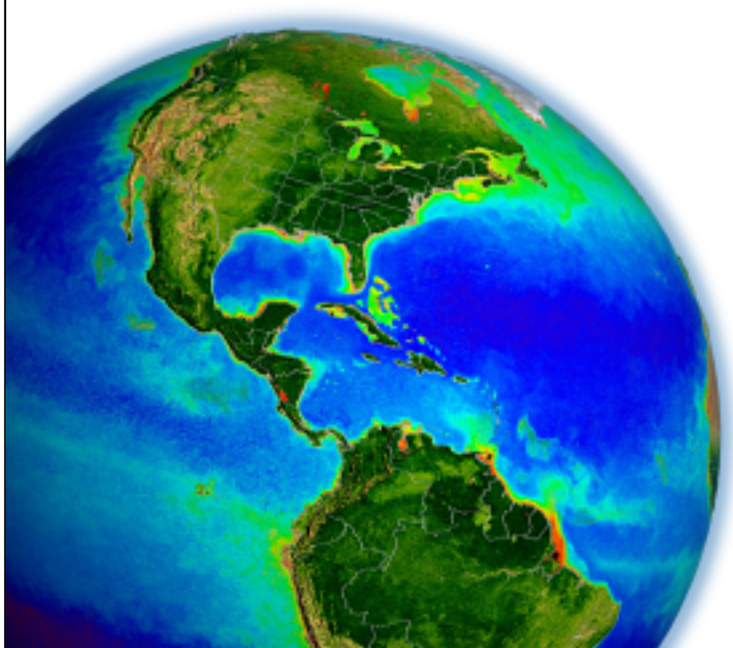
In situ data support for ocean color satellite calibration & validation



Jeremy Werdell

NASA Goddard Space Flight Center

UMaine Ocean Optics Summer Course
6 – 31 July 2015

“cal/val”

“cal/val” = calibration & validation

“cal/val” has become the catch-all phrase in our community for all activities related to the on-orbit calibration of a satellite instrument, the execution of field programs, the validation of biogeophysical satellite data records, & the development of related atmospheric & bio-optical algorithms

jeremy.werdell@nasa.gov

outline

the purpose of this presentation is to provide an overview of how *in situ* data are used in an operational cal/val environment & to describe some of the issues we wrestle with within this environment

jeremy.werdell@nasa.gov

outline

great field data enable great satellite data products

an abundance of field data is hard to come by

emerging technologies can provide rich data streams

QA/QC metrics are essential (or this all falls apart)
= quality assurance & quality control

NASA Ocean Biology & Biogeochemistry Program

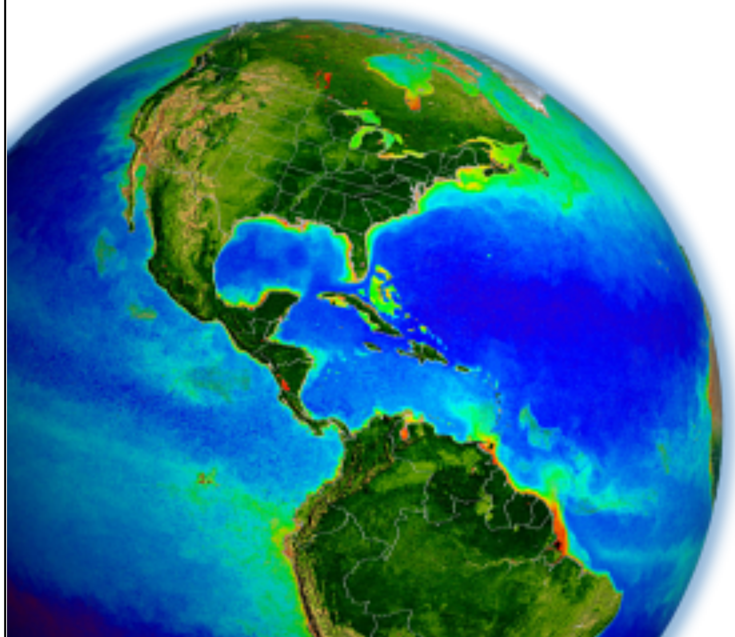
field work funded by OBB Program

QA/QC

by data contributor

in situ data submitted to NASA SeaBASS (GSFC) within 1-year

by NASA

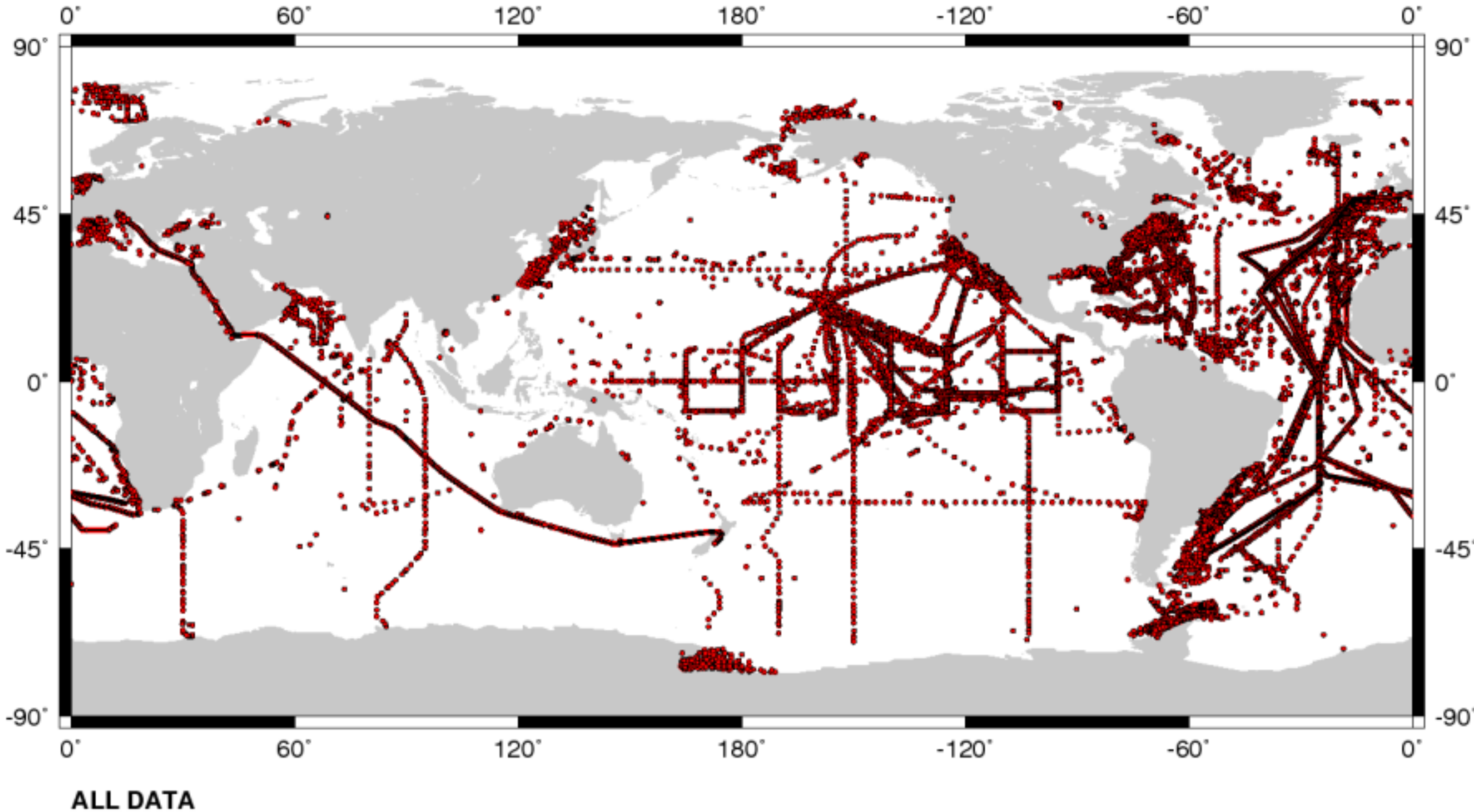


in situ data publicly released

in situ data used to validate satellite data products & to develop / evaluate algorithms

in situ used to calibrate satellite

SeaBASS @ seabass.gsfc.nasa.gov



AOPs, IOPs, carbon stocks, CTD, pigments, aerosols, etc.

continuous & discrete profiles; some fixed observing or along-track

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satellite vicarious calibration (instrument + algorithm adjustment)

satellite data product validation

bio-optical algorithm development, tuning, & evaluation

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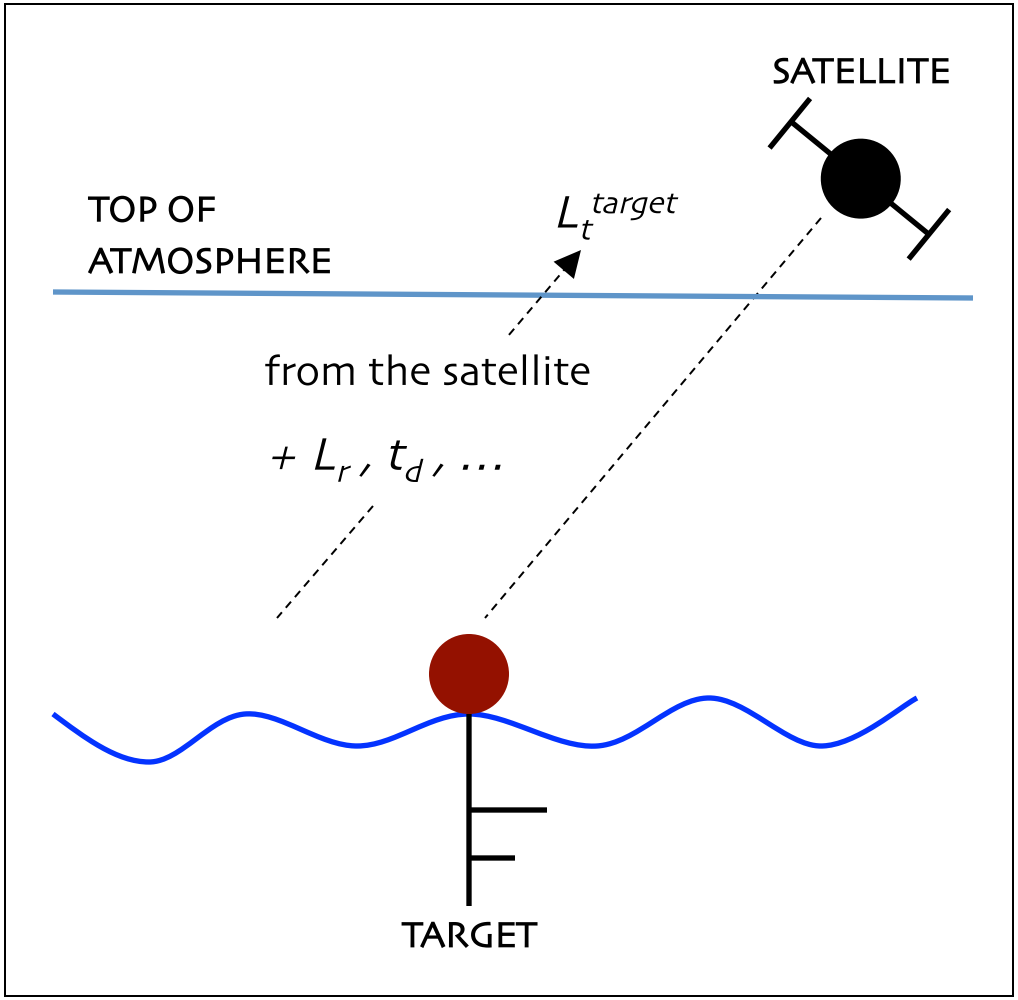
vicarious calibration

what is vicarious calibration?

<u>spectral on-orbit calibrations</u>

1. instrument calibration
   - e.g., focal plane temperature
2. temporal calibration
   - reference Sun or Moon
3. absolute (vicarious) calibration
   - reference Earth surface
   - final, single gain adjustment
   - calibration of the combined instrument + algorithm system

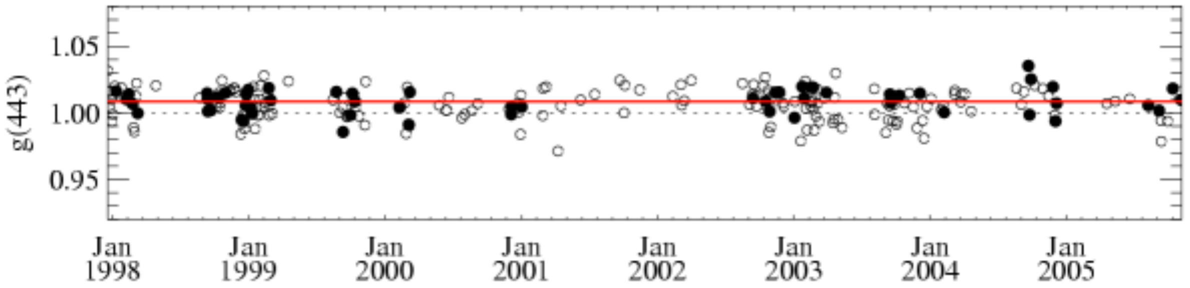
$g = L_t^{target} \,/\, L_t^{satellite}$



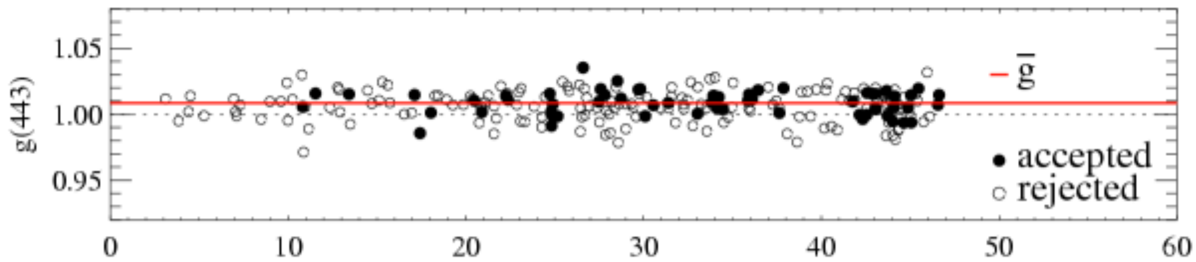
vicarious calibration

a single, spectral radiometric adjustment

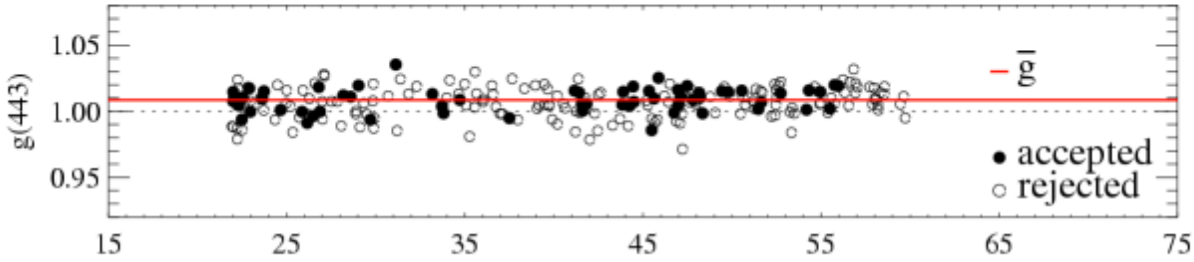
gain vs. time



gain vs. solar zenith angle



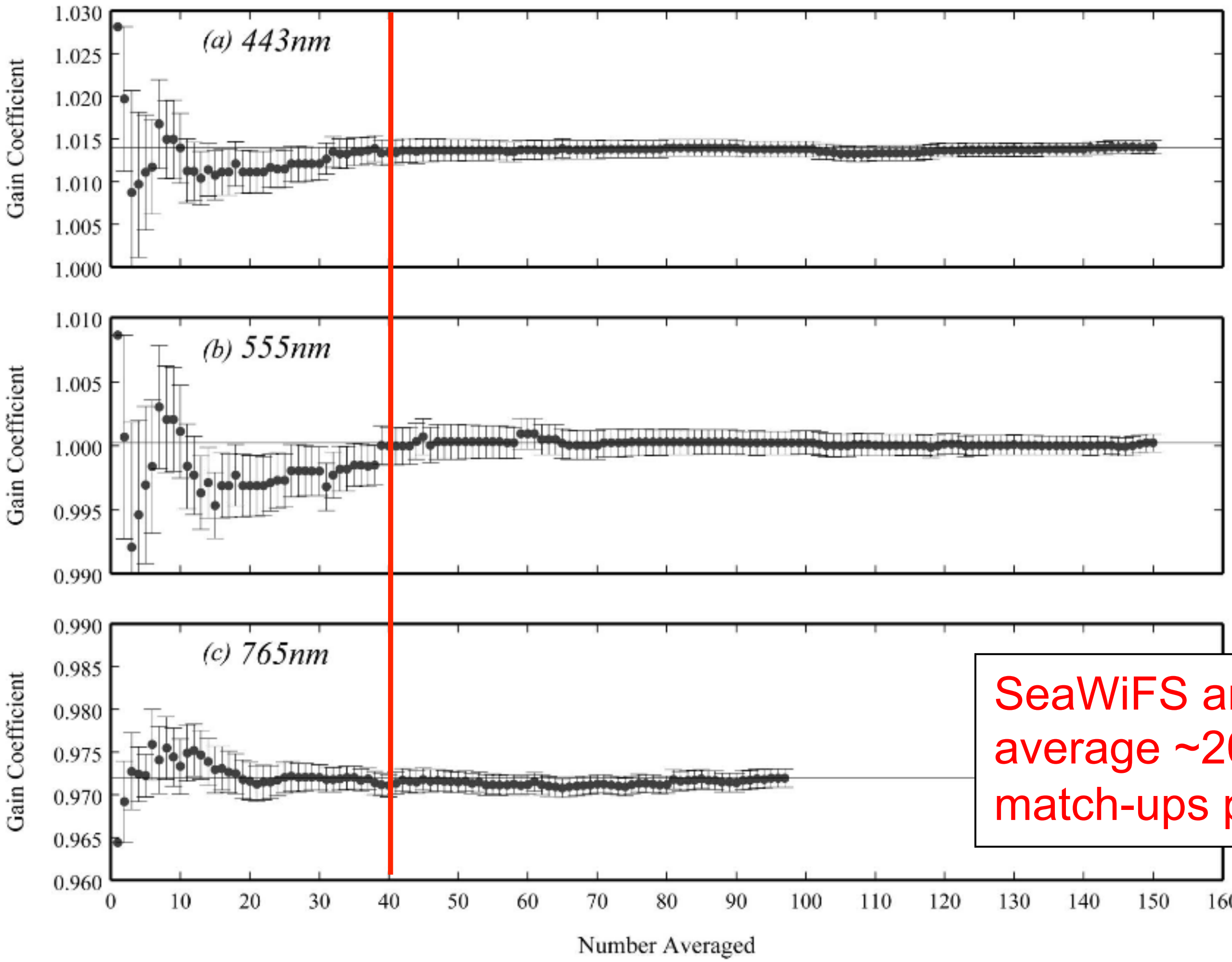
gain vs. satellite zenith angle



Franz et al. 2007

vicarious calibration

~40 match-ups required to achieve "stable" vicarious gain



SeaWiFS and Aqua average ~20 MOBY match-ups per year

Franz et al. 2007

operational vicarious calibration

MOBY - the Marine Optical BuoY

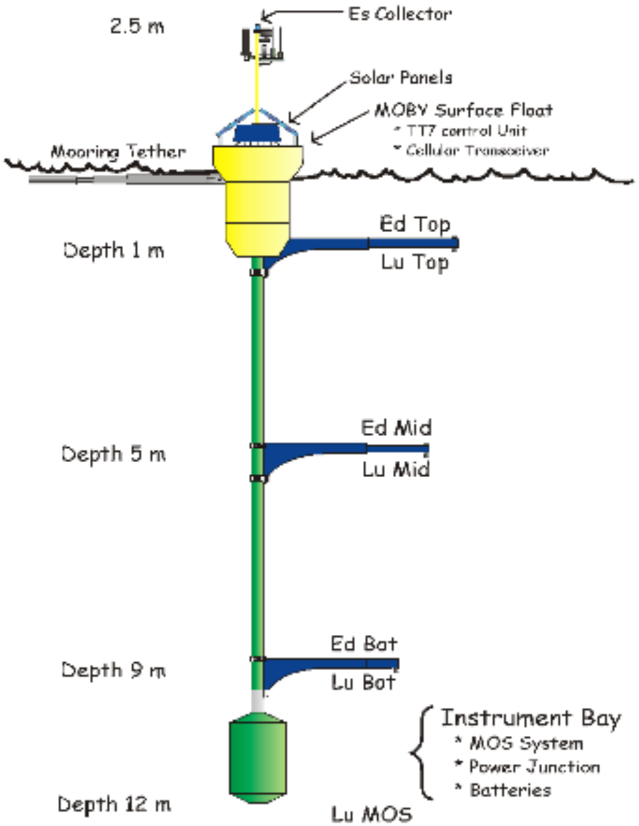


Fig. 1. Schematic diagram of MOBY.

maintained by NOAA & Moss Landing Marine Laboratory

20 miles west of Lanai, Hawaii

$L_u(\lambda)$ and $E_d(\lambda)$ at nominal depths of 1, 5, and 9 meters, plus $E_s(\lambda)$

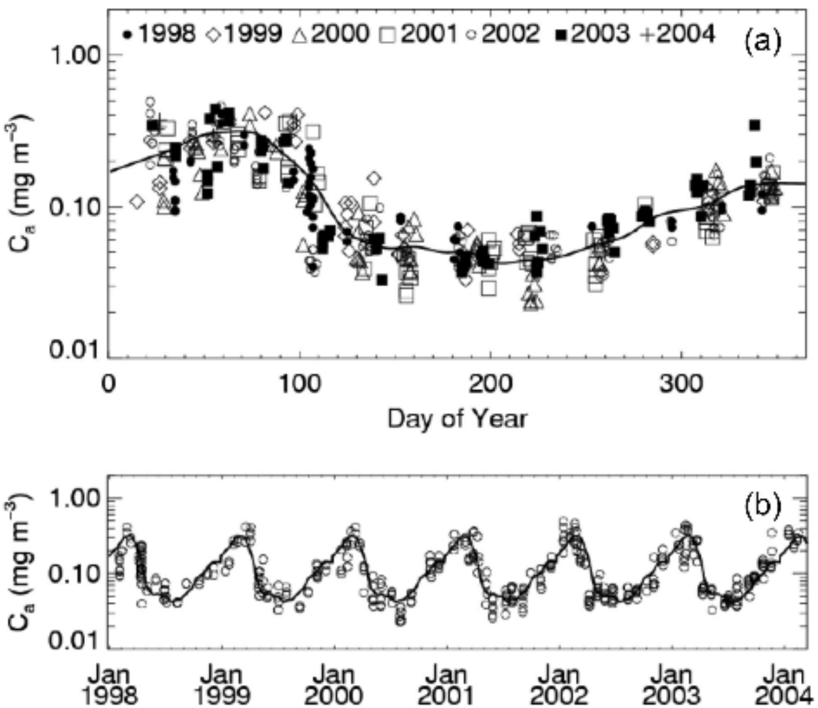
spectral range is 340-955 nm & spectral resolution is 0.6 nm

hyperspectral data convolved to specific bandpasses of each satellite

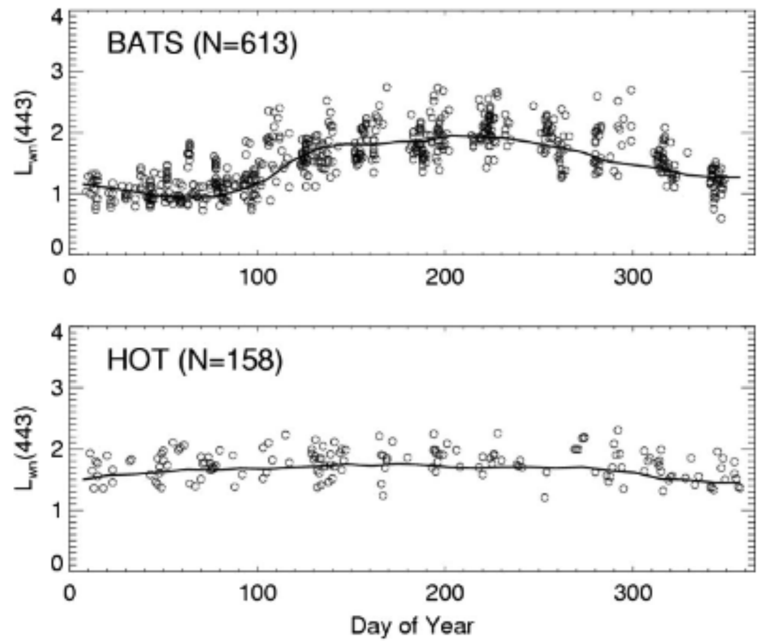
approximately 450-700 samples per year for MODIS-Aqua

model-based vicarious calibration

build a climatology using a long-term chlorophyll-a record (this is for BATS, near Bermuda) …



Werdell et al. 2007



$$L_{wn}(\lambda) = fcn(\text{Chl-a})$$

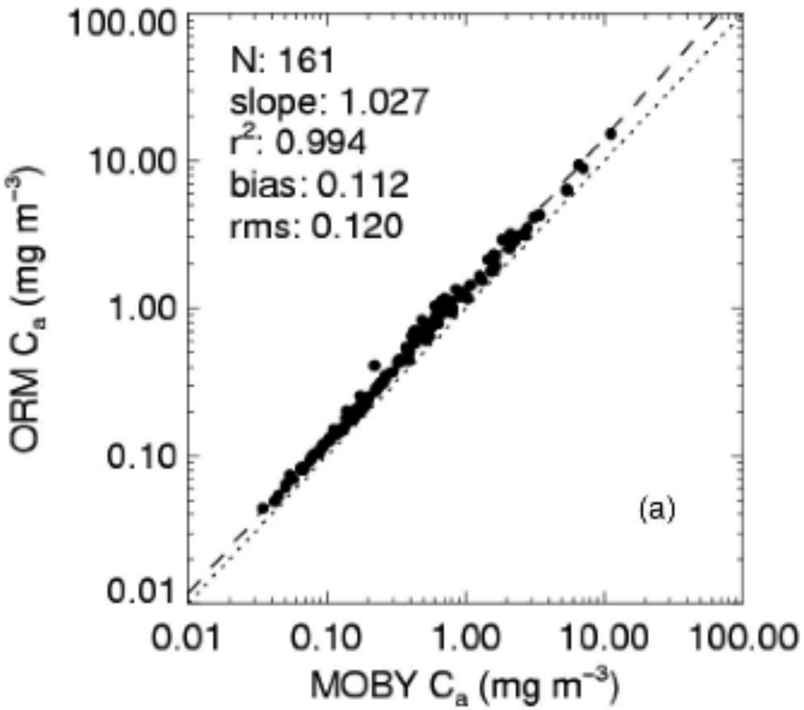
… then, develop a radiometric climatology using an ocean reflectance model (e.g., Morel and Maritorena 2001)

model-based vicarious calibration

Table 3. Percent Differences[a] Between the MOBY and ORM $\bar{g}$

	412	443	490	510	555	670
BATS	−0.31	−1.18	−1.14	−0.52	0.14	−0.07
HOTS	−0.74	−0.53	−0.48	−0.14	0.44	−0.21
BATS + HOTS	−0.52	−0.86	−0.81	−0.33	0.29	−0.13

[a]Calculated using $(\bar{g}_{\mathrm{ORM}} - \bar{g}_{\mathrm{MOBY}}) \times 100\%/\bar{g}_{\mathrm{MOBY}}$.

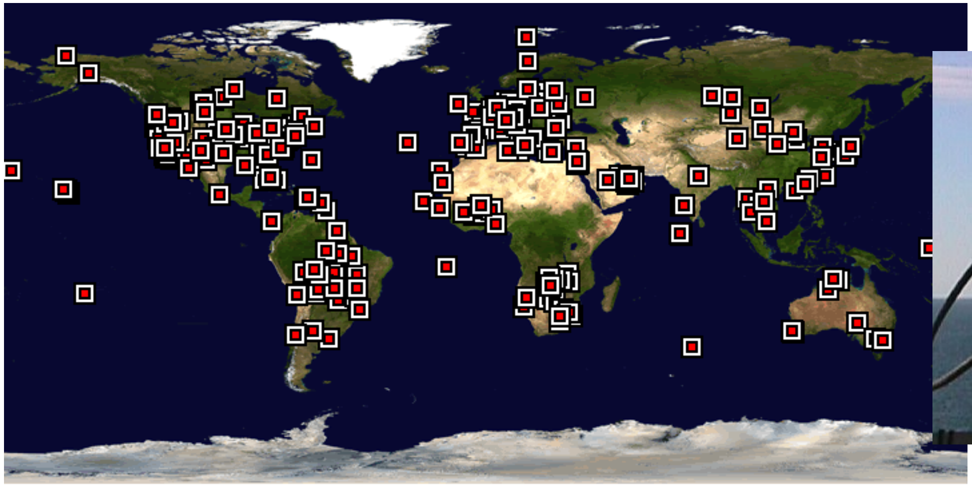


model-based gains typically differ from MOBY gains by < 1%

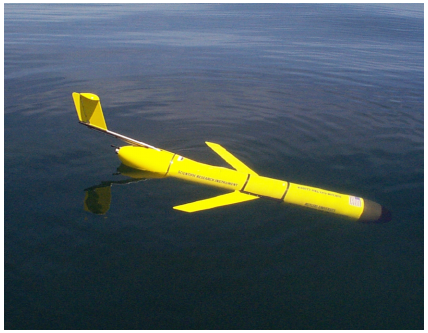
Werdell et al. 2007

alternative data for vicarious calibration

AERONET (fixed-above water platforms)

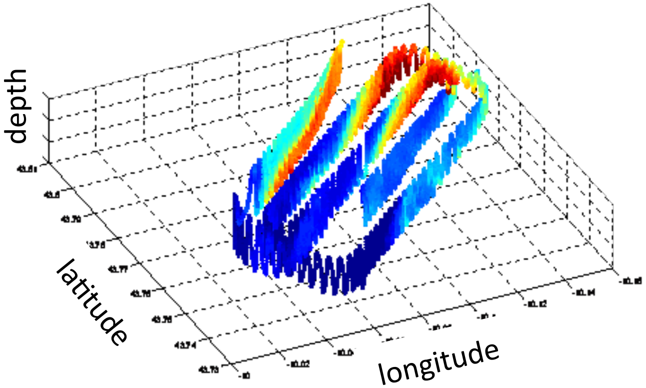


buoy networks



gliders, drifters, & other autonomous platforms

towed & underway sampling



jeremy.werdell@nasa.gov

alternative for vicarious calibration

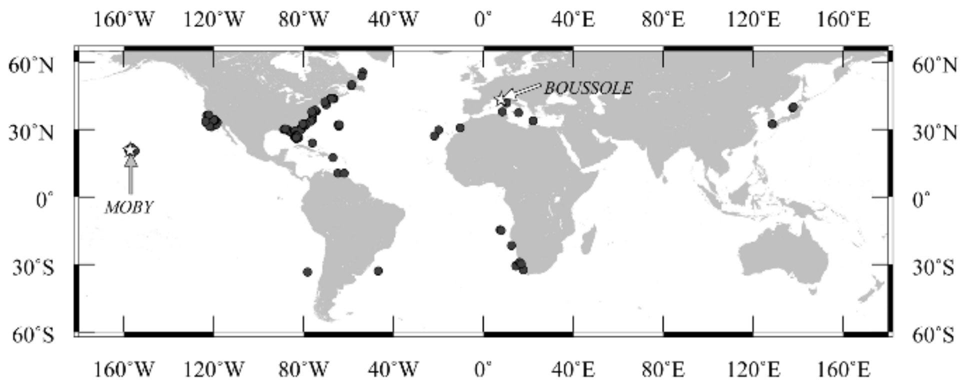


Fig. 1. Map showing the locations for the *in situ* data used in this study.

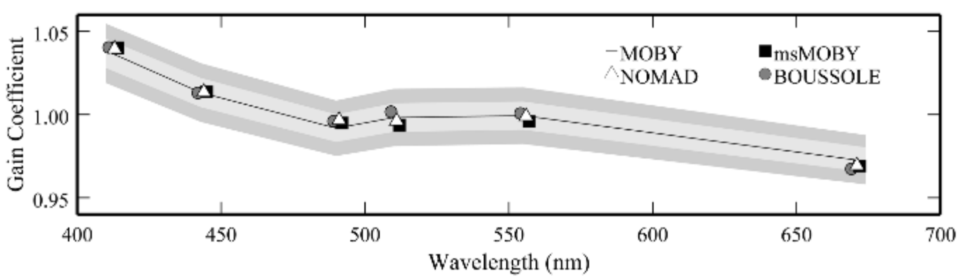


Fig. 3. Vicarious calibration coefficients as a function of wavelength. The standard MOBY-derived $\bar{g}_\lambda'$ (solid curve) are overplotted by the msMOBY-, NOMAD-, and BOUSSOLE-derived $\bar{g}_\lambda'$. The shaded regions indicate the ranges for the first (light-gray) and second (dark-gray) standard deviations of the mean for $\bar{g}_\lambda'$.

Bailey et al. 2008

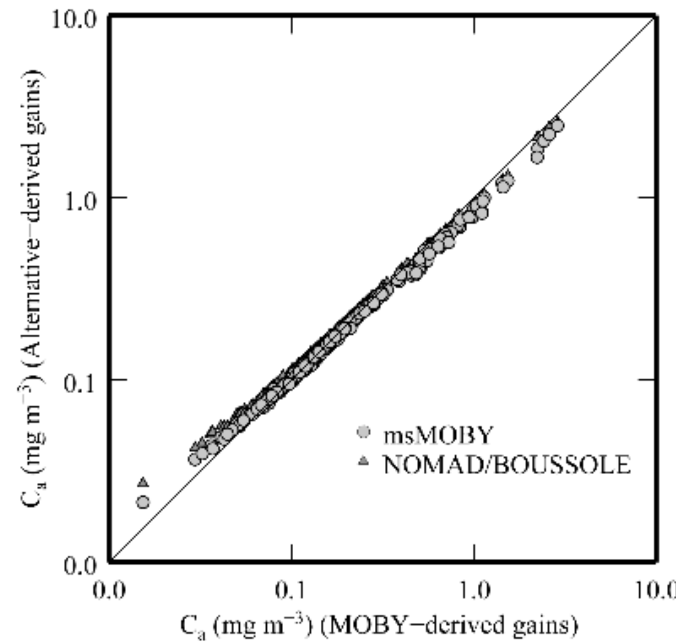


Fig. 7. Satellite-derived chlorophyll estimated from the two alternative $\bar{g}'$ gain sets (msMOBY and NOMAD/BOUSSOLE) plotted versus the corresponding chlorophyll estimated from the standard MOBY $\bar{g}$.

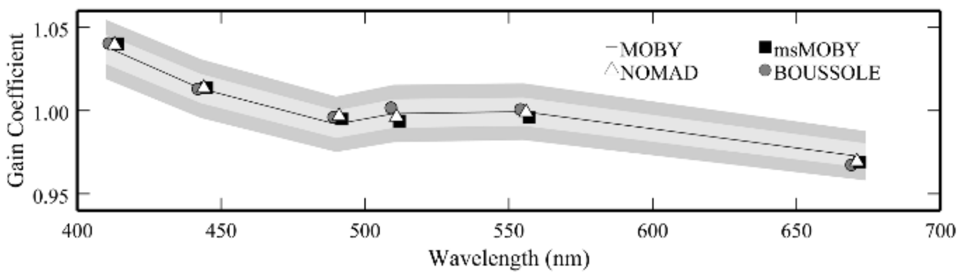
gains calculated using alternative *in situ* data typically differ from MOBY by < 0.3%

jeremy.werdell@nasa.gov

selecting vicarious calibration sources

the gains shown previously for the multiple "ground-truth" targets differ only from 0.3 to 1%, but there are spectral dependencies in their differences …

spectral differences impart changes in derived products



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great field data enable great satellite data products

satellite vicarious calibration (instrument + algorithm adjustment)

satellite data product validation

bio-optical algorithm development, tuning, & evaluation

jeremy.werdell@nasa.gov

Level-2 match-ups

general flow of match-up process, with exclusion criteria

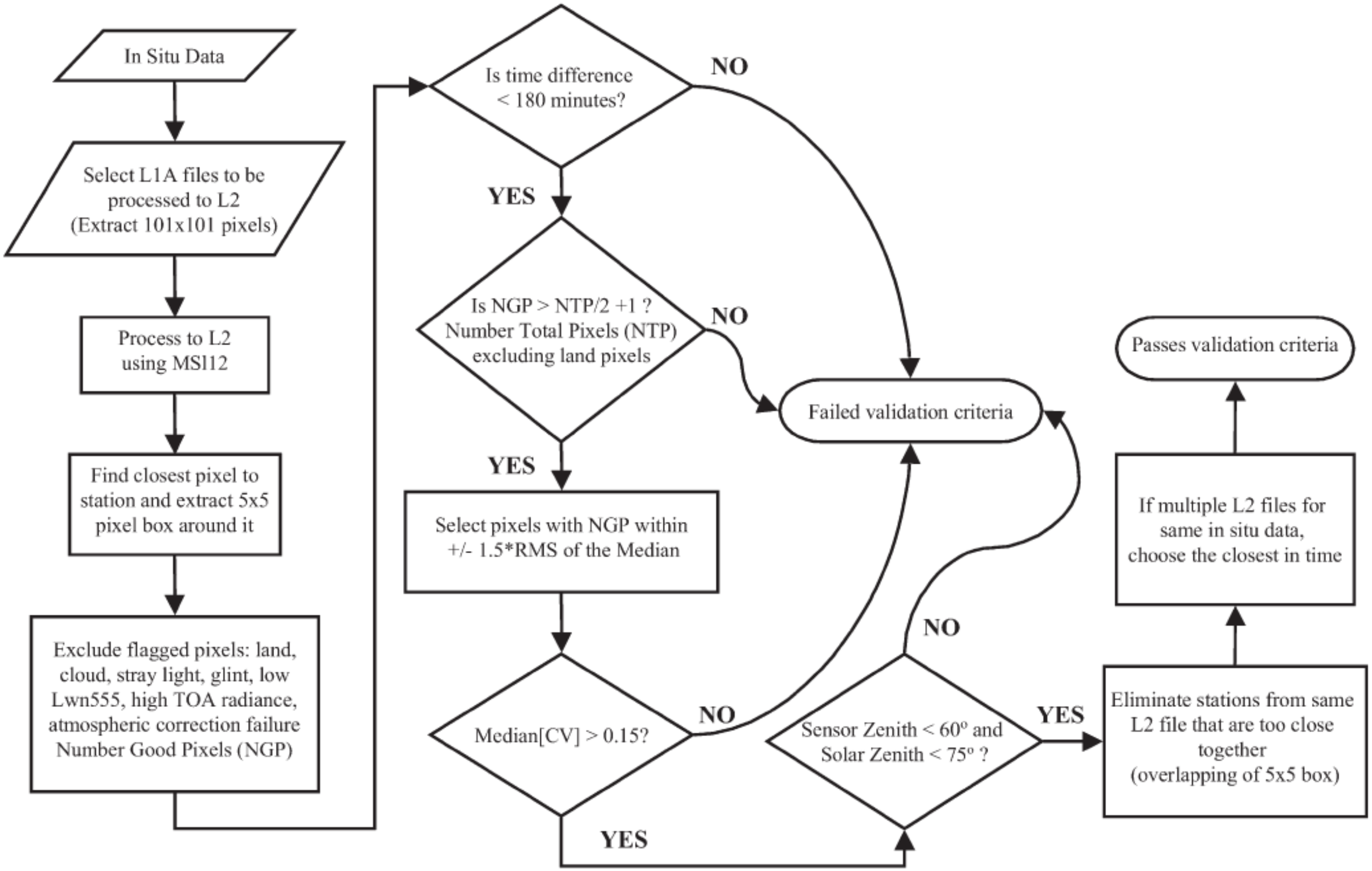


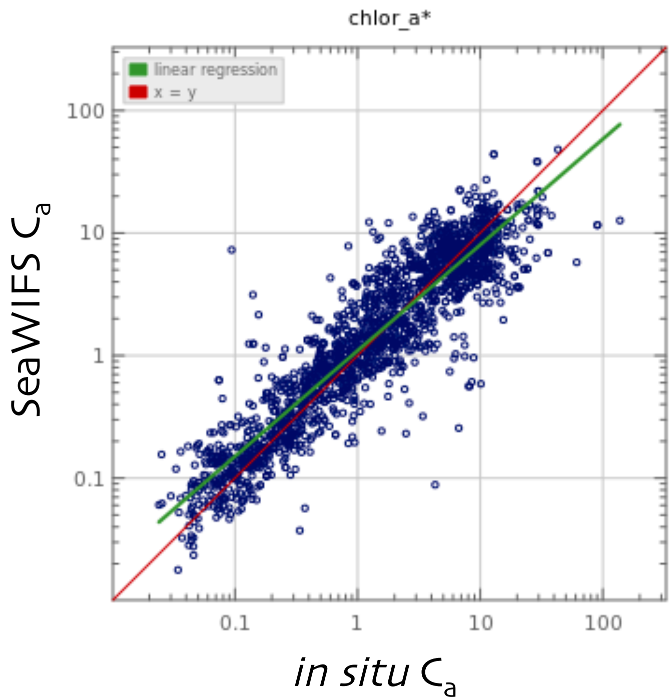
Fig. 1. Flowchart of the validation process highlighting the applied exclusion criteria.

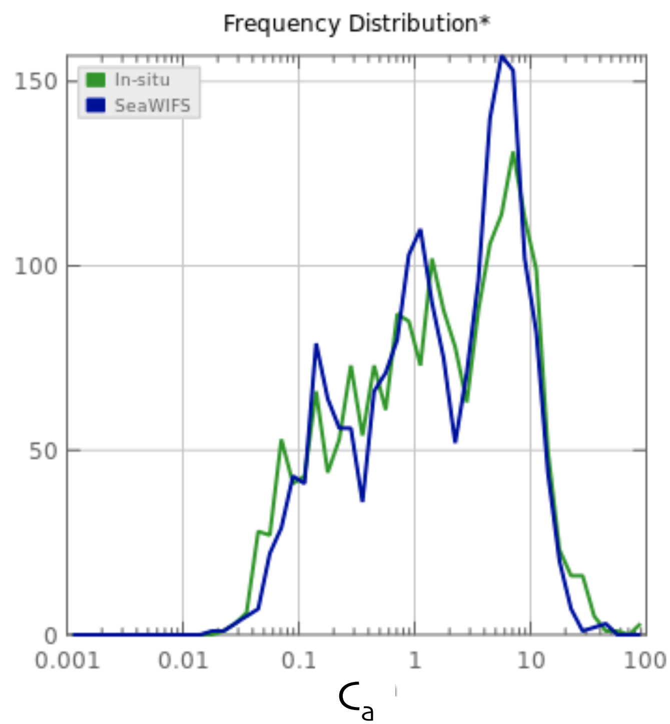
Level-2 match-ups

comparison of “coincident” *in situ* & satellite measurements

Product Name	SeaWIFS Range	In-situ Range	#	Best Fit Slope*	Best Fit Intercept*	R^2*	Median Ratio	Abs % Difference	RMSE*
chlor_a	0.01782, 48.08236	0.02400, 138.04700	1968	0.86322	0.03969	0.84667	1.05656	36.22945	0.28465

* statistical calculations based on log10

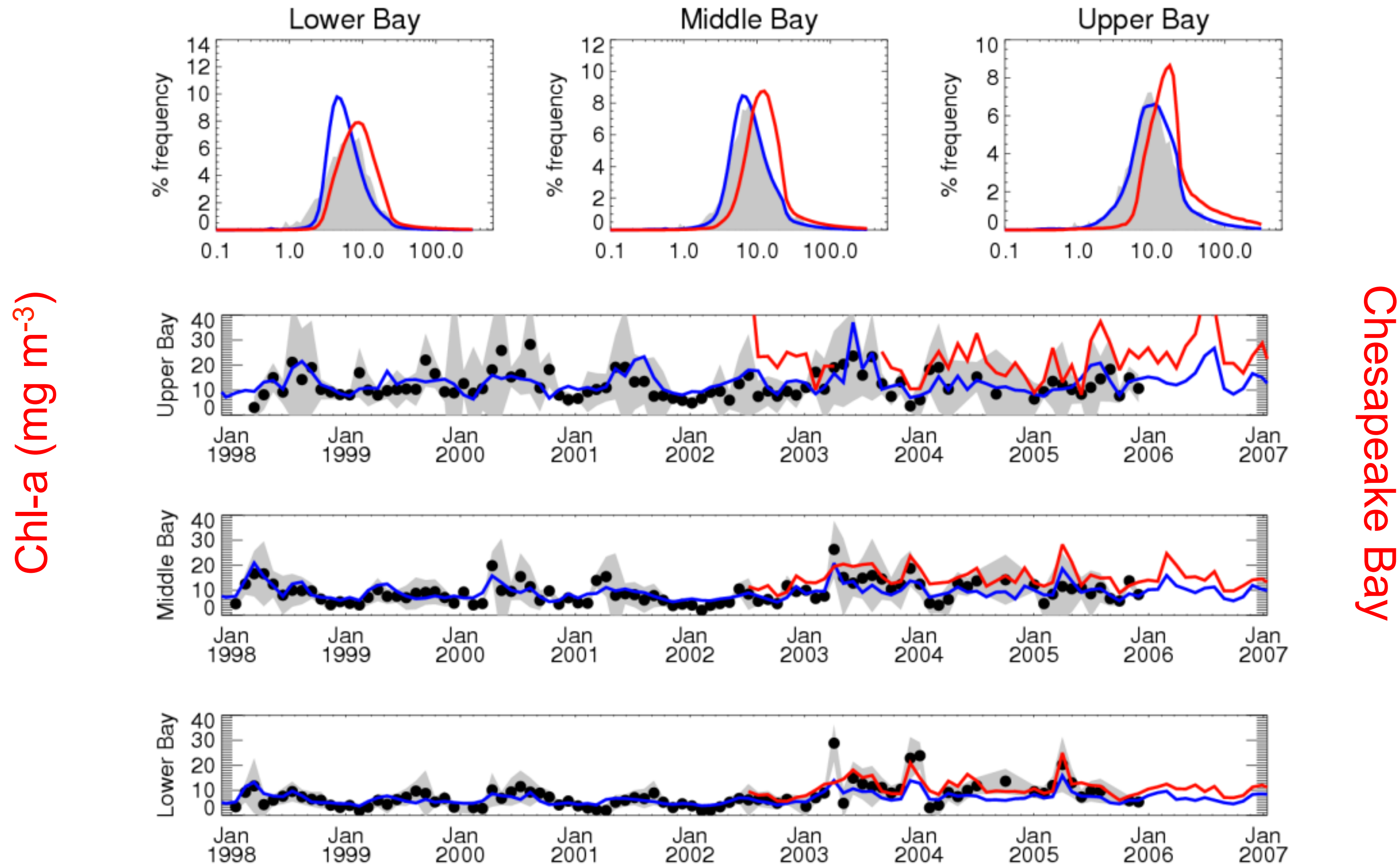




Bailey & Werdell 2006

seabass.gsfc.nasa.gov/seabasscgi/search.cgi

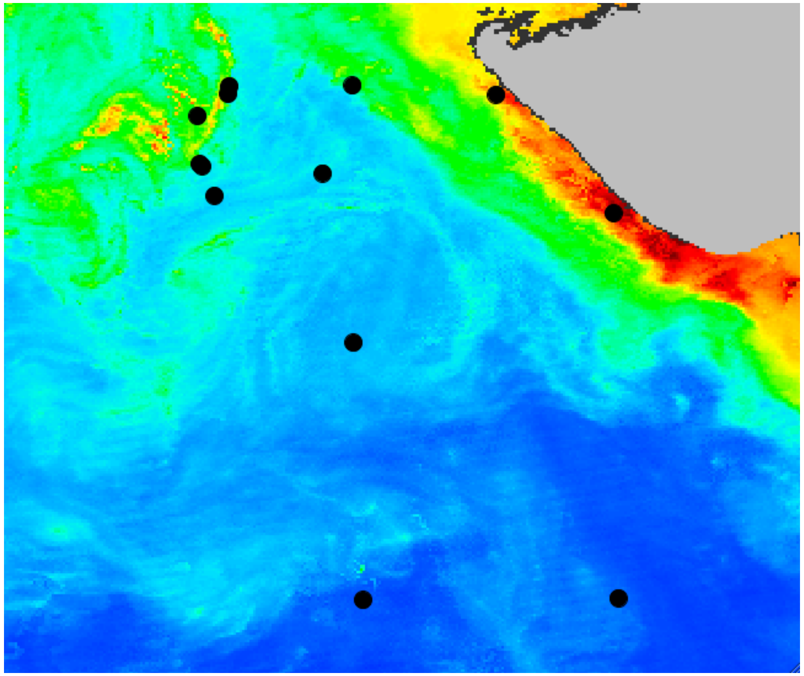
Level-2 time-series

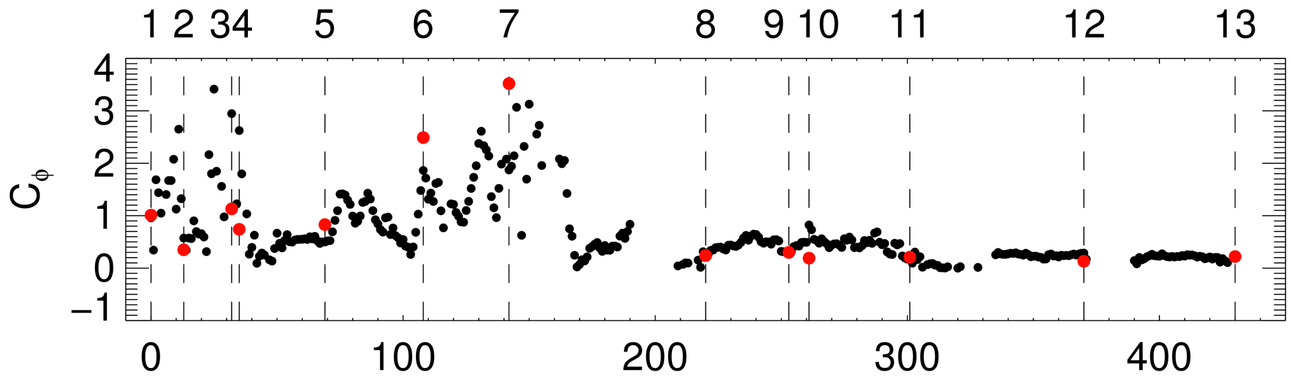


in situ: circles & shaded areas
satellite: SeaWiFS MODIS–Aqua

Werdell et al. 2009

along-track comparisons





along track satellite pixel (in situ, Aqua)

jeremy.werdell@nasa.gov

common limitations

quality of *in situ* data is highly variable & difficult to assess

in situ data coverage is limited, both geographically & temporally

availability of *in situ* data in future is unknown

highly localized (~meters) measurements represent pixel (>km) area

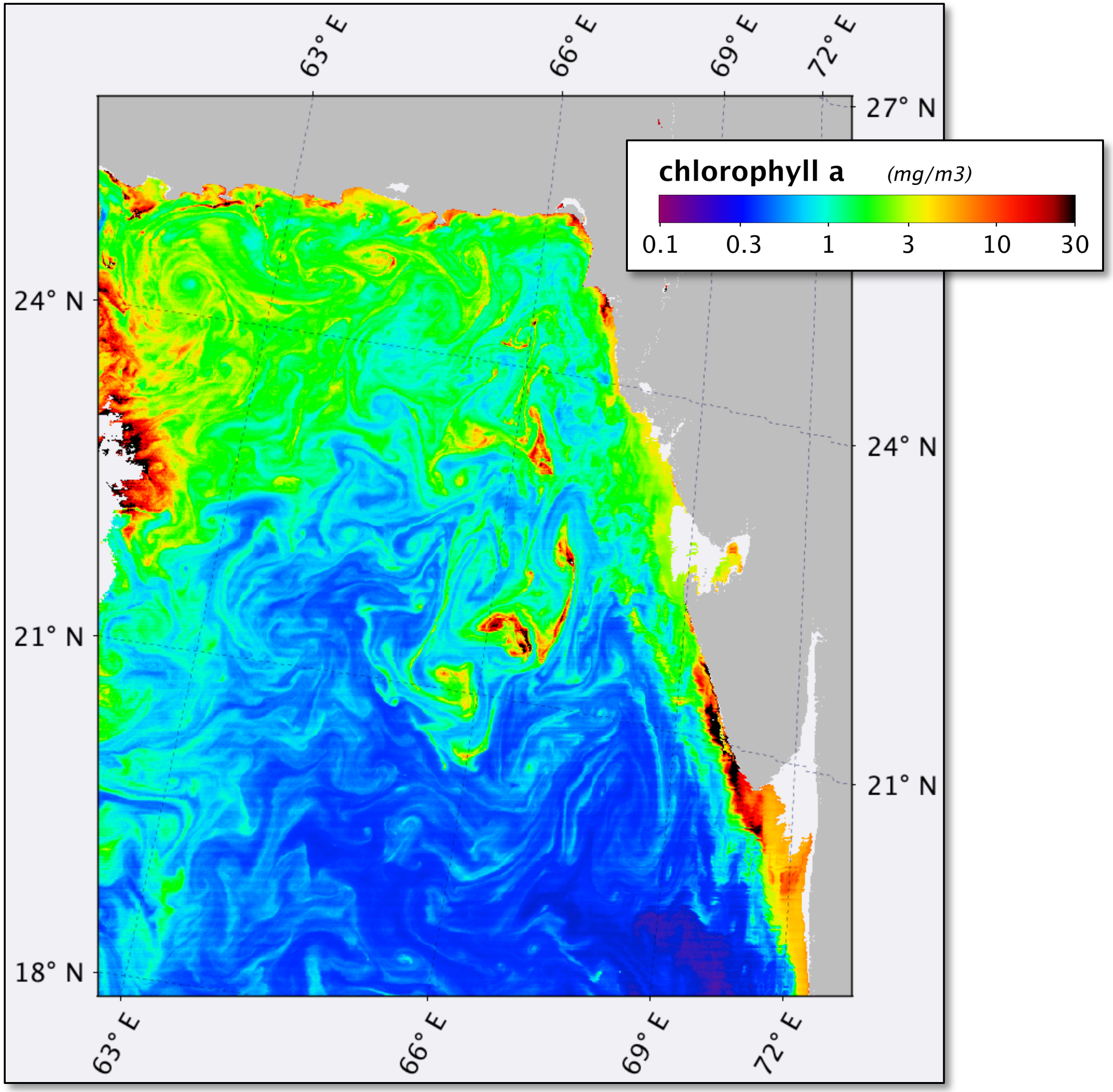
satellite-to-*in situ* comparisons require expertise to prepare & evaluate

generally useful only for assessing static biases in final products

jeremy.werdell@nasa.gov

lessons learned & anticipated challenges

data collection
- horizontal resolution
- temporal resolution
- vertical resolution



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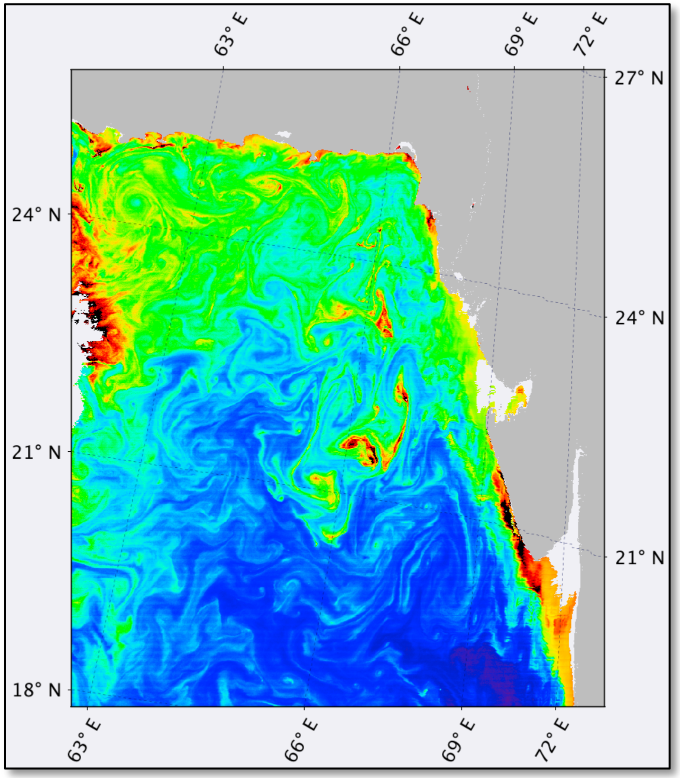

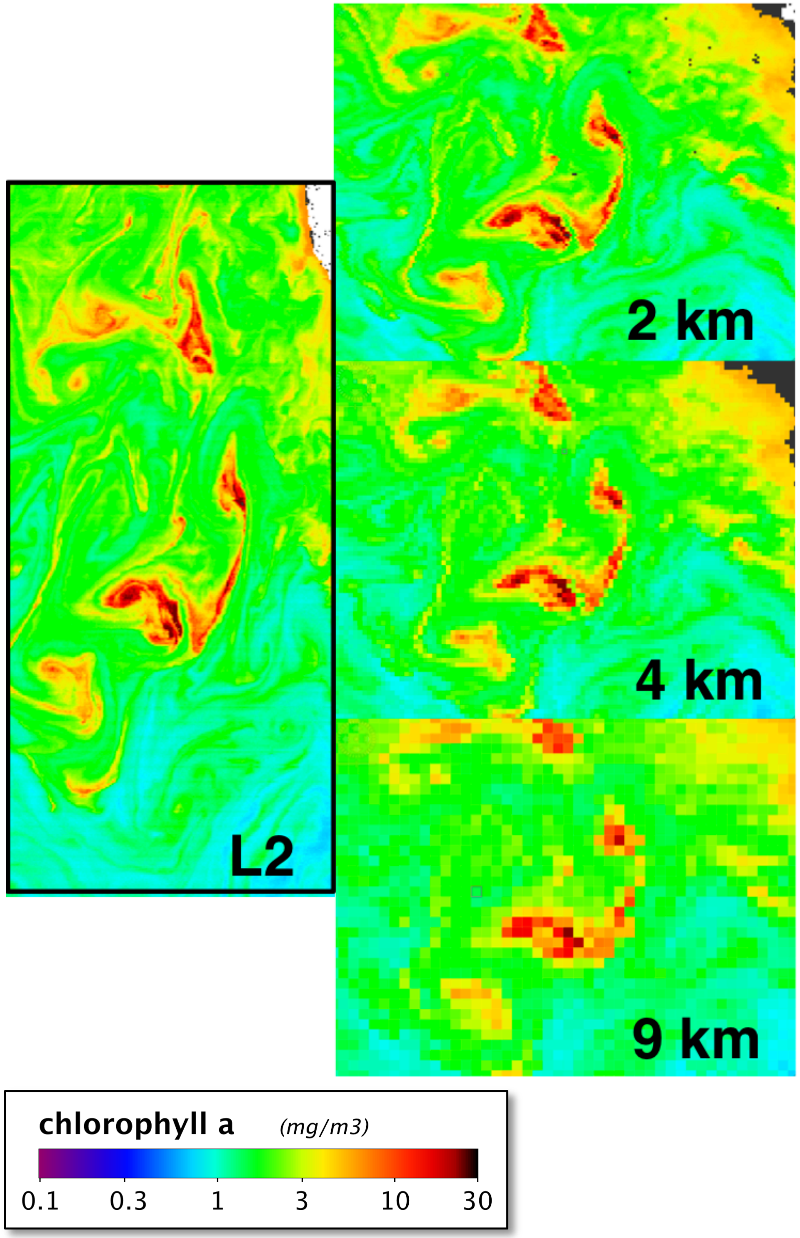

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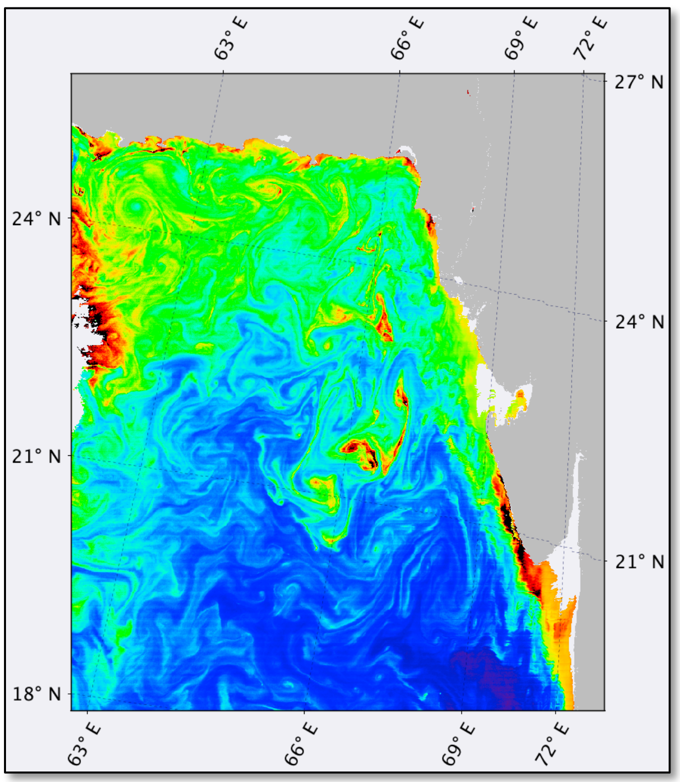

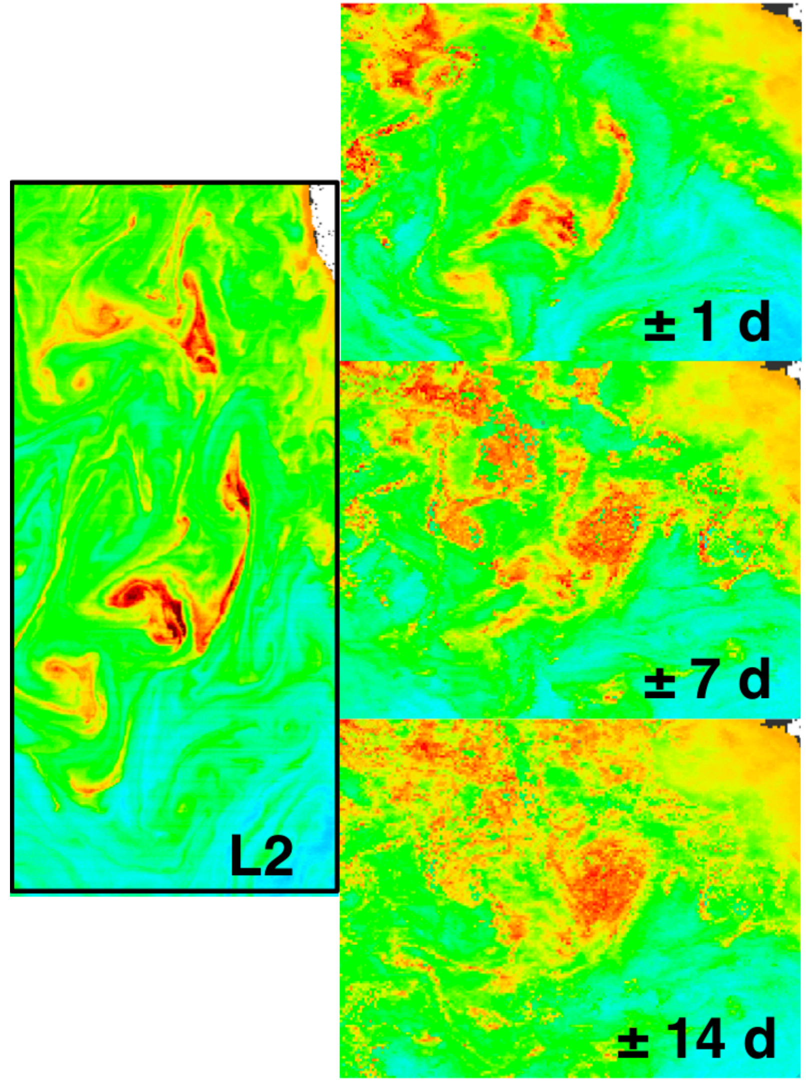

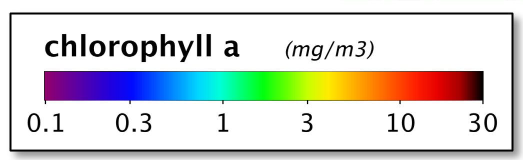

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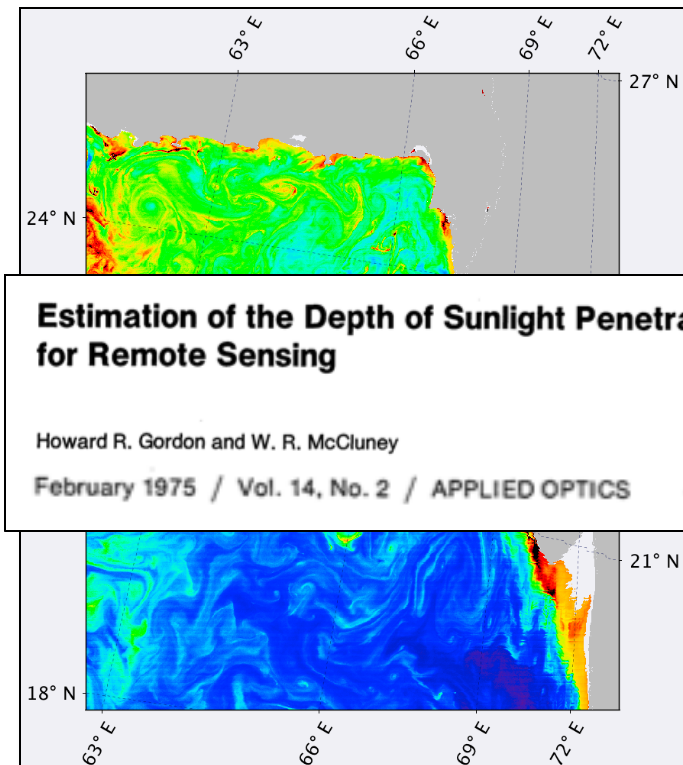
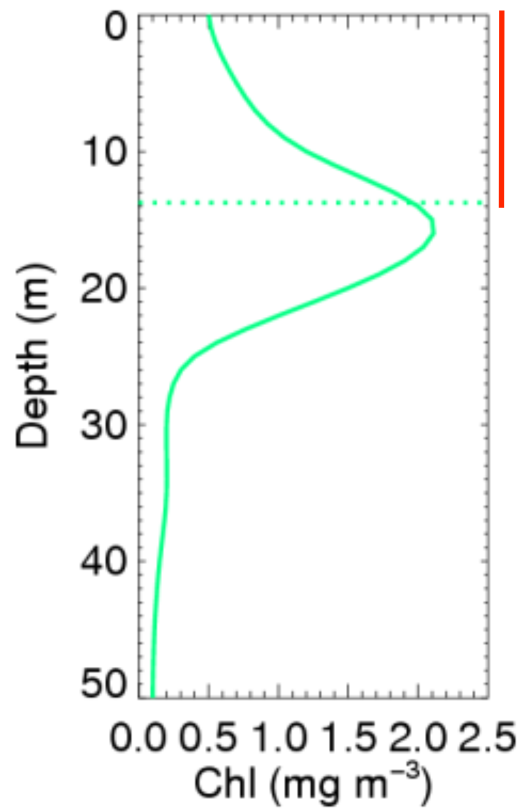


Estimation of the Depth of Sunlight Penetration in the Sea for Remote Sensing

Howard R. Gordon and W. R. McCluney

February 1975 / Vol. 14, No. 2 / APPLIED OPTICS 413

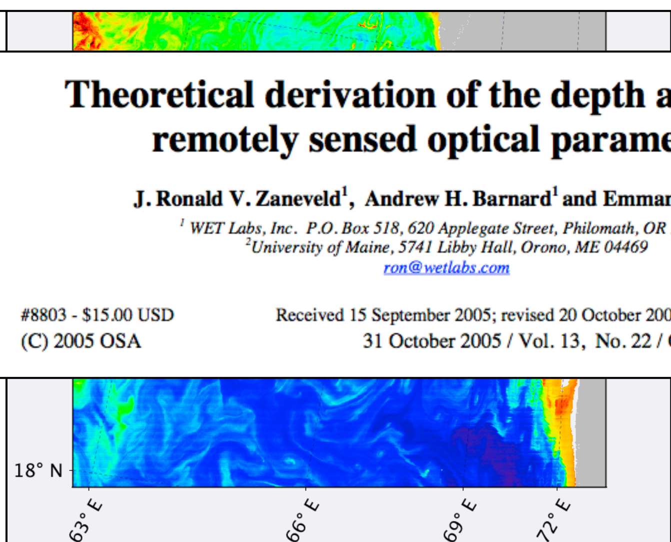


first optical depth
$0.37 = \exp(-K_d z)$
$-1 = -K_d z$

lessons learned & anticipated challenges

data collection
- horizontal resolution
- temporal resolution
- vertical resolution

not only is the resolution of vertical sampling important, but we must also understand (accept & ultimately consider) what the satellite sees & does not see



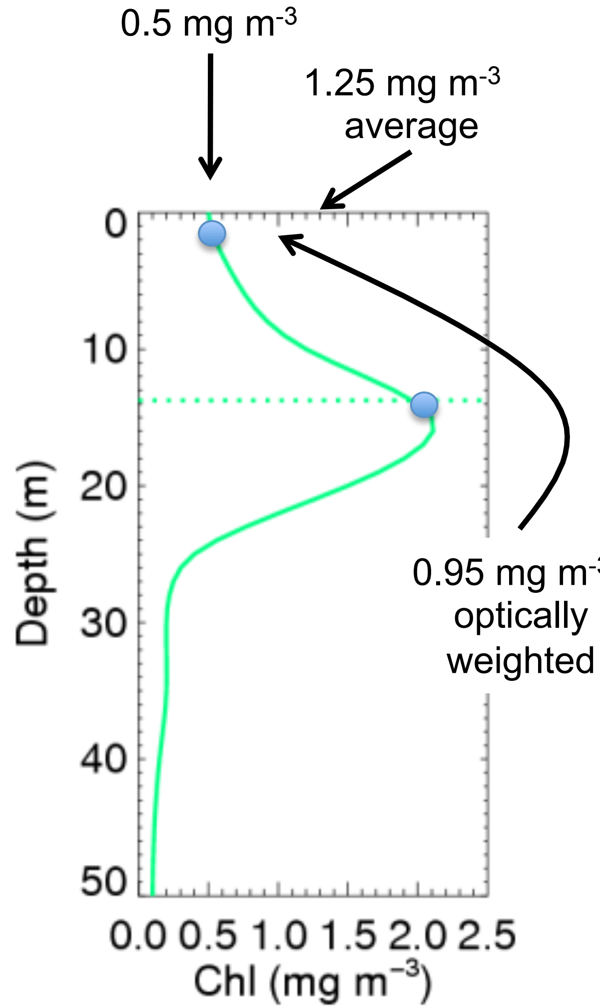
Theoretical derivation of the depth average of remotely sensed optical parameters

J. Ronald V. Zaneveld[1], Andrew H. Barnard[1] and Emmanuel Boss[2]

[1] WET Labs, Inc. P.O. Box 518, 620 Applegate Street, Philomath, OR 97370
[2] University of Maine, 5741 Libby Hall, Orono, ME 04469
ron@wetlabs.com

#8803 - $15.00 USD Received 15 September 2005; revised 20 October 2005; accepted 24 October 2005

31 October 2005 / Vol. 13, No. 22 / OPTICS EXPRESS 9052



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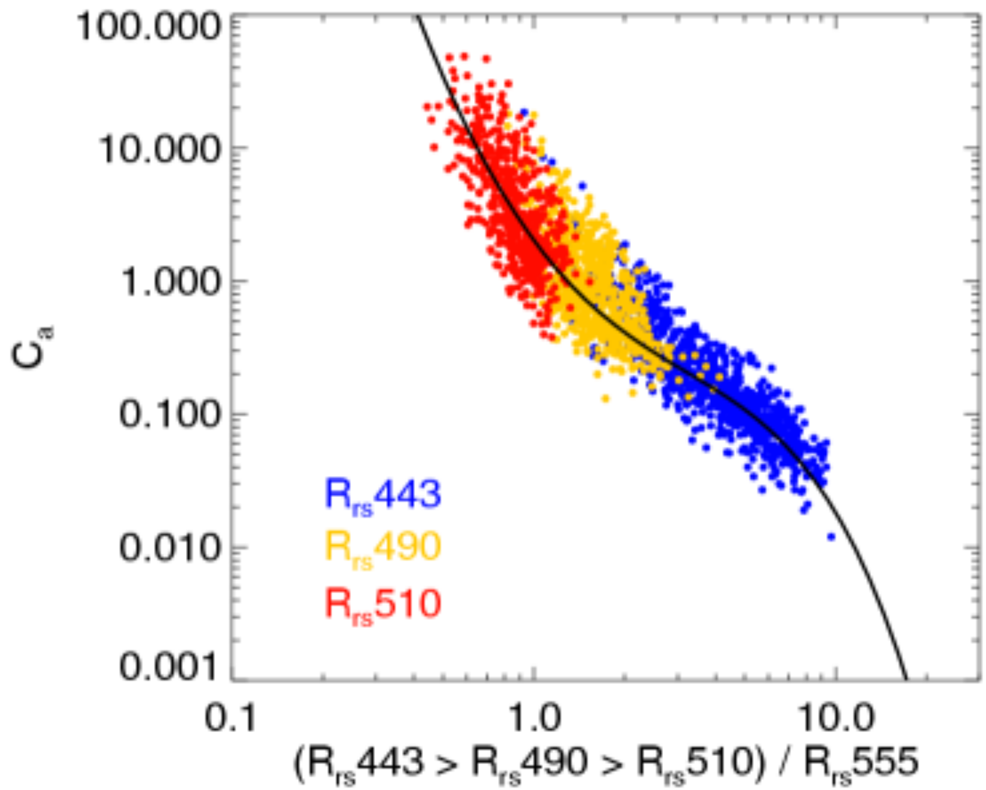
bio-optical algorithm development, tuning, & evaluation

empirical algorithms



$\underbrace{R_{rs}}_{\text{what satellite sees}}$ related to $\underbrace{\text{pigments, IOPs, carbon stocks, etc.}}_{\text{what you might want to study}}$

atmospheric correction

in situ data are used in the development of:

aerosol tables (via AERONET)

the correction for non-zero R_{rs}(NIR)

the correction for bidirectional effects (f/Q)

the correction for spectral bandpass effects

jeremy.werdell@nasa.gov

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jeremy.werdell@nasa.gov

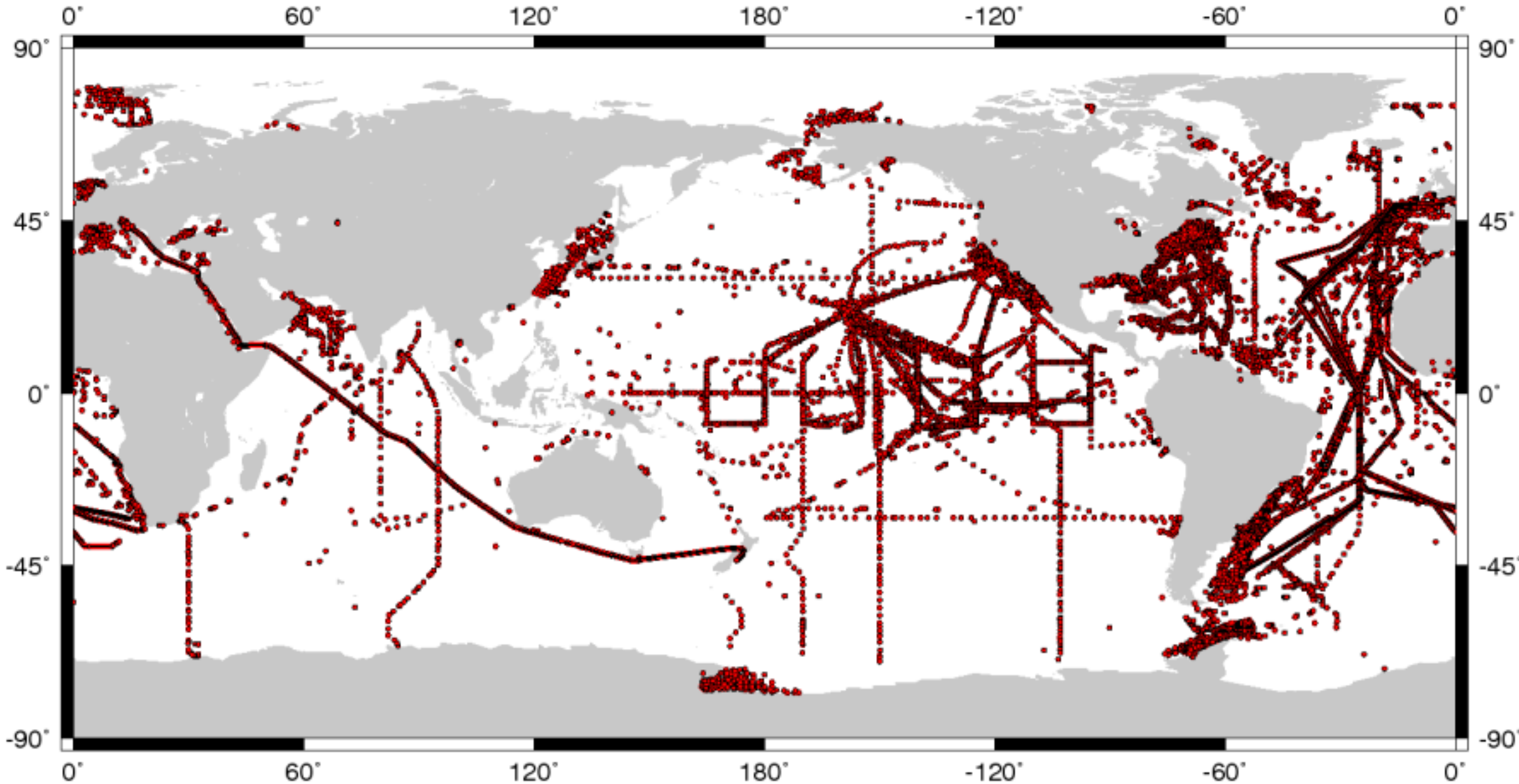
an abundance of field data is hard to come by

spatial & temporal distributions

"complete" suites of measurements (R_{rs}, IOPs, biogeochemistry)

jeremy.werdell@nasa.gov

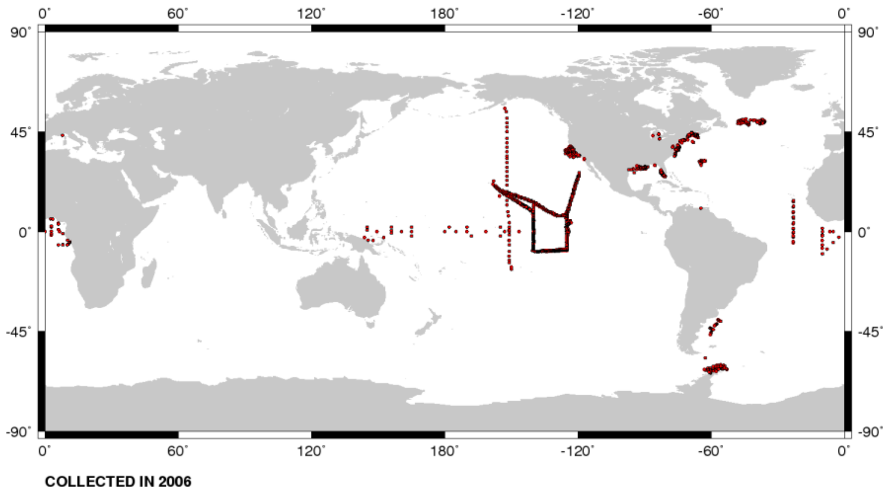
SeaBASS @ seabass.gsfc.nasa.gov



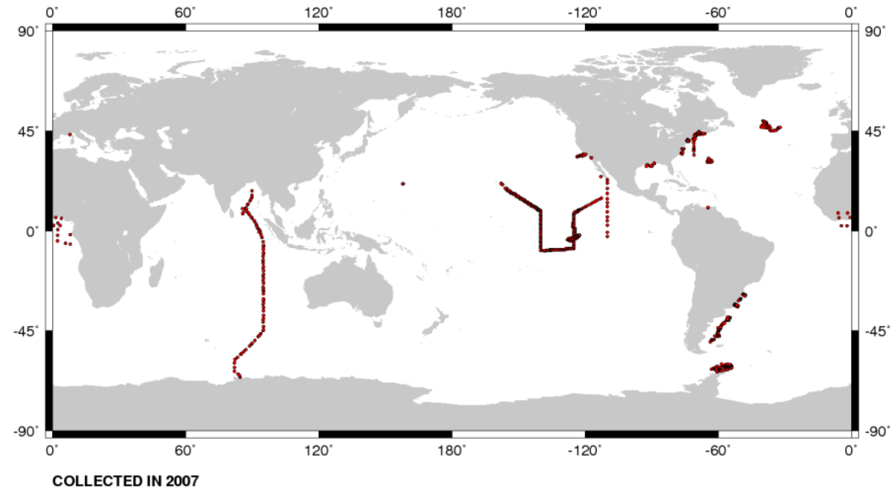
ALL DATA

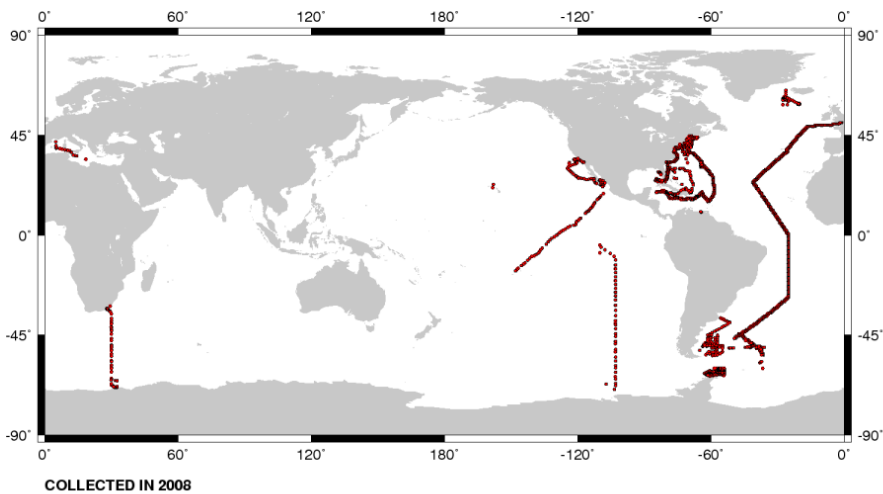
SeaBASS holdings by year: 2006-2009

2006

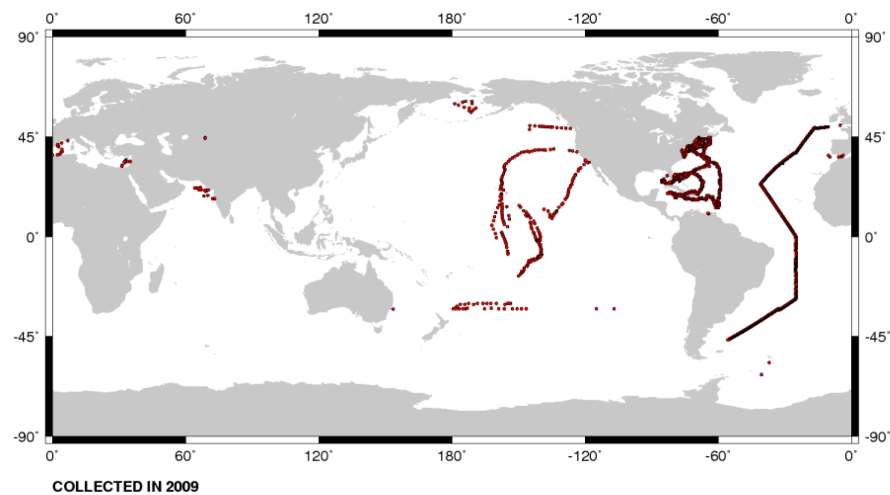


2007





2008



2009

jeremy.werdell@nasa.gov

Level-2 match-ups

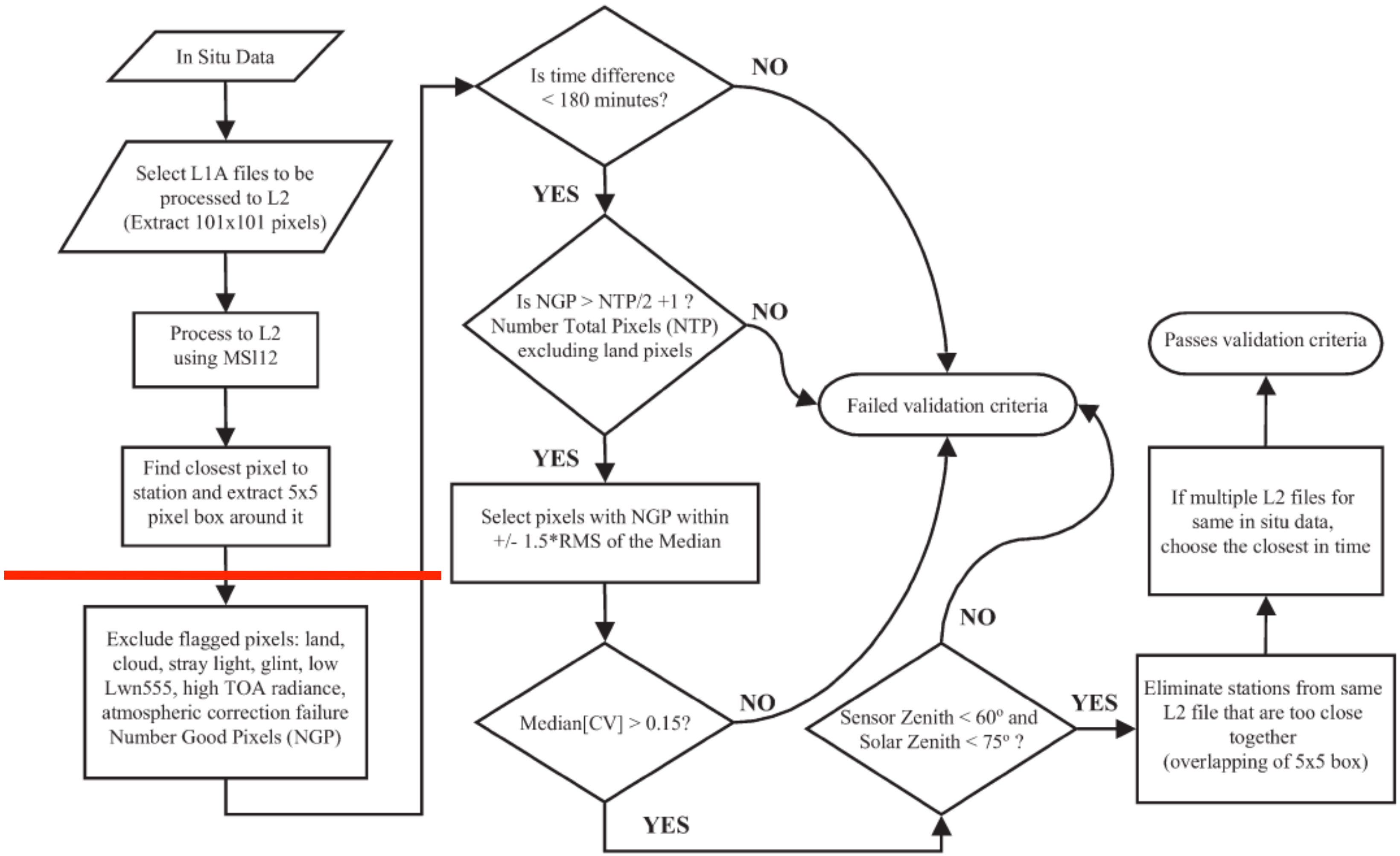
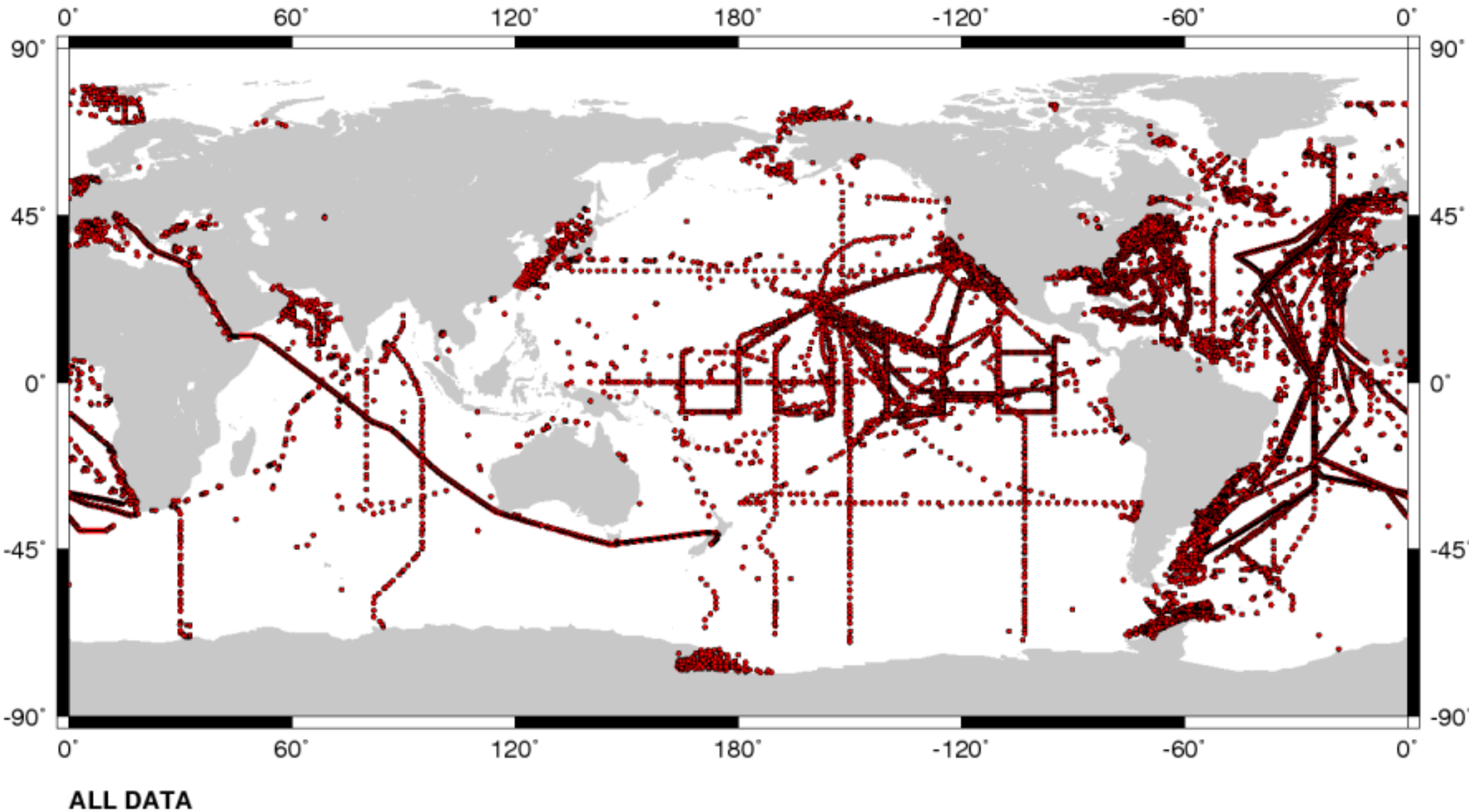


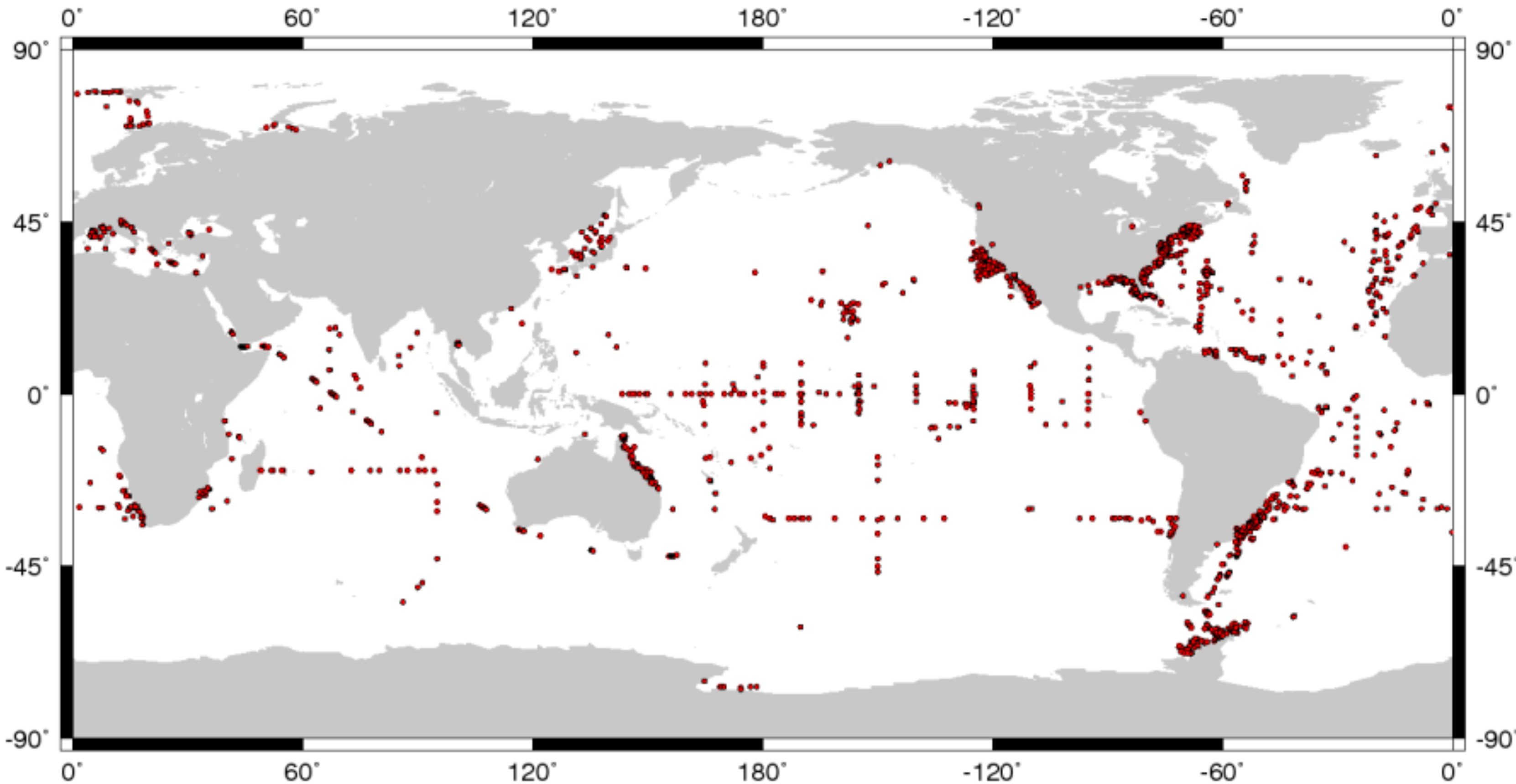
Fig. 1. Flowchart of the validation process highlighting the applied exclusion criteria.

S.W. Bailey and P.J. Werdell, “A multi-sensor approach for the on-orbit validation of ocean color satellite data products,” Rem. Sens. Environ. 102, 12-23 (2006).

all available SeaBASS data



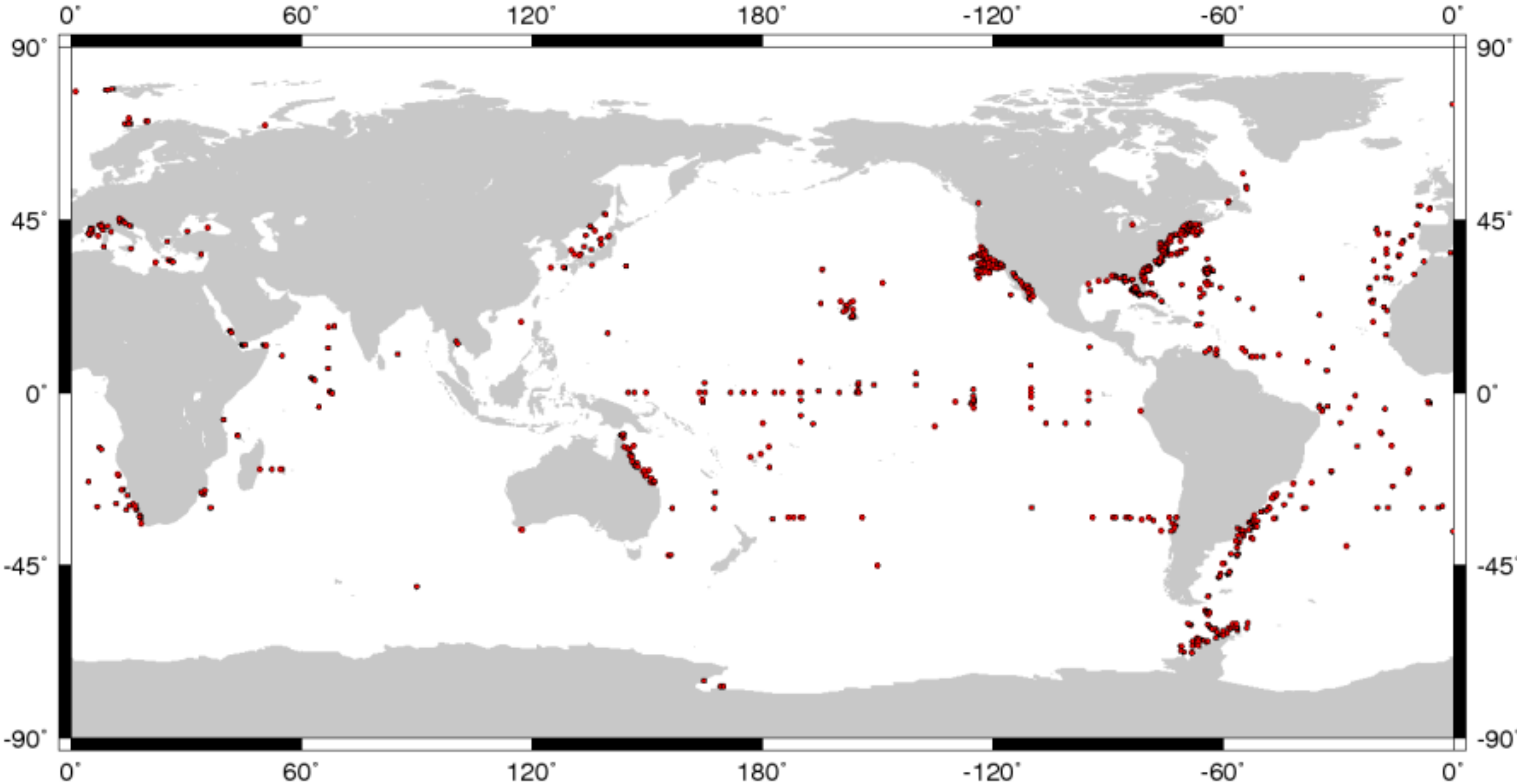
coincident SeaWiFS & in situ data



POSSIBLE SEAWIFS MATCH-UPS

jeremy.werdell@nasa.gov

valid SeaWiFS match-ups

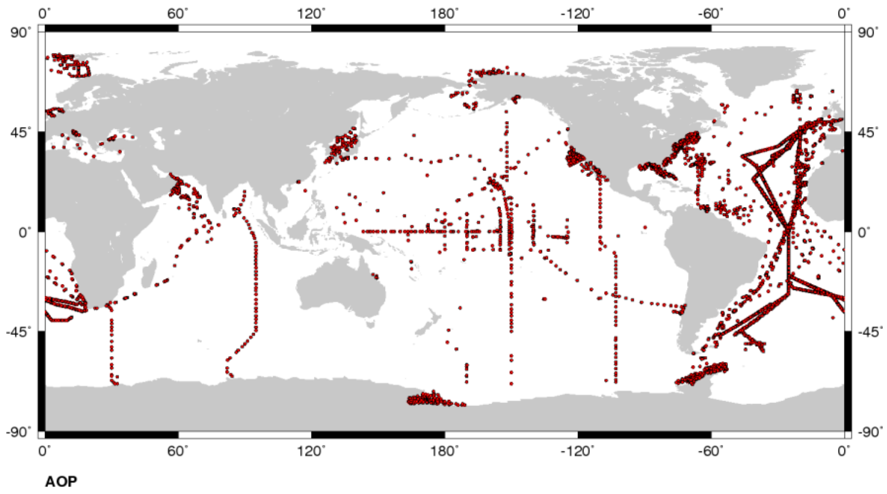


VALID SEAWIFS MATCH-UPS

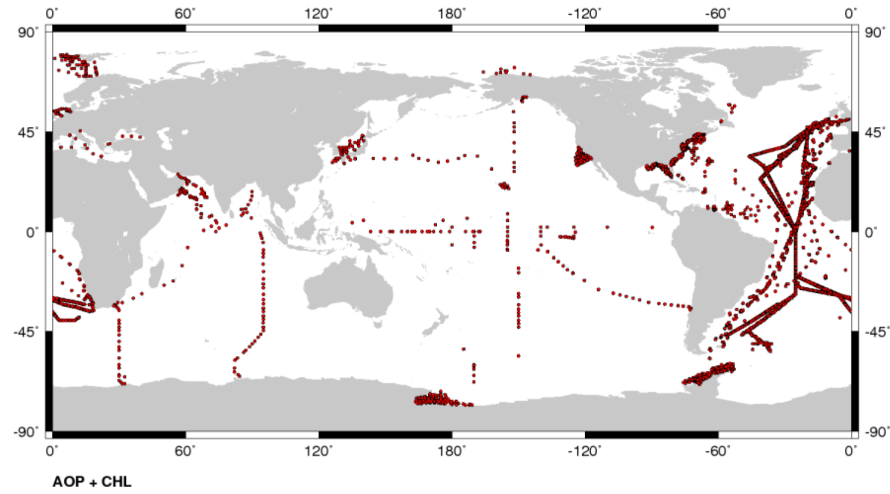
jeremy.werdell@nasa.gov

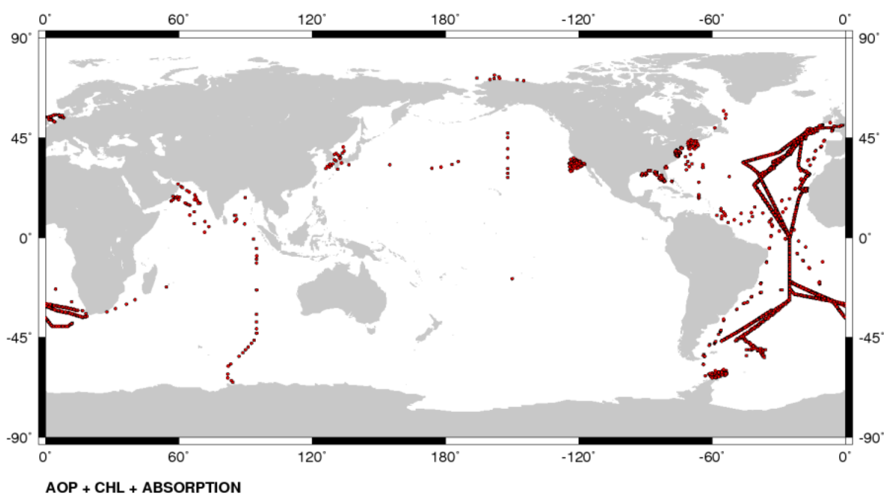
bio-optical algorithm development data sets

R_{rs}

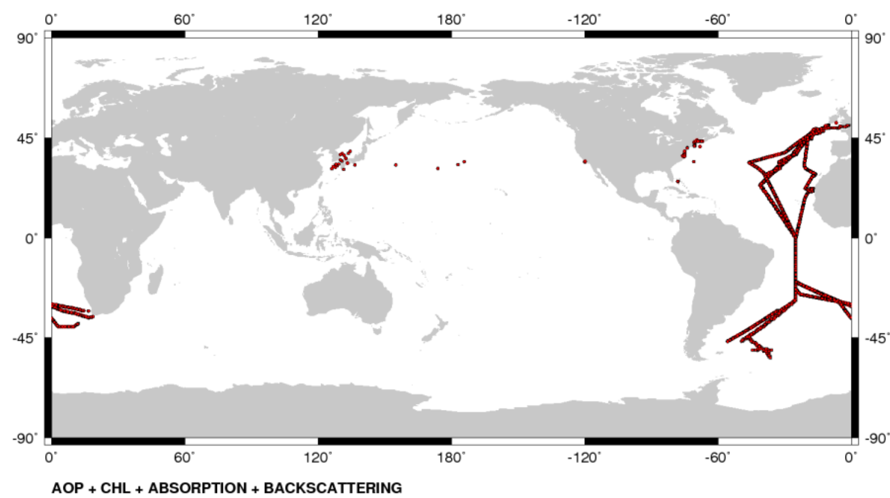


R_{rs} & Chl



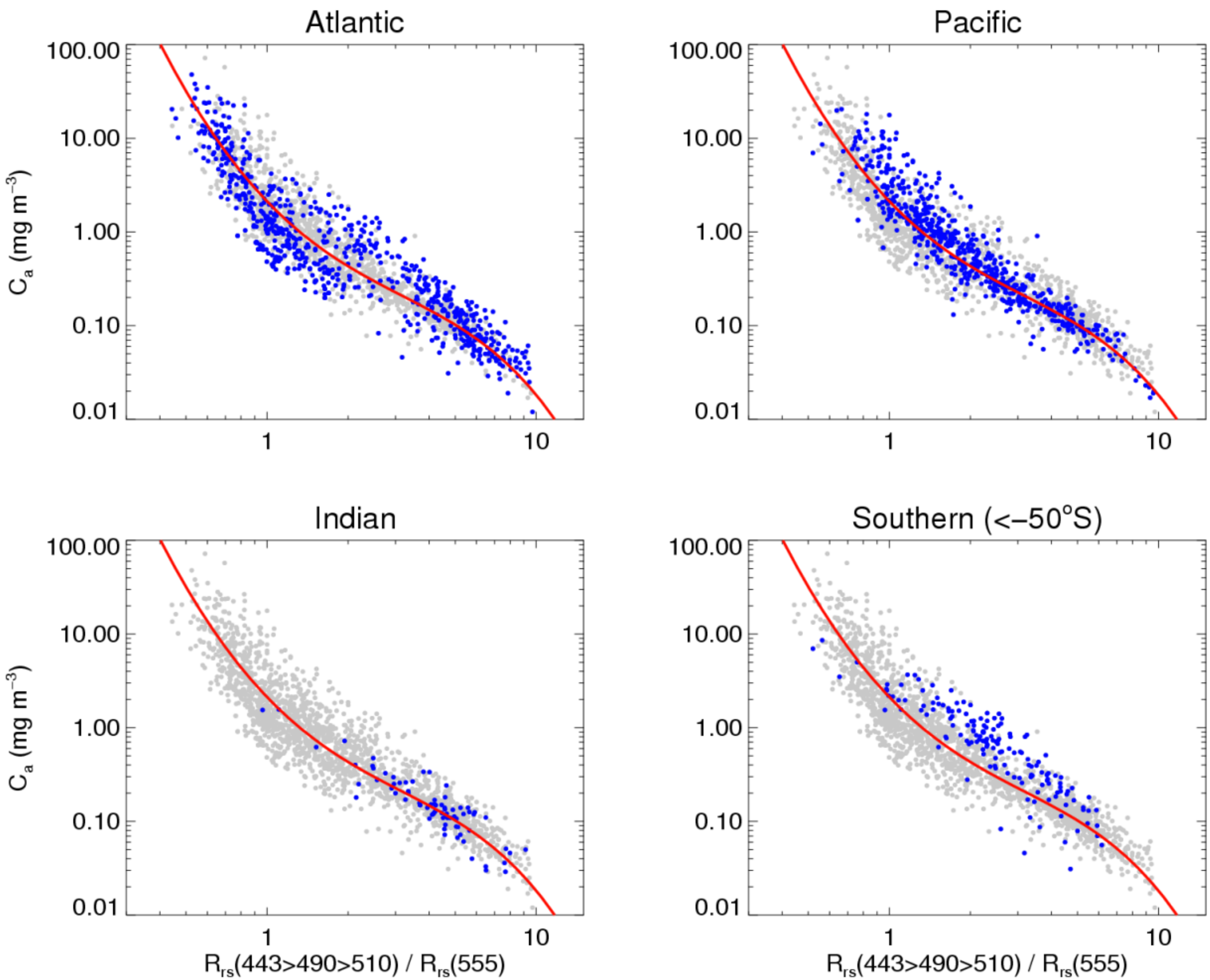


R_{rs} & Chl & absorption



Rrs & Chl & absorption & backscattering

bio-optical algorithm development data sets



outline

great field data enable great satellite data products

an abundance of field data is hard to come by

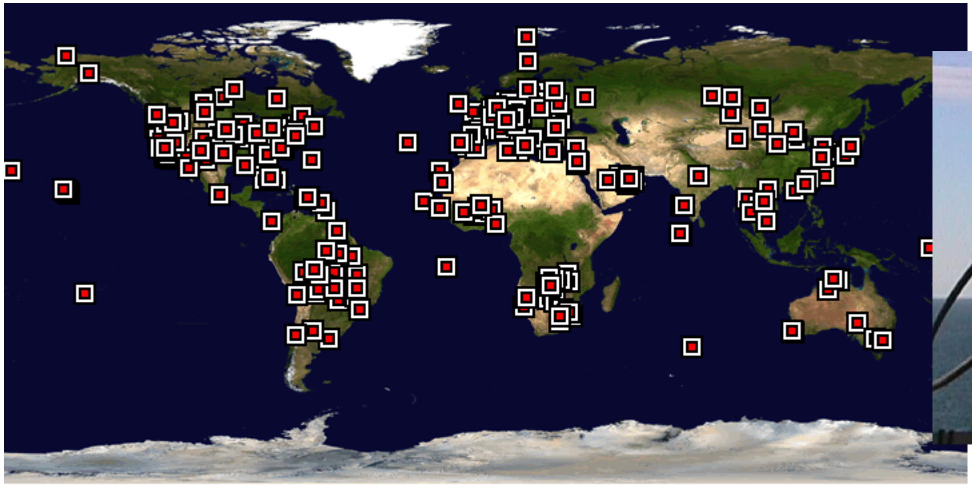
emerging technologies can provide rich data streams

QA/QC metrics are essential (or this all falls apart)

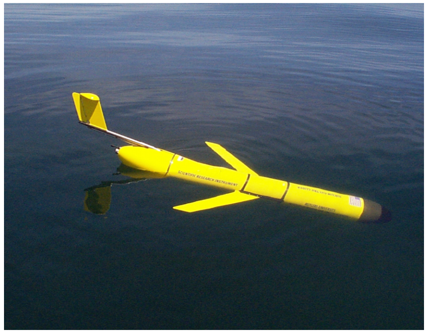
jeremy.werdell@nasa.gov

moving forward – community innovations

AERONET (fixed-above water platforms)

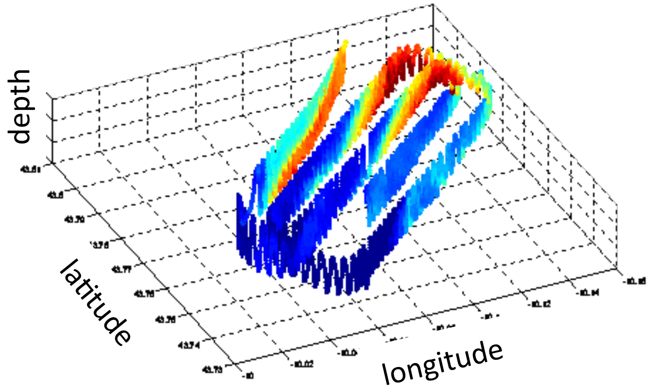


buoy networks



gliders, drifters, & other autonomous platforms

towed & underway sampling

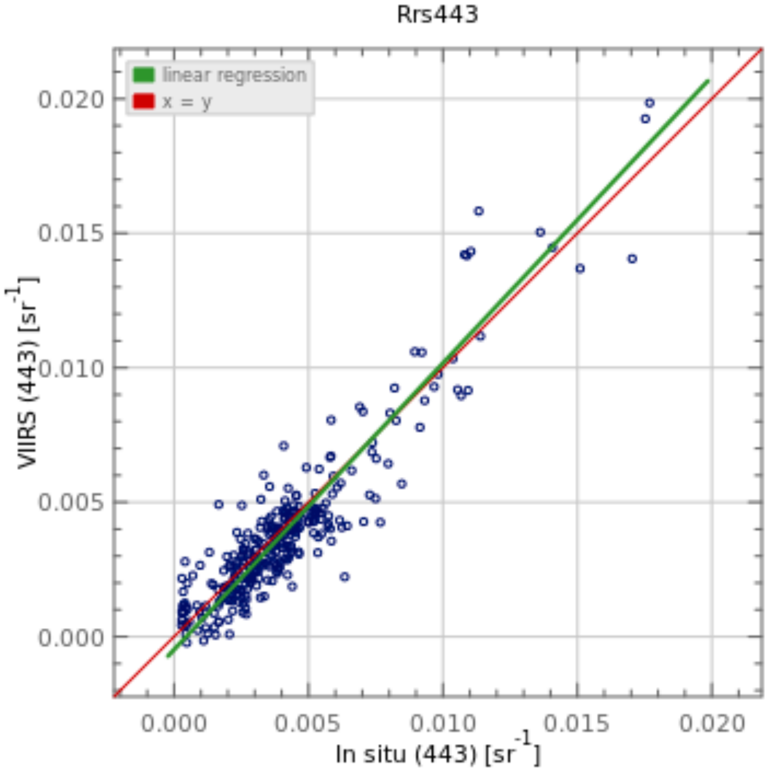


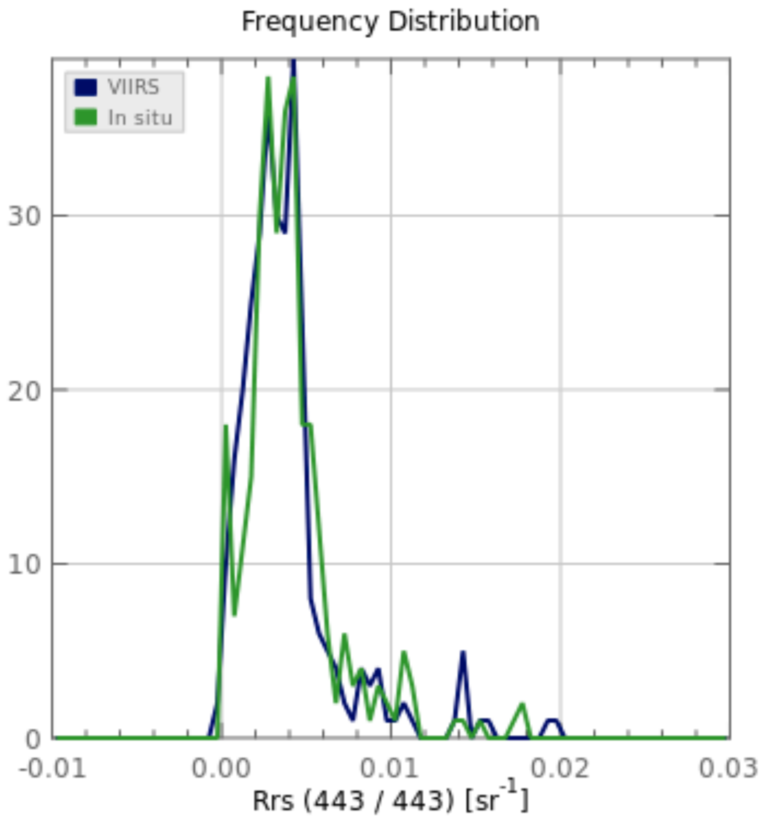
validation exercises using autonomous data

AERONET-OC match-ups with VIIRS (satellite data since Feb 2012)

Product Name	VIIRS Range	In situ Range	#	Best Fit Slope	Best Fit Intercept	R^2	Median Ratio	Abs % Difference	RMSE
Rrs410	-0.00188, 0.01572	0.00006, 0.01480	370	1.15891	-0.00075	0.72848	0.91371	30.62030	0.00151
Rrs443	-0.00022, 0.01985	0.00028, 0.01769	312	1.06528	-0.00048	0.86995	0.92035	18.64367	0.00114
Rrs486	0.00066, 0.02486	0.00101, 0.02520	370	0.95921	-0.00056	0.92048	0.83444	18.33002	0.00130
Rrs551	0.00097, 0.02519	0.00008, 0.02453	370	0.93824	-0.00055	0.94017	0.81644	18.58145	0.00131
Rrs671	-0.00007, 0.00920	0.00007, 0.00864	296	1.05955	-0.00043	0.86652	0.57489	45.94727	0.00057

The linear regression algorithm has been changed to reduced major axis.

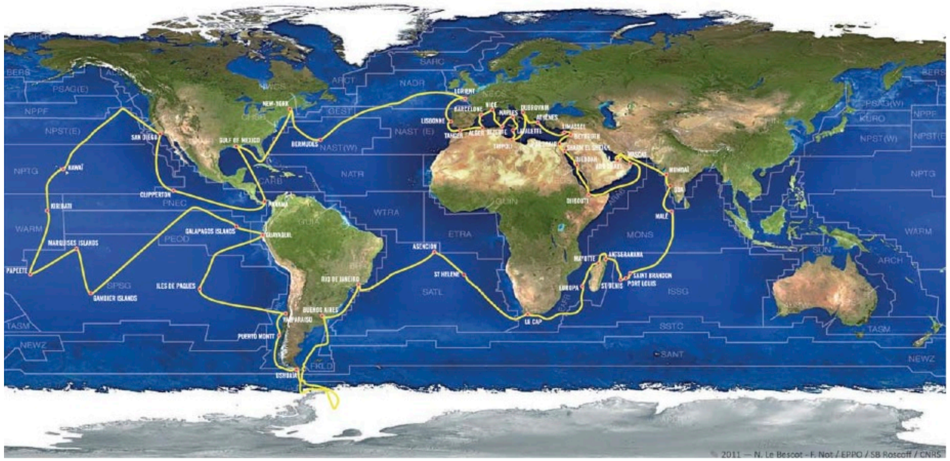


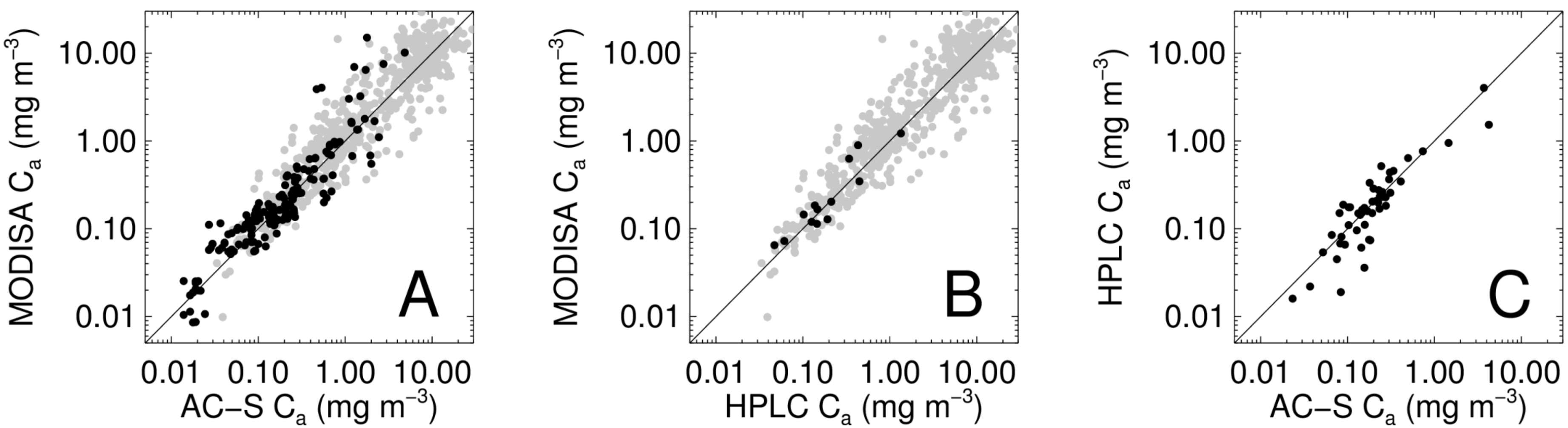


jeremy.werdell@nasa.gov

validation exercises using autonomous data

Tara Oceans expedition (2009-2012) AC-S products vs. MODISA





jeremy.werdell@nasa.gov

outline

great field data enable great satellite data products

an abundance of field data is hard to come by

emerging technologies can provide rich data streams

QA/QC metrics are essential (or this all falls apart)

jeremy.werdell@nasa.gov

QA/QC metrics are essential

a single entity (e.g., NASA or equivalent) cannot collect sufficient volumes of *in situ* data to satisfy its operational calibration & validation needs

following, flight projects rely on multiple entities to collect *in situ* data

jeremy.werdell@nasa.gov

QA/QC metrics are essential

QA/QC methods vary in maturity – exist for many established instruments & platforms, but not always for newer or autonomous systems

jeremy.werdell@nasa.gov

for example, variance in AOP data sets

AOP instrumentation in SeaBASS or available commercially:

- many companies & instruments
  Biospherical, Satlantic, HOBI, Trios/Ramses, DALEC, SIMBAD-A, ASD, Spectron, custom
- many platforms & deployment strategies
  profilers, buoys, above-water (ship, permanent, hand-held), gliders, AUVs

dynamic range of problem set is growing:

- new missions emphasize research in shallow, optically complex water
- spectral domain stretching to UV and SWIR
- new missions have immediate, operational requirements

jeremy.werdell@nasa.gov

bonus material!

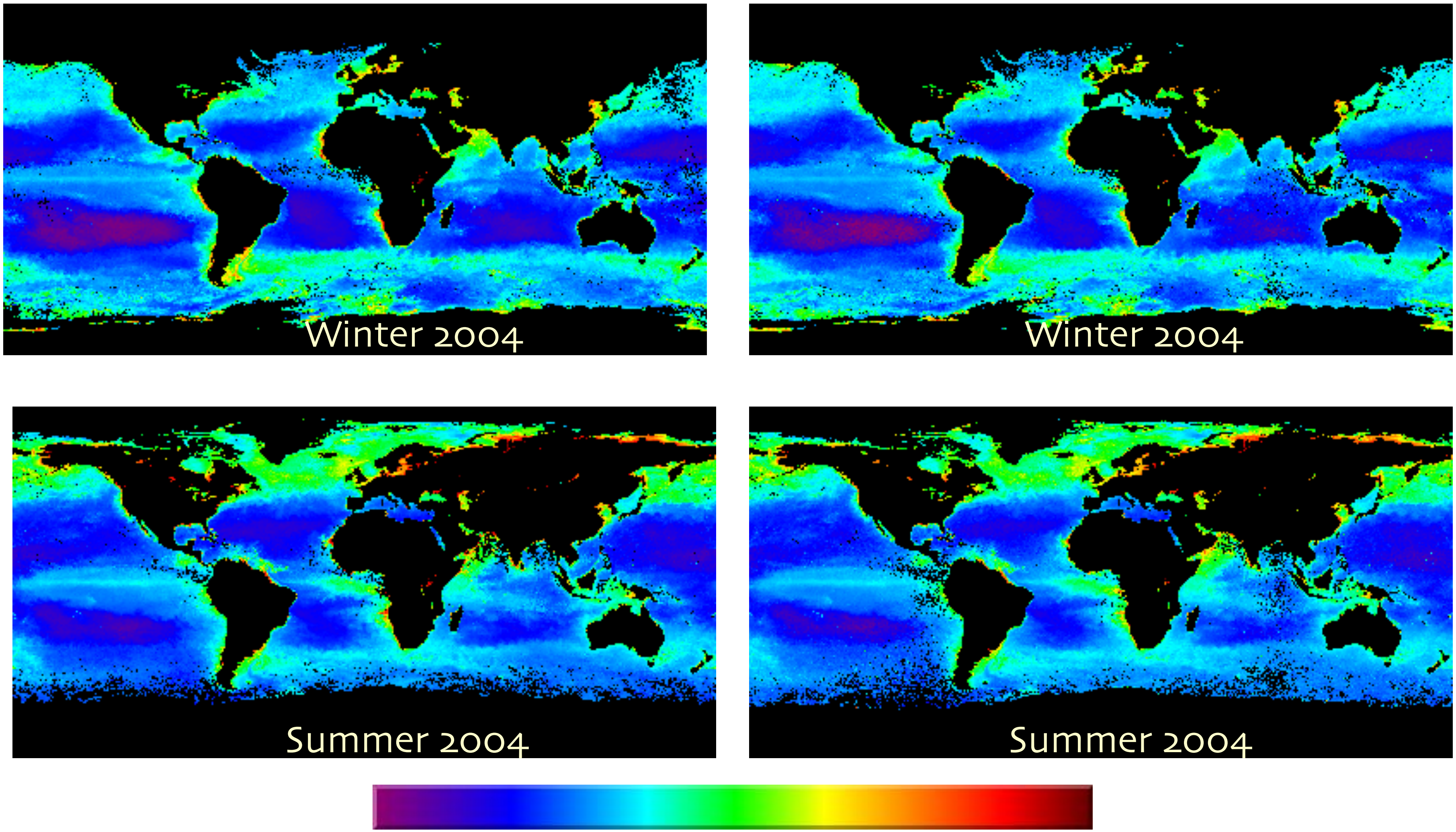
satellite-to-satellite comparisons

jeremy.werdell@nasa.gov

Level-3 comparisons

Seasonal Chlorophyll Images

MODIS/Aqua SeaWiFS



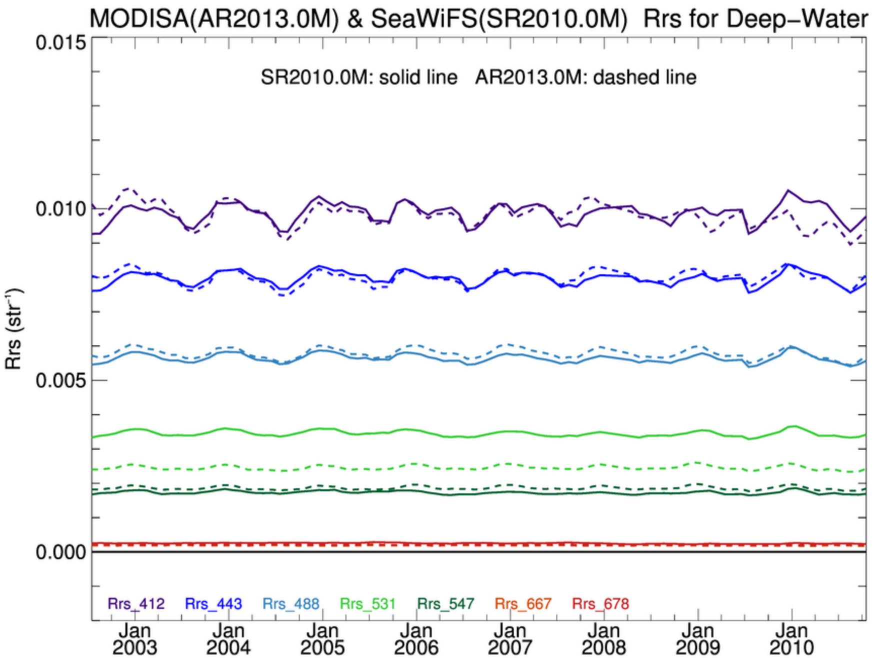
0.01-64 mg m^{-3}

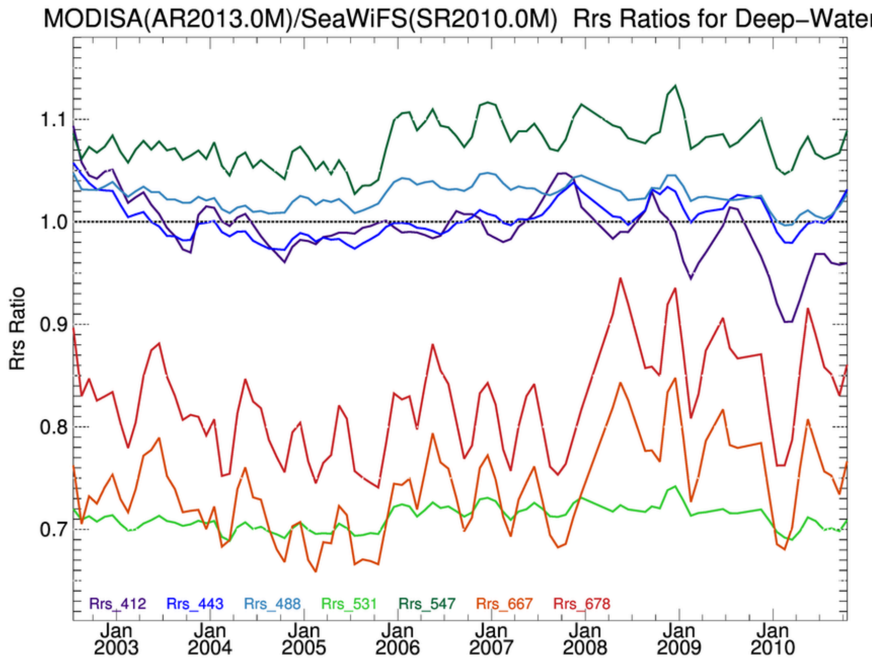
Level-3 time-series

Level-3 parameters (e.g., Rrs) compared for common spectral bands

common bins extracted & compared over the period of overlap between the sensors

comparisons performed globally, trophically, zonally & for specified regions

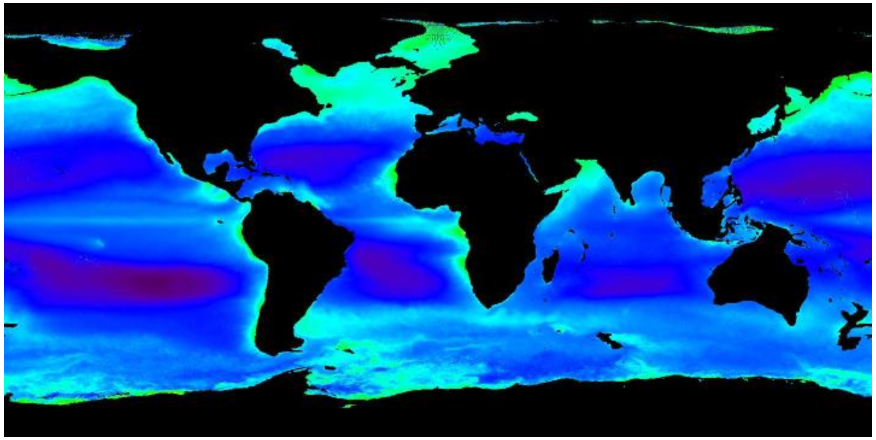




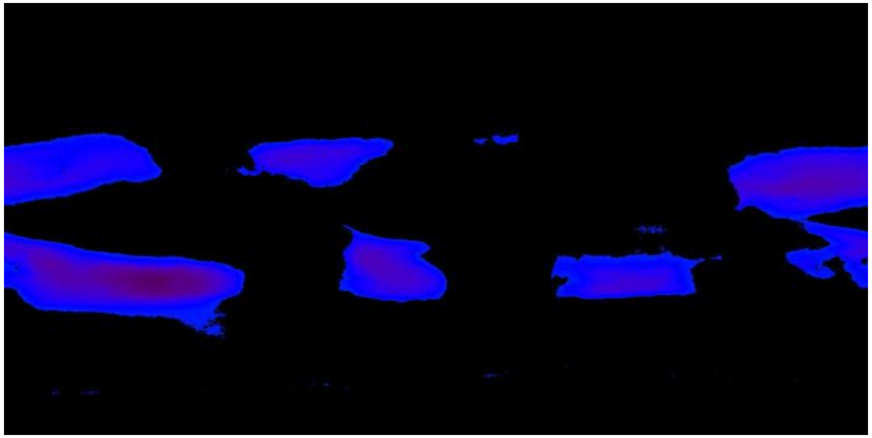
Level-3 comparisons

definitions of trophic subsets

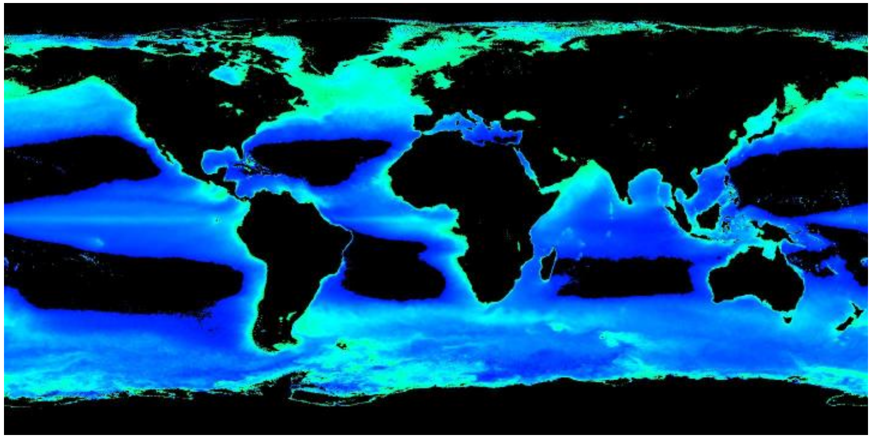
Deep-Water (Depth > 1000m)



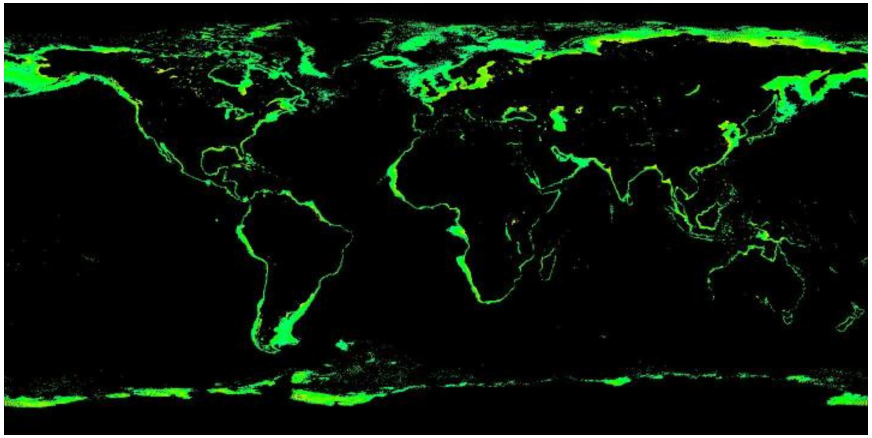
Oligotrophic (Chlorophyll < 0.1)



Mesotrophic (0.1 < Chlorophyll < 1)

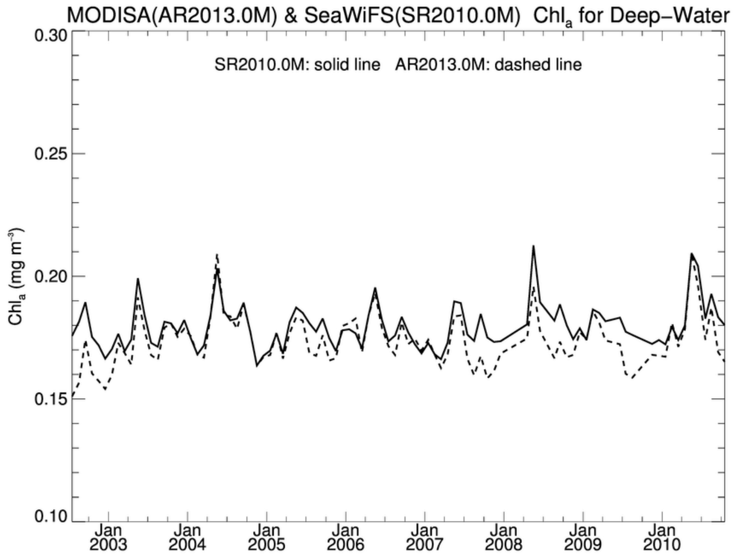


Eutrophic (1 < Chlorophyll < 10)

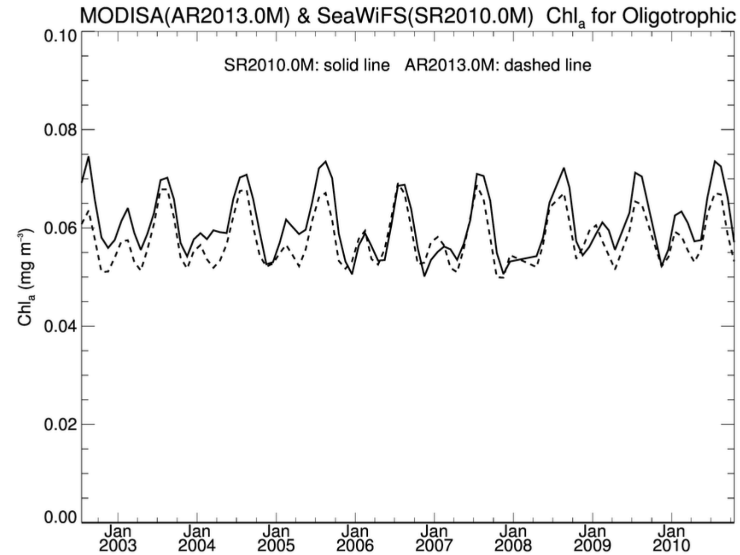


Level-3 time-series

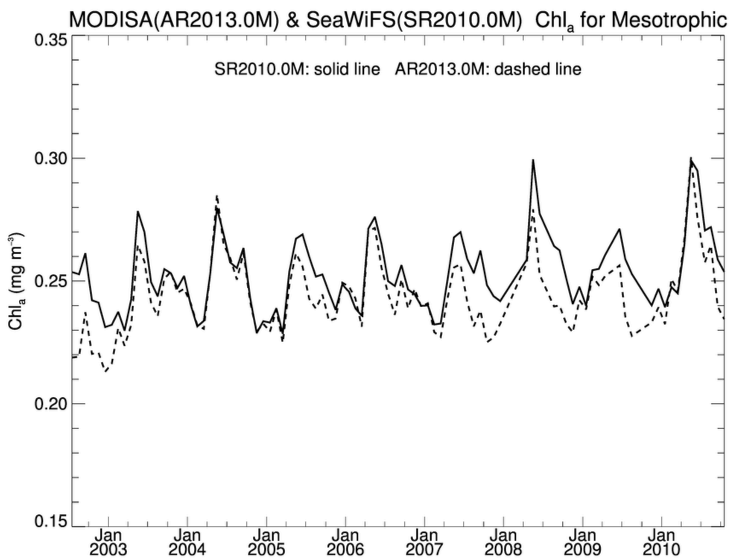
deep water



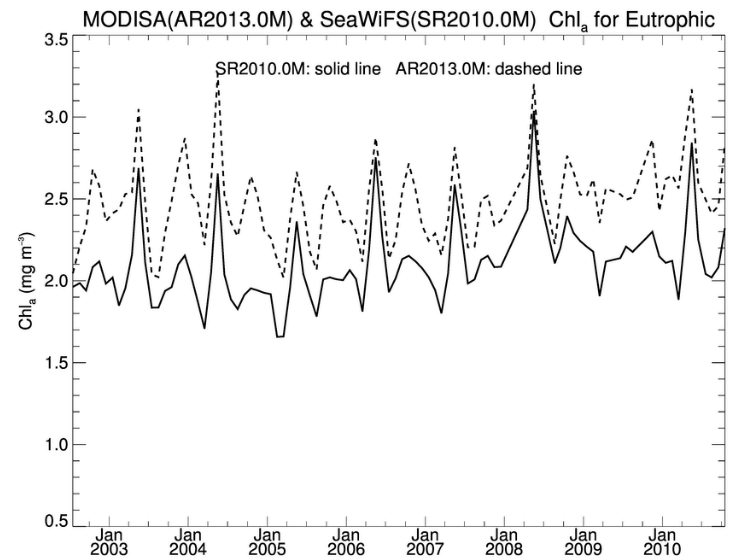
oligotrophic



mesotrophic



eutrophic



Level-3 time-series

strengths:

sensitive to small differences in products from different sensors/algorithms

excellent coverage available, both temporal & geographic

can assess continuity among data sets (Climate Data Records)

limitations:

no obvious truth in comparisons.

sensitive to band-pass differences.

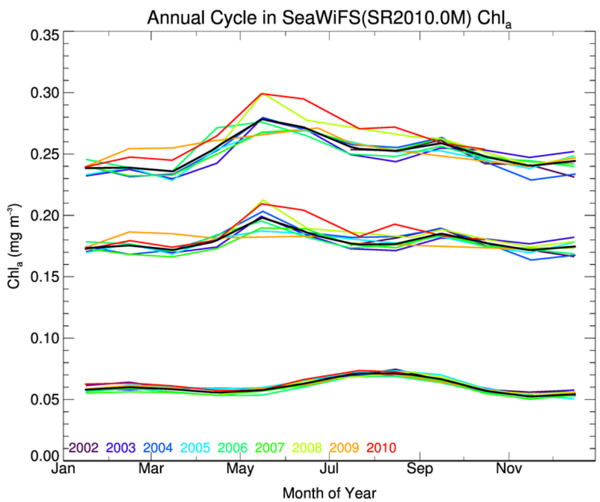
may be affected by time-of-observation differences.

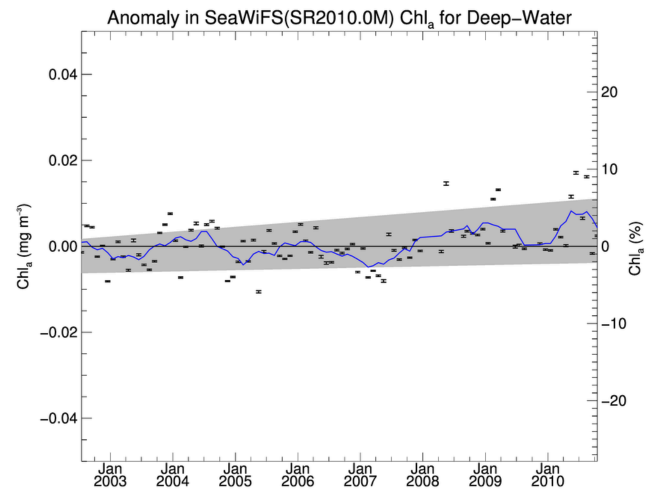
jeremy.werdell@nasa.gov

Level-3 anomalies

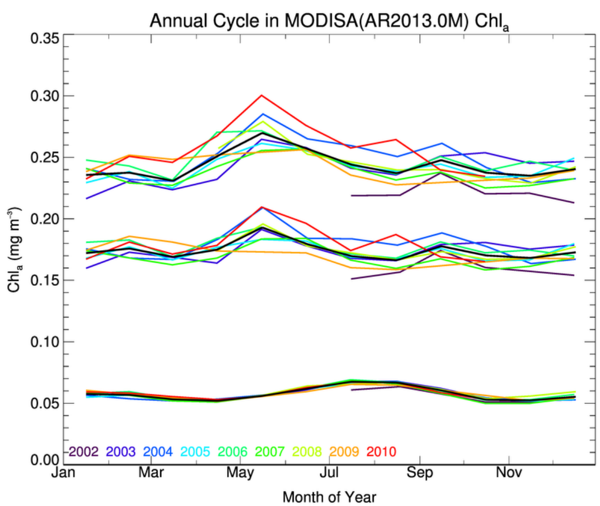
Level-3 global averages for the entire mission are fit to a periodic function to remove natural annual variability; the differences between the global averages & the annual cycle are then plotted over the mission

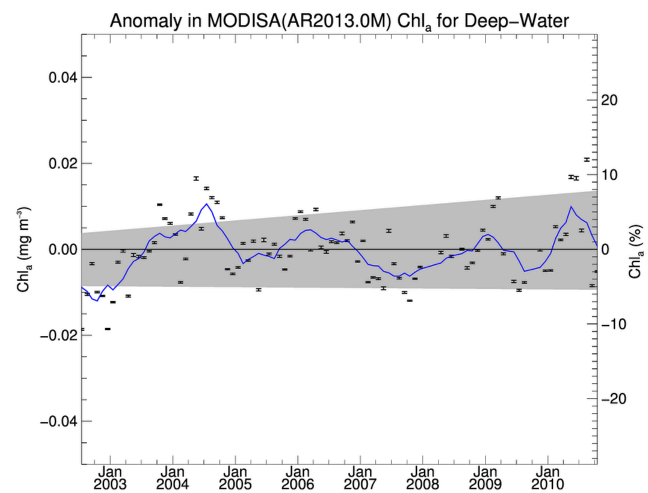
SeaWiFS





MODIS-Aqua





jeremy.werdell@nasa.gov

Level-3 anomaly time-series

strengths:

very sensitive to small changes in instrument performance

limitations:

difficult to distinguish sensor from real geophysical challenges

can be affected by sampling variations

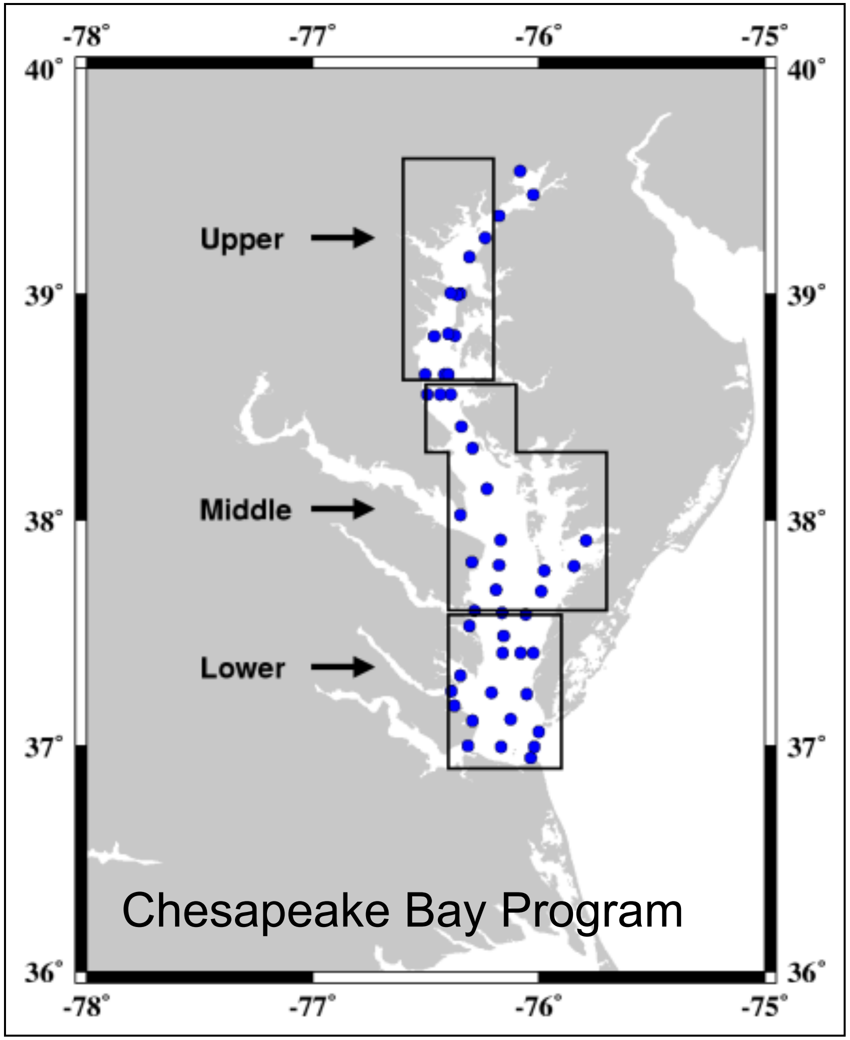
jeremy.werdell@nasa.gov

questions?
comments?
concerns?

jeremy.werdell@nasa.gov

backup slides

Level-2 time-series



http://www.chesapeakebay.net

routine data collection since 1984
12-16 cruises / year

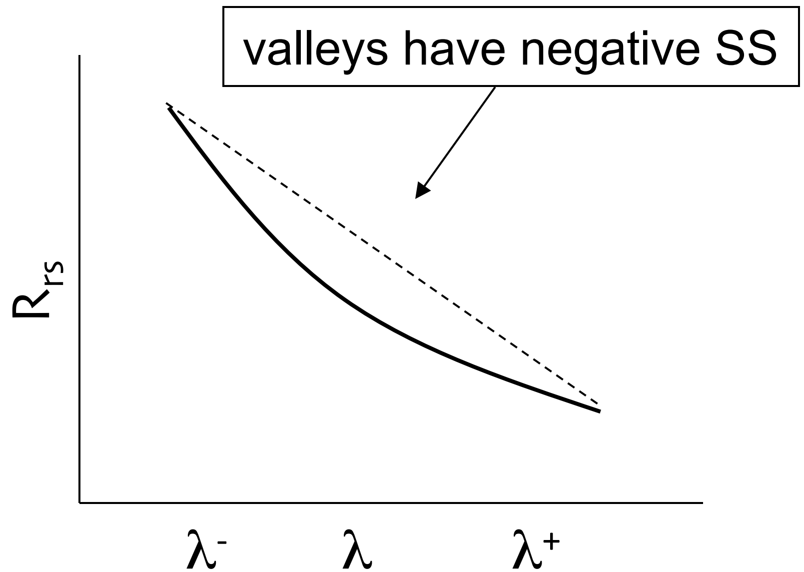
49 stations
19 hydrographic measurements

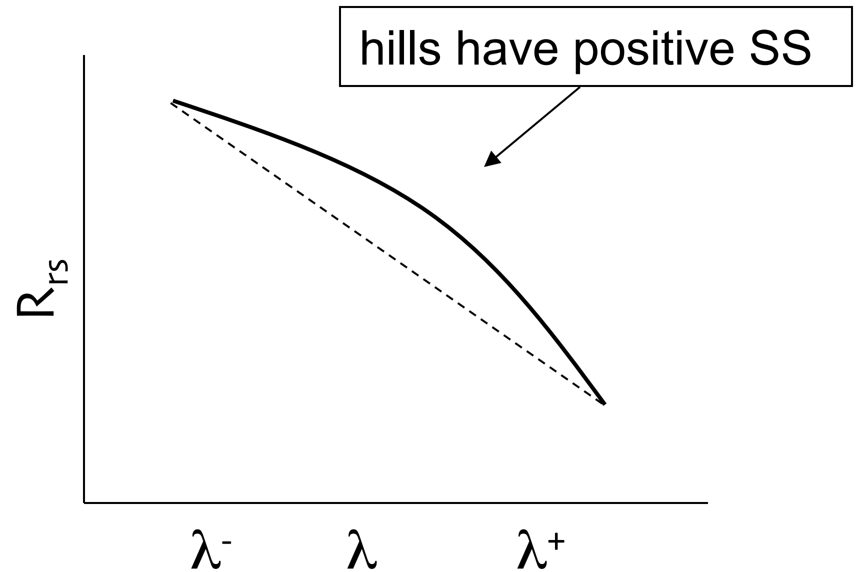
algal biomass
water clarity
dissolved oxygen
others

population statistics for vicarious calibration

compare spectral shapes of *in situ* & satellite populations

$$SS(\lambda) = R_{rs}(\lambda) - R_{rs}(\lambda^{-}) - \left[R_{rs}(\lambda^{+}) - R_{rs}(\lambda^{-})\right]\left(\frac{\lambda - \lambda^{-}}{\lambda^{+} - \lambda^{-}}\right)$$



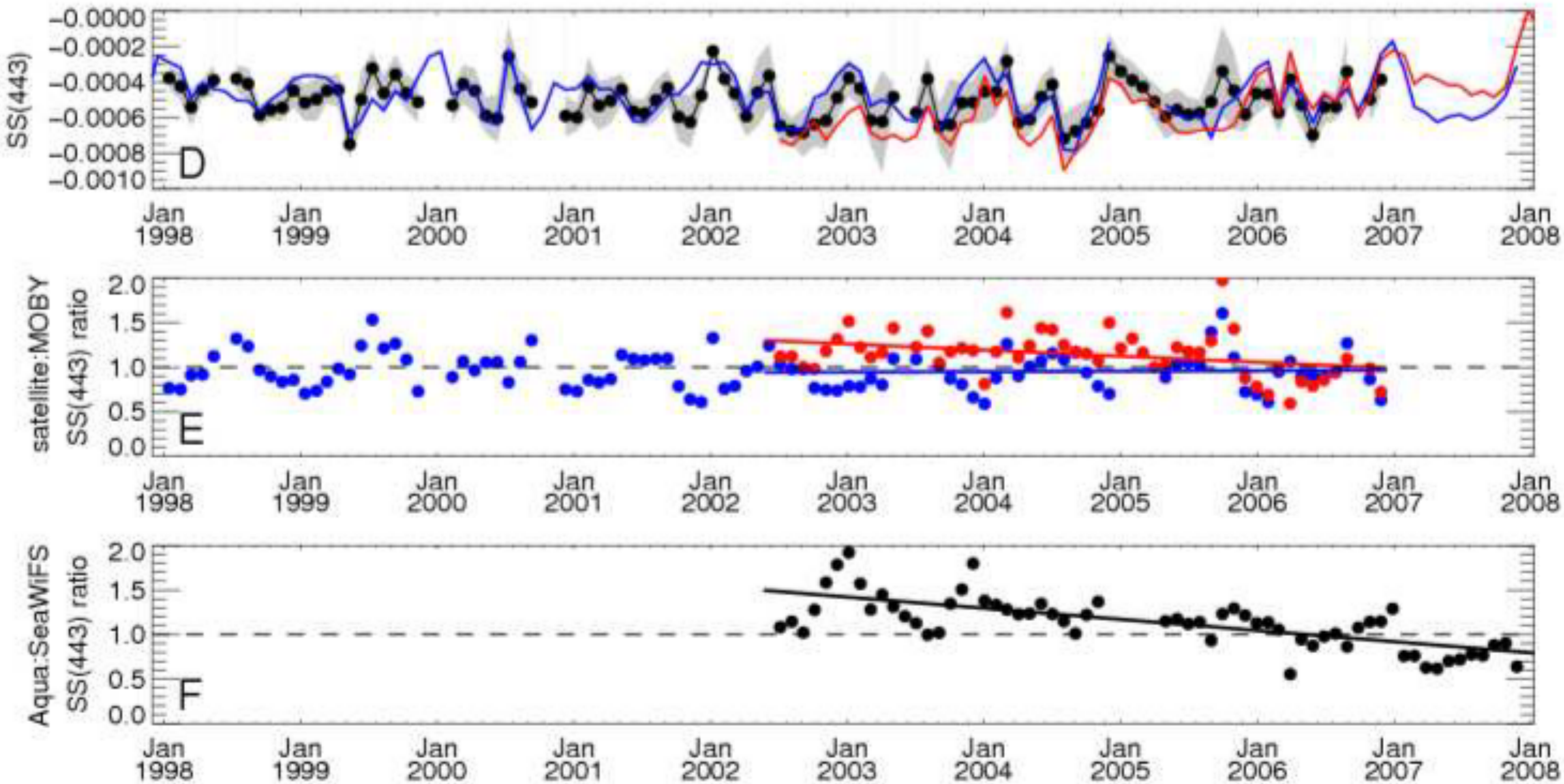


spectral shape @ 443 nm, SS(443), uses $R_{rs}(412)$, $R_{rs}(443)$, & $R_{rs}(490)$

Stumpf & Werdell 2010

population statistics for vicarious calibration

in situ, SeaWiFS, & MODIS-Aqua spectral shapes compared at MOBY site

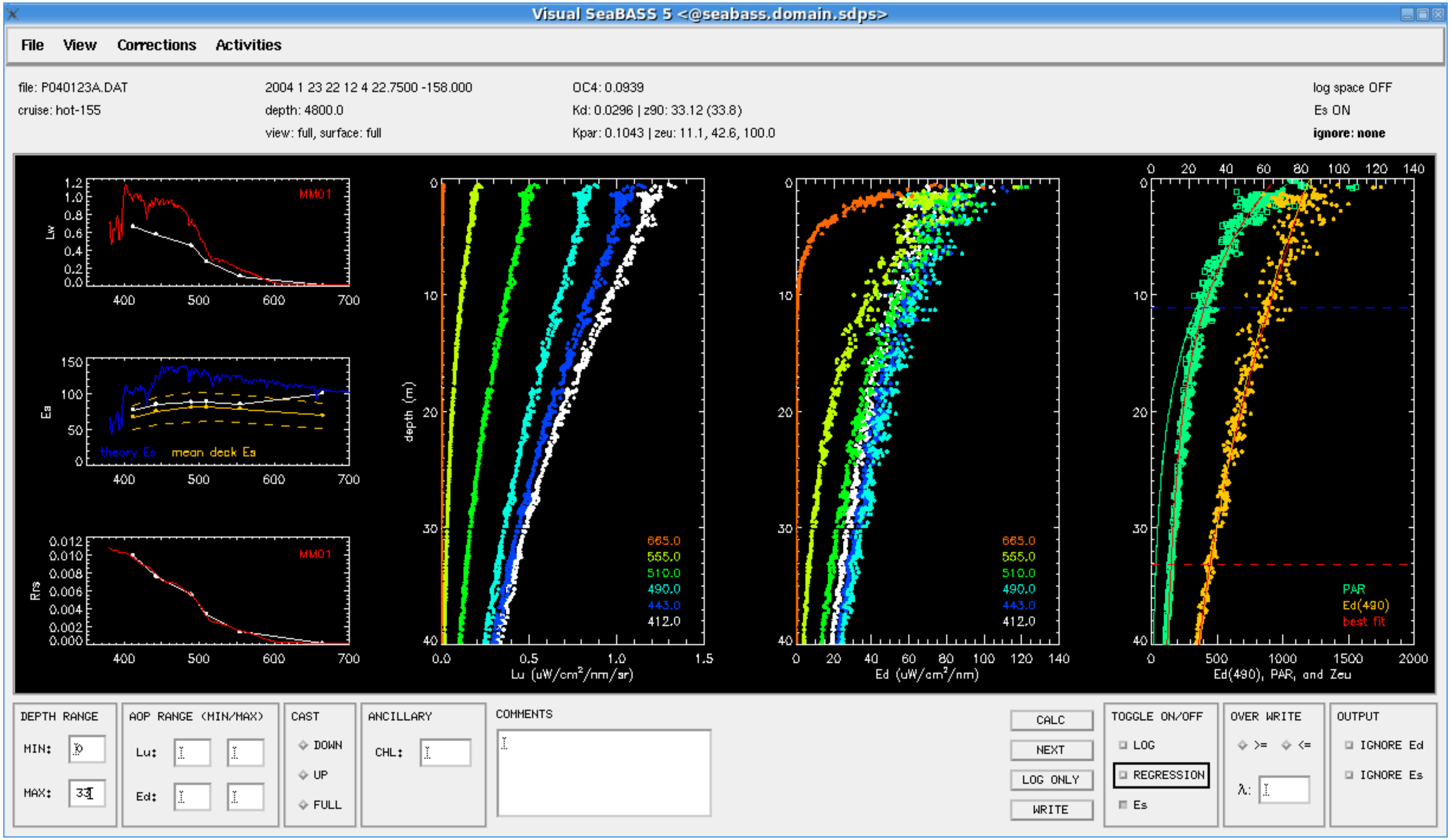


Stumpf & Werdell 2010

jeremy.werdell@nasa.gov

AOP data analysis

$L_u(z)$, $E_d(z)$ -> L_w, E_s



jeremy.werdell@nasa.gov

inversion models

several flavors of a “semi-analytical” inversion algorithm …

$$R_{rs} \approx func\left(\frac{b_b}{a+b_b}\right)$$

satellite provides $R_{rs}(\lambda)$

$a(\lambda)$ and $b_b(\lambda)$ are desired products

1

Spectral Optimization:

- define shape functions for (e.g.) $b_{bp}(\lambda)$, $a_{dg}(\lambda)$, $a_{ph}(\lambda)$
- solution via L-M, matrix inversion, etc.
- ex: RP95, HL96, GSM

2

Spectral Deconvolution:

- partially define shape functions for $b_{bp}(\lambda)$, $a_{dg}(\lambda)$
- piece-wise solution: $b_{bp}(\lambda)$, then $a(\lambda)$, then $a_{dg}(\lambda) + a_{ph}(\lambda)$
- ex: QAA, PML, NIWA

3

Bulk Inversion:

- no predefined shapes
- piece-wise solution: $b_{bp}(\lambda)$, then $a(\lambda)$, via empirical $K_d(\lambda)$ via RTE
- ex: LS00