

Remote Monitoring of Growth and Pigmentation in Algal Cultures

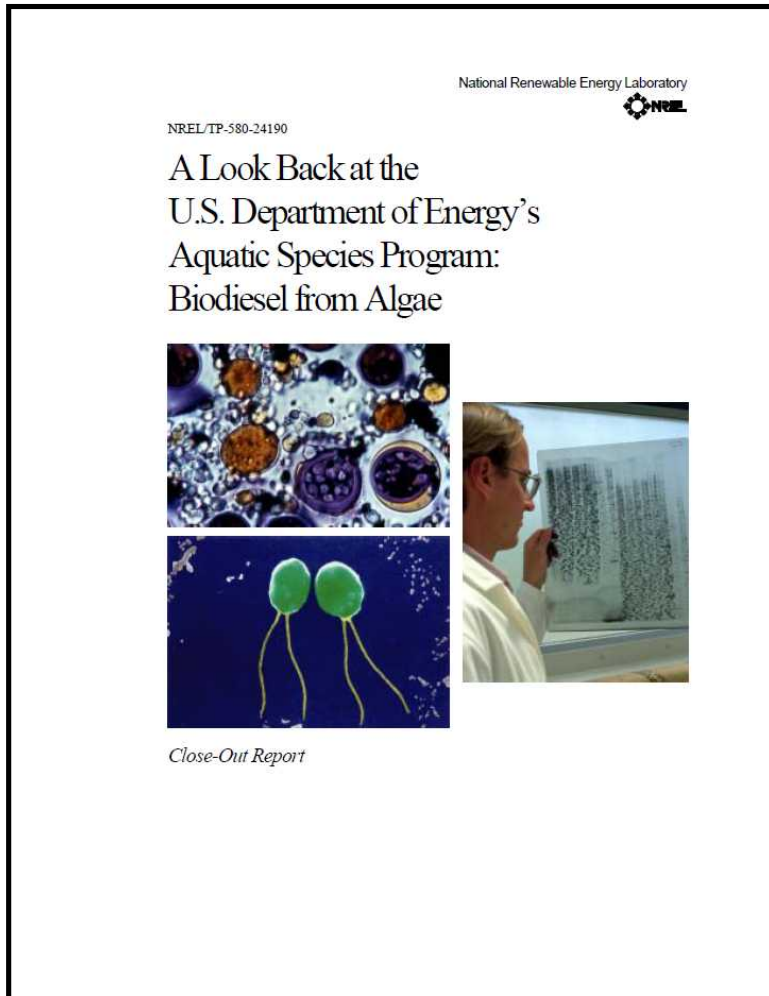
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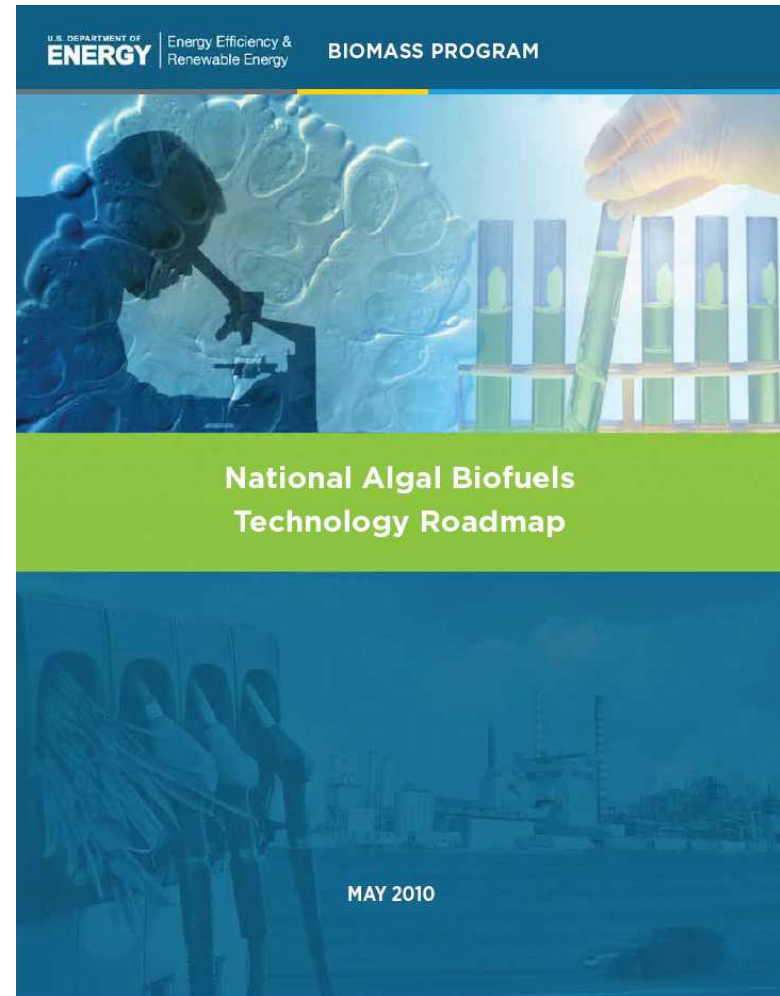
Supported by the U. S. DOE's Office of Energy Efficiency and Renewable Energy (DOE/EERE)

Algae and the U. S. DOE

1978-1996

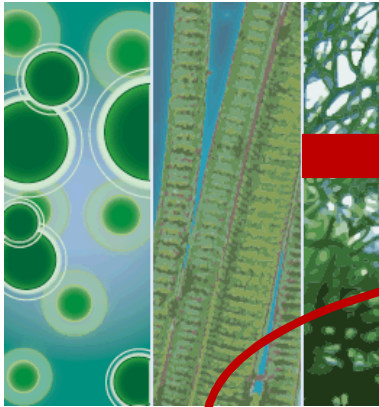


2010-future

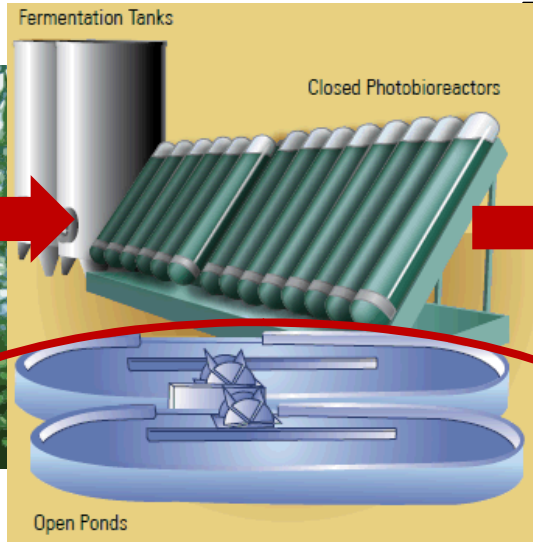


From Algae to Fuel

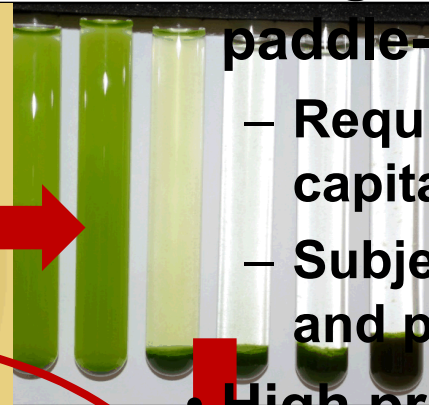
Algae
feedstocks



Cultivation



Harvesting/Dewatering

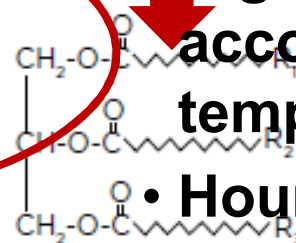


• Typically a raceway design circulated by a paddle-wheel

- Requires the least capital cost
- Subject to predators and pathogens

• High productivity accompanied by high temporal variability

Extraction



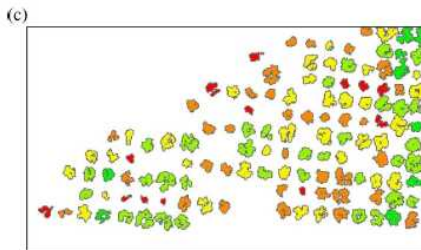
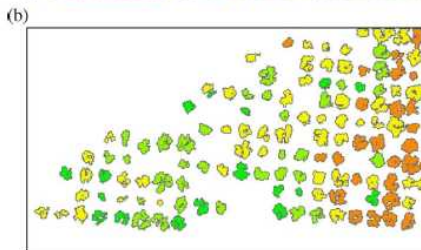
• Hours versus days Conversion



Rapid, broad-area assessment of growth and conditions in open systems

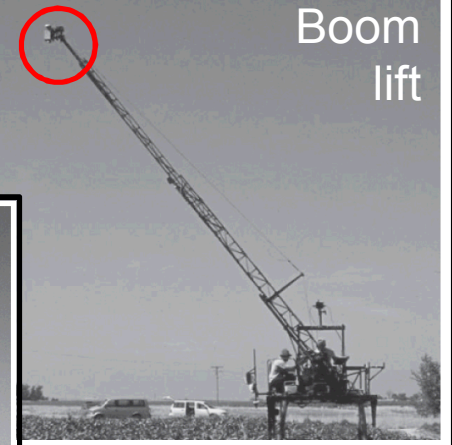


UAV

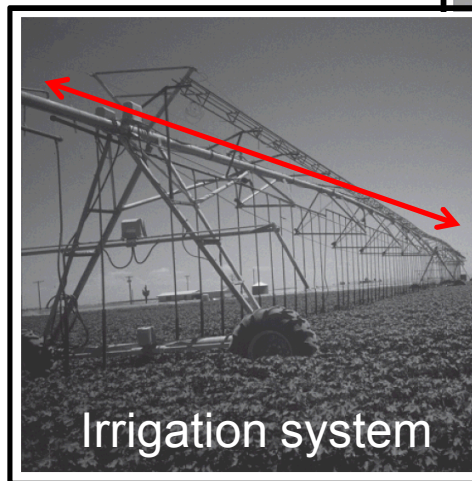


J. A. J. Berni et al, IEEE Trans. Geosci. & Rem. Sens. **47**, 2009.

Boom lift



Irrigation system



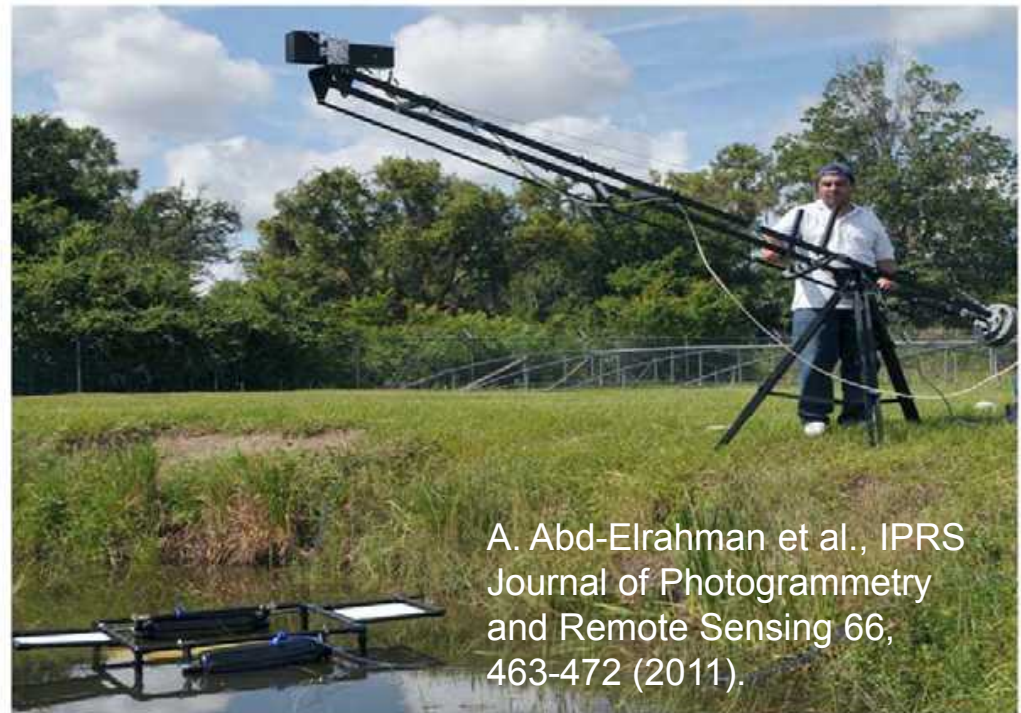
S. Moran et al., Photogrammetric Eng. & Rem. Sens., June 2003, 705-718.

Aquaculture Pond Monitoring

- **A. Gitelson et al. (Ben-Gurion Univ. of the Negev)**

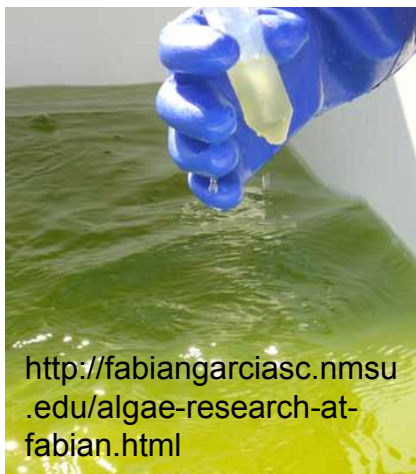
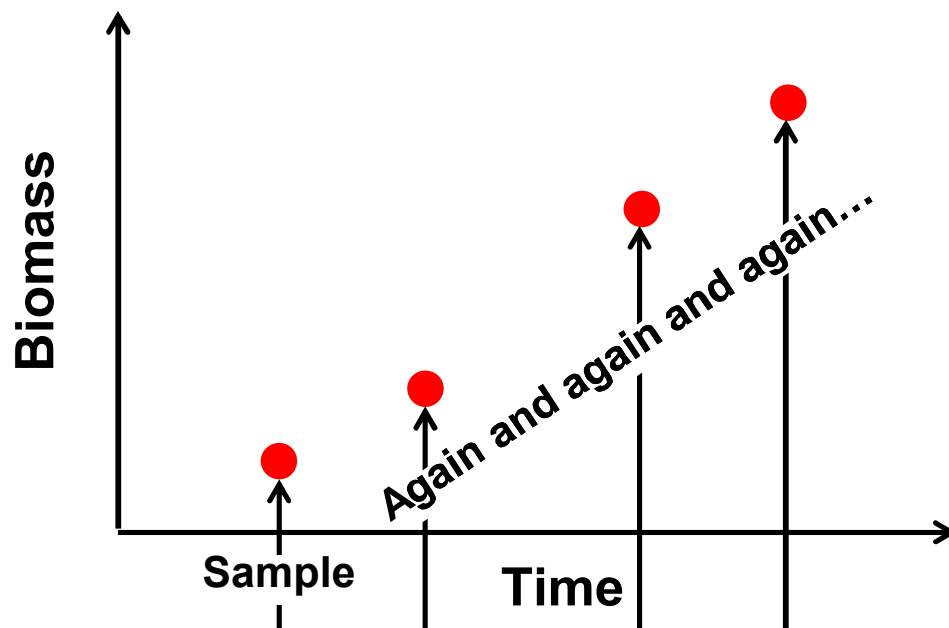
- “Optical properties of dense algal cultures outdoors and their application to remote estimation of biomass and pigment concentration in *Spirulina platensis* (cyanobacteria),” J. Phycol. **31** (1995).
- “Quantitative near-surface remote sensing of wastewater quality in oxidation ponds and reservoirs: a case study,” Water Environ. Res. **69** (1997).
- “Comparative reflectance properties of algal cultures with manipulated densities,” J. Appl. Phycol. **11** (1999).
- “Optical characteristics of the phototroph *Thiocapsa roseopecticina* and implications for real-time monitoring of the bacteriochlorophyll concentration,” Appl. & Environ. Microbiology, **65**, (1999).
- “Optical properties of *Nannochloropsis* sp and their application to remote estimation of cell mass,” Biotech. & Bioeng. **69** (2000).

- **Recent demonstration by group at Univ. of Florida (Gainesville/Wimauma)**



A. Abd-Elrahman et al., IPRS Journal of Photogrammetry and Remote Sensing 66, 463-472 (2011).

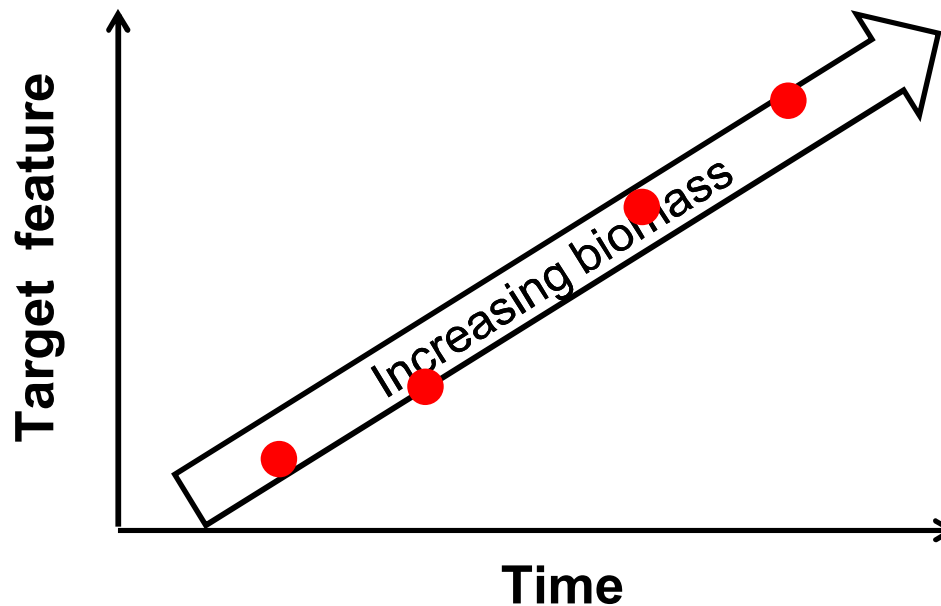
Specific question: Can biomass be measured without sampling the culture?



<http://fabiangarciasc.nmsu.edu/algae-research-at-fabian.html>

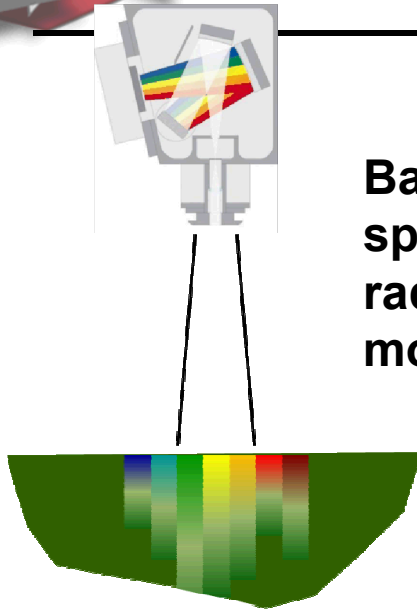


Specific question: Can biomass be measured without sampling the culture?



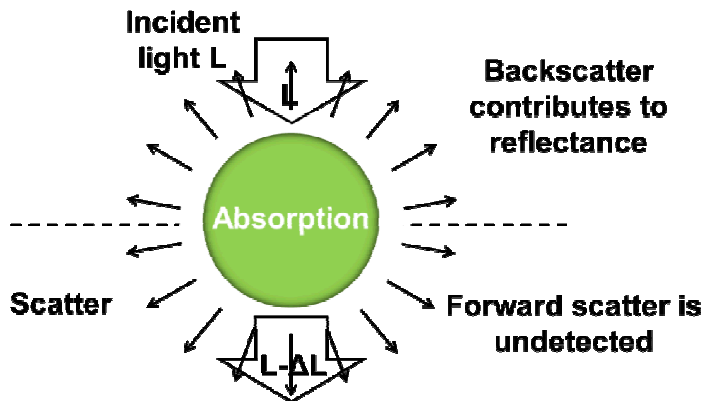
- Target feature based on collection of light
- Change in feature requires change in optical properties
- 3 effects: scattering, absorption, and re-emission (fluorescence)

Discussion Topics

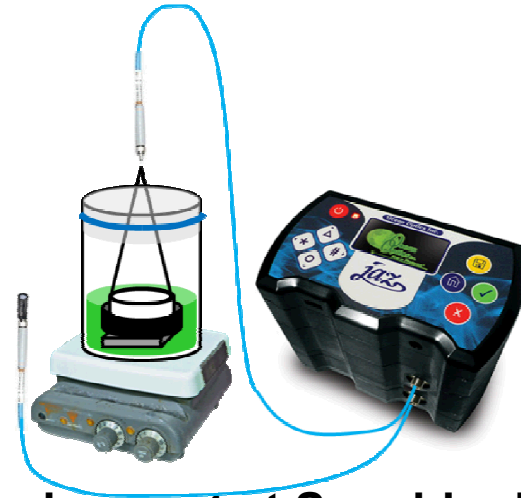


Basics of
spectro-
radiometric
monitoring

Reflectance model to extract
culture properties from data



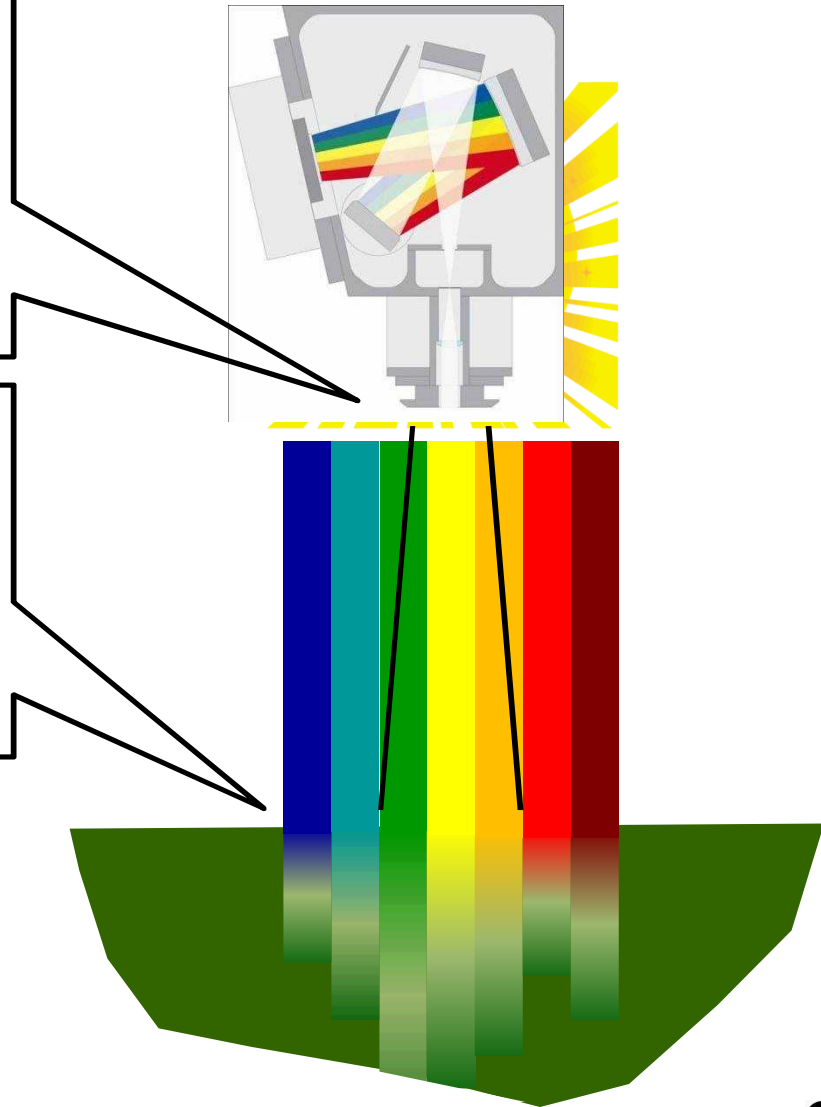
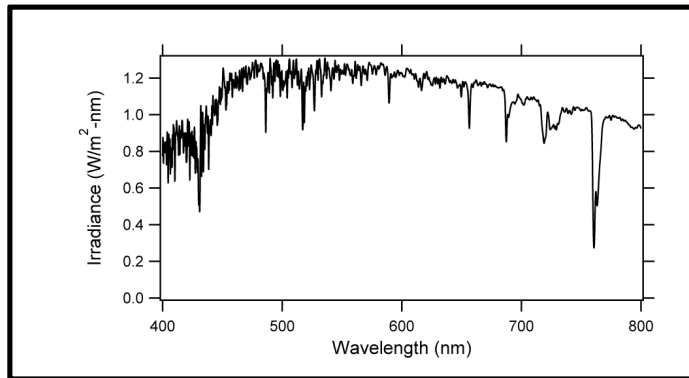
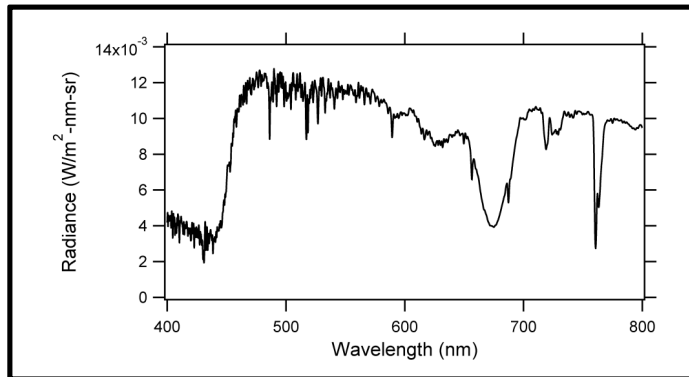
Benchtop-scale reflectivity measurements



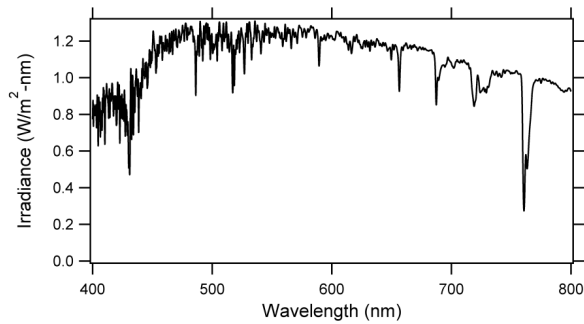
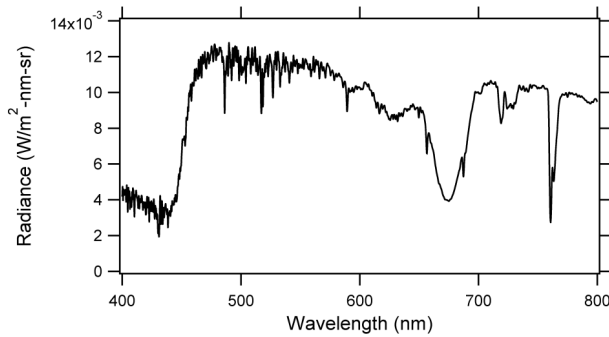
Field deployment at Sapphire Energy



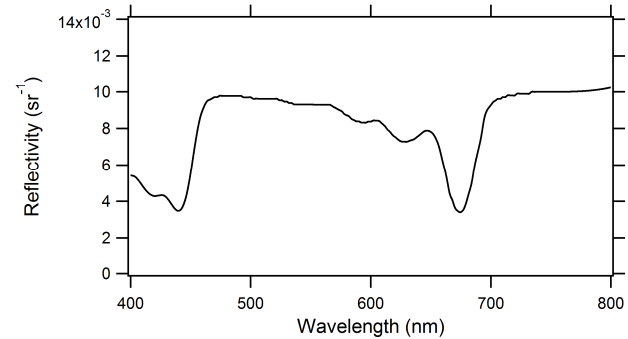
Spectroradiometric Monitoring



Spectroradiometric Monitoring



=

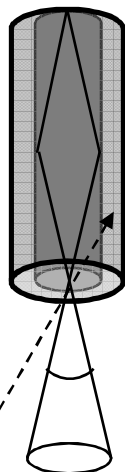
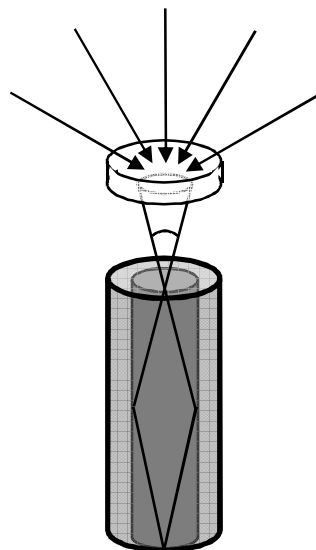


Dual-Channel Spectroradiometer

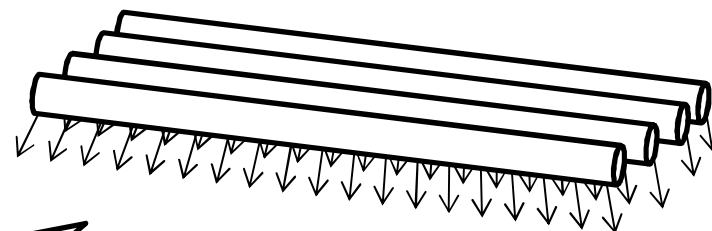
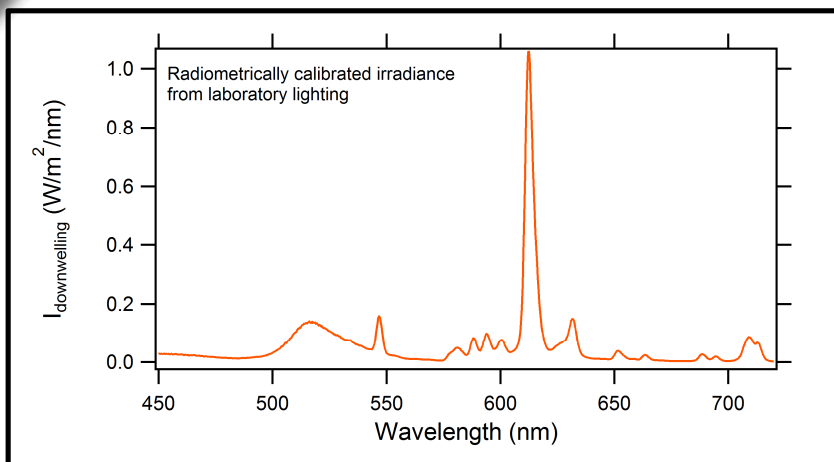
- Diffuser randomizes the direction of incoming light
- Fiber captures light from all downwelling angles
- Refractive indices of core and cladding limit field-of-view to 25° cone of light

Escapes into cladding

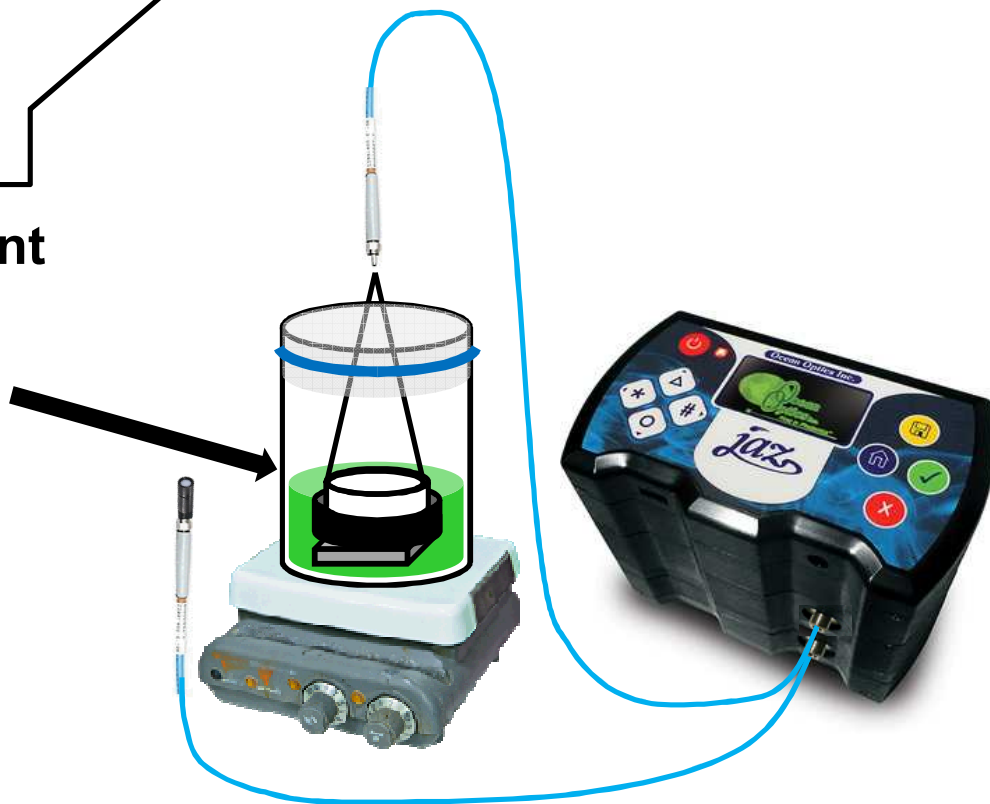
Trapped by core



Benchtop-scale reflectivity measurements

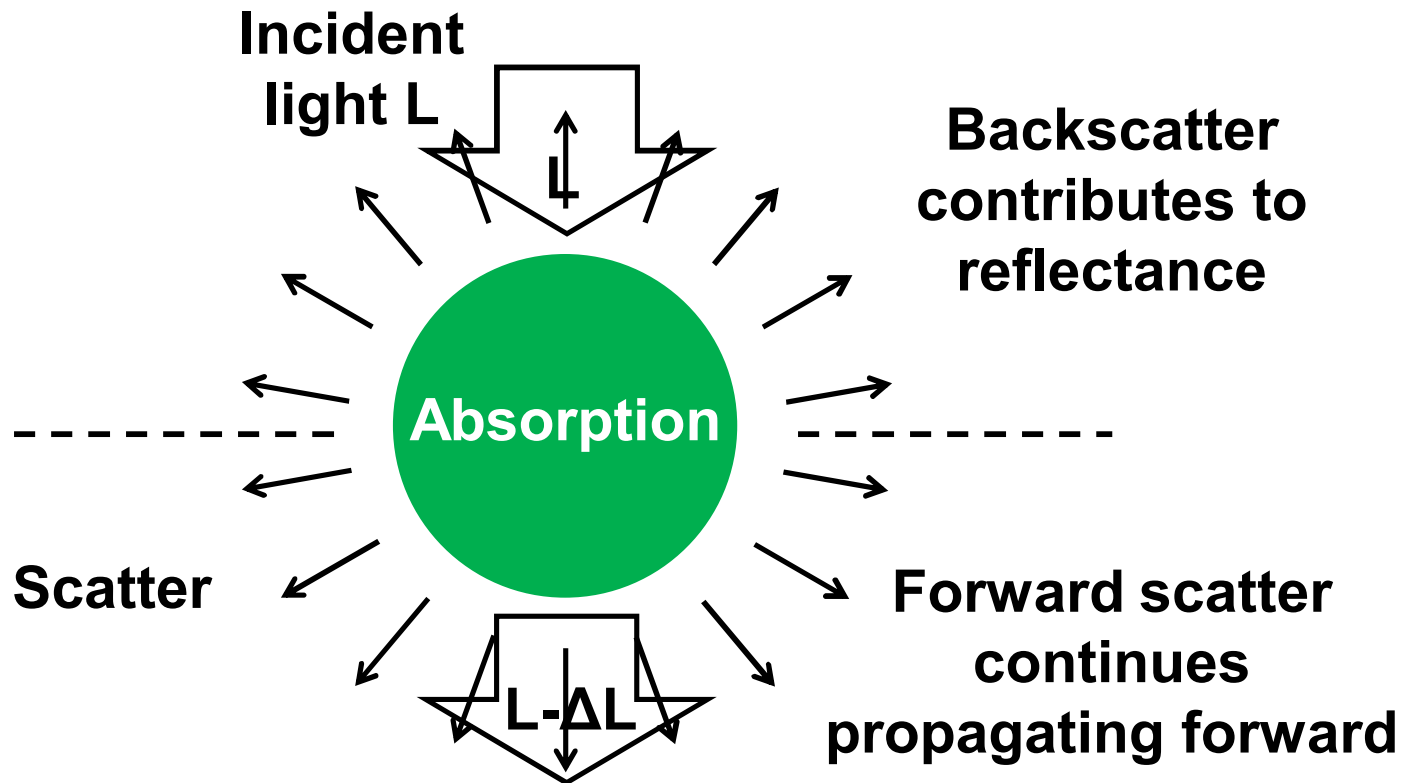


- Fluorescent lamp has significant spectral structure
- Algae replaced with calibrated target for absolute reflectivity measurements



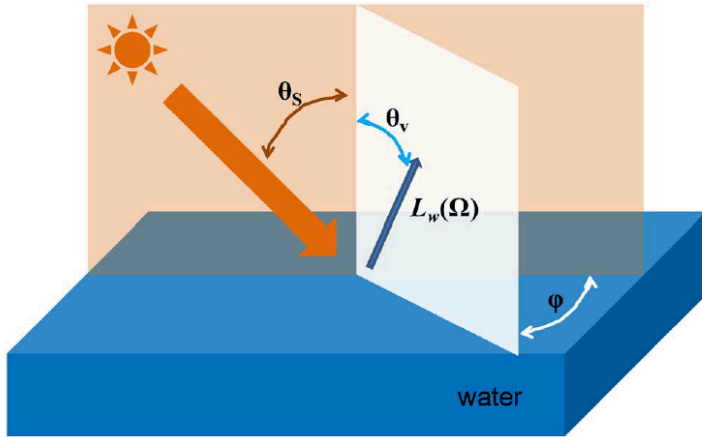
Reflectance depends on *single scattering albedo* (u)

$$u(\lambda) = \frac{\text{Backscatter}(\lambda)}{\text{Backscatter}(\lambda) + \text{Absorption}(\lambda)} = \frac{b_b(\lambda)}{b_b(\lambda) + a(\lambda)}$$



Reflectance Model of Z. Lee et al.

- Multiple scattering: $r(\lambda) = G_1 u + G_2 u^2$



- G_1 and G_2
 - Determined from numerical radiative transfer simulations
 - Validated with measurements

$$u(\lambda) = \frac{\text{Backscatter}(\lambda)}{\text{Backscatter}(\lambda) + \text{Absorption}(\lambda)} = \frac{b_b(\lambda)}{b_b(\lambda) + a(\lambda)}$$

An inherent-optical-property-centered approach to correct the angular effects in water-leaving radiance

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²State Key Laboratory of Remote Sensing Science, Research Center for Remote Sensing and GIS, School of Geography, Beijing Normal University, Beijing, 100875, China

³Department of Physics, University of Miami, Coral Gables, Florida 33124, USA

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⁶Naval Research Laboratory, Stennis Space Center, Mississippi 39529, USA

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posted 19 April 2011 (Doc. ID 141059); published 22 June 2011

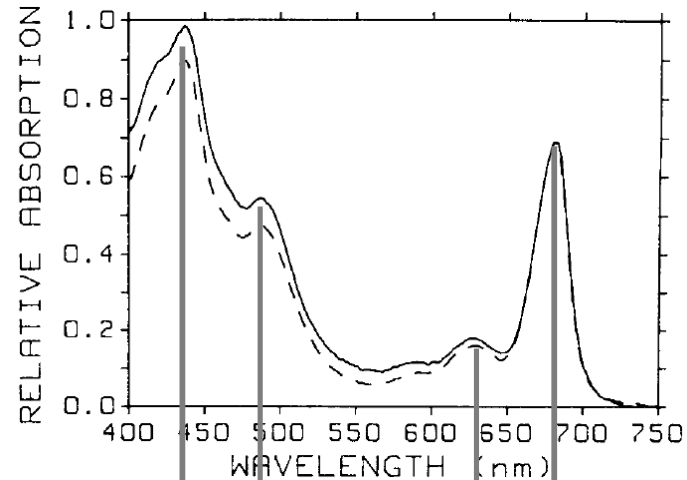
Remote-sensing reflectance (R_{rs}), which is defined as the ratio of water-leaving radiance (L_w) to downwelling irradiance just above the surface ($E_d(0^+)$), varies with both water constituents (including bottom properties of optically-shallow waters) and angular geometry. L_w is commonly measured in the field or by satellite sensors at convenient angles, while $E_d(0^+)$ can be measured in the field or estimated based on atmospheric properties. To isolate the variations of R_{rs} (or L_w) resulting from a change of water constituents, the effects of $E_d(0^+)$ need to be removed. This is also a necessity for the calibration of R_{rs} (or L_w) measurements. To reach this objective, for optically-deep waters, a system centered on water's inherent optical properties is proposed, and offers an alternative to the

Reflectance $r(\lambda)$: What is expected?

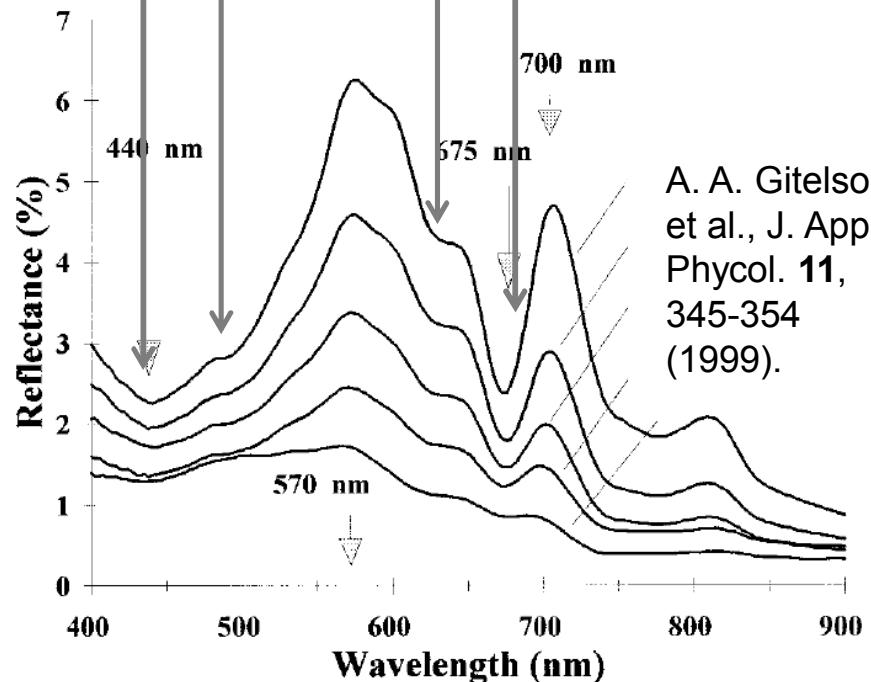
$$r(\lambda) \propto u(\lambda)$$

$$\propto \frac{b_b(\lambda)}{b_b(\lambda) + a(\lambda)}$$

- $a(\lambda)$ is in the denominator
- Absorbance maxima should approximately correspond to reflectance minima
- More on this when we discuss the reflectance model



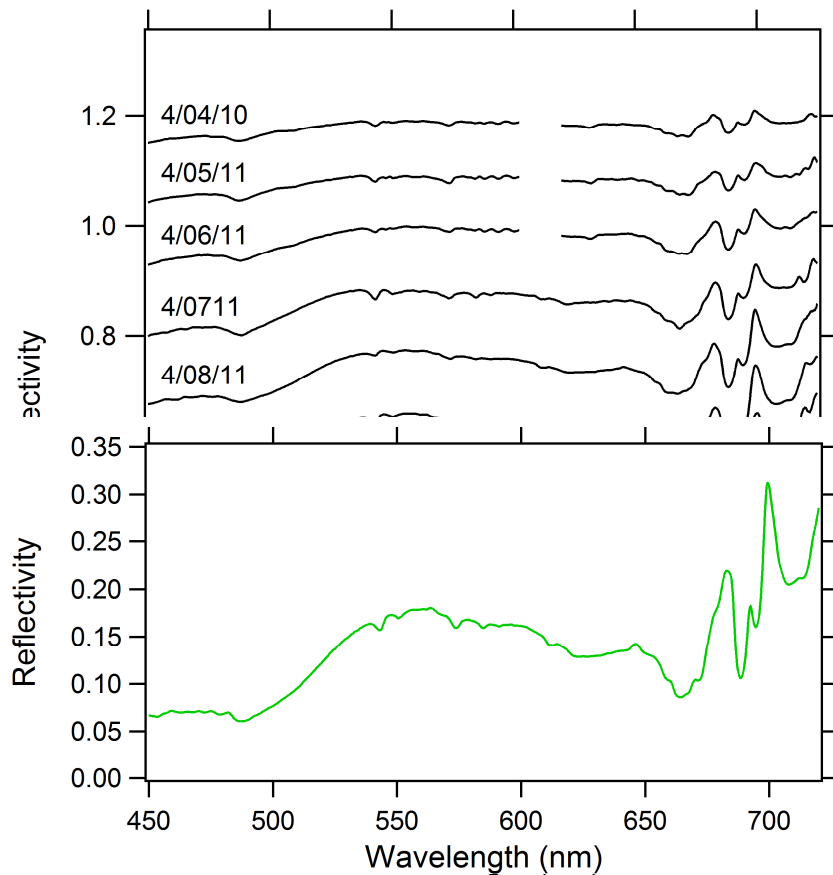
T. G. Owens
et al., J.
Phycol. **23**,
79-85 (1987).



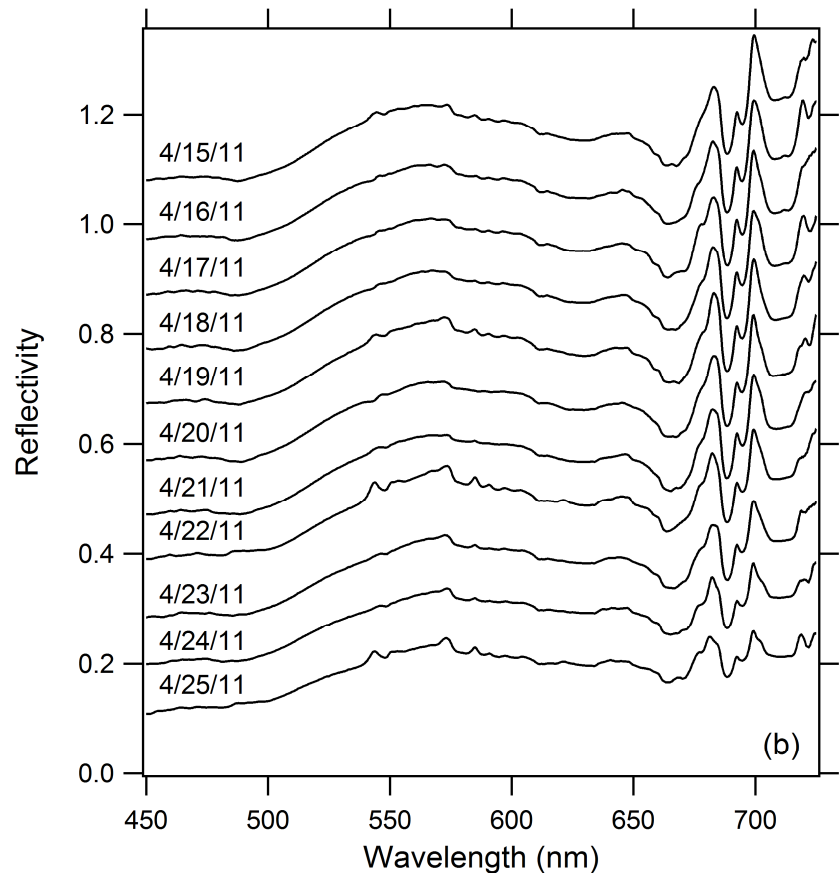
A. A. Gitelson
et al., J. Appl.
Phycol. **11**,
345-354
(1999).

Laboratory spectra (4/4/11 – 4/25/11)

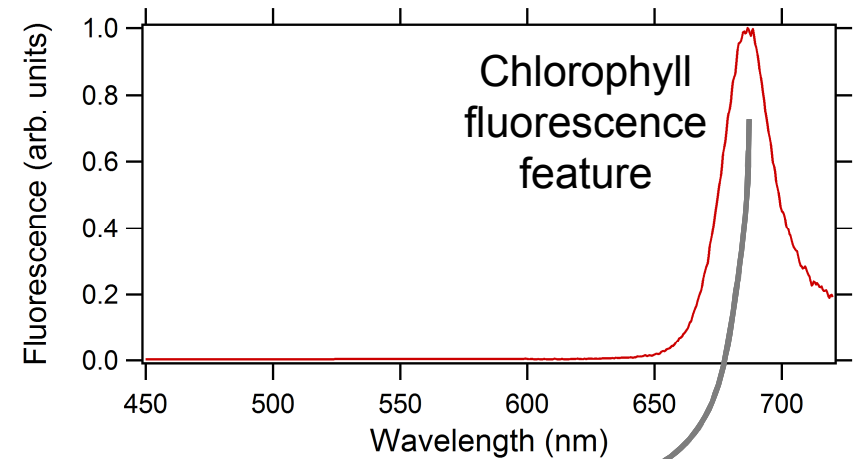
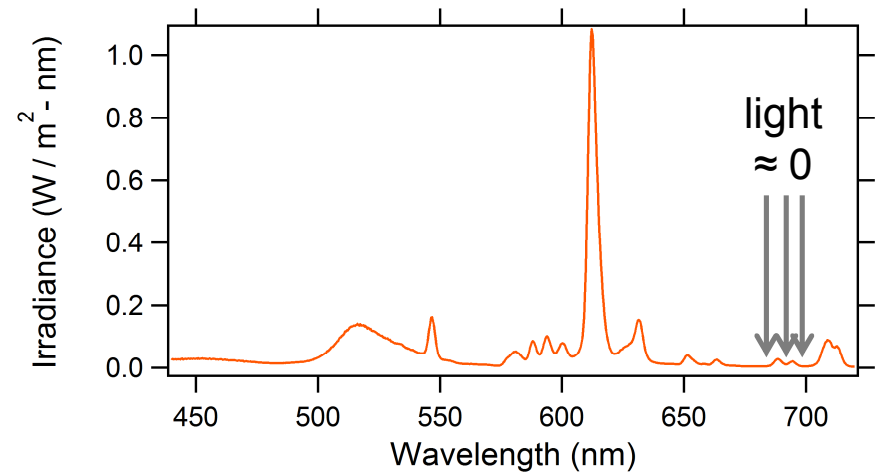
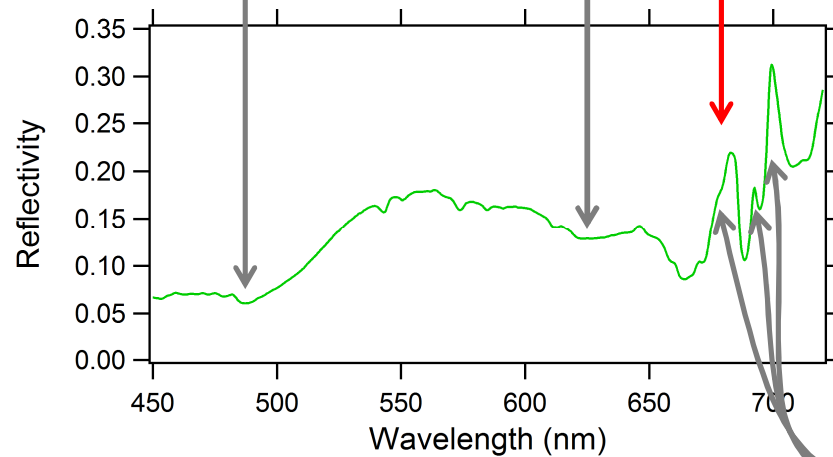
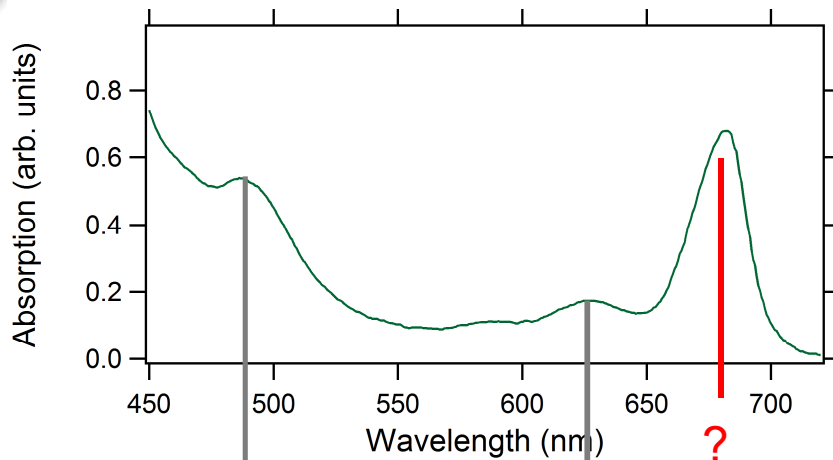
Days 1-11



Days 12-22

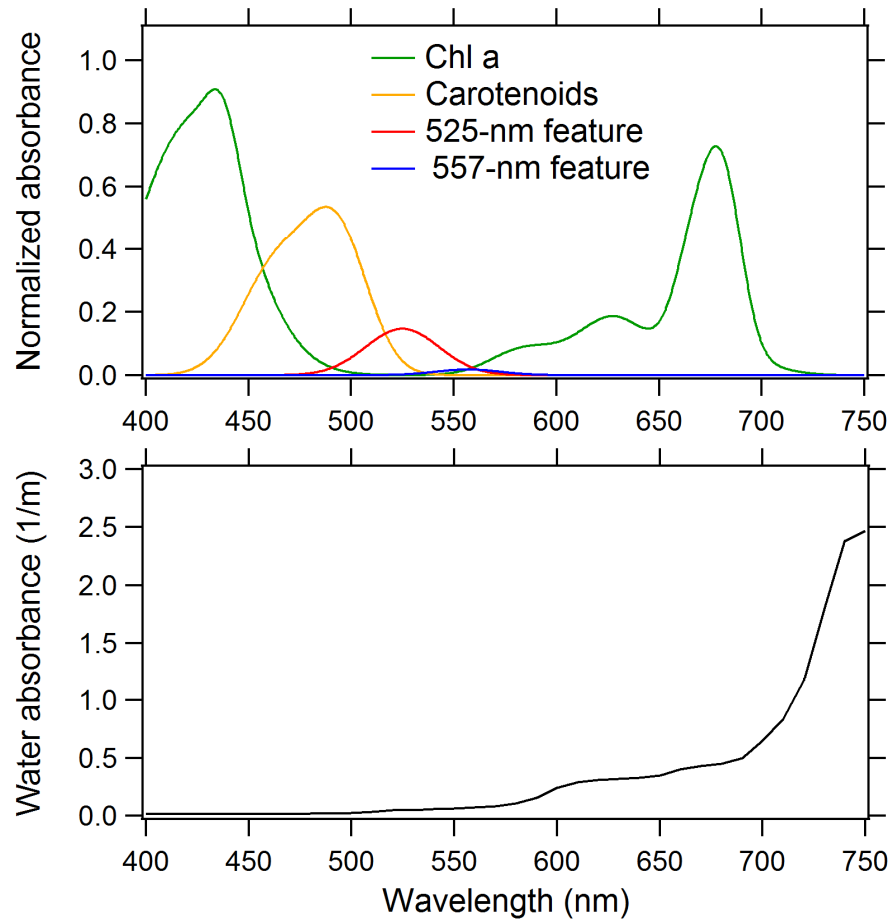


Laboratory spectra (4/4/11 – 4/25/11)

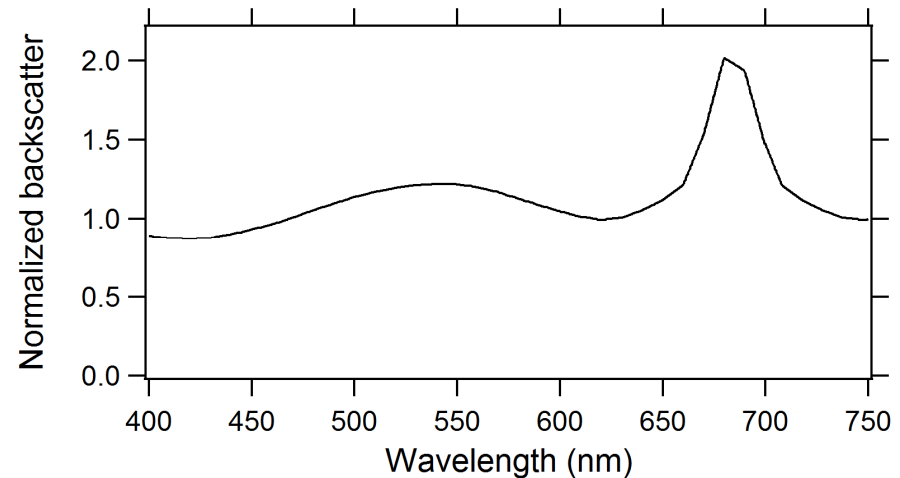


This leaves only $a(\lambda)$ and $b_b(\lambda)$

$a(\lambda)$: Algal pigments and water



$b_b(\lambda)$: Generic phytoplankton backscattering spectrum from F. Lahet et al., *Remote Sens. Environ.* **72**, 181-190 (2000).



The unknowns of $r(\lambda)$

Term in $r(\lambda)$

- $a(\lambda)$ = scaled sum of four components
- $b_b(\lambda)$ = scaled phytoplankton backscatter spectrum
- Fluorescence = Scaled optically thin spectrum with re-absorption

Unknowns

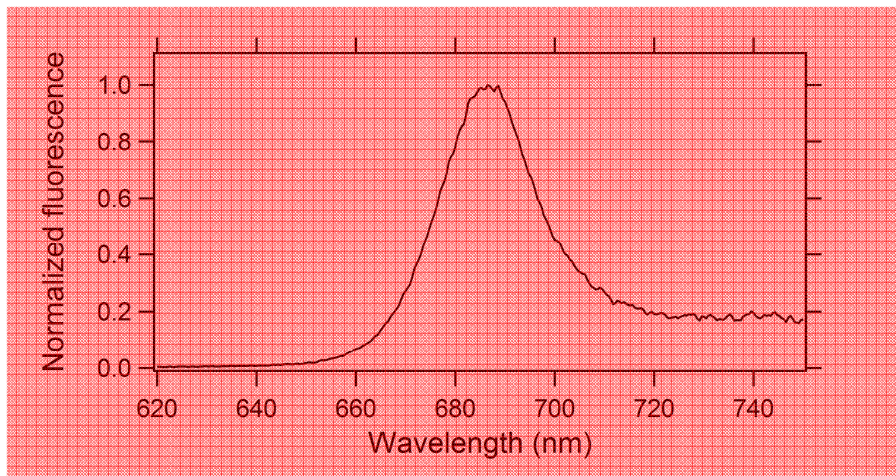
C_1, C_2, C_3, C_4

C_5

C_6, L_f

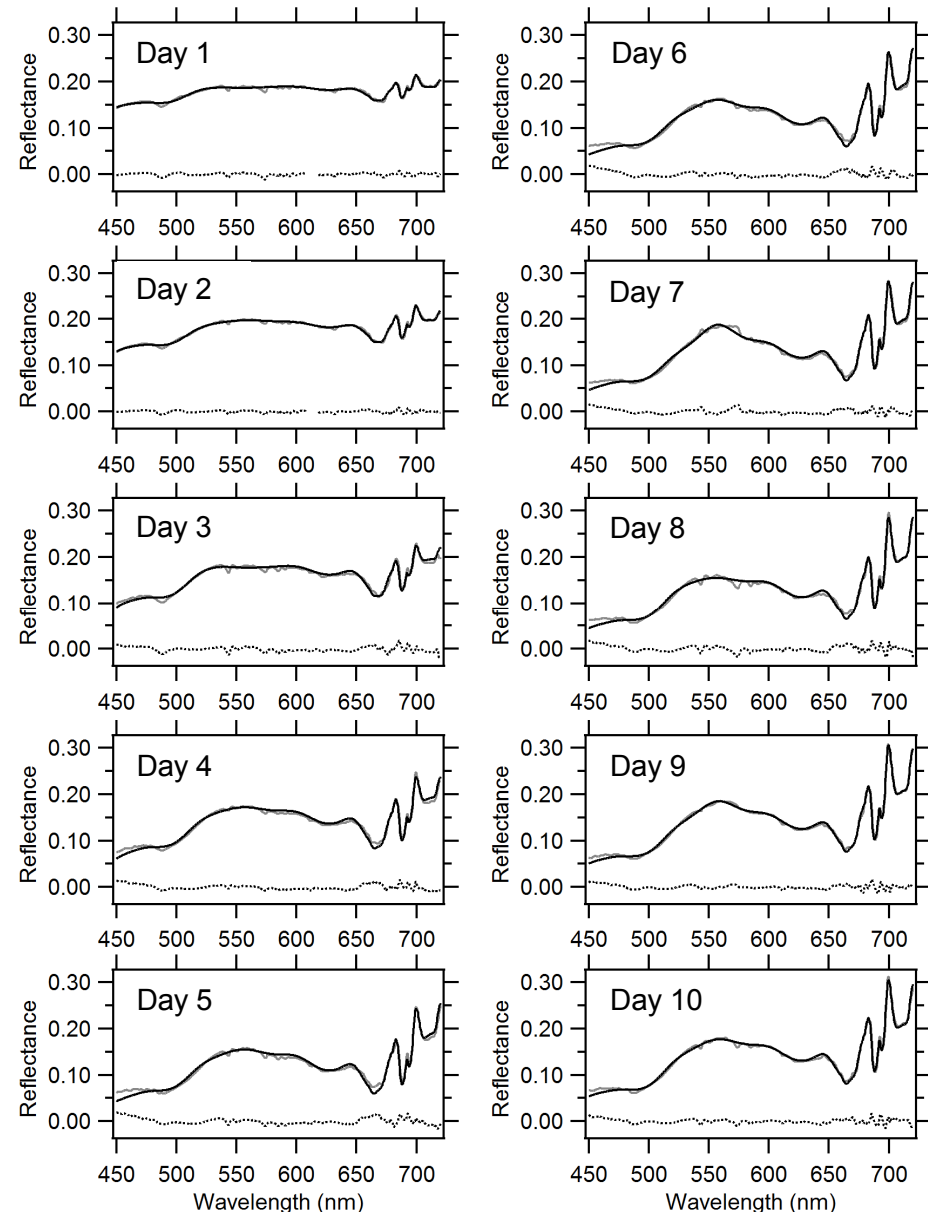
$$F = C_6 e^{F^{ot}} \exp(-\kappa L_f)$$

L_f



Fitting the reflectance model to the reflectance measurements

- Displaying spectrum acquired 30 minutes after the lights were cycled on each day
- Values of C_1 - C_7 are optimized to minimize the RMS error between the measurements and model
 - MATLAB's *fminsearch* routine
- Model captures the absorption and fluorescence features evident in data
- **Caution: 7 free parameters**



Potential ambiguity accompanying our model inversion

K. Lumme, A. Penttillä / Journal of Quantitative Spectroscopy & Radiative Transfer 112 (2011) 1658–1670

1659

To interpret the polarimetric data the CB explanation is now universally accepted instead of some earlier semi empirical suggestions with full of various parameters. Although the mechanism itself is known, full scale fits to data are still greatly underway. An obvious reason for this is the fact that the computations are so heavy that even modern computers cannot yet handle all of those. This is particularly true for the regoliths of the atmospheric bodies which would require large model geometries to explain the opposition effect. The situation for the cometary aggregates for their polarization is easier because those of those are on the order of few tens of microns as compared to their low density in the coma there are no multiple scattering effects.

Lasue et al. [7] and the references therein, fitted two cometary data sets of Halley and Hale-Bopp with a reasonable accuracy although the number of all kinds of free parameters in their model was rather excessive. The authors claim that the number is five, although there are a lot of hidden parameters which the authors assume to be known. Even with these parameters the authors are not satisfied with the fits at small phase angles. The old phrase goes: “give me seven free parameters and I can fit an elephant”. A reasonable method to study the sensitivity of the derived parameters for a model in a case of a good data set would be to use only some parts of the whole set and check how well the model predicts the other parts. The more the parameters used in a model, the more sensitive will the fit be to the other parts.

Unfortunately there are no recent articles concerning CB fits to the large amount of observational data of the brightness behavior of the atmosphereless bodies. Therefore, no quantitative results exist for the opposition effect. Known to be the correct explanation CB still remains without exact proofs for that part. In this spirit a new semi-analytical approach was suggested by Muinonen [8,18] who showed that the combination of the classical ray tracing radiative transfer formalism with the CB formalism explains nicely the exact superposition 7-matrix method (CTM) [9] results in small geometries. Extension of this to very large geometries also seems to explain the extremely sharp opposition effect.

2. Structure and morphology of cometary and regolith dust

What will follow we assume that all the constituent particles (monomers) have a touching neighbor. This applies both to the aggregates and regolith models. If this is not the case we would have a cloud of particles. The requirement need not be actually quite true because some electrostatic forces can produce some separation. Our computations have shown, however, that if the separation of two monomers is less than about 10% of the radii the results are fairly insensitive to that assumption.

2.1. Cometary and regolith dust

Altogether we will assume two kinds of monomer shapes: spheres and Gaussian random spheres (GRS). We also have an efficient code for the packing of general

ellipsoids of varying sizes. We do not accept the state-

satisfied with the fits at small phase angles. The old phrase goes: “give me seven free parameters and I can fit an elephant”. A reasonable method to study the

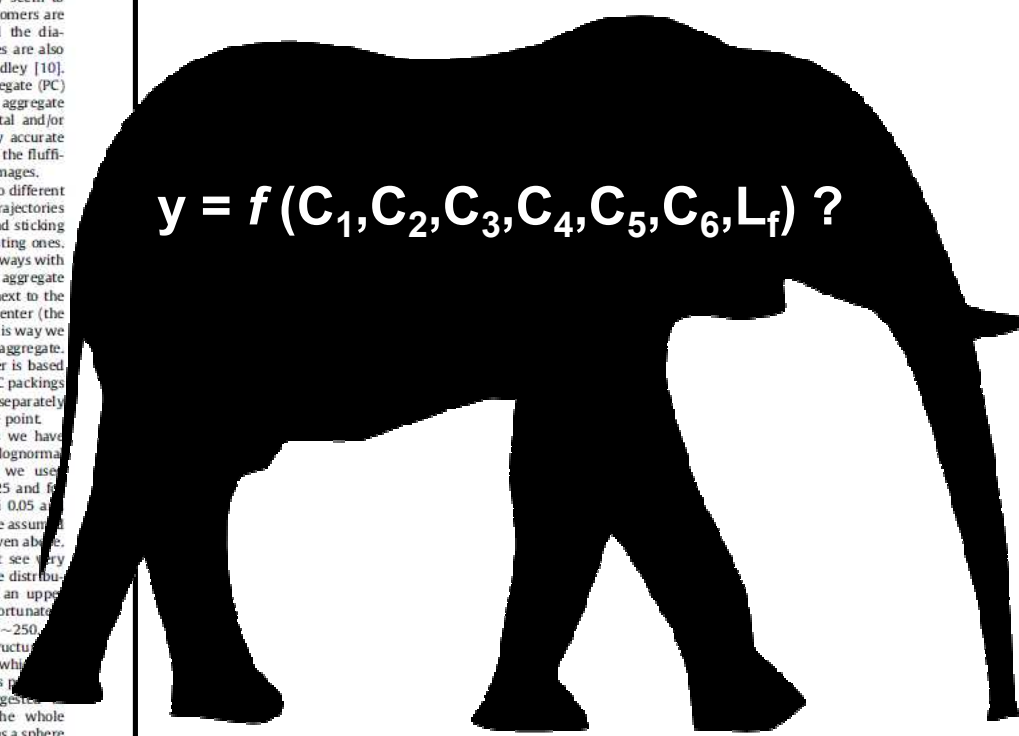
We have used a model which included scale invariance in the dimensions of the aggregates. They are neither space filling nor do they seem to have a characteristic size. The result of the monomers are typically in the range $0.05 < r < 0.25 \mu\text{m}$ and the diameters of the aggregates $\sim 20 \mu\text{m}$. These values are also in accordance with those of Hanner and Bradley [10]. Some of them resemble a particle-cluster aggregate (PC) while the others are closer to a cluster-cluster aggregate (CC). The terms often used for these are fractal and/or fluffy aggregates. This terminology is not very accurate because either the possible fractal structure or the fluffiness cannot be deduced reliably from the 2D images.

In building our PC packings we have used two different schemes. The first one assumes ballistic linear trajectories from random directions for a new monomer and sticking to the aggregate when meeting any of the existing ones. This first scheme produces aggregates almost always with roughly the same packing density. Our second aggregate building scheme tries to put a new monomer next to the existing ones so close/far from the aggregate center (the position of the first monomer) as possible. By this way we can vary the resulting packing density of the aggregate. The selection of the position of a new monomer is based on the binomial distribution statistics. In the CC packings we build certain number of sub-PC aggregates separately and let them collide with the others at a single point.

For the size distribution of the monomers we have tried two different statistics: power law and lognormal distribution. In the case of the power law we used different exponents in the range $2.75 < \gamma < 3.25$ and for the lower and upper limits of the cut-off radii $0.05 \mu\text{m}$ and $0.25 \mu\text{m}$. For the lognormal distribution we have assumed that 98% of the monomers are in the interval given above. In the final light scattering results we cannot see any much difference between the two choices of the distributions. Our existing light scattering codes put an upper limit to the number of monomers to $n \sim 2000$. Fortunately the results are not too sensitive to n when $n > \sim 250$.

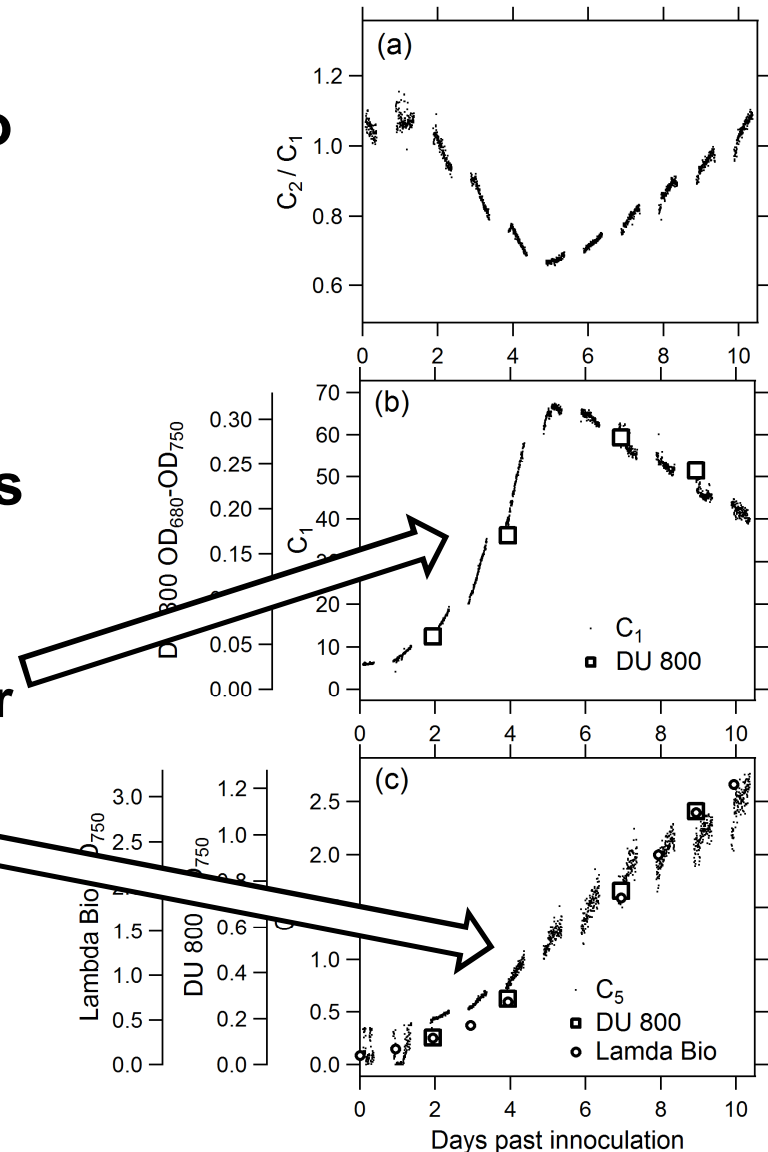
An important quantity related to the structure of an aggregate is the packing or volume density which we shall denote by pD , which is equal to one minus porosity. Several reference geometries have been suggested to estimate the volume which encompasses the whole aggregate. In the past the standard geometry was a sphere which for the elongated aggregates can largely exaggerate

$$y = f(C_1, C_2, C_3, C_4, C_5, C_6, L_f) ?$$



Comparison to expectations (and offline sampling measurements)

- During exponential-phase growth, the carotenoid-to-chlorophyll ratio decreases
 - Expected because chlorophyll plays a more central role in photosynthesis
- Spectrophotometer measurements conducted on grab samples
 - Chl-a coefficient in good agreement with spectrophotometer
 - Backscatter in good agreement with OD750 measured with 2 different spectrophotometers

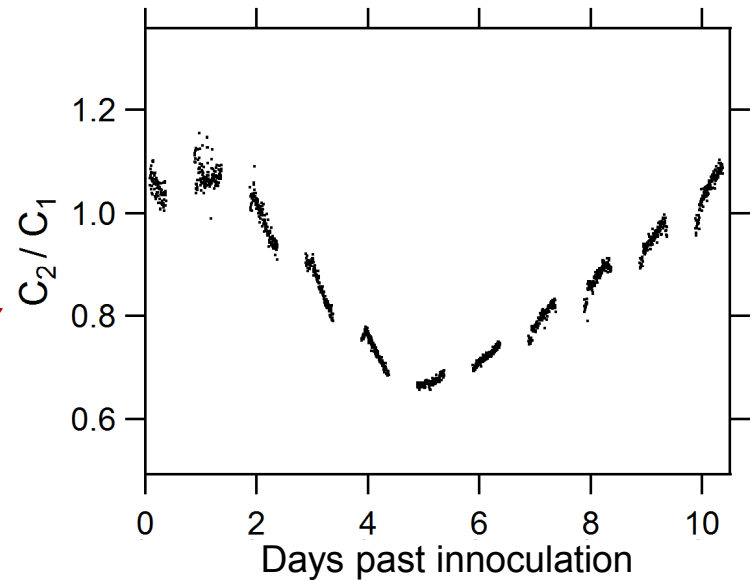


Acknowledging the elephant:

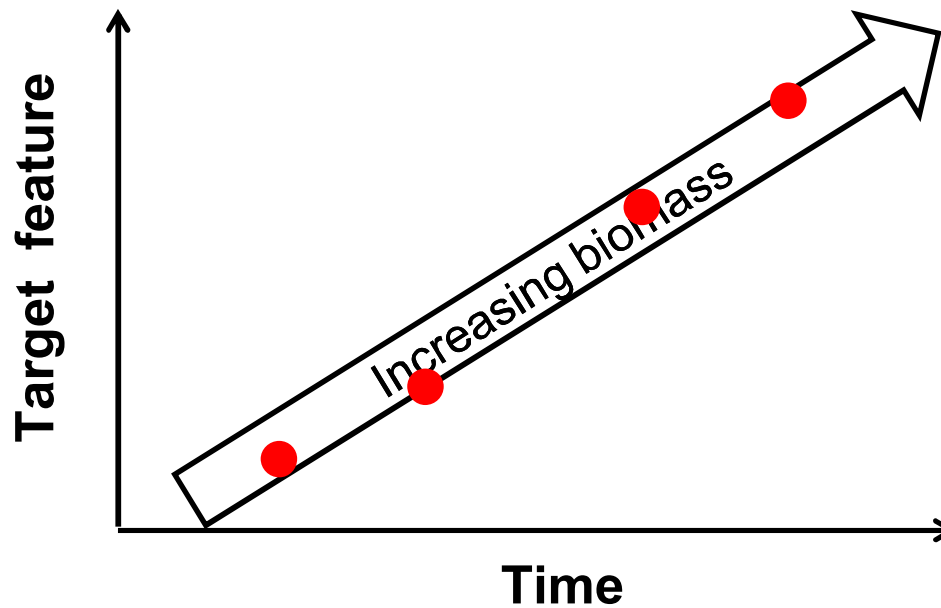
Comparison to expectations and sampling

- During exponential-phase growth, the carotenoid-to-chlorophyll ratio decreases

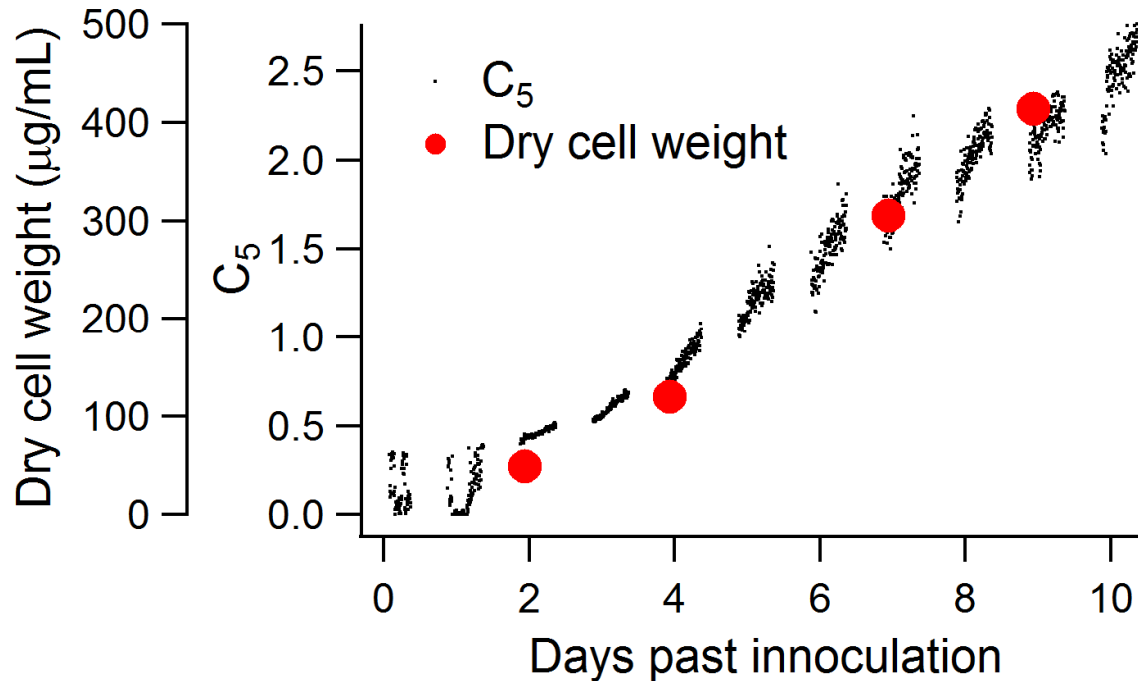
- C_1 : Chlorophyll coefficient
- C_2 : Carotenoid coefficient
- Trend expected:
Chlorophyll more central
in photosynthesis



Original question: Can biomass be measured without sampling the culture?

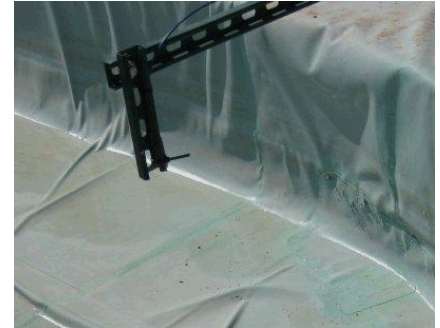
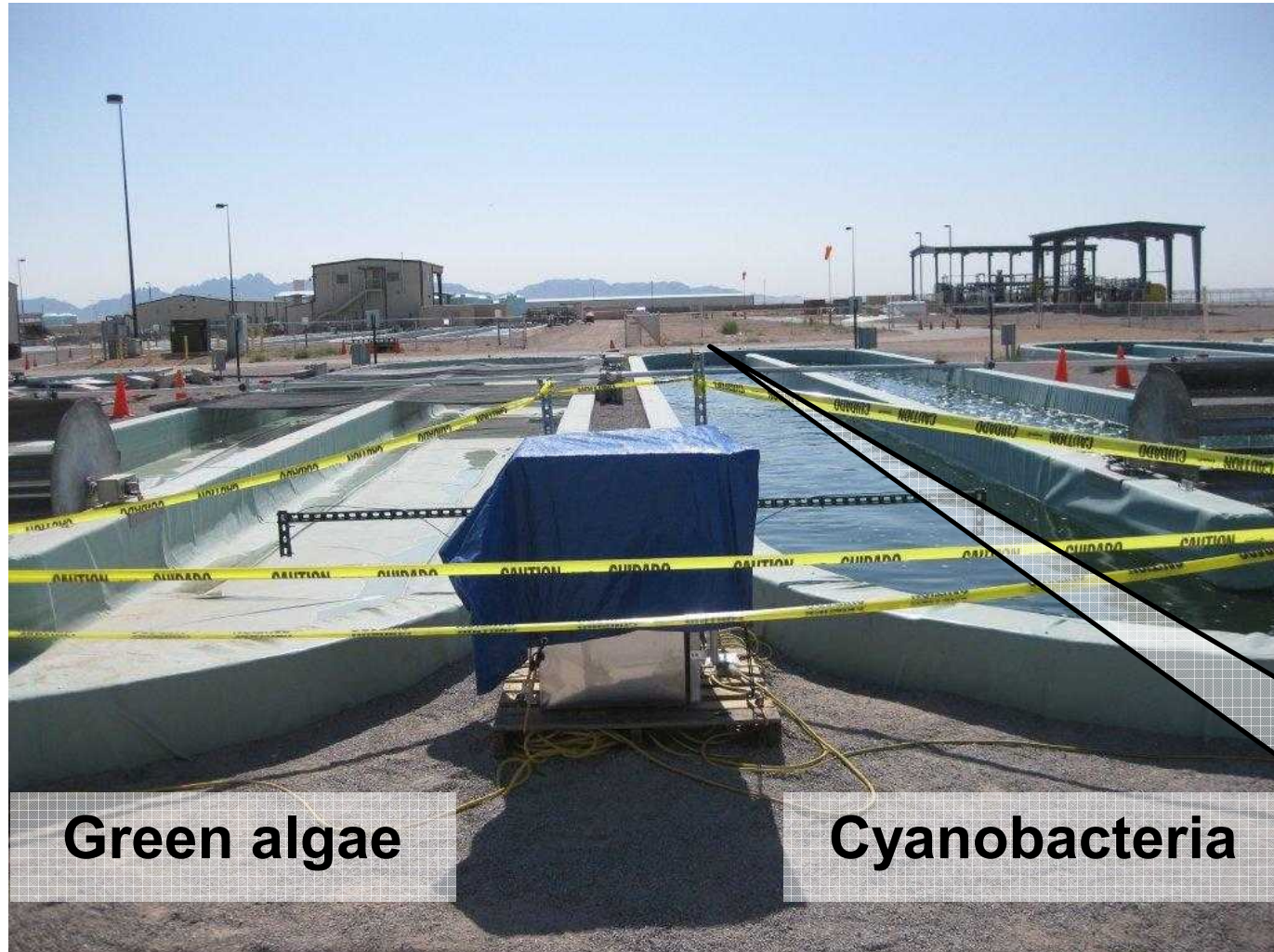


Original question: Can biomass be measured without sampling the culture?



- **Answer: Yes – the algal backscatter coefficient scales with algal dry cell weight.**
- **Also, pigment absorption and fluorescence provide information on algal health and state-of-growth**

Deployed at Sapphire Energy (Las Cruces, NM)

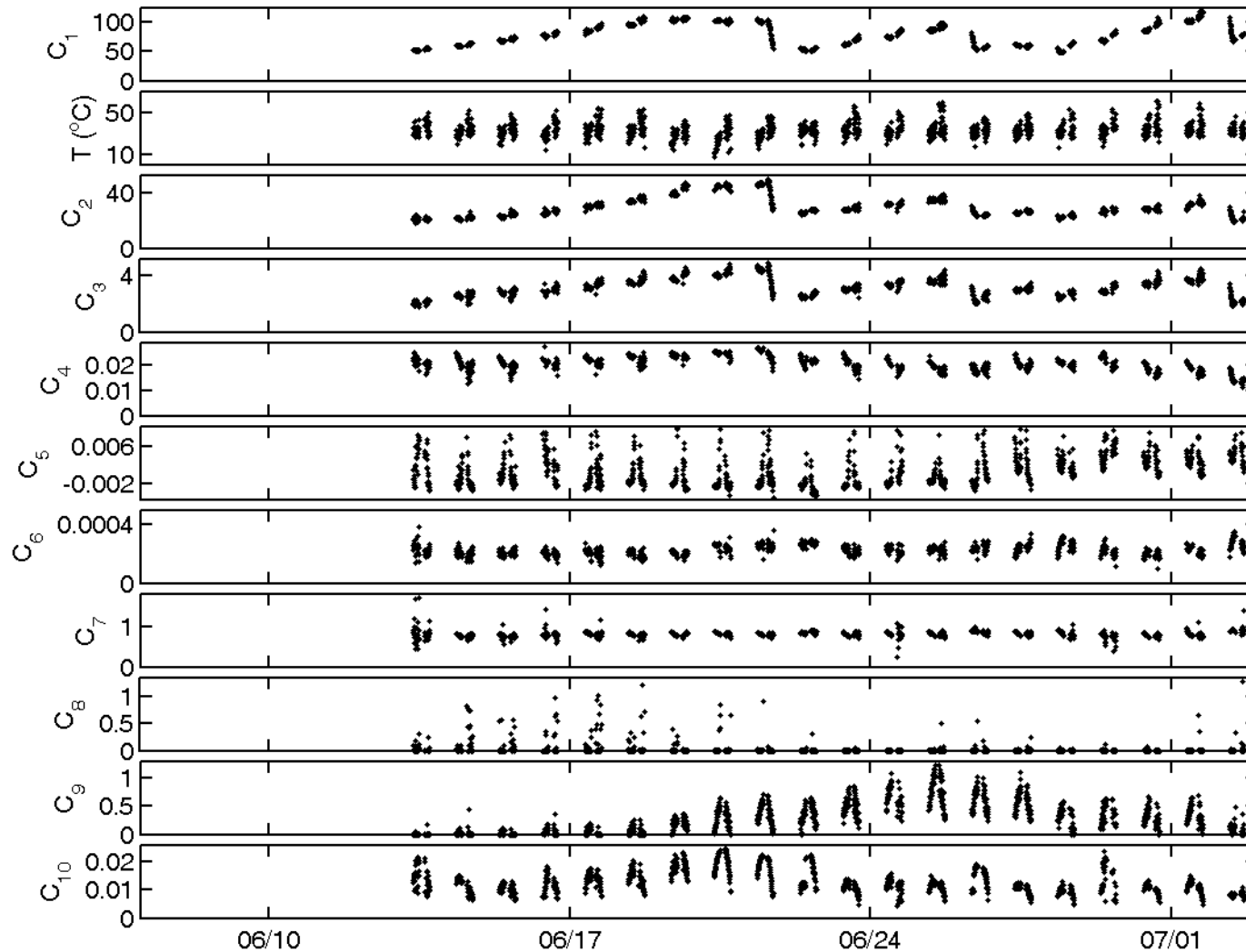




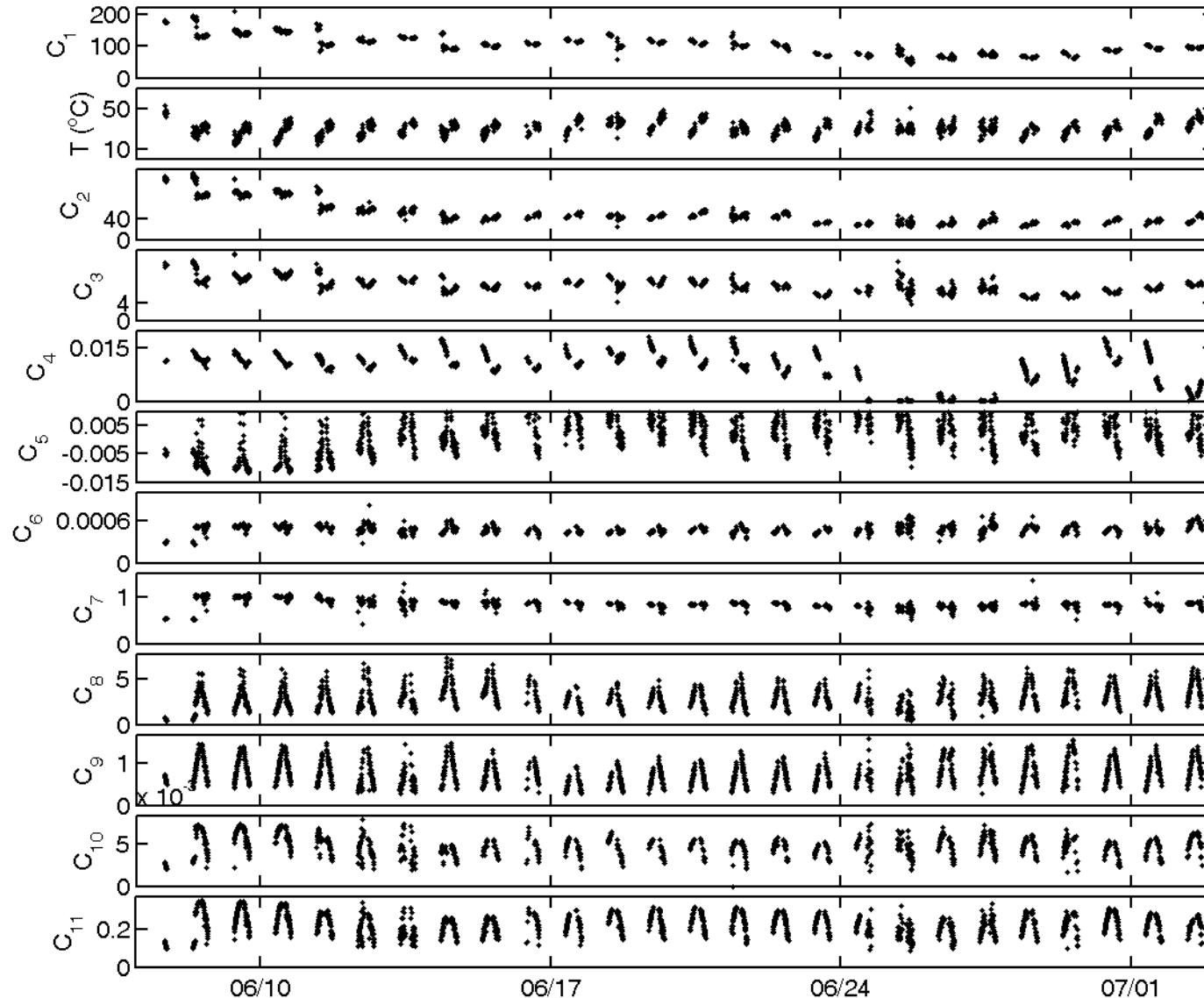
Field Deployment Brings New Challenges

- 1) Need a backscattering spectrum specific to the algal species**
 - 2) Need to account for variable position of the sun**
 - 3) Need to account for different downwelling light fields from the sun (direct) and sky (diffuse)**
 - 4) Need to account for shadows and variable clouds**
-
- Each challenge is expected to add ≥ 1 terms to the reflectance model.**

Fitting Parameters for Green Algal Culture



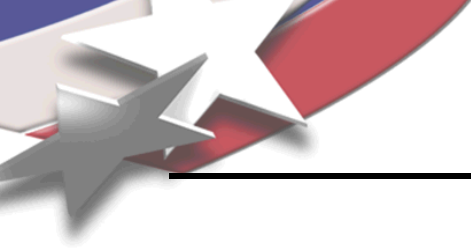
Fitting Parameters for Cyanobacterial Culture





Summary

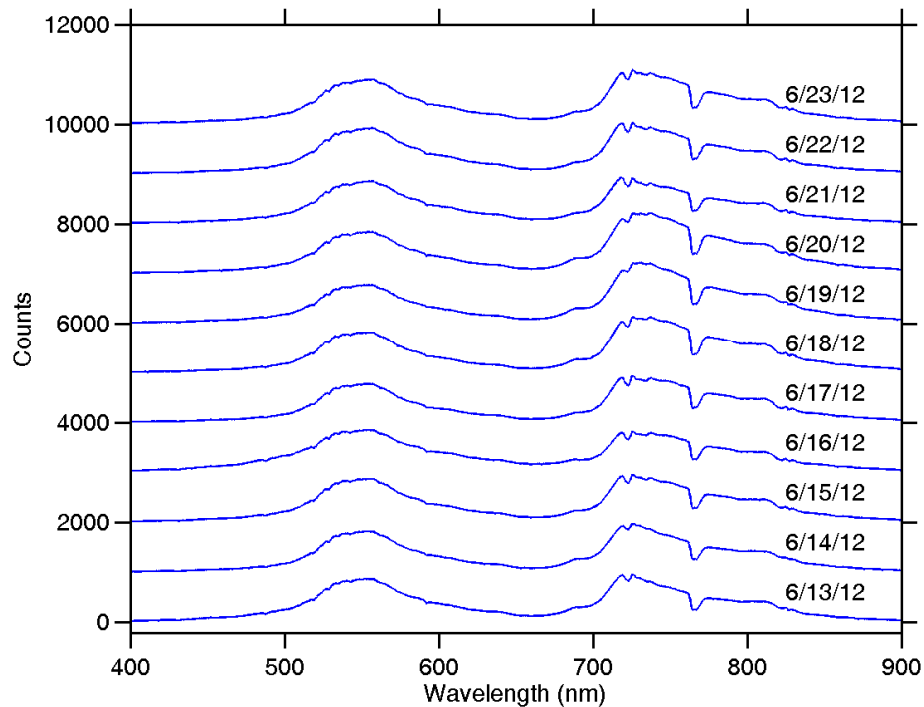
- ***In-situ* measurement of biomass and pigment optical activity**
 - **Extremely rapid (~5-min) measurement times**
- **Non-sampling**
 - **No laboratory access required**
- **Integrates rigorous light transport physics into the data analysis**
 - **No extensive pre-calibration required**
- **Non-contact**
 - **Avoids instrument fouling**
- **Fully autonomous operation**
 - **Deployed over several months in the field**



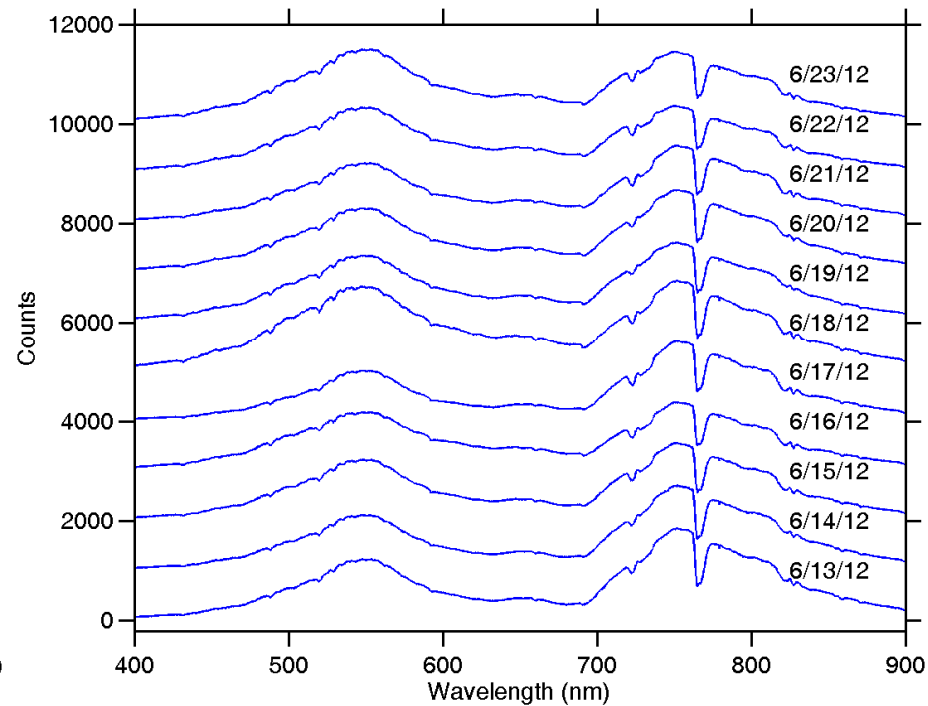
Backup Slide deck

Example data acquired at ~8:30 AM

Green algae

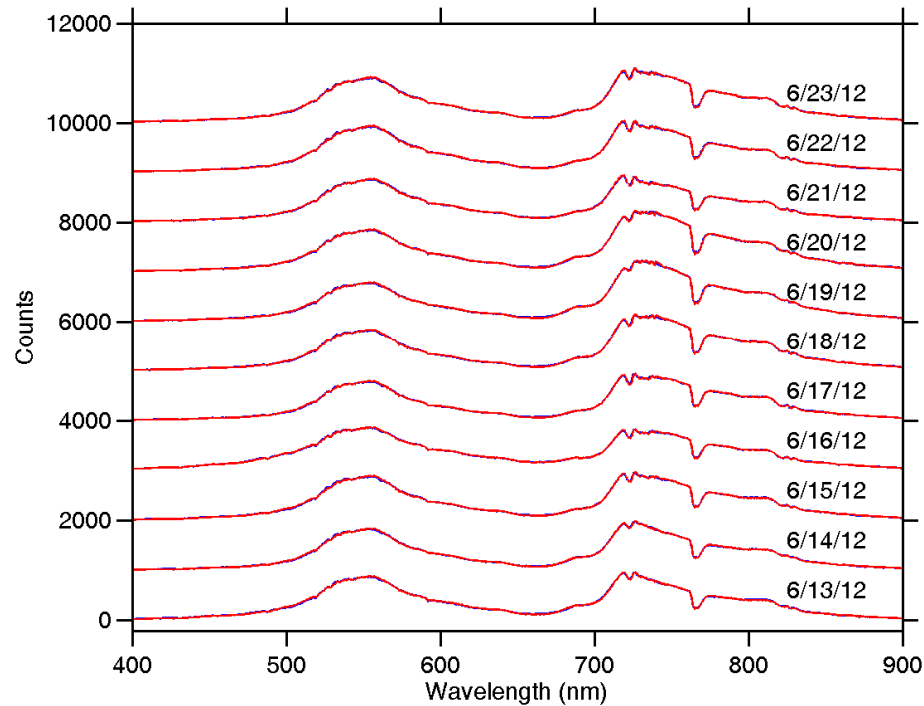


Cyanobacteria



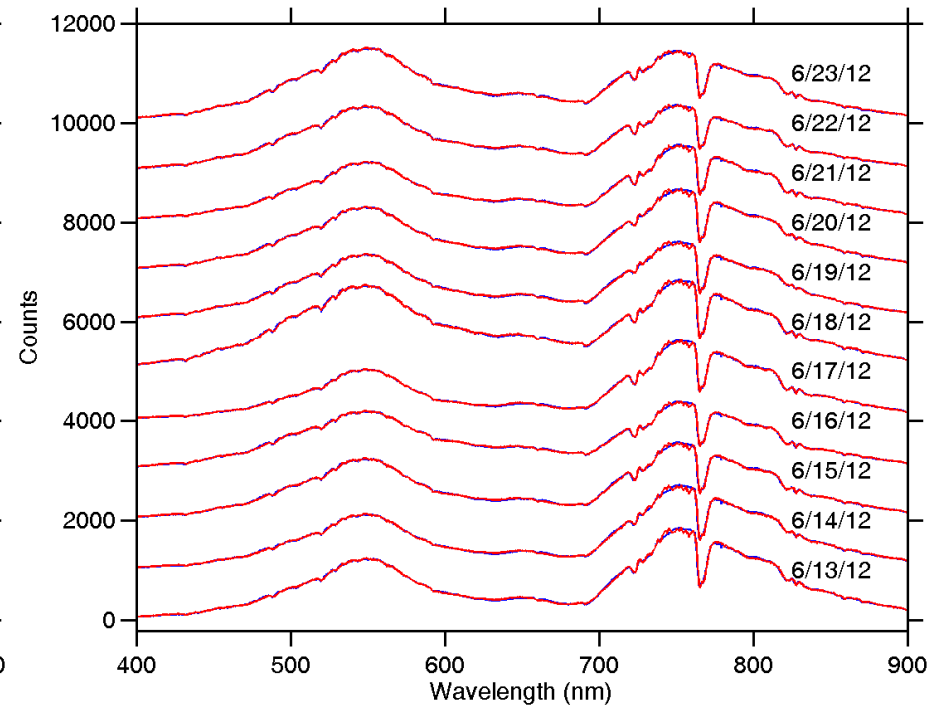
Example fitting results

Green algae



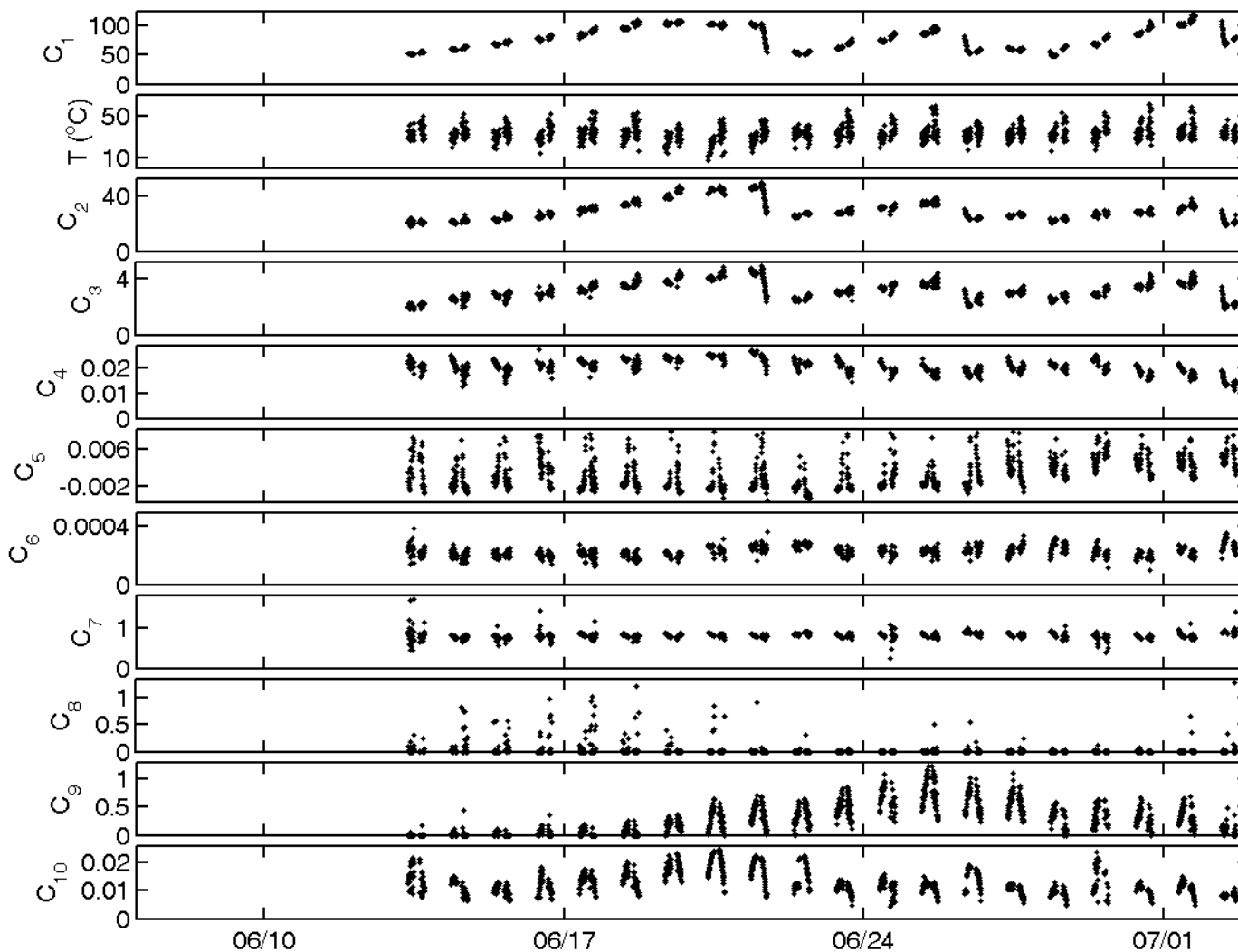
11 fitting parameters

Cyanobacteria

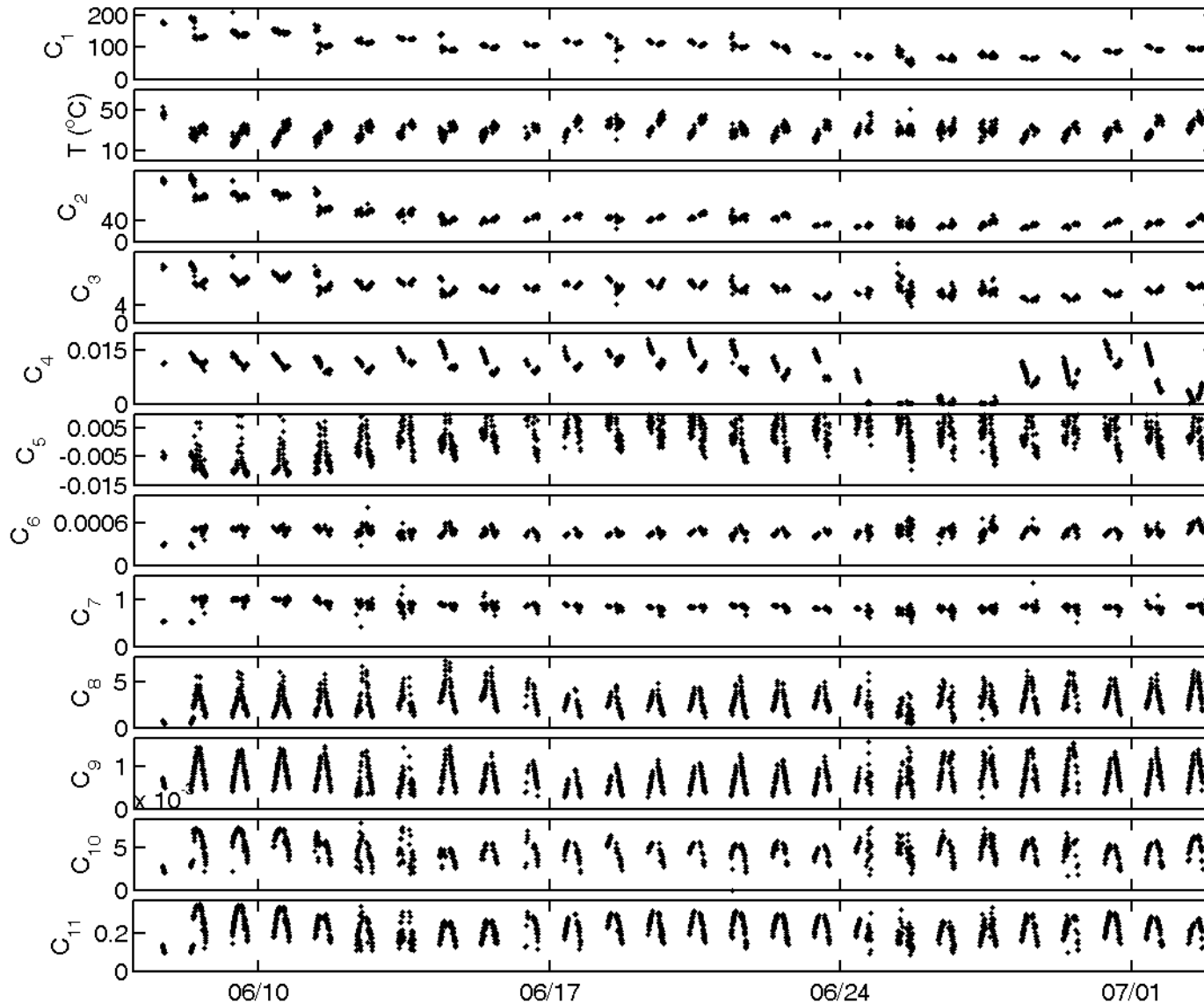


12 fitting parameters

Fitting Parameters for Green Algal Culture



Fitting Parameters for Cyanobacterial Culture



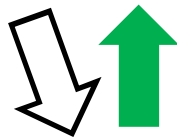
Shallow-water reflectance model

Lee et al., U. of S. Florida (1998,1999)

Incident
light



ρ^{sr} : Above-surface specular reflectance



r_{bs}^C : Below-surface volumetric reflectance
from water column



r_{bs}^B : Below-surface reflectance from
bottom

Multiple scatter results in two effects:

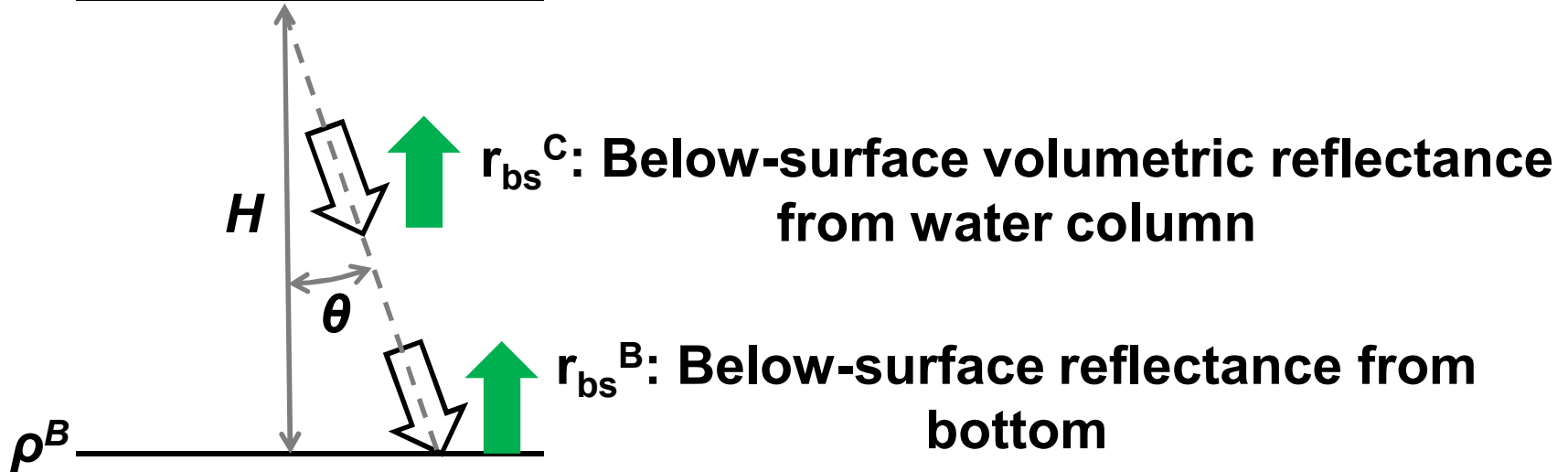
- (1) Increased angular spreading of light field
- (2) Higher-order dependence on scatter: $r(\lambda) \propto [u(\lambda)]^n, n>1$

Shallow-water reflectance model

Lee et al., U. of S. Florida (1998,1999)

Incident
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ρ^{sr} : Above-surface specular reflectance



Multiple scatter results in two effects:

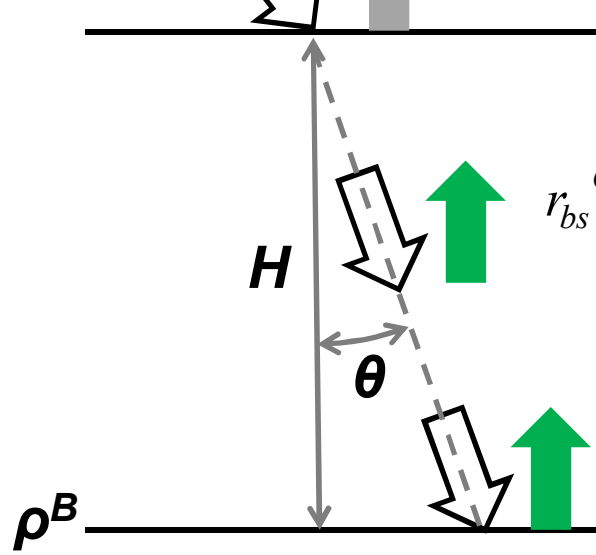
- (1) Increased angular spreading of light field
- (2) Higher-order dependence on scatter: $r(\lambda) \propto [u(\lambda)]^n, n>1$

Shallow-water reflectance model

Lee et al., U. of S. Florida (1998,1999)

Incident
light

ρ^{sr} : Above-surface specular reflectance



$$r_{bs}^{dp} = (g_0 + g_1 u^{g_2}) u \quad \text{Higher-order dependence on } u$$

$$r_{bs}^C = r_{bs}^{dp} \left(1 - \alpha_0 \exp \left\{ - \left[\frac{1}{\cos(\theta)} + D_0 \underbrace{(1 + D_1 u)^{0.5}}_{\text{Angular spreading}} \right] \kappa H \right\} \right)$$

$$r_{bs}^B = \alpha_1 \rho^B \exp \left(- \left[\frac{1}{\cos(\theta)} + D_0' \underbrace{(1 + D_1' u)^{0.5}}_{\text{Angular spreading}} \right] \kappa H \right)$$

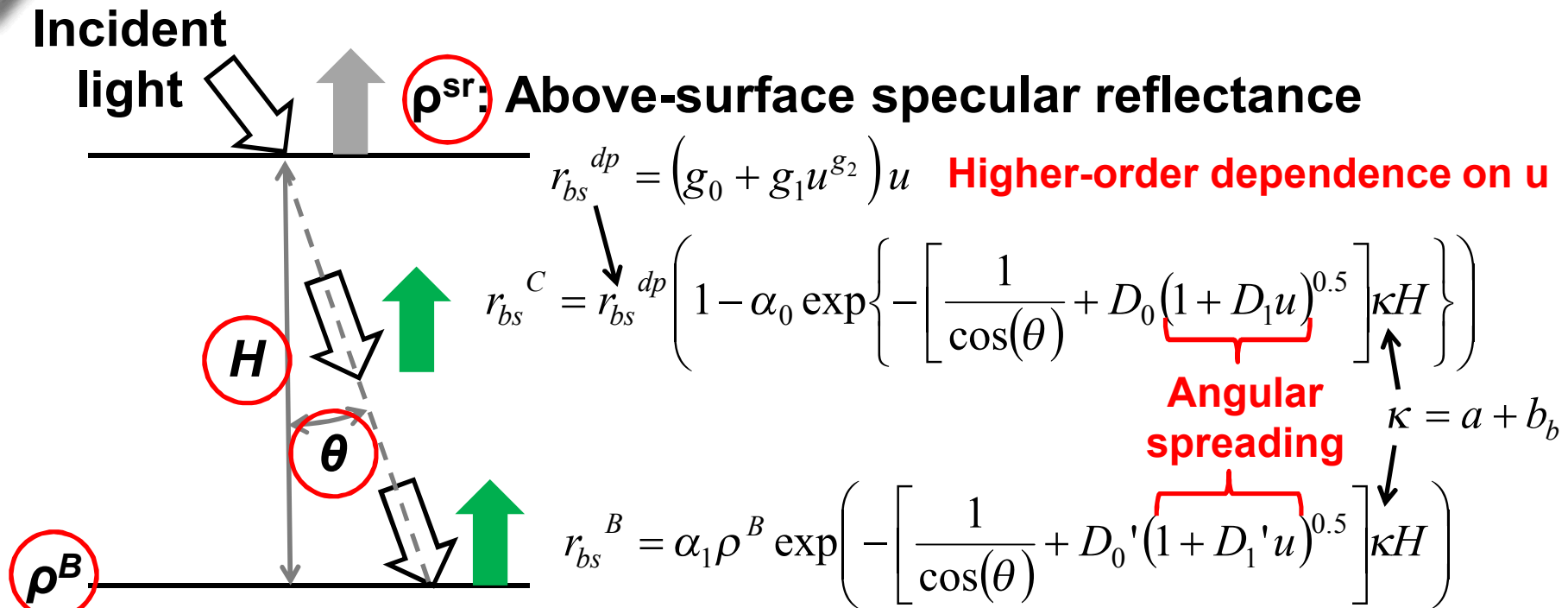
$\kappa = a + b_b$

Multiple scatter results in two effects:

- (1) Increased angular spreading of light field
- (2) Higher-order dependence on scatter: $r(\lambda) \propto [u(\lambda)]^n, n > 1$

Shallow-water reflectance model

Lee et al., U. of S. Florida (1998,1999)



- Lee et al. ran radiative transfer simulations to provide values for 9 of these parameters
 - $g_0, g_1, g_2, \alpha_0, \alpha_1, D_0, D_1, D_0', D_1'$
- H, θ, ρ^B , and ρ^{sr} can be measured.

