.05.014

Hyperspectral Approaches: Examples of Phytoplankton Diversity Applications….Cyanobacteria

Table 3. Spectral indices (x) derived from AISA reflectance spectra and their relationships to correlation to measured phycocyanin concentration (y).

Spectral index	Model	R^2	RMSE($\mu g\ l^{-1}$)
[1]$0.5(R_{600} + R_{647}) - R_{628}$	$\log_{10}(y) = 0.008x^{-0.93}$	0.69	30.42
[2]R_{647} / R_{628}	$\log_{10}(y) = -99.61x^2 + 218.5x - 117.8$	0.62	30.92
[3]R_{704} / R_{628}	$\log_{10}(y) = -3.137(\log_{10}(x))^2 + 10.21\log_{10}(x) - 6.256$	0.47	32.46
[4]R_{628}	$\log_{10}(y) = 0.2896e^{-1.104}\log_{10}(x)$	0.80	25.52

[1] Dekker (1993); [2] Schalles and Yacobi (2000); [3] Simis *et al.* (2005); [4] Millie *et al.* (1992).

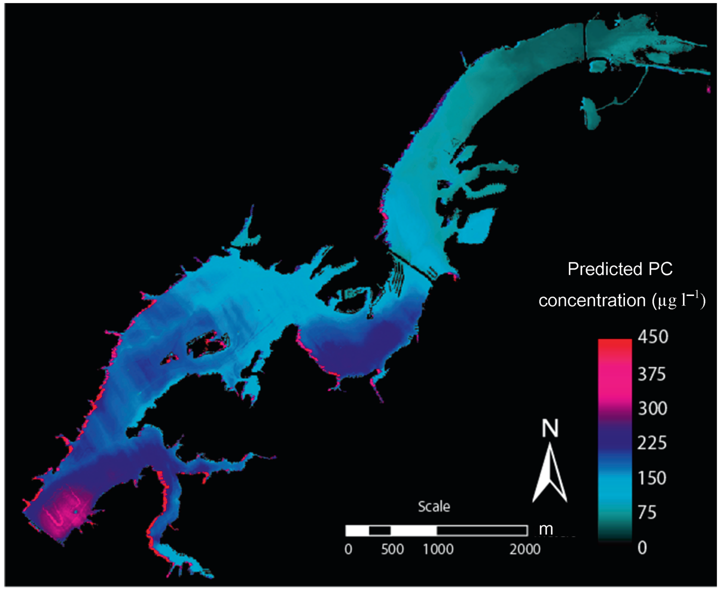

Figure 7. Phycocyanin (PC) concentration derived by applying the relationship shown in figure 5 to the calibrated AISA imagery of Geist Reservoir (see figure 1 for its location). Note that a PC 'hot spot' is located on the left side of the figure, and the high PC value along the shore of this reservoir is due to the effect of the bottom reflection, which cannot be accounted for by the relationship in figure 5.

Spectral ratio based approach

Lin Li , Rebecca E. Sengpiel , Denise L. Pascual , Lenore P. Tedesco , Jeffrey S. Wilson & Emmanuel Soyeux (2010) Using hyperspectral remote sensing to estimate chlorophyll-a and phycocyanin in a mesotrophic reservoir, International Journal of Remote Sensing, 31:15, 4147-4162

Hyperspectral Approaches: Examples of Phytoplankton Diversity Applications….Cyanobacteria

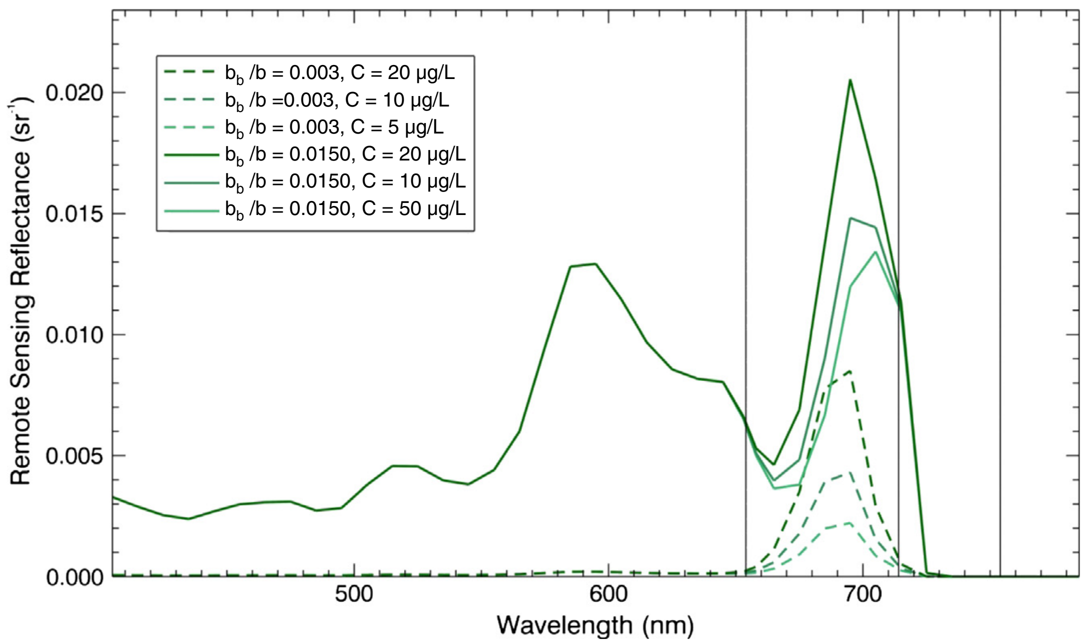

Fig. 4. Results from the SLH algorithm derived from Hydrolight simulations of cyanobacteria, with varying concentrations of chlorophyll and backscattering ratios. SLH is relatively insensitive to changes in chlorophyll. Vertical gray lines indicate MASTER bands used for SLH.

Scattering based approach

Kudela, R.M., et al., Application of hyperspectral remote sensing to cyanobacterial blooms in inland waters, Remote Sens- ing of Environment (2015), http://dx.doi.org/10.1016/j.rse.2015.01.025

Hyperspectral Approaches: Examples of Phytoplankton Diversity Applications….Phaeocystis

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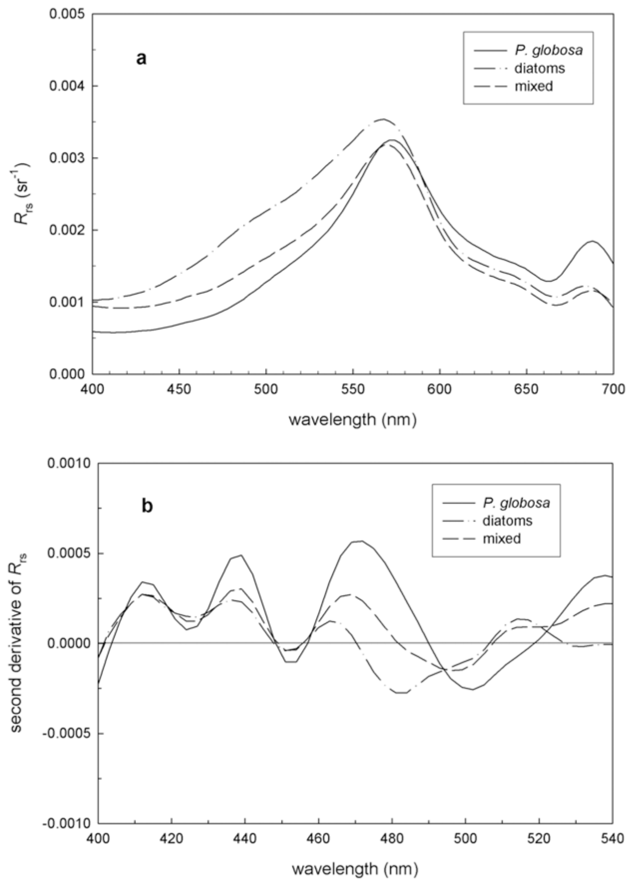


Figure 4. (a) Mean and (b) second derivatives spectra of $R_{rs}(\lambda)$ associated with the group 1 (*P. globosa*), group 2 (mixed), and group 3 (diatoms) (see Table 1).

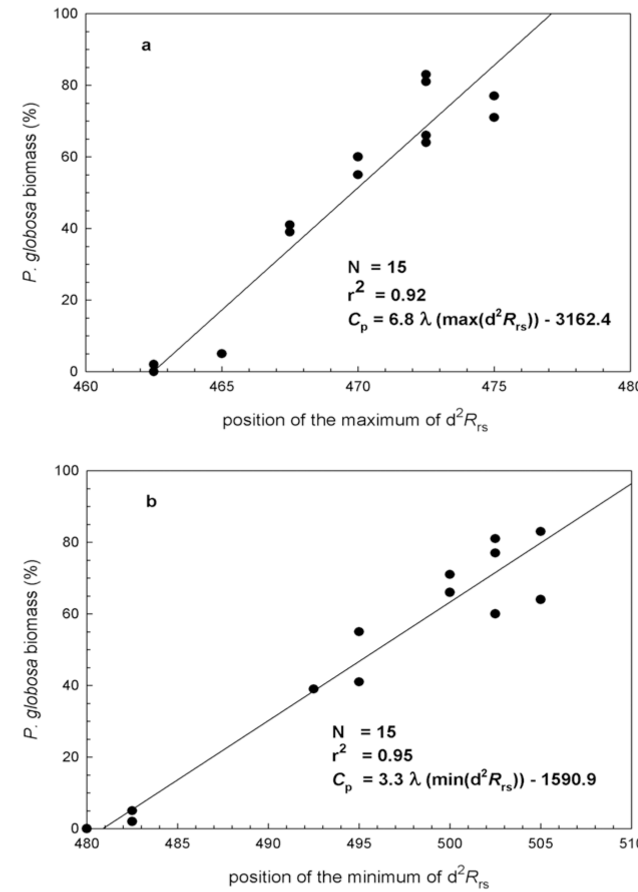
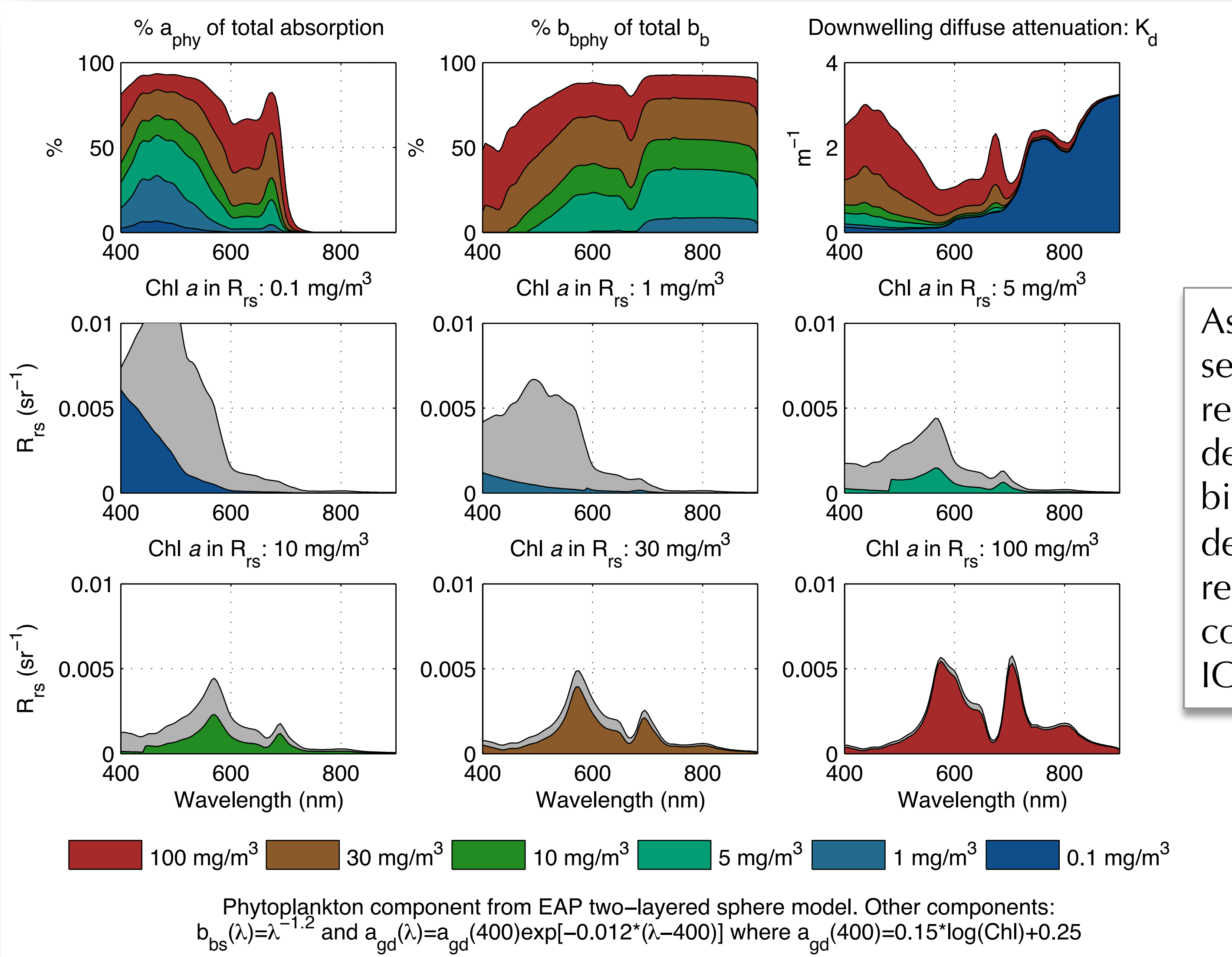


Figure 5. Variation of the *P. globosa* biomass (C_p, expressed in %) as a function of (a) the position of the maximum of the second derivative of $R_{rs}(\lambda)$ in the range 460–480 nm ($\lambda(\max(d^2R_{rs}))$), and (b) the position of the minimum of the second derivative of $R_{rs}(\lambda)$ in the range 480–510 nm ($\lambda(\min(d^2R_{rs}))$). The black lines represent the linear regressions between Figure 5a C_p and $\lambda(\max(d^2R_{rs}))$, and Figure 5b C_p and $\lambda(\min(d^2R_{rs}))$. The regression equations, the number of observations (N), and the squared correlation coefficient (r^2) are given.

Lubac, B., H. Loisel, N. Guiselin, R. Astoreca, L. Felipe Artigas, and X. Mériaux (2008), Hyperspectral and multispectral ocean color inversions to detect Phaeocystis globosa blooms in coastal waters, J. Geophys. Res., 113,

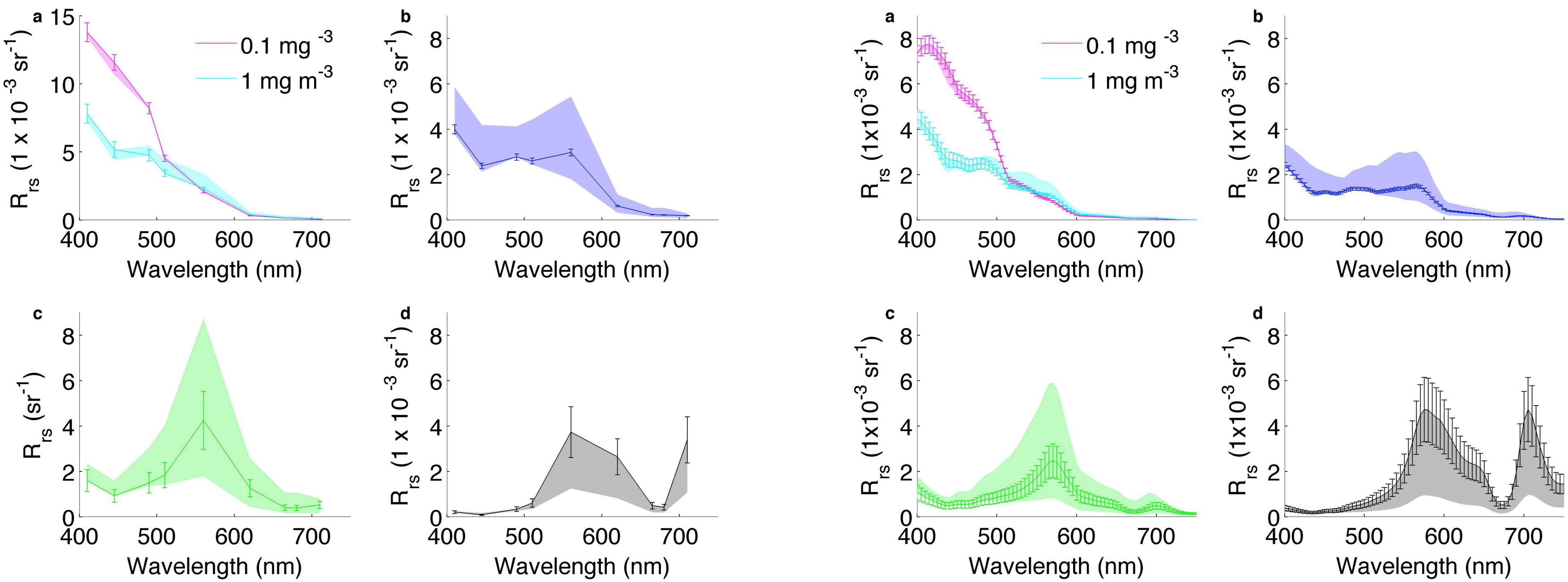
IOP Budget Based Assemblage Contribution to the Ocean Colour Signal



Assemblage related sensitivity in reflectance is highly dependent on algal biomass, as determined by the relative algal contribution to the IOP budget…

after Robertson Lain, L., Bernard, S., and Evers-King, H. (2014) Biophysical modelling of phytoplankton communities from first principles using two-layered spheres: Equivalent Algal Populations (EAP) model. Optics Express, 22(14), 16745–16758..

Phytoplankton size and the changing hyperspectral signal with increasing biomass



reflectance over modelled size range (suitable for biomass based on allometry) at a) 0.1, 1 b) 3 c) 10 and d) 100 mg/ m3 [Chl a]. The central solid line represents the modelled value plus expected measurement uncertainties at effective diameter = 10 microns

An Equivalent Algal Population model coupled to Ecolight allows description of the reflectance range associated with assemblage effective diameters from 4 to 40 μm. Case 1 waters only, i.e. the best case scenario….

after Evers-King, H., Bernard, S., Robertson Lain, L., and Probyn, T. A. (2014) Sensitivity in reflectance attributed to phytoplankton cell size: forward and inverse modelling approaches. Optics Express, 22(10), 11536–11551.

Phytoplankton size and the changing hyperspectral signal with increasing biomass

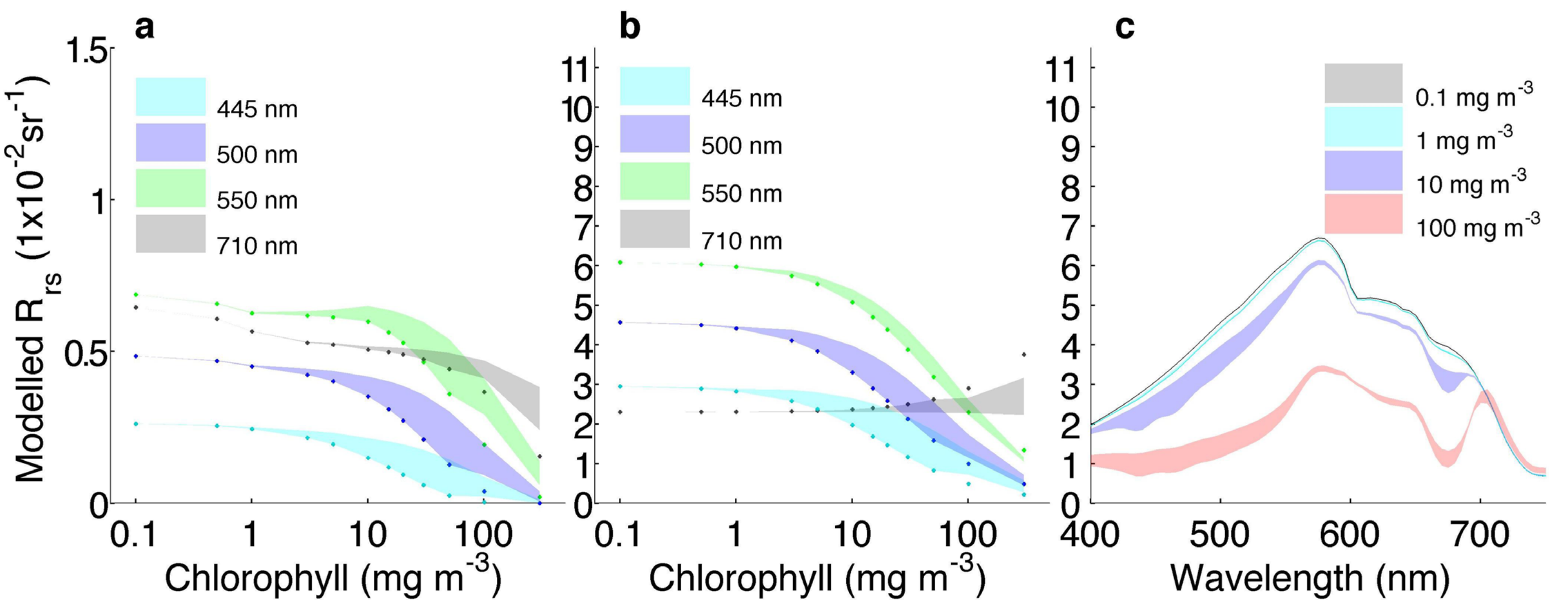


Fig. 2. Ranges of modelled R_{rs} to variations in D_{eff} and [Chl *a*], under high b_{bs} and high a_{gd} conditions. Note the differences in scale, where (b - ES) shows much higher R_{rs} values than (a - REFA). Dots indicate R_{rs} associated with smallest cells. c) Shows example ranges of spectral R_{rs} at selected [Chl *a*] across the modelled size range using ES.

Note that in highly scattering waters the size related signal is very much reduced…..

Evers-King, H., Bernard, S., Robertson Lain, L., and Probyn, T. A. (2014) Sensitivity in reflectance attributed to phytoplankton cell size: forward and inverse modelling approaches. Optics Express, 22(10), 11536–11551.

Phytoplankton ultrastructure and the changing hyperspectral signal with increasing biomass

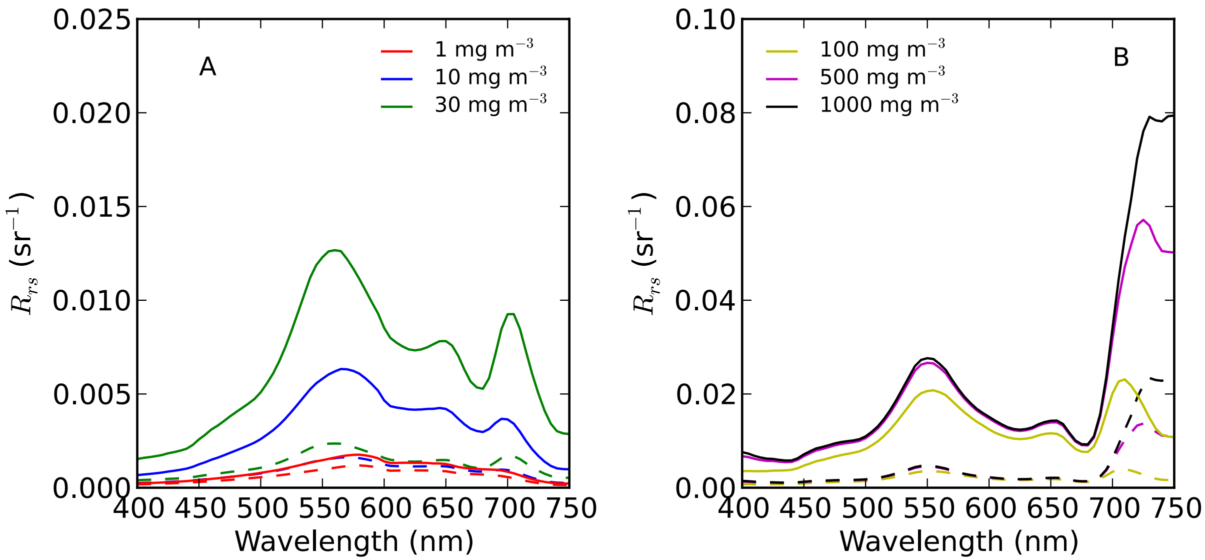
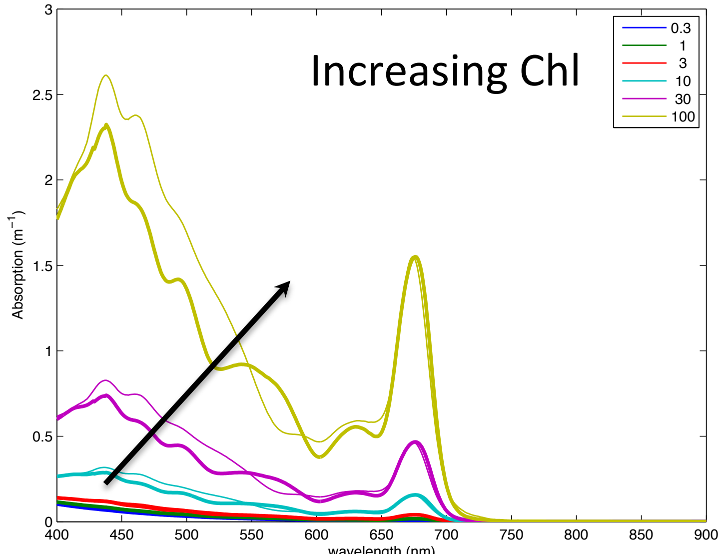


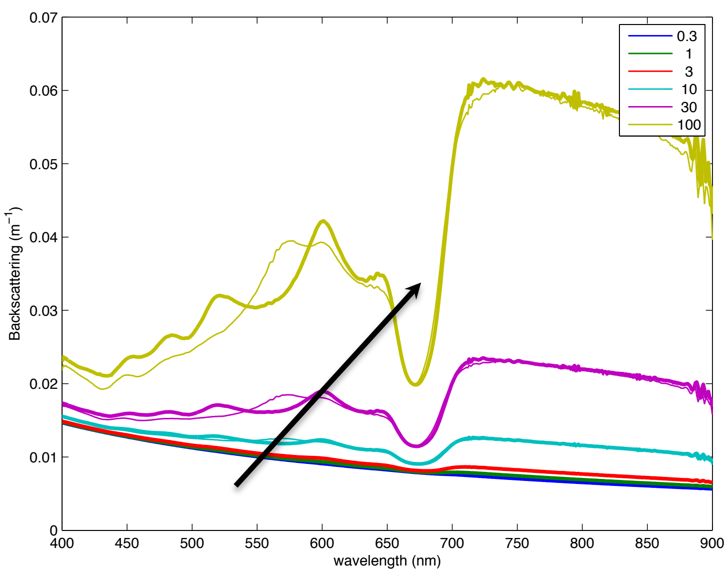
Fig. 9. R_{rs} modelled at various concentrations of Chl *a* showing the difference between vacuolate (solid lines) and non-vacuolate (dotted lines) populations of *M. aeruginosa*. Vacuolate cells were modelled with shell $1+\epsilon$ of 1.12 and $V_{\mathrm{g}} = 50\,\%$. Non-vacuolate cells were homogeneous cells with $1+\epsilon$ of 1.080. The values for $a_{\mathrm{tr}}(440)$ and $a_{\mathrm{g}}(440)$ were constant at 0.5 and $1.5\,\mathrm{m}^{-1}$, respectively. For more details, see the text.

Vacuoles greatly increase the scattering for equivalent cells – this is a clear and easily used signal, at least for high biomass inland/coastal waters…

Matthews, M. W. and Bernard, S.: Using a two-layered sphere model to investigate the impact of gas vacuoles on the inherent optical properties of Microcystis aeruginosa, Biogeosciences, 10, 8139-8157, doi:10.5194/bg-10-8139-2013, 2013.

Phytoplankton accessory pigments and the hyperspectral signal with increasing biomass: a brief experiment…





How does the accessory pigment related component of the reflectance signal change with increasing biomass – and increasing algal contribution to the IOP budget?

A small experiment – modelling changing reflectance based on the Equivalent Algal Population/Hydrolight model, comparing dinoflagellate- and cryptophyte (*Mesodinium rubrum*) based IOPs. Average cell size and all other IOPs are the same – the only difference comes from the spectral refractive indices i.e. the different pigment content of the assemblage, and obviously the increasing biomass. Case 1 waters only, i.e. the best case scenario….

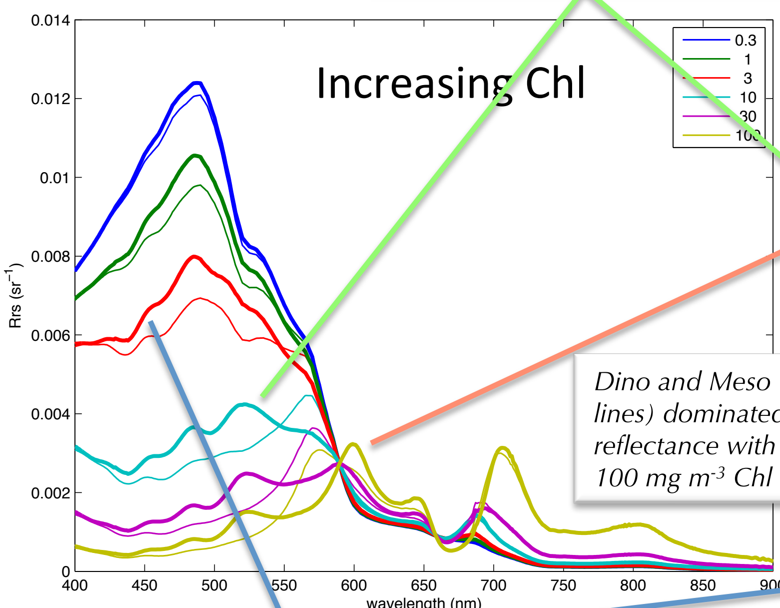
Total absorption and backscattering on the left, thick lines represent *Mesodinium* i.e. phycoerythrin containing cells, spectrally variable phase functions based on the backscattering probability used…

Robertson, unpublished

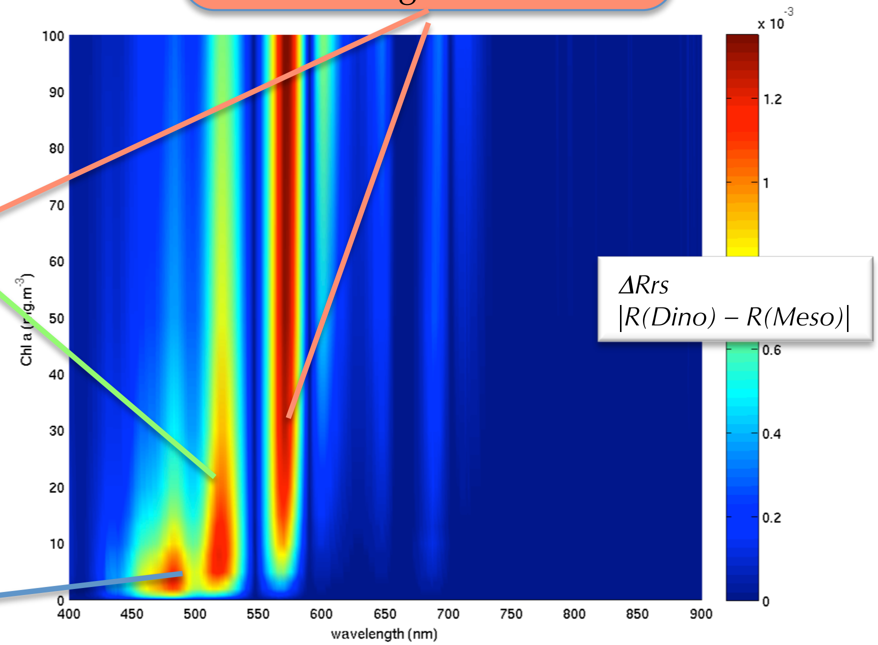
Phytoplankton accessory pigments and the hyperspectral signal with increasing biomass: a brief experiment…

High Δ around 520 nm absorption peak (Phycoerythrin) from ± 4 mg m^{-3} Chl a

High Δ around shifting 580 – 590 nm reflectance peak (Phycoerythrin) from ± 10 mg m^{-3} Chl a



Dino and Meso (thick lines) dominated reflectance with 0.3 -> 100 mg m^{-3} Chl a



High Δ around 470 nm absorption peak (Chl c/ carotenoid) from ± 2 to 20 mg m^{-3} Chl a

Quantitatively useful pigment related differences – in this fairly extreme case – are apparent from ± 2 mg m^{-3} Chl a in the blue. As the biomass increase the higher Δ signals shift to longer wavelengths….
Robertson, unpublished

Phytoplankton Biodiversity in the Coastal Zone using Hyperspectral Sensing

1) What do you think are the driving science questions in your sub-discipline that will guide your community in the coming decade?
Better understanding of the drivers and effects of variable primary production across oceanic and aquatic systems, and the importance of resolving phytoplankton community structure, preferably at the submeso- and event scale…

2) How will hyperspectral data help to address those questions?
Offering more information on phytoplankton community structure, if we can better understand the causali

3) How does 'scale' (e.g., spectral, spatial, and/or temporal) affect your ability to address these science questions? What is the smallest measurement 'scale' needed to address your science?
The most challenging scale is the the temporal/spatial, probably the daily or less revisit /300m spatial resolution boundary i.e. constellation/geostationary approaches

4) What are the common challenges across sub-disciplines in working with hyperspectral data?
Engineering: quality of radiometry & spatial/temporal aspects. Science : better understanding of signal variability and constraints, robust error handling needed.

5) How do we coordinate and integrate common algorithm development efforts?
Community platforms for collaboration/comparison; shared measured/synthetic data sets; realise that the atmospheric correction algorithms currently more of a constraint than the in-water algorithms

6) Are there any observational or programmatic gaps across the planned hyperspectral missions?
Yes, routine and well constrained phytoplankton community structure measurements

7) What other space-based measurements or modeled data, done in parallel to hyperspectral measurements, would you like to have to obtain more out of ocean color?
Hydrodynamic/biogeochemical/particle models using the same bio-optical models to allow convergence at Lw level