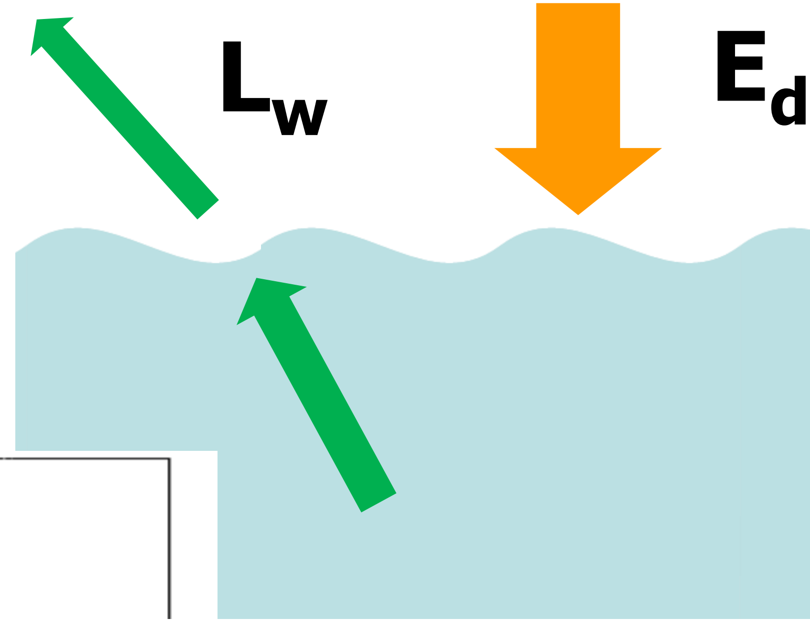
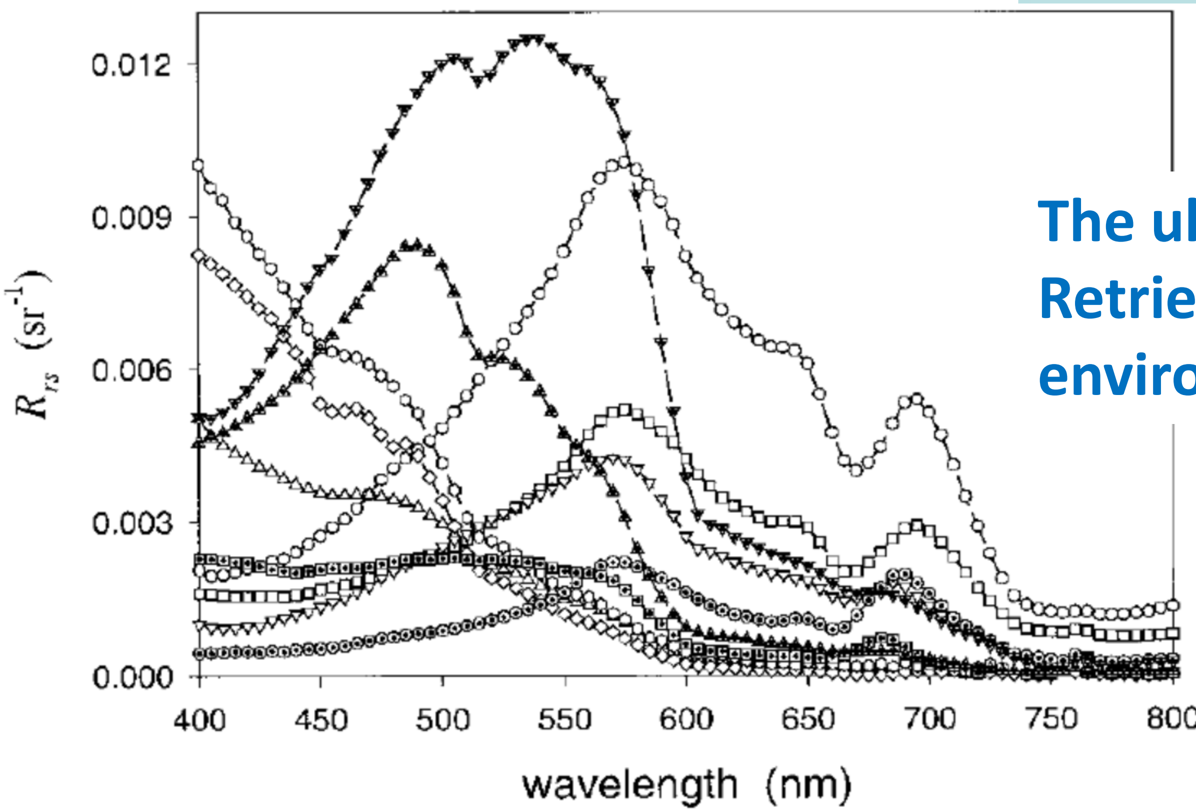
Inherent Optical Properties (IOPs)

Lecture 2: Inversion

Remote-sensing reflectance (sr^{-1}):

$$R_{rs}(\lambda) = \frac{L_w(\lambda, 0^+)}{E_d(\lambda, 0^+)}$$

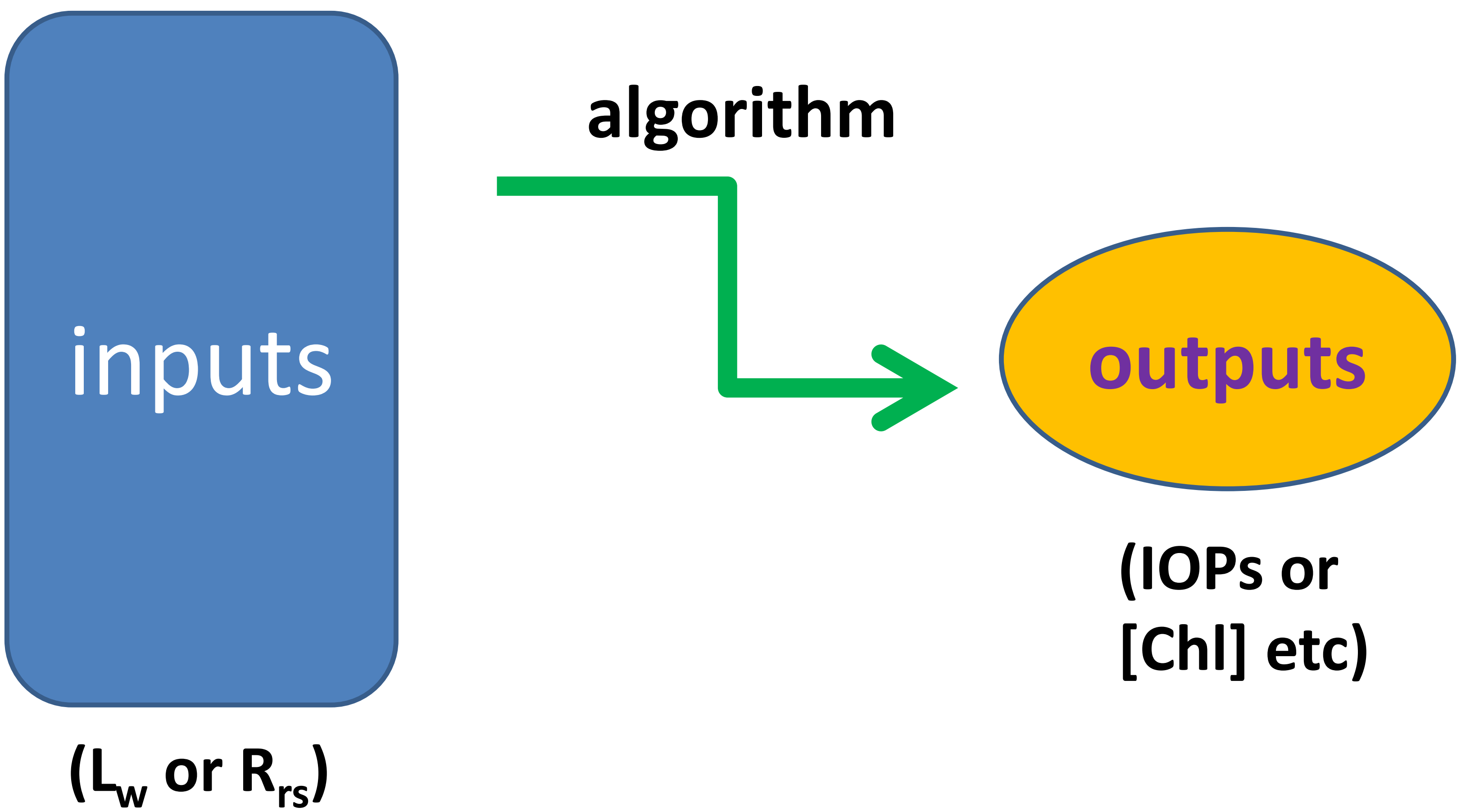




The ultimate objective of RS: Retrieval useful/important environmental information

How?

algorithm!



inputs
algorithm
outputs
(L$_w$ or R$_{rs}$)
(IOPs or
[Chl] etc)

Empirical
(explicit or implicit)

Bio-optical models： **No need**

Semi-analytical
(algebraic， LUT, optimization)

Bio-optical models： **Yes**

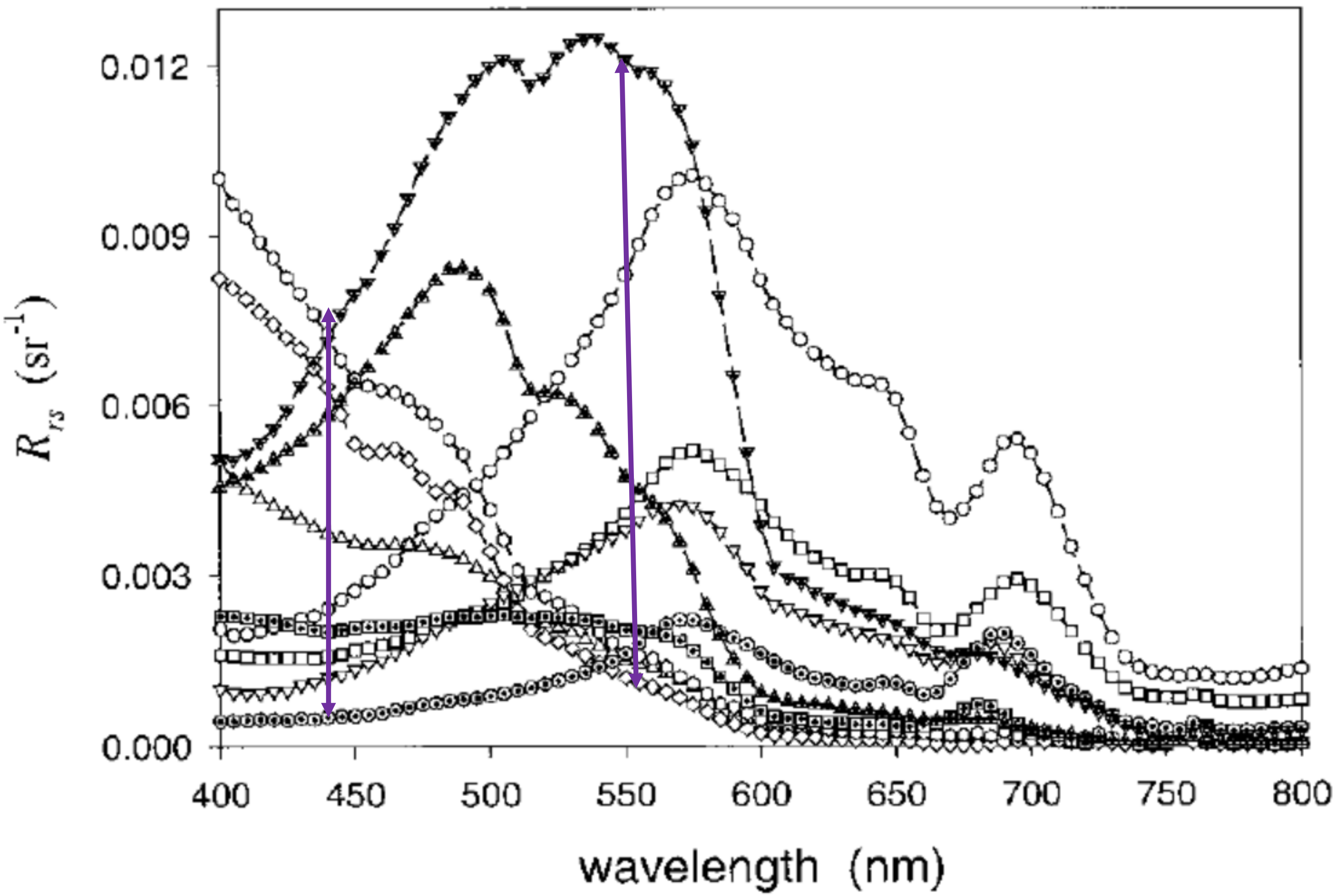
Bottom Up Strategy (BUS)

Top Down Strategy (TDS)

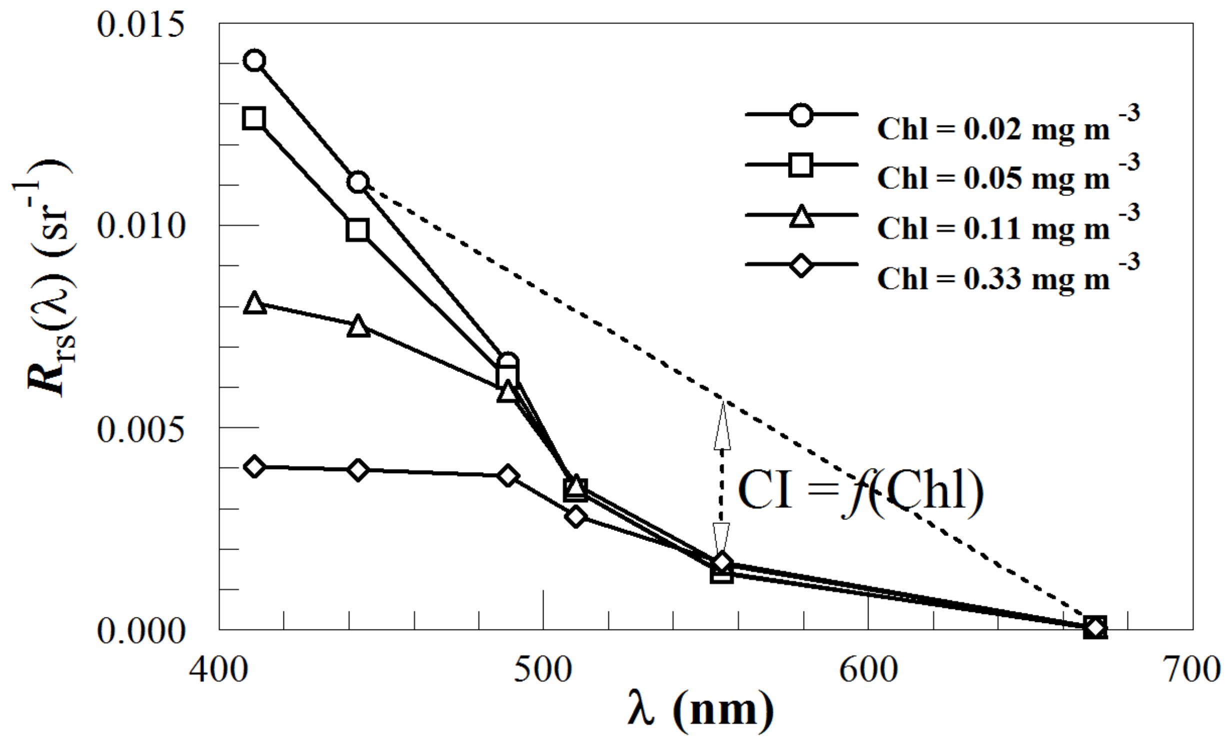
Chl centered band-ratio algorithms

Algorithm	Type	Result Equation(s)	Band Ratio (R), Coefficients (a)
Global processing (GPs)	power	$C_{13} = 10^{(a0+a1*R1)}$ $C_{23} = 10^{(a2+a3*R2)}$ $[C + P] = C_{13}$; if C_{13} and $C_{23} > 1.5\ \mu g\ L^{-1}$ then $[C + P] = C_{23}$	$R1 = \log(Lwn443/Lwn550)$ $R2 = \log(Lwn520/Lwn550)$ $a = [0.053,\ 1.705,\ 0.522,\ 2.440]$
Clark three-band (C3b)	power	$[C + P] = 10^{(a0+a1*R)}$	$R = \log((Lwn443 + Lwn520)/Lwn550)$ $a = [0.745, -2.252]$
Aiken-C	hyperbolic + power	$C_{21} = \exp(a0 + a1*\ln(R))$ $C_{23} = (R + a2)/(a3 + a4*R)$ $C = C_{21}$; if $C < 2.0\ \mu g\ L^{-1}$ then $C = C_{23}$	$R = Lwn490/Lwn555$ $a = [0.464, -1.989, -5.29, 0.719, -4.23]$
Aiken-P	hyperbolic + power	$C_{22} = \exp(a0 + a1*\ln(R))$ $C_{24} = (R + a2)/(a3 + a4*R)$ $[C + P] = C_{22}$; if $[C + P] < 2.0\ \mu g\ L^{-1}$ then $[C + P] = C_{24}$	$R = Lwn490/Lwn555$ $a = [0.696, -2.085, -5.29, 0.592, -3.48]$
OCTS-C	power	$C = 10^{(a0+a1*R)}$	$R = \log((Lwn520 + Lwn565)/Lwn490)$ $a = [0.55006, 3.497]$
OCTS-P	multiple regression	$[C + P] = 10^{(a0+a1*R1+a2*R2)}$	$R1 = \log(Lwn443/Lwn520)$ $R2 = \log(Lwn490/Lwn520)$ $a = [0.19535, -2.079, -3.497]$
POLDER	cubic	$C = 10^{(a0+a1*R+a2*R^2+a3*R^3)}$	$R = \log(Rrs443/Rrs565)$ $a = [0.438, -2.114, 0.916, -0.851]$
CalCOFI two-band linear	power	$C = 10^{(a0+a1*R)}$	$R = \log(Rrs490/Rrs555)$ $a = [0.444, -2.431]$
CalCOFI two-band cubic	cubic	$C = 10^{(a0+a1*R+a2*R^2+a3*R^3)}$	$R = \log(Rrs490/Rrs555)$ $a = [0.450, -2.860, 0.996, -0.3674]$
CalCOFI three-band	multiple regression	$C = \exp(a0 + a1*R1 + a2*R2)$	$R1 = \ln(Rrs490/Rrs555)$ $R2 = \ln(Rrs510/Rrs555)$ $a = [1.025, -1.622, -1.238]$
CalCOFI four-band	multiple regression	$C = \exp(a0 + a1*R1 + a2*R2)$	$R1 = \ln(Rrs443/Rrs555)$ $R2 = \ln(Rrs412/Rrs510)$ $a = [0.753, -2.583, 1.389]$
Morel-1	power	$C = 10^{(a0+a1*R)}$	$R = \log(Rrs443/Rrs555)$ $a = [0.2492, -1.768]$
Morel-2	power	$C = \exp(a0 + a1*R)$	$R = \ln(Rrs490/Rrs555)$ $a = [1.077835, -2.542605]$
Morel-3	cubic	$C = 10^{(a0+a1*R+a2*R^2+a3*R^3)}$	$R = \log(Rrs443/Rrs555)$ $a = [0.20766, -1.82878, 0.75885, -0.73979]$
Morel-4	cubic	$C = 10^{(a0+a1*R+a2*R^2+a3*R^3)}$	$R = \log(Rrs490/Rrs555)$ $a = [1.03117, -2.40134, 0.3219897, -0.291066]$

(O'Reilly et al 1998)


0.012
0.009
0.006
0.003
0.000
R_{rs} (sr^{-1})
400
450
500
550
600
650
700
750
800
wavelength (nm)

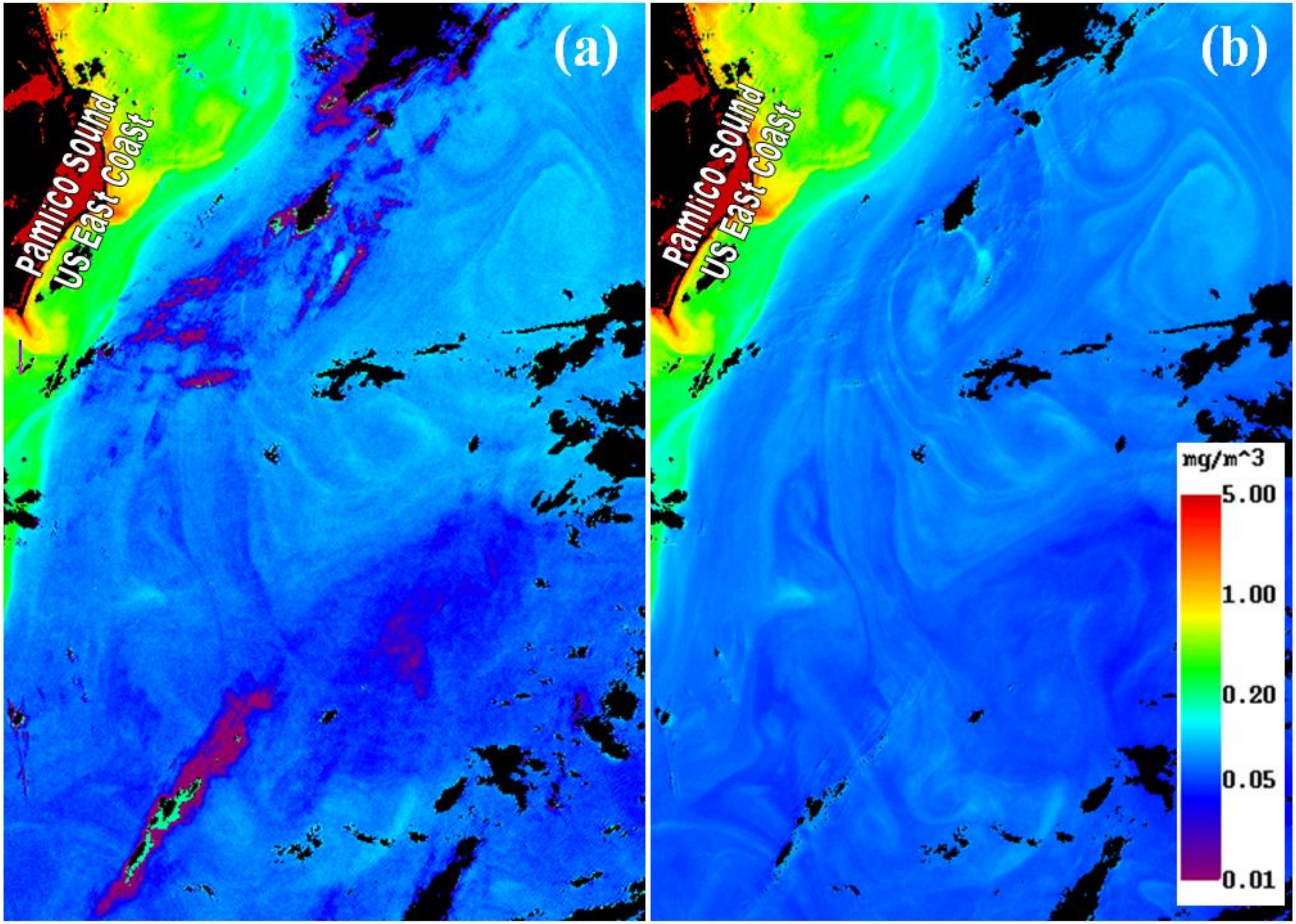
Chl based on band difference



$$CI = R_{rs}(555) - \left\{ R_{rs}(443) + \frac{555-443}{670-443} \times \left[R_{rs}(670) - R_{rs}(443) \right] \right\}$$

$$Chl = 10^{-0.49+191.66\,CI}; \qquad CI \leq -0.0005\,\mathrm{sr}^{-1}$$

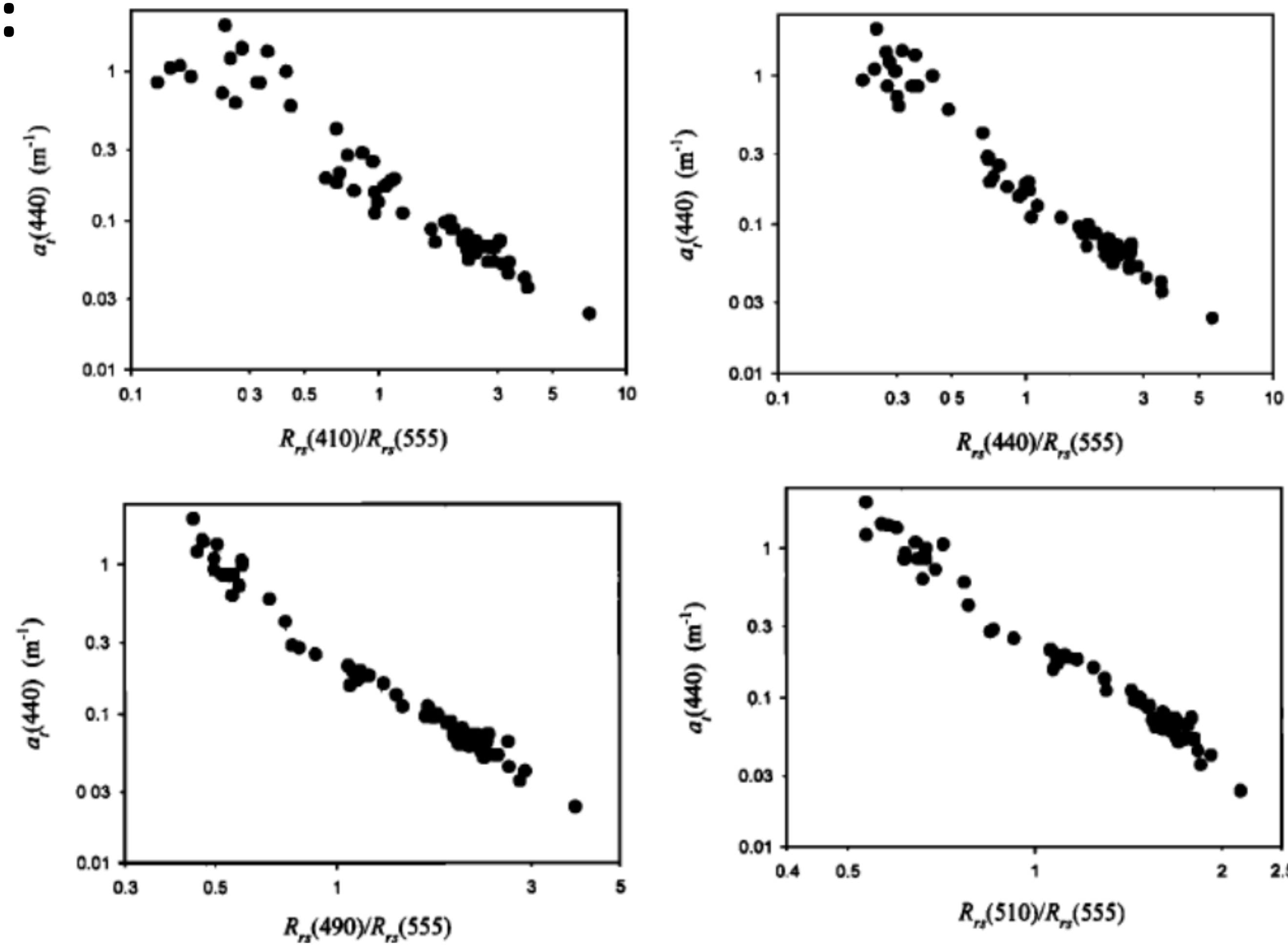
(Hu et al 2012)



(a)
(b)
Pamlico Sound
US East coast
Pamlico Sound
US East coast
mg/m^3
5.00
1.00
0.20
0.05
0.01

(Hu et al 2012)

Empirical:



$$a_t(440) = 10^{-0.674-0.531\rho_{25}-0.745\rho_{25}^2-1.469\rho_{35}+2.375\rho_{35}^2}, \qquad (14)$$

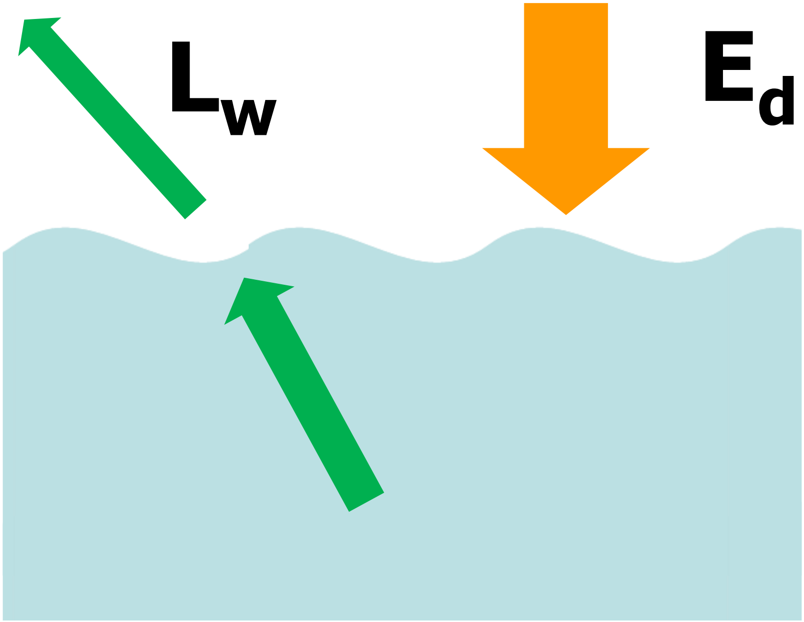
$$a_\phi(440) = 10^{-0.919+1.037\rho_{25}-0.407\rho_{25}^2-3.531\rho_{35}+1.579\rho_{35}^2}, \qquad (20)$$

(Lee et al 1998)

Physics-based algorithms (mechanistic)

Remote-sensing reflectance (sr^{-1}):

$$R_{rs}(\lambda) = \frac{L_w(\lambda, 0^+)}{E_d(\lambda, 0^+)}$$



How is R_{rs} related to water's optical (biogeochemical) properties?

Physics-based algorithms (mechanistic)

How is R_{rs} related to water's optical (biogeochemical) properties?

Radiative Transfer Equation (no inelastic scattering):

$$\frac{d\,L(\Omega)}{d\,l} = -c\,L(\Omega) + \int L(\Omega')\,\beta(\Omega',\Omega)\,d\omega$$

$$\frac{d\,L_u(\pi,z)}{d\,z} = -c\,L_u(\pi,z) + \int L(\Omega')\,\beta(\Omega',\Omega)\,d\omega$$

Exact solution (no inelastic scattering):

$$r_{rs}(\lambda,\Omega') = L_u(0^-,\Omega') \Big/ E_d(0^-)$$

$$r_{rs}(\lambda,\Omega') \equiv \frac{D_d(\lambda,\theta_S')}{c(\lambda)+k_L(\lambda,\Omega')-f_L(\lambda,\Omega')b_f(\lambda)} \frac{\int_0^{2\pi}\int_0^{\pi/2}\beta(\Omega',\Omega)\,L(\lambda,\Omega')\sin(\theta')\,d\theta'\,d\varphi'}{E_{od}(0^-,\lambda,\theta_S')}$$

(Zaneveld 1995)

Albert and Mobley (2003) :

$$r_{rs}(\lambda,\Omega') = q(\Omega',w)\sum_{i=1}^{4} p_i \left(\frac{b_b(\lambda)}{a(\lambda)+b_b(\lambda)}\right)^i$$

Lee et al (2004)

$$r_{rs}(\lambda,\Omega') = g_w(\Omega')\frac{b_{bw}(\lambda)}{a(\lambda)+b_b(\lambda)} + g_p(\lambda,\Omega')\frac{b_{bp}(\lambda)}{a(\lambda)+b_b(\lambda)}$$

Park and Ruddick (2005)

$$r_{rs}(\lambda,\Omega') = \sum_{i=1}^{4} g_i(\Omega',\nu_b)\left(\frac{b_b(\lambda)}{a(\lambda)+b_b(\lambda)}\right)^i$$

Van Der Woerd and Pasterkamp (2008)

$$\ln[r_{rs}(\lambda,\Omega')] = \sum_{i=1}^{4}\sum_{j=1}^{4} P_{ij}(\Omega')[\ln(a(\lambda))]^i[\ln(b(\lambda))]^j$$

Morel et al (1993, 1996, 2002):

$$r_{rs}(\lambda, \Omega') = g(\lambda, Chl, \Omega') \frac{b_b(\lambda)}{a(\lambda) + b_b(\lambda)}$$

Gordon et al (1988):

$$r_{rs}(\lambda, \pi) = \sum_{i=1}^{2} g_i \left(\frac{b_b(\lambda)}{a(\lambda) + b_b(\lambda)} \right)^i;$$

$$g_1 = 0.0949,\ g_2 = 0.0794$$

$r_{rs} \rightarrow R_{rs}$?

$$R_{rs} = \frac{L_w}{E_d(0^+)}$$

$$E_d(0^-) = t_E E_d(0^+) + \gamma E_u(0^-)$$

$$L_w = \frac{t_L}{n_w^{\ 2}} L_u(0^-)$$

$$\boldsymbol{R_{rs}} = \frac{\boldsymbol{t_E\, t_L}}{\boldsymbol{n_w}^{2}} \frac{\boldsymbol{r_{rs}}}{\boldsymbol{1-\gamma R}} = \frac{0.52\, r_{rs}}{1-1.7\, r_{rs}}$$

Solve Rrs for IOPs or in-water constituents?

Two basic strategies:

1. Bottom-up strategy (BUS):

Assume we know the spectral shapes of the optically active components

2. Top-down strategy (TDS):

Only need the spectral shape information when it is necessary

What are we facing in RS algorithms?

$$R_{rs}(\lambda) = F(a(\lambda), b_b(\lambda))$$

⇓

$$R_{rs}(\lambda) = F(a_w(\lambda), a_{ph}(\lambda), a_{dg}(\lambda), b_{bw}(\lambda), b_{bp}(\lambda))$$

⇓

$$\begin{cases} R_{rs}(\lambda_1) = F(a_w(\lambda_1), a_{ph}(\lambda_1), a_{dg}(\lambda_1), b_{bw}(\lambda_1), b_{bp}(\lambda_1)) \\ R_{rs}(\lambda_2) = F(a_w(\lambda_2), a_{ph}(\lambda_2), a_{dg}(\lambda_2), b_{bw}(\lambda_2), b_{bp}(\lambda_2)) \\ \vdots \\ R_{rs}(\lambda_n) = F(a_w(\lambda_n), a_{ph}(\lambda_n), a_{dg}(\lambda_n), b_{bw}(\lambda_n), b_{bp}(\lambda_n)) \end{cases}$$

# of unknowns > # of equations!

An ill formulated math problem!

Have to increase # of equations or decrease # of unknowns!

1. Bottom-up strategy (BUS):

Build-up an Rrs spectrum block-by-block:

$$a(\lambda) = a_w(\lambda) + \sum a_{xi}(\lambda) \qquad b_b(\lambda) = b_{bw}(\lambda) + \sum b_{bxi}(\lambda)$$

$$a(\lambda) = a_w(\lambda) + a_{ph}(\lambda) + a_d(\lambda) + a_g(\lambda)$$

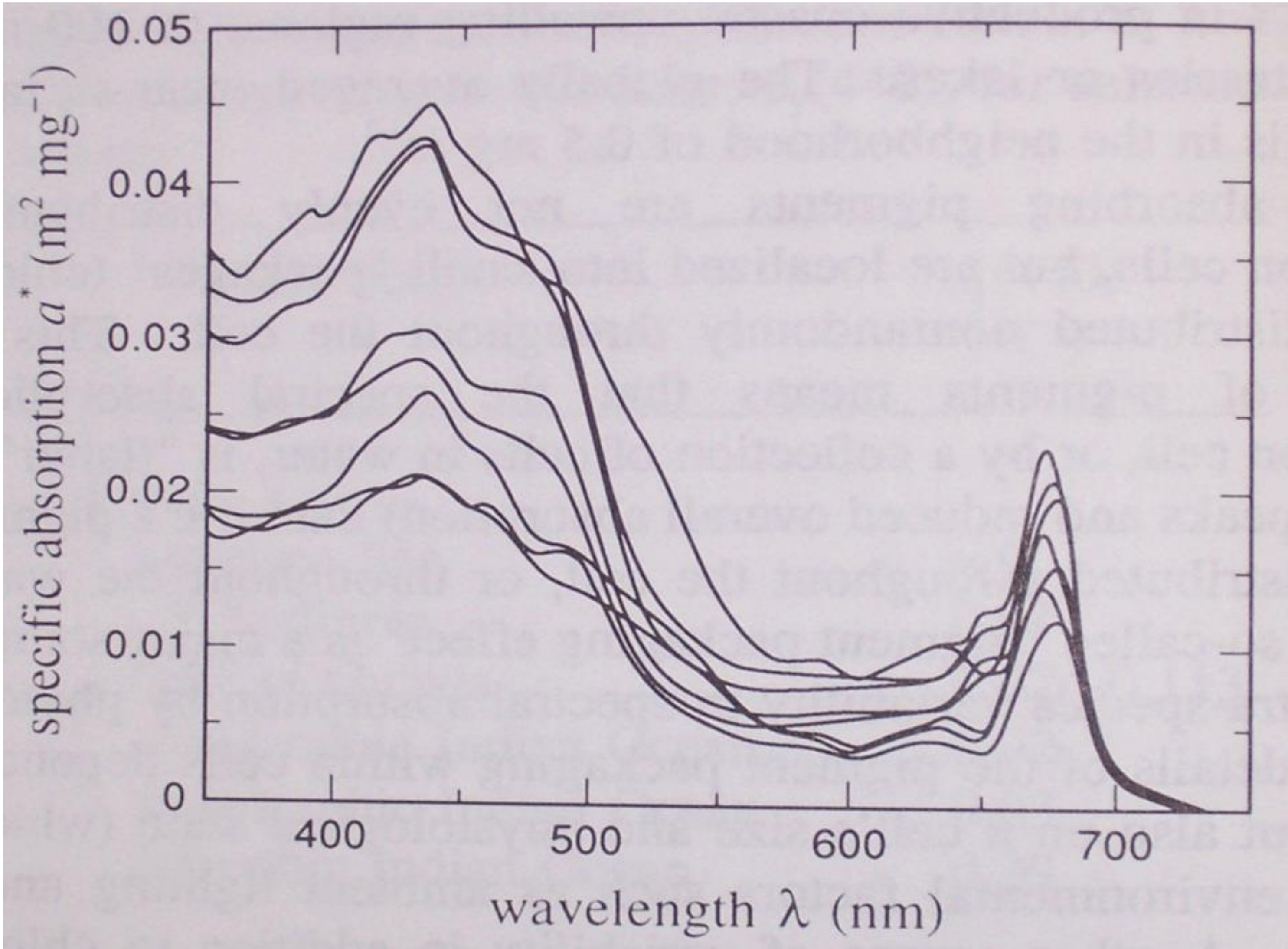
$$a(\lambda) = a_w(\lambda) + a_{ph}(\lambda) + a_{dg}(\lambda)$$

$$a(\lambda) = a_w(\lambda) + M_1 \langle a_{ph}(\lambda) \rangle + M_2 \langle a_{dg}(\lambda) \rangle$$

$$b_b(\lambda) = b_{bw}(\lambda) + b_{bp}(\lambda)$$

$$b_b(\lambda) = b_{bw}(\lambda) + M_3 \langle b_{bp}(\lambda) \rangle$$

Bio-optical models (forward model)



Modeling a_{ph} spectrum

Example of one parameter hyperspectral $a_{ph}(\lambda)$ model:

Bricaud et al (1995):

$$a_{ph}(\lambda) = A_{ph}(\lambda)\,Chl^{1-B_{ph}(\lambda)}$$

Table 2. Spectral Values of the Constants Obtained When Fitting the Variations of $a^*_{ph}(\lambda)$ Versus the (chl a + di a) Concentration ⟨Chl⟩ to Power Laws of the Form $a^*_{ph}(\lambda) = A(\lambda)\,\langle Chl\rangle^{-B(\lambda)}$ and Determination Coefficients on the Log-Transformed Data r^2

λ, nm	A	B	r^2	λ, nm	A	B
400	0.0263	0.282	0.702	402	0.0271	0.281
404	0.0280	0.282	0.706	406	0.0290	0.281
408	0.0301	0.282	0.710	410	0.0313	0.283
412	0.0323	0.286	0.718	414	0.0333	0.291
416	0.0342	0.293	0.725	418	0.0349	0.296
420	0.0356	0.299	0.733	422	0.0359	0.306
424	0.0362	0.313	0.746	426	0.0369	0.316
428	0.0376	0.317	0.749	430	0.0386	0.314
432	0.0391	0.318	0.750	434	0.0395	0.324
436	0.0399	0.328	0.757	438	0.0401	0.332
440	0.0403	0.332	0.762	442	0.0398	0.339
444	0.0390	0.348	0.774	446	0.0383	0.355
448	0.0375	0.360	0.783	450	0.0371	0.359
452	0.0365	0.362	0.783	454	0.0358	0.366
456	0.0354	0.367	0.789	458	0.0351	0.368
460	0.0350	0.365	0.789	462	0.0347	0.366
464	0.0343	0.368	0.792	466	0.0339	0.369
468	0.0335	0.369	0.793	470	0.0332	0.368
472	0.0325	0.371	0.792	474	0.0318	0.375
476	0.0312	0.378	0.793	478	0.0306	0.379
480	0.0301	0.377	0.791	482	0.0296	0.377
484	0.0290	0.376	0.788	486	0.0285	0.373
488	0.0279	0.369	0.783	490	0.0274	0.361
492	0.0267	0.356	0.774	494	0.0258	0.349
496	0.0249	0.341	0.763	498	0.0240	0.332
500	0.0230	0.321	0.747	502	0.0220	0.311
504	0.0209	0.300	0.722	506	0.0199	0.288
508	0.0189	0.275	0.686	510	0.0180	0.260
512	0.0171	0.249	0.641	514	0.0163	0.237
516	0.0156	0.224	0.578	518	0.0149	0.211
520	0.0143	0.196	0.498	522	0.0137	0.184
524	0.0131	0.173	0.417	526	0.0126	0.162
528	0.0121	0.151	0.332	530	0.0117	0.139
532	0.0113	0.129	0.248	534	0.0108	0.119
536	0.0104	0.109	0.176	538	0.0100	0.100
540	0.0097	0.090	0.116	542	0.0093	0.081

Lee (1994); Lee et al (1998):

$$a_{ph}(\lambda) = \left(a_0(\lambda) + a_1(\lambda)\ln(P)\right)P$$

$$P = a_{ph}(440)$$

Table 2. Parameters for the Empirical $a_\phi(\lambda)$ Simulation by Eq. (12)[a]

Wavelength	$a_0(\lambda)$	$a_1(\lambda)$
390	0.5813	0.0235
400	0.6843	0.0205
410	0.7782	0.0129
420	0.8637	0.006
430	0.9603	0.002
440	1.0	0
450	0.9634	0.006
460	0.9311	0.0109
470	0.8697	0.0157
480	0.789	0.0152
490	0.7558	0.0256
500	0.7333	0.0559
510	0.6911	0.0865
520	0.6327	0.0981
530	0.5681	0.0969
540	0.5046	0.09
550	0.4262	0.0781
560	0.3433	0.0659
570	0.295	0.06
580	0.2784	0.0581

Example of two-parameters model: (Ciotti et al 2002)

$$a_\phi(\lambda) = a_\phi(505)\cdot[S_f\cdot\bar{a}_{<pico>}(\lambda)] + [(1-S_f)\cdot\bar{a}_{<micro>}(\lambda)]$$

Table 3. Basis vectors representing the normalized absorption for the smallest ($\bar{a}_{(pico)}(\lambda)$, *Prochlorococcus*) and biggest ($\bar{a}_{(micro)}(\lambda)$, average microplankton) cell sizes in our data set. Wavelength (λ) in nm. Basis vectors for $a^*_{ph}(\lambda)$ can be constructed by setting $\bar{a}_{(pico)}(676)$ to 0.023 $m^2\ mg^{-1}$, $\bar{a}_{(micro)}(674)$ to 0.0086 $m^2\ mg^{-1}$, and scaling for the other wavelengths accordingly.

λ	Pico	Micro	λ	Pico	Micro	λ	Pico	Micro	λ	Pico	Micro	λ	Pico	Micro
400	1.682	1.574												
402	1.734	1.584	462	2.526	1.623	522	0.544	1.013	582	0.111	0.459	642	0.191	0.528
404	1.800	1.600	464	2.455	1.616	524	0.522	0.992	584	0.072	0.452	644	0.174	0.526
406	1.890	1.617	466	2.402	1.606	526	0.486	0.977	586	0.073	0.452	646	0.197	0.528
408	1.978	1.633	468	2.331	1.592	528	0.448	0.959	588	0.073	0.449	648	0.176	0.538
410	2.057	1.654	470	2.281	1.568	530	0.391	0.944	590	0.099	0.443	650	0.168	0.549
412	2.162	1.669	472	2.205	1.542	532	0.375	0.927	592	0.070	0.433	652	0.160	0.574
414	2.269	1.674	474	2.136	1.509	534	0.336	0.909	594	0.095	0.424	654	0.217	0.605
416	2.327	1.684	476	2.063	1.481	536	0.305	0.888	596	0.085	0.416	656	0.244	0.655
418	2.398	1.697	478	2.049	1.459	538	0.292	0.868	598	0.090	0.406	658	0.286	0.720
420	2.457	1.708	480	1.998	1.437	540	0.288	0.847	600	0.086	0.401	660	0.381	0.798
422	2.533	1.710	482	1.930	1.415	542	0.261	0.826	602	0.068	0.400	662	0.437	0.889
424	2.614	1.716	484	1.918	1.399	544	0.245	0.806	604	0.078	0.403	664	0.520	0.979
426	2.663	1.737	486	1.897	1.387	546	0.214	0.785	606	0.069	0.408	666	0.660	1.068
428	2.749	1.763	488	1.867	1.377	548	0.194	0.764	608	0.090	0.416	668	0.716	1.147
430	2.804	1.793	490	1.812	1.367	550	0.187	0.737	610	0.096	0.429	670	0.824	1.207
432	2.840	1.812	492	1.776	1.349	552	0.138	0.711	612	0.094	0.443	672	0.846	1.243
434	2.915	1.827	494	1.701	1.338	554	0.137	0.682	614	0.084	0.458	674	0.816	1.249
436	2.947	1.830	496	1.648	1.319	556	0.111	0.653	616	0.105	0.473	676	0.891	1.227
438	2.978	1.834	498	1.522	1.301	558	0.094	0.626	618	0.128	0.487	678	0.869	1.174
440	3.014	1.824	500	1.439	1.271	560	0.095	0.604	620	0.119	0.495	680	0.812	1.096
442	3.032	1.800	502	1.373	1.242	562	0.070	0.580	622	0.126	0.499	682	0.741	1.004
444	3.011	1.771	504	1.270	1.222	564	0.053	0.555	624	0.138	0.504	684	0.605	0.893

Multiple-parameters model:

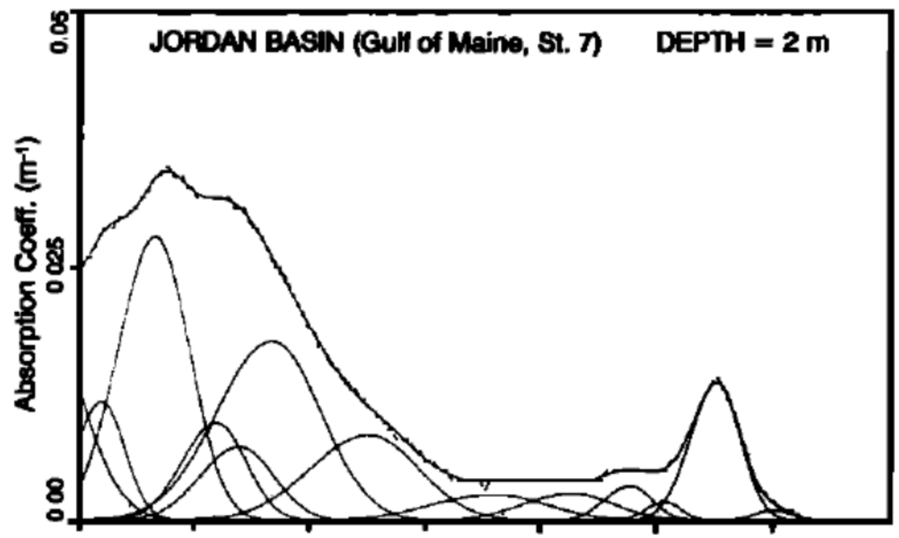
$$a_{ph}(\lambda) = \sum_{j=1}^{l} C_j a_j^*(\lambda_{mj}) \exp\left[\frac{(\lambda - \lambda_{mj})^2}{2\sigma_j^2}\right] \qquad (7)$$

TABLE 2. Input Values and Mean Characteristics of Gaussian Bands Reflecting Absorption by Chlorophylls and Carotenoids

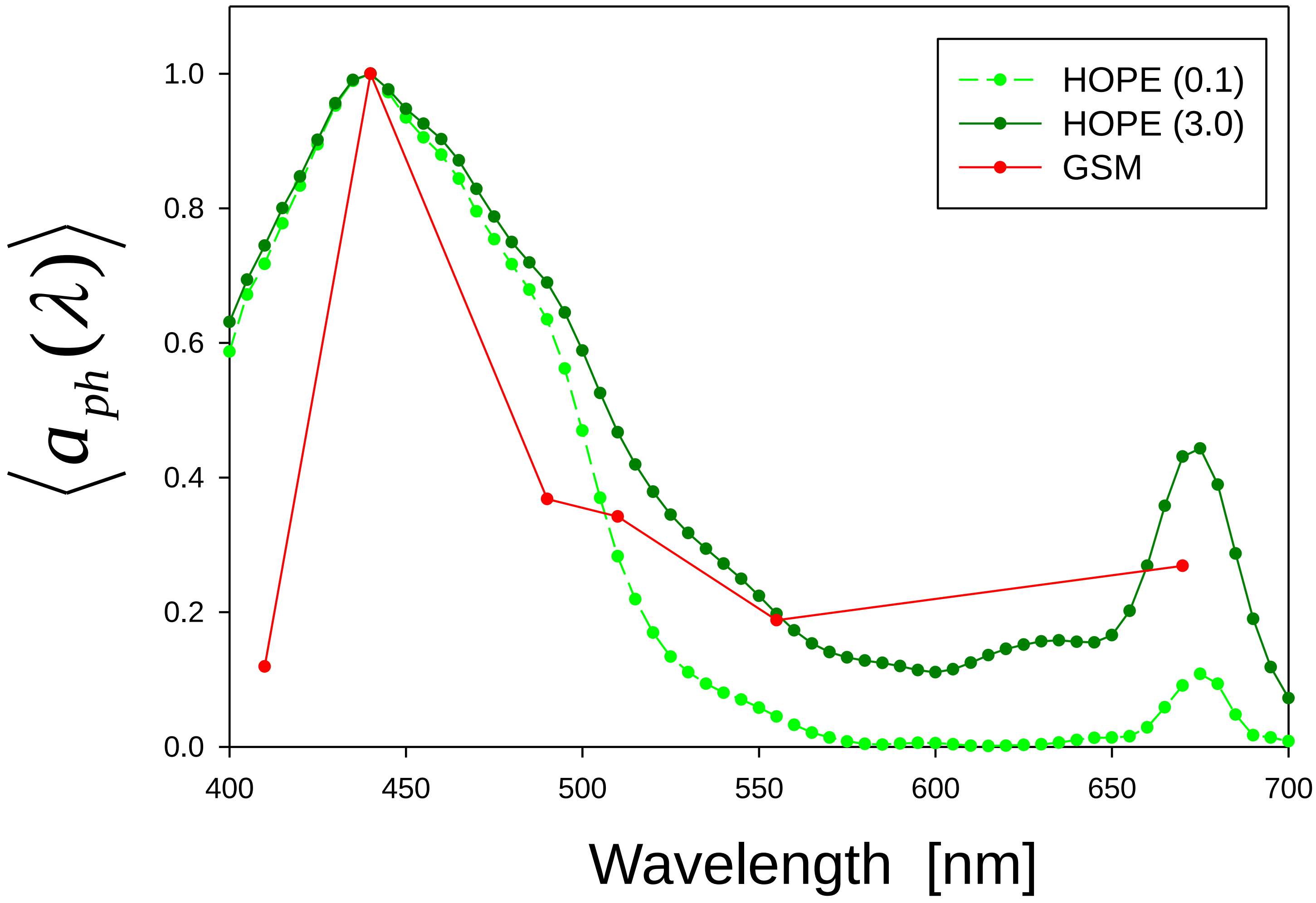
Characteristic	Gaussian Band Number and Associated Pigment Species												
	1 chl *a*	2 chl *a*	3 chl *a*	4 chl *c*	5 chl *b*	6 carot.	7 carot.	8 chl *c*	9 chl *a*	10 chl *c*	11 chl *b*	12 chl *a*	13 chl *a*
Input parameters													
Half width, nm	53.8	21.3	32.1	27.2	45.0	45.4	45.9	46.3	35.0	28.9	24.4	21.6	33.5
Center, nm	384	413	435	461	464	490	532	583	623	644	655	676	700
Output parameters													
Half width, nm	43.2	22.7	34.5	29.3	36.0	46.8	49.6	46.8	38.0	24.9	25.4	24.7	29.0
Center, nm	381.5	410.8	433.5	459.2	466.6	487.8	532.0	585.6	620.6	640.7	652.9	675.6	699.8
Specific absorption coefficient, m^2 (mg pigment)$^{-1}$	0.042	0.019	0.047	0.110	0.115	0.035	0.019	0.044	0.005	0.044	0.029	0.021	0.002

Specific absorption coefficients of each pigment are ratios of Gaussian band absorptions (in reciprocal meters) to high-performance liquid chromatography concentrations (in milligrams per cubic meter) of that pigment. Chl, chlorophyll; Carot., carotenoid.

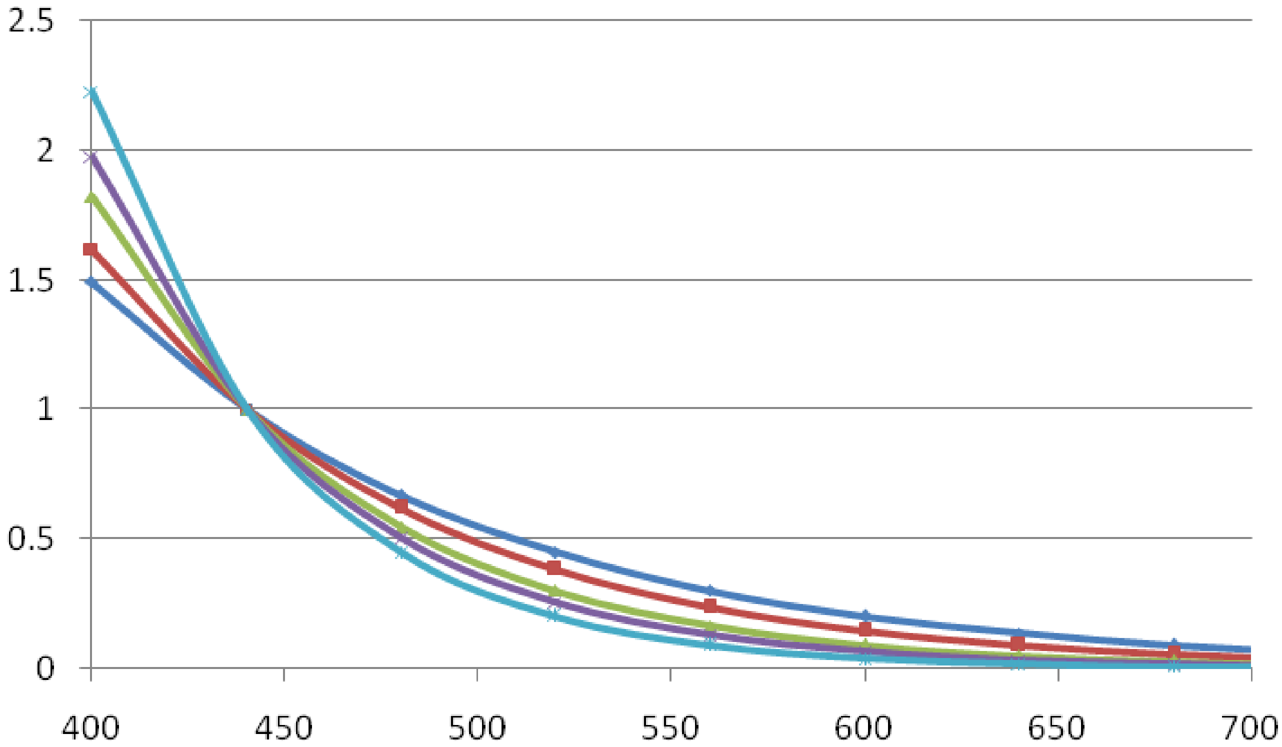
(Hoepffner and Sathyendranath, 1993)



Examples of modeled $\left\langle a_{ph}(\lambda) \right\rangle$ spectra



Absorption components: a_{dg} spectrum shapes



$$\langle a_{dg}(\lambda) \rangle = e^{-S(\lambda - 440)}$$

S: 0.01 – 0.02 nm^{-1}

(*Bricaud et al* 1981)

$$\left\langle b_{bp}(\lambda) \right\rangle = \left(\frac{440}{\lambda} \right)^{\eta}$$

$$R_{rs}(\lambda) = G \frac{b_b(\lambda)}{a(\lambda) + b_b(\lambda)}$$

$$R_{rs}(\lambda) = G \frac{b_{bw}(\lambda) + M_3 \langle b_{bp}(\lambda) \rangle}{a_w(\lambda) + M_1 \langle a_{ph}(\lambda) \rangle + M_2 \langle a_{dg}(\lambda) \rangle + b_{bw}(\lambda) + M_3 \langle b_{bp}(\lambda) \rangle}$$

3-variable model to describe an Rrs spectrum

(Sathyendranath et al 1989)

$M_{1\text{-}3}$ are wavelength independent variables!

Then they could be derived by comparing the modeled Rrs spectrum with the measured Rrs spectrum.

Spectral ranges used for solutions (e.g. examples of BUS):

The **blue-green** domain: e.g., Hoge and Lyon (1996), Carder et al (1999)

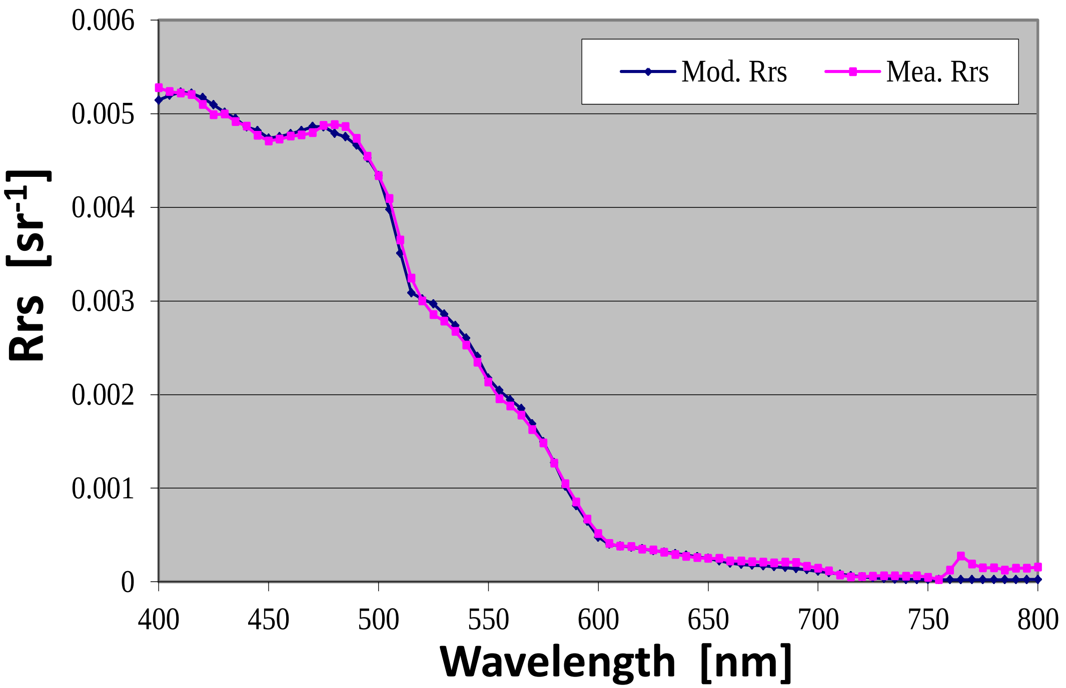
The **red-infrared** domain: e.g., Binding et al (2012)

The **entire spectrum** (**spectral optimization**): e.g., Bukata et al (1995), Lee et al (1994,1996,1999), Maritorena et al (2002), Boss and Roesler (2006), Brando et al (2012)， Werdell et al (2013)

Look-Up-Tables (LUT): e.g., Carder et al (1991); Mobley et al (2005)

Spectral Optimization

Matching between measured and modeled R_{rs}



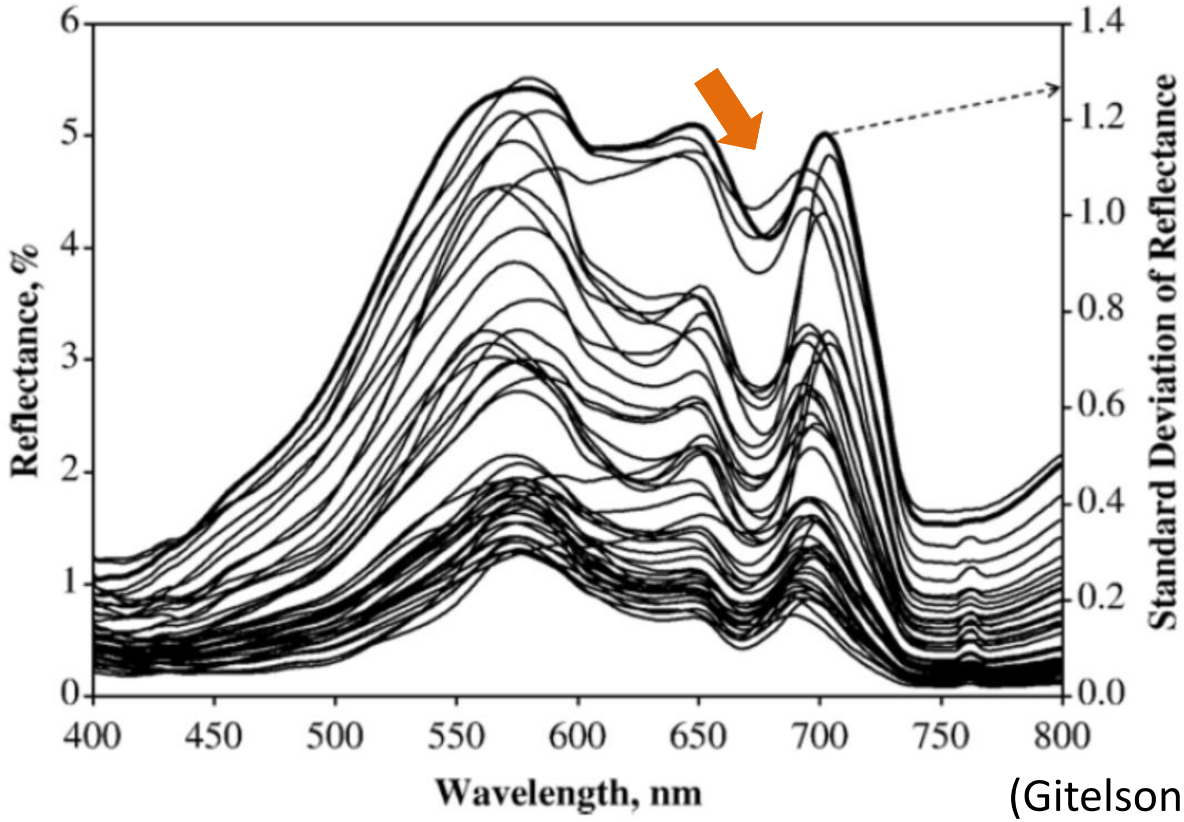
Quantitative measure of the closure (**error function**):

$$\delta_{R_{rs}} = \frac{\sqrt{\Lambda_{\lambda 1}^{\lambda 2}\left(\tilde{R}_{rs}(\lambda) - R_{rs}(\lambda)\right)^2}}{\Lambda_{\lambda 1}^{\lambda 2} R_{rs}(\lambda)} = \sqrt{n}\,\frac{\sqrt{\sum_{\lambda 1}^{\lambda 2}\left(\tilde{R}_{rs}(\lambda) - R_{rs}(\lambda)\right)^2}}{\sum_{\lambda 1}^{\lambda 2} R_{rs}(\lambda)}$$

Logic (assumption) behind SOA:

A unique set of bio-optical properties for each Rrs spectrum.

Algorithms using information in the red-infrared bands



(Gitelson et al 2007)

Two bands

$$Chl = f\left(\frac{Rrs(75x)}{Rrs(67x)}\right)$$

Three bands

$$Chl = f\left(\frac{Rrs(75x)}{Rrs(67x)} - \frac{Rrs(75x)}{Rrs(70x)}\right)$$

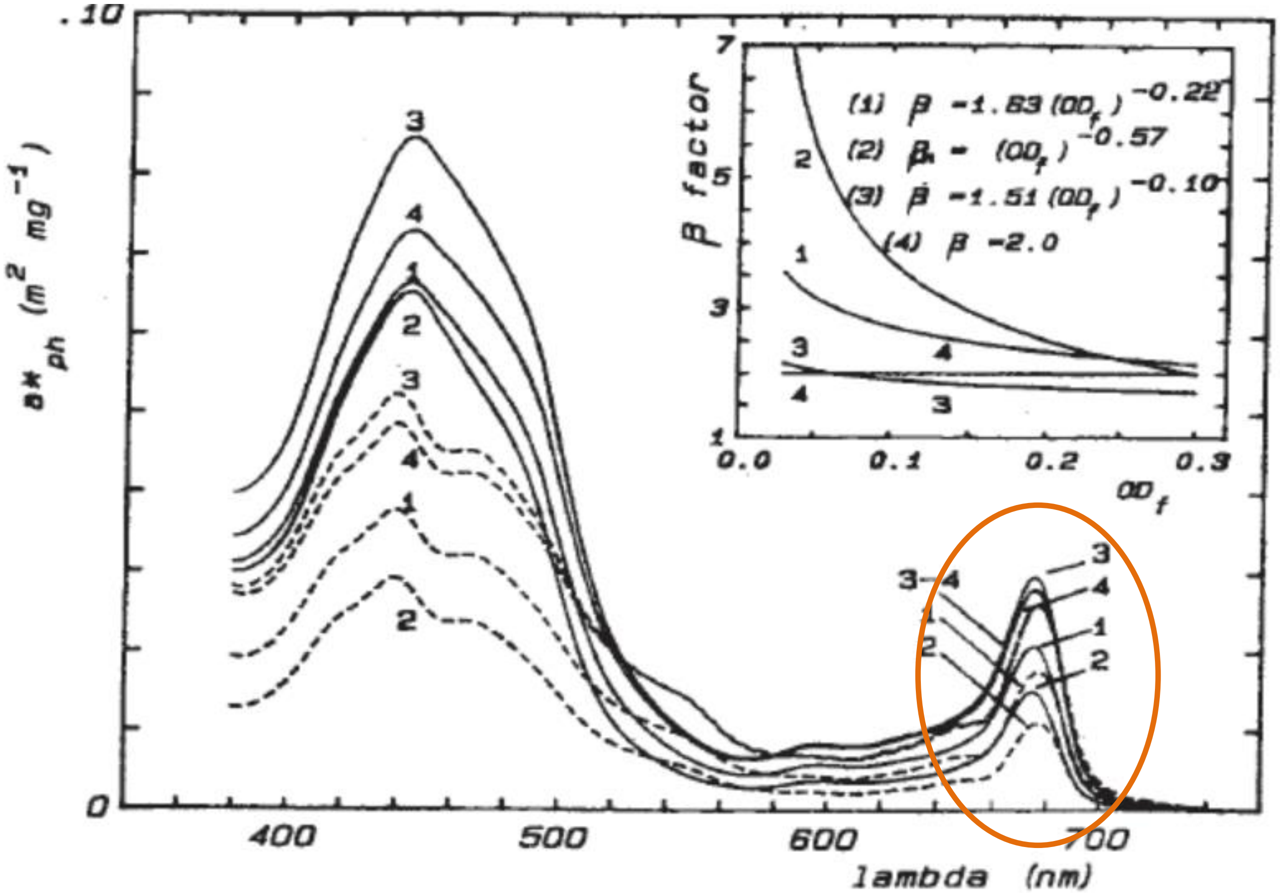
$$R_{rs}(\lambda) = G \frac{b_{bw}(\lambda) + M_3 \langle b_{bp}(\lambda) \rangle}{a_w(\lambda) + M_1 \langle a_{ph}(\lambda) \rangle + M_2 \langle a_{dg}(\lambda) \rangle + b_{bw}(\lambda) + M_3 \langle b_{bp}(\lambda) \rangle}$$

$$R_{rs}(\lambda) \approx G \frac{M_3 \langle b_{bp}(\lambda) \rangle}{a_w(\lambda) + M_1 \langle a_{ph}(\lambda) \rangle}$$

$$\frac{R_{rs}(\lambda_{red1})}{R_{rs}(\lambda_{red2})} = \frac{\langle b_{bp}(\lambda_{red1}) \rangle}{\langle b_{bp}(\lambda_{red2}) \rangle} \frac{a_w(\lambda_{red2}) + M_1 \langle a_{ph}(\lambda_{red2}) \rangle}{a_w(\lambda_{red1}) + M_1 \langle a_{ph}(\lambda_{red1}) \rangle}$$

Proper contrast of Rrs at λ_1 and λ_2 then leads to M_1.

a_{ph}



.10
0
400
500
600
700
lambda (nm)
a*ph (m2 mg-1)
β factor
(1) β = 1.83 (ODf) -0.22
(2) β = (ODf) -0.57
(3) β = 1.51 (ODf) -0.10
(4) β = 2.0
0.0
0.1
0.2
0.3
ODf

2. Top-down strategy (TDS):

$$R_{rs} = G\frac{b_b}{a+b_b}$$

$$\boldsymbol{R_{rs} \rightarrow b_b\&a \rightarrow a_x}$$

⇩

Clarity (Secchi depth, light depth, TSM/SPM, etc)

Remote sensing measures the *total* effect:

Water clarity (or turbidity) is also a measure of total effect.

Examples of TDS:

Loisel & Stramski (2000), QAA (Lee et al, 2002); Smyth et al (2006); Doran et al (2007).

The Quasi-Analytical Algorithm (QAA)

Forward modeling:

$(a, b_b, \text{etc}) \Rightarrow Rrs$

$$R_{rs} \approx 0.05 \frac{b_b}{a + b_b}$$

QAA:

$(a, b_b) \Leftarrow Rrs$

The data flow of QAA:

$$r_{rs}(\lambda)$$

$$\eta$$

$$a(\lambda_0) = a_w(\lambda_0) + \Delta a(\lambda_0)$$

$$b_{bp}(\lambda_0) = F_2\left(r_{rs}(\lambda_0), a(\lambda_0), b_{bw}(\lambda_0)\right)$$

$$b_{bp}(\lambda) = b_{bp}(\lambda_0)\left(\frac{\lambda_0}{\lambda}\right)^{\eta}$$

$$a(\lambda) = F_3\left(r_{rs}(\lambda), b_{bp}(\lambda), b_{bw}(\lambda)\right)$$

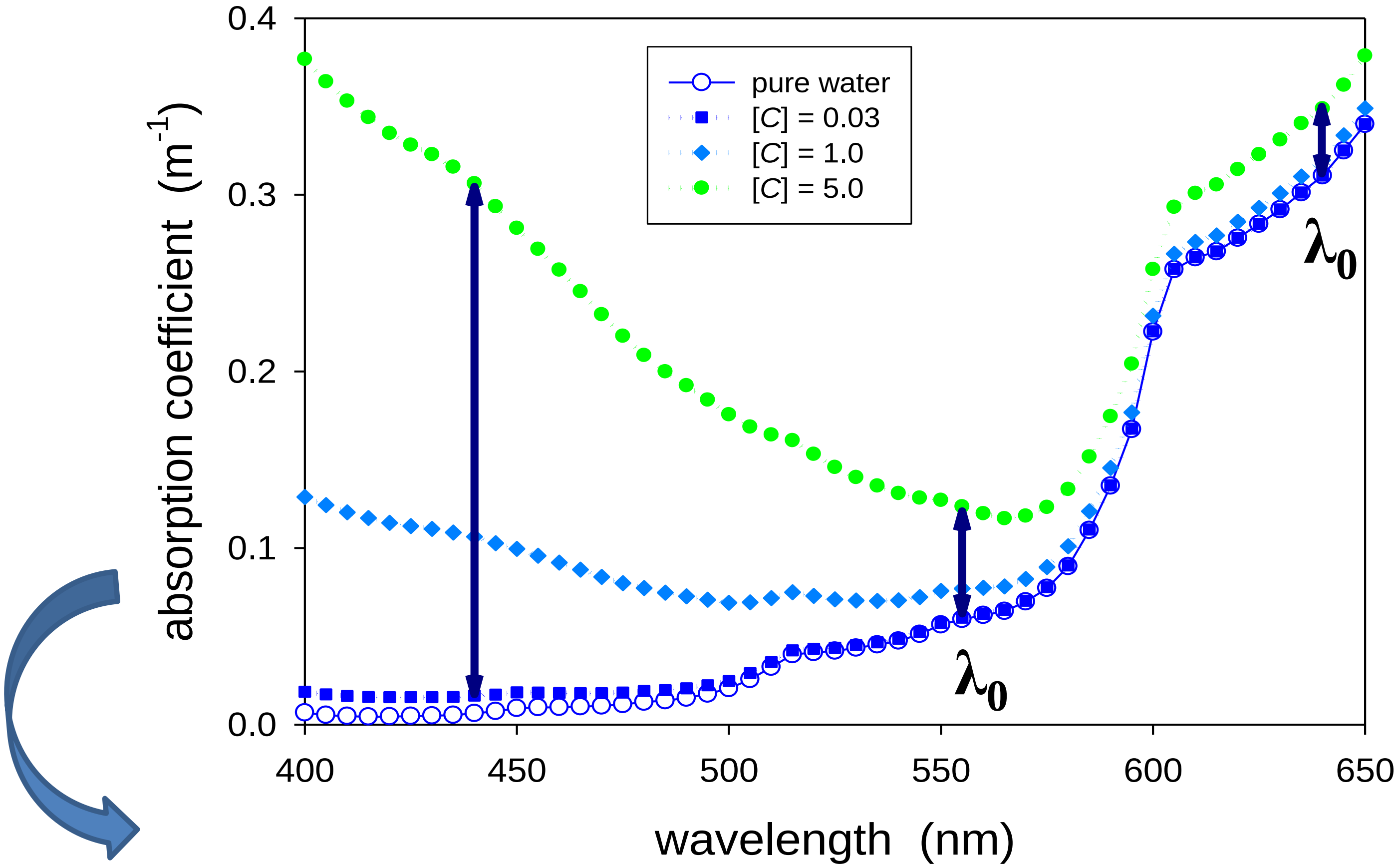
$$\begin{cases} a(411) = a_w(411) + \zeta a_{ph}(443) + \xi a_{dg}(443) \\ a(443) = a_w(443) + a_{ph}(443) + a_{dg}(443) \end{cases}$$

$$\zeta = \frac{a_{ph}(411)}{a_{ph}(443)}$$

$$\xi = \frac{a_{dg}(411)}{a_{dg}(443)}$$

(Lee et al 2002)

Logic behind QAA (and its updated versions):



For a reference wavelength, λ_0, variation of $a(\lambda_0)$ is limited.

Known $a(\lambda_0)$, enables calculation of $b_b(\lambda_0)$ from $R_{rs}(\lambda_0)$; propagate $b_b(\lambda_0)$ to $b_b(\lambda)$, then enables calculation of $a(\lambda)$ from $R_{rs}(\lambda)$.

No need of spectral model of $a_x(\lambda)$ in this process!

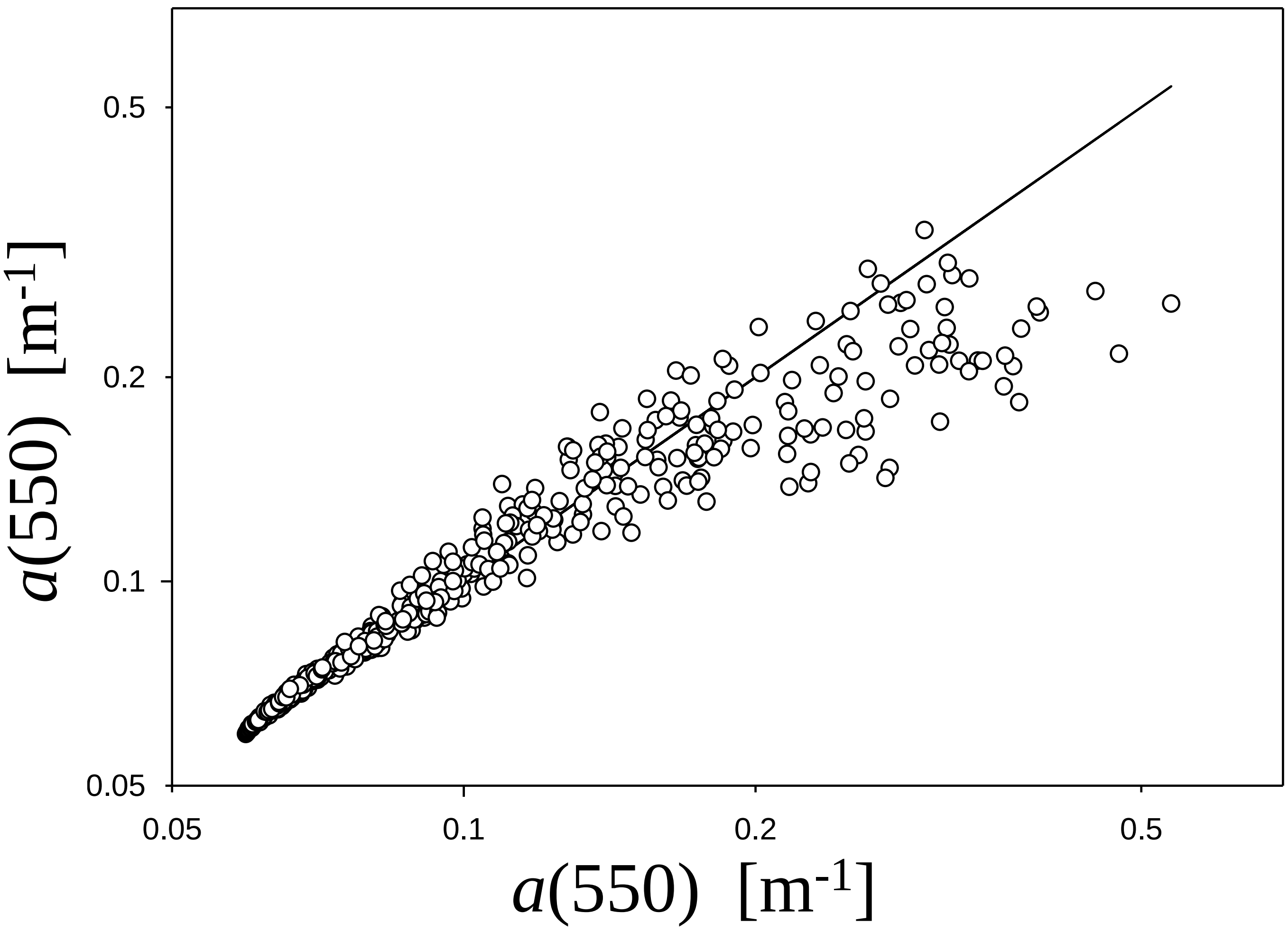
When 550 nm as the reference wavelength (λ_0)

$$a(550) = a_w(550) + 10^{-1.146-1.366\chi-0.469\chi^2}$$

$$\chi = \log\left(\frac{r_{rs}(443) + r_{rs}(490)}{r_{rs}(\lambda_0) + 5\frac{r_{rs}(667)}{r_{rs}(490)} r_{rs}(667)}\right)$$

$a_w(550) = 0.0565$

Empirical!



0.5
0.2
0.1
0.05
0.05
0.1
0.2
0.5
a(550) [m-1]
a(550) [m-1]

Invert Rrs:

R_{rs} ⇨ r_{rs} ⇨ $\{a\&b_b\}$

$r_{rs}(\lambda) = R_{rs}(\lambda)/(0.52 + 1.7\, R_{rs}(\lambda))$

$$r_{rs} = g_0\left(\frac{b_b}{a+b_b}\right) + g_1\left(\frac{b_b}{a+b_b}\right)^2$$

$g_0=0.089, g_1=0.125$

$$u(\lambda) = \frac{b_b(\lambda)}{a(\lambda)+b_b(\lambda)} = \frac{-g_0 + \sqrt{(g_0)^2 + 4g_1 * r_{rs}(\lambda)}}{2g_1}$$

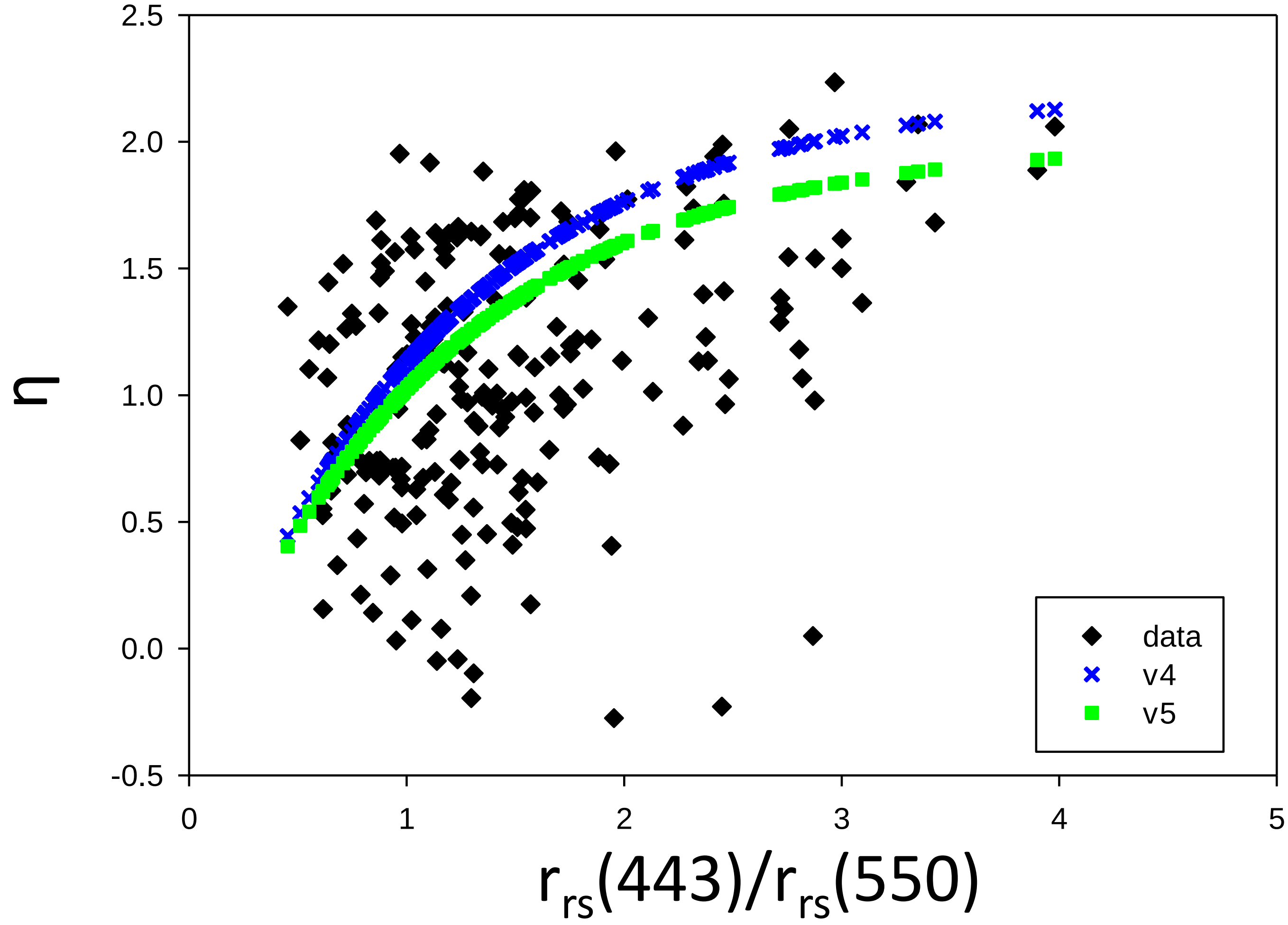
$$a(550) = a_w(550) + 10^{-1.146-1.366\chi-0.469\chi^2}$$

$$\Rightarrow \quad b_{bp}(550) = \frac{u(550)\, a(550)}{1-u(550)} - b_{bw}(550)$$

$$b_{bp}(\lambda) = b_{bp}(550)\left(\frac{550}{\lambda}\right)^{\eta}$$

Empirical:

$$\eta = 2.0\left(1 - 1.2\ \exp\left(-0.9\frac{r_{rs}(443)}{r_{rs}(55x)}\right)\right)$$



$$b_b(\lambda) = b_{bw}(\lambda) + b_{bp}(\lambda)$$

$$a(\lambda) = \frac{(1 - u(\lambda))\, b_b(\lambda)}{u(\lambda)}$$

$$a(\lambda) = a_w(\lambda) + a_{ph}(\lambda) + a_{dg}(\lambda)$$

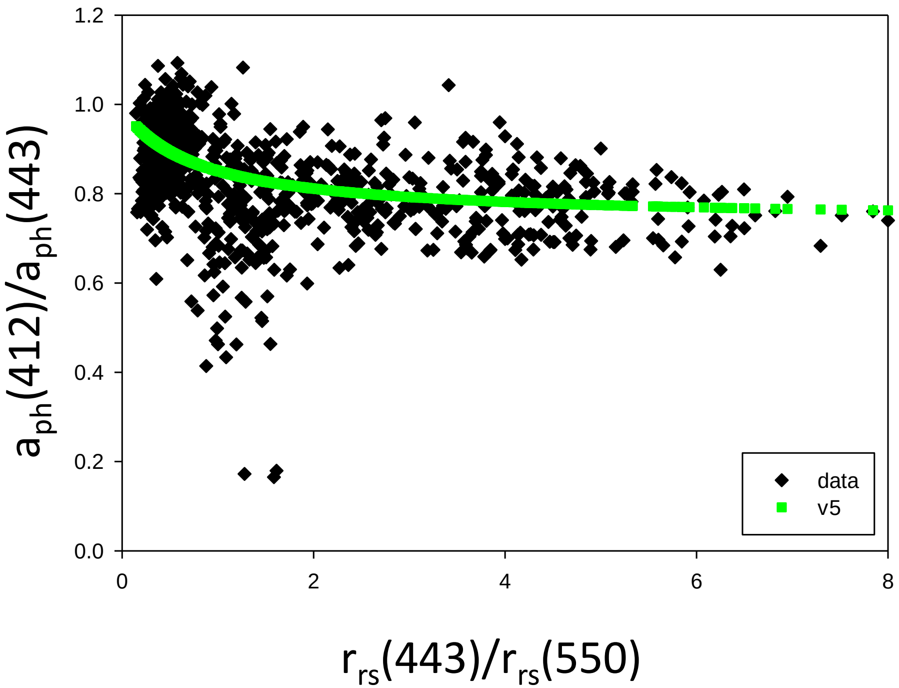
$$\begin{cases} a(410) = a_w(410) + a_{ph}(410) + a_{dg}(410), \\ a(440) = a_w(440) + a_{ph}(440) + a_{dg}(440). \end{cases}$$

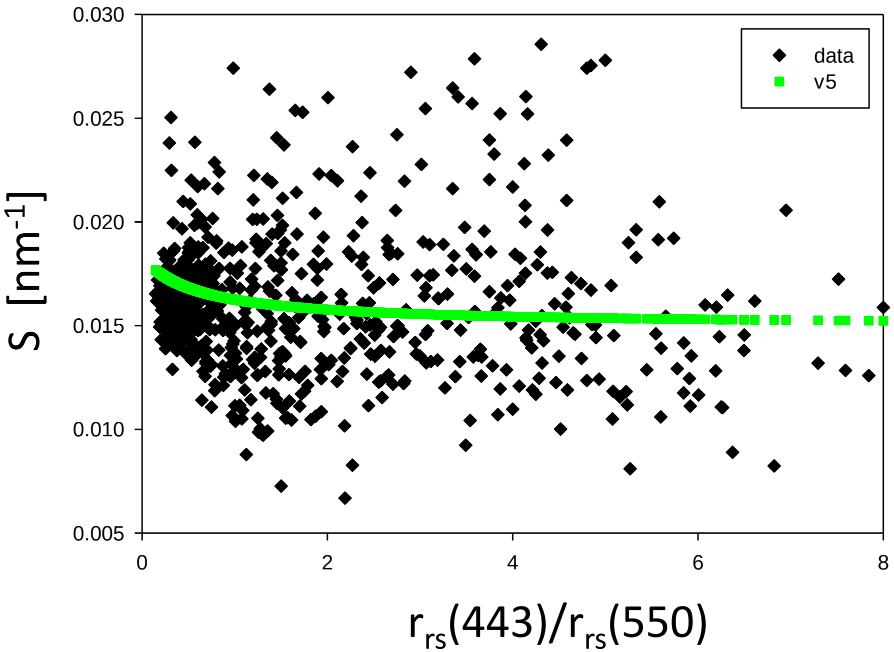
$$\zeta = \frac{a_{ph}(410)}{a_{ph}(440)} \qquad \xi = \frac{a_{dg}(410)}{a_{dg}(440)}$$

$$\begin{cases} a(410) = a_w(410) + \zeta\, a_{ph}(440) + \xi\, a_{dg}(440), \\ a(440) = a_w(440) + a_{ph}(440) + a_{dg}(440). \end{cases}$$

$$\begin{cases} a(410) = a_w(410) + \zeta\, a_{ph}(440) + \xi\, a_{dg}(440), \\ a(440) = a_w(440) + a_{ph}(440) + a_{dg}(440). \end{cases}$$

$$\begin{cases} a_g(440) = \dfrac{\big(a(410) - \zeta\, a(440)\big) - \big(a_w(410) - \zeta\, a_w(440)\big)}{\xi - \zeta}, \\ a_{ph}(440) = a(440) - a_w(440) - a_{dg}(440). \end{cases}$$





$$\zeta = 0.74 + \frac{0.2}{0.8 + r_{rs}(443)/r_{rs}(550)}$$

$$\xi = e^{S(443-411)},$$

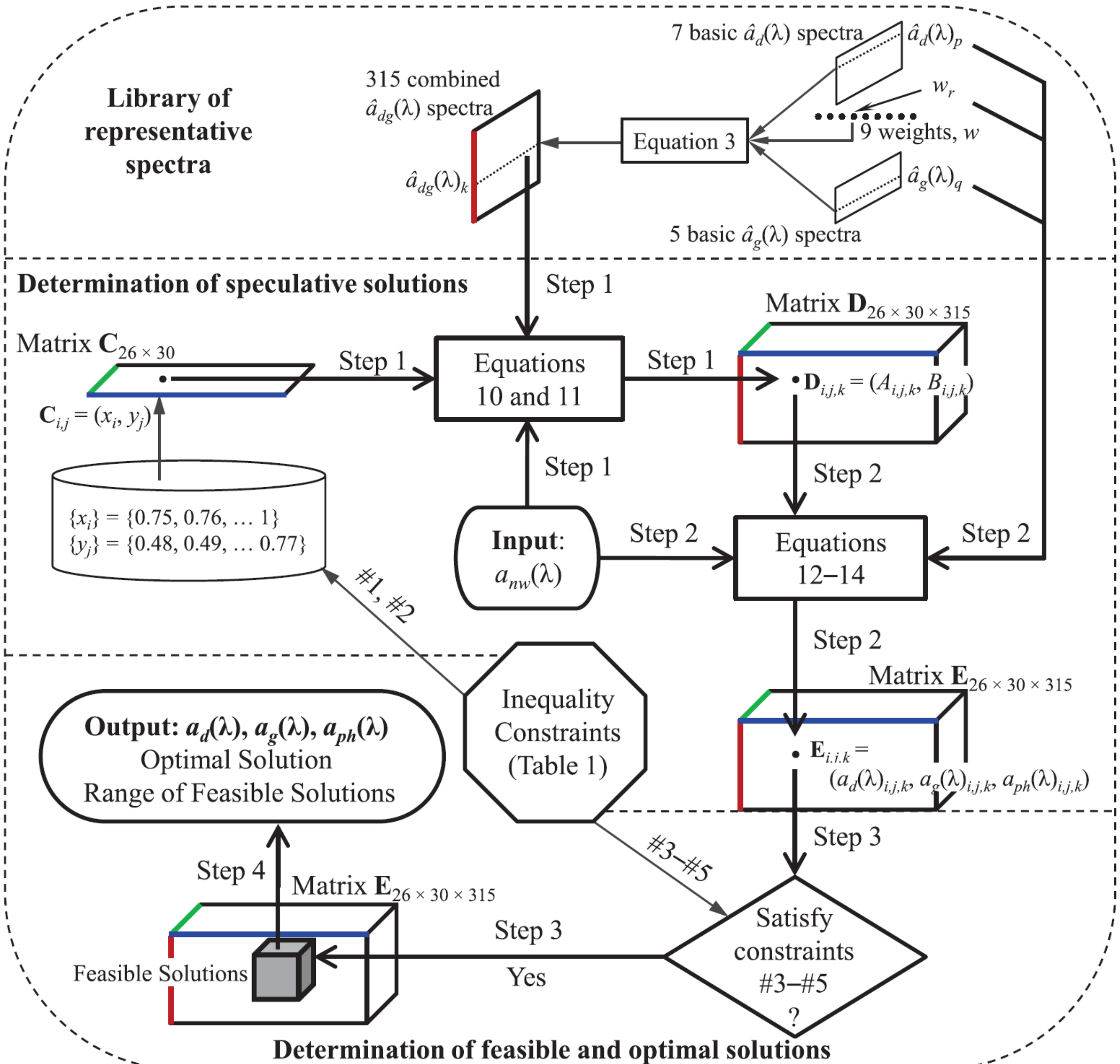
$$S = 0.015 + \frac{0.002}{0.6 + r_{rs}(443)/r_{rs}(550)}$$

Empirical!

Ensemble solutions:

Wang et al. 2006; Zheng et al. 2015

$$a(\lambda) = a_w(\lambda) + \mathrm{M}_1 \left\langle a_{ph}(\lambda) \right\rangle + M_2 \left\langle a_{dg}(\lambda) \right\rangle$$



(Zheng et al. 2015)

Key Points:

1. Various inversion algorithms for IOPs have been developed; but more/better ones are also expected.

2. BUS derives every component first, then (simultaneously) derives the total optical property.

> Assume the spectral shapes of the optically active components are well characterized!
>
> BUS relies more on the accuracy of forward bio-optical model

3. TDS derives total first, then decompose to separate components.

> TDS relies more on the accuracy of Rrs measurement