Marine inherent optical properties (IOPs) from MODIS Aqua & Terra

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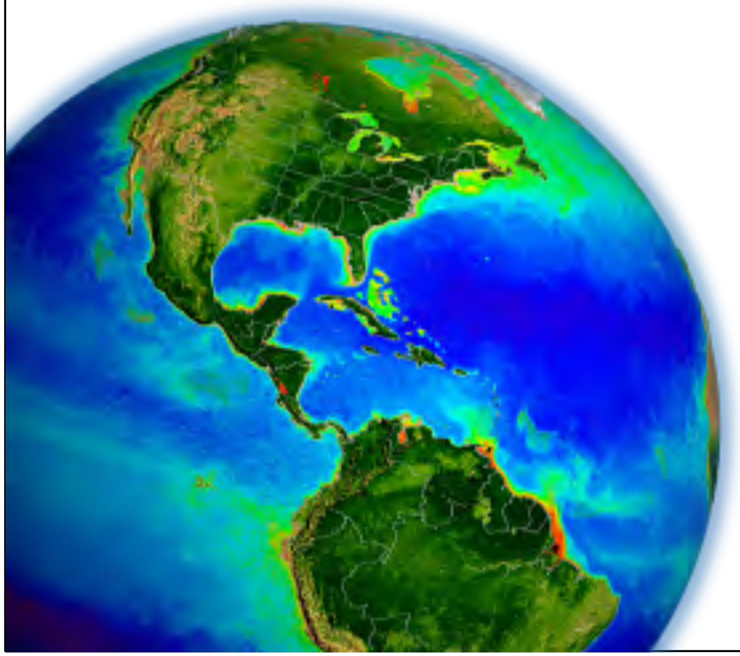
MODIS Science Team Meeting
Columbia, Maryland
30 Apr 2014



what are marine inherent optical properties (IOPs)?

spectral absorption & scattering coefficients

what can marine IOPs tell me?

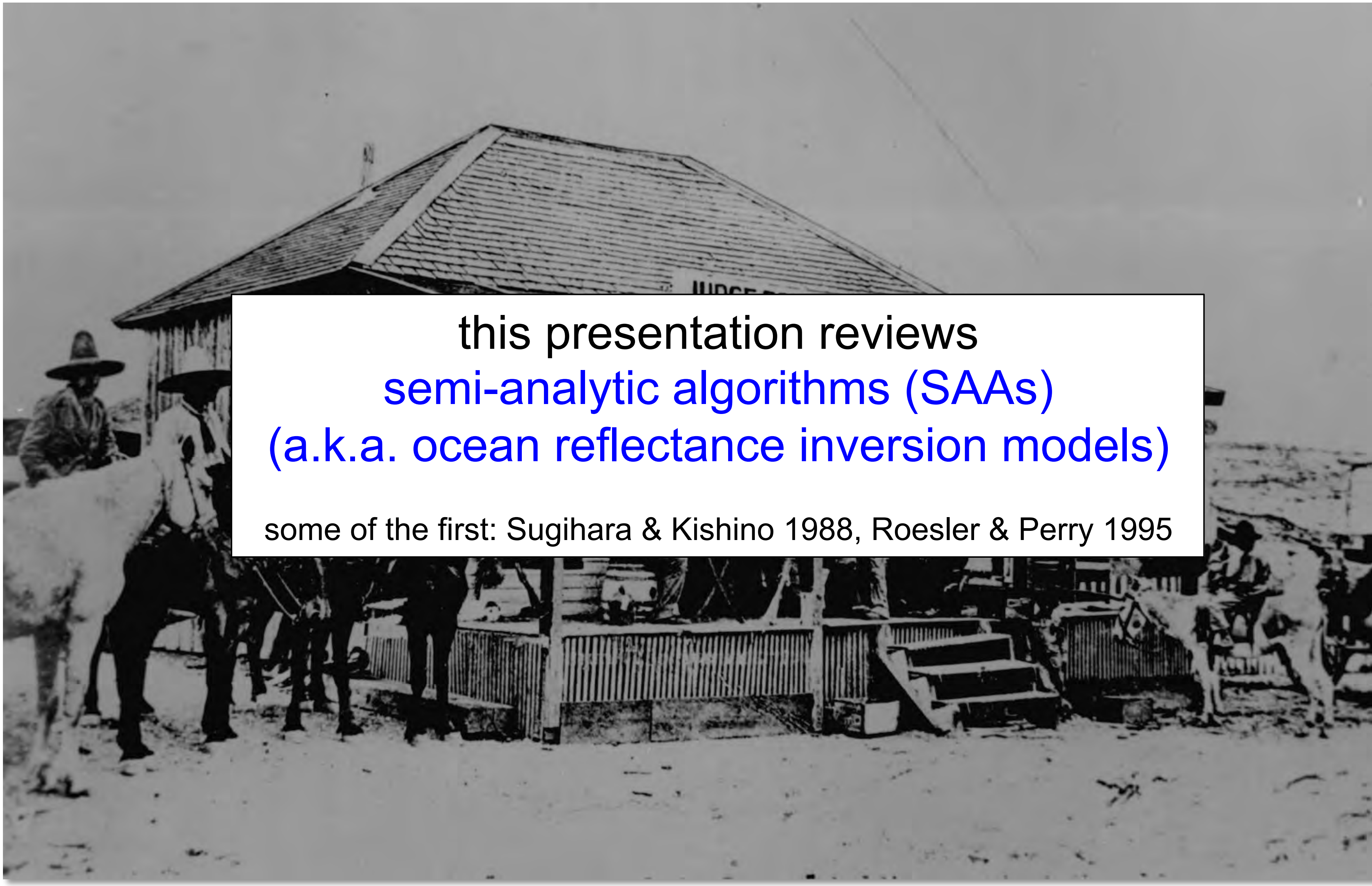
they describe the contents of the upper ocean

- phytoplankton abundance & community structure
- non-algal suspended particles
- particulate & dissolved carbon
- diffuse attenuation / water clarity

why study marine IOPs from space?

satellite time-series provide “big picture” views to better understand responses to climate change & for inclusion in bio-hydrographic models

a variety of ocean color approaches exist …



this presentation reviews
semi-analytic algorithms (SAAs)
(a.k.a. ocean reflectance inversion models)

some of the first: Sugihara & Kishino 1988, Roesler & Perry 1995

presentation outline

Part 1: brief review of the theoretical basis

Part 2: state of the art

Part 3: future plans

relating ocean color & in-water optical properties

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

measured by satellite

apparent optical properties (AOPs)

desired products

inherent optical properties (IOPs)

← forward model

inverse model →

photon entering a medium has two fates: absorbed (a) or scattered (b)

radiative transfer equations provide exact solutions (simplifications exist)

relating ocean color & in-water optical properties

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

phytoplankton

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

dissolved + non-phytoplankton particles

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

particles

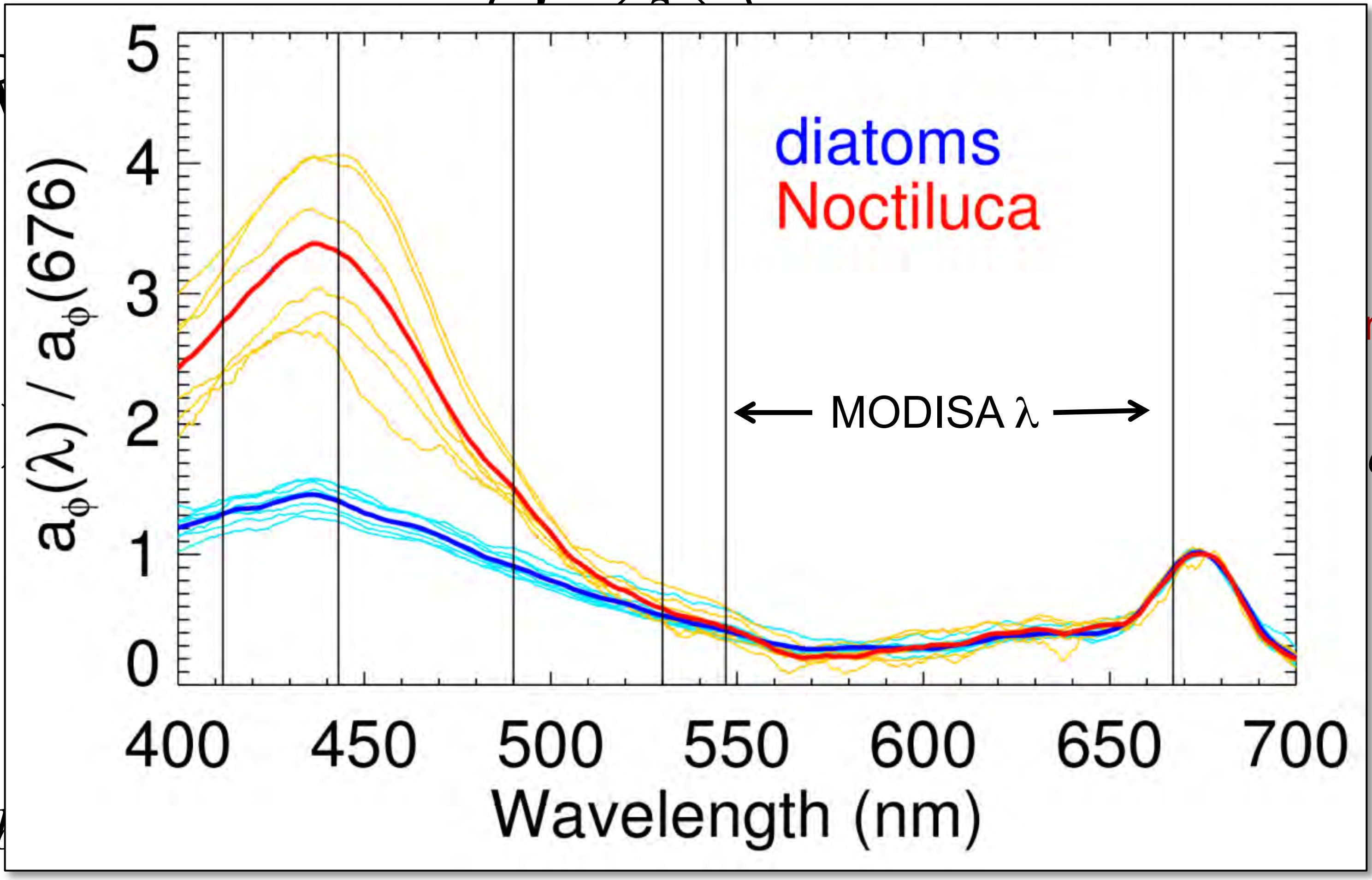
relating ocean color & in-water optical properties

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

$$a(\lambda) = a_w(\lambda) + \underbrace{M_{dg}}_{\text{eigenvalue (magnitude)}}\underbrace{a^*_{dg}(\lambda)}_{\text{eigenvector (shape)}} + M_\phi a^*_\phi(\lambda)$$

$$b_b(\lambda) = b_{bw}(\lambda) + M_{bp} b^*_{bp}(\lambda)$$

relating ocean color & in-water optical properties



miliaris

relating ocean color & in-water optical properties

$$R_{rs} = G\left(\frac{b_{bw} + M_{bp} b^{*}_{bp}}{a_w + M_{dg} a^{*}_{dg} + M_{\phi} a^{*}_{\phi}}\right)$$

$N = 6$ knowns (the 6 visible MODISA $R_{rs}(\lambda_N)$)

User defined: $G(\lambda_N)$, $a^{*}_{dg}(\lambda_N)$, $a^{*}_{\phi}(\lambda_N)$, $b^{*}_{bp}(\lambda_N)$

3 (< N) unknowns: M_{dg}, M_{ϕ}, M_{bp}

solve for M using spectral optimization/unmixing/deconvolution

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relating ocean color & in-water optical properties

SAAs developed routinely over 30 yrs
many successfully retrieve **three** components
many overlapping approaches exist

power-law, η:
- fixed
- Lee et al. (2002)
- Ciotti et al. (1999)
- Hoge & Lyon (1996)
- Loisel & Stramski (2001)
- Morel (2001)

$$R_{rs} = G\left(\frac{b_{bw} + M_{bp} b^{*}_{bp}}{a_w + M_{dg} a^{*}_{dg} + M_{\phi} a^{*}_{\phi}}\right)$$

Levenberg-Marquardt
SVD matrix inversion

Morel f/Q
Gordon quadratic

exponential, S_{dg}:
- fixed (= 0.018)
- Lee et al. (2002)
- Werdell (2010)

tabulated $a^{*}_{dg}(\lambda)$

tabulated $a^{*}_{\phi}(\lambda)$
Bricaud et al. (1998)
Ciotti & Bricaud (2006)

state of the art

Reports of the International
Ocean-Colour Coordinating Group

An Affiliated Program of the Scientific Committee on Oceanic Research (SCOR)
An Associate Member of the Committee on Earth Observation Satellites (CEOS)

IOCCG Report Number 5, 2006

Remote Sensing of Inherent Optical Properties: Fundamentals, Tests of Algorithms, and Applications

Editor:
ZhongPing Lee (Naval Research Laboratory, Stennis Space Center, USA)

Report of an IOCCG working group on ocean-colour algorithms, chaired by ZhongPing Lee and based on contributions from (in alphabetical order):

Robert Arnone, Marcel Babin, Andrew H. Barnard, Emmanuel Boss, Jennifer P. Cannizzaro, Kendall L. Carder, F. Robert Chen, Emmanuel Devred, Roland Doerffer, KePing Du, Frank Hoge, Oleg V. Kopelevich, ZhongPing Lee, Hubert Loisel, Paul E. Lyon, Stéphane Maritorena, Trevor Platt, Antoine Poteau, Collin Roesler, Shubha Sathyendranath, Helmut Schiller, Dave Siegel, Akihiko Tanaka, J. Ronald V. Zaneveld

first comprehensive survey & evaluation of SAA approaches

ARTICLE IN PRESS

RSE-08816; No of Pages 24

Remote Sensing of Environment xxx (2013) xxx–xxx

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

The Ocean Colour Climate Change Initiative: III. A round-robin comparison on in-water bio-optical algorithms

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ARTICLE INFO

Article history:
Received 9 November 2012
Received in revised form 8 August 2013
Accepted 15 September 2013
Available online xxxx

Keywords:
Phytoplankton
Ocean colour
Inherent Optical Properties
Remote sensing
Chlorophyll-a

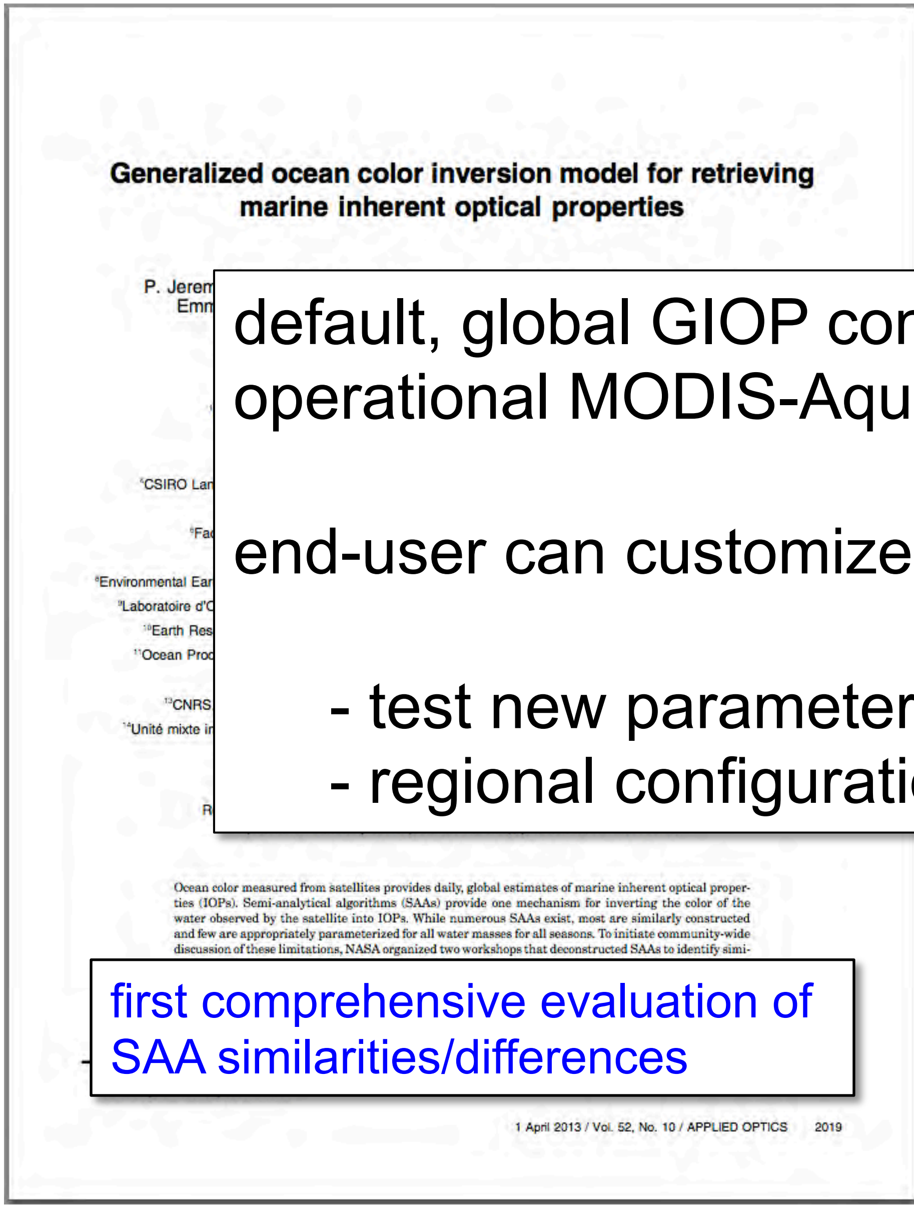
ABSTRACT

Satellite-derived remote-sensing reflectance can be used for mapping biogeochemically relevant variables, such as the chlorophyll concentration and the Inherent Optical Properties (IOPs) of the water, at global scales for use in climate-change studies. Prior to generating such products, suitable algorithms have to be selected that are appropriate for the purpose. Algorithm selection needs to account for both qualitative and quantitative requirements. In this paper we develop an objective methodology designed to rank the quantitative performance of a suite of bio-optical models. The objective classification is applied using the NASA bio-Optical Marine Algorithm Dataset (NOMAD). Using in situ R_{rs} as input to the models, the performance of eleven semi-analytical models, as well as five empirical chlorophyll algorithms and an empirical diffuse attenuation coefficient algorithm, is ranked for spectrally-resolved IOPs, chlorophyll concentration and the diffuse attenuation coefficient at 489 nm. The sensitivity of the objective classification and the uncertainty in the ranking are tested using a Monte-Carlo approach (bootstrapping). Results indicate that the performance of the semi-analytical models varies depending on the product and wavelength of interest. For chlorophyll retrieval, empirical algorithms perform better than semi-analytical models, in general. The performance of these empirical models reflects either their immunity to scale errors or instrument noise in R_{rs} data, or simply that the data used for model parameterisation were not independent of NOMAD. Nonetheless, uncertainty in the classification suggests that the performance of some semi-analytical algorithms at retrieving chlorophyll is comparable with the empirical algorithms. For phytoplankton absorption at 443 nm, some semi-analytical models also perform with similar accuracy to an empirical model. We discuss the potential biases, limitations and uncertainty in the approach, as well as additional qualitative considerations for algorithm selection for climate-change studies. Our classification has the potential to be routinely implemented, such that the performance of emerging algorithms can be compared with existing algorithms as they become available. In the long-term, such an approach will further aid algorithm development for ocean-colour studies.

modern survey & evaluation of SAA (& other) approaches

Please cite this article as: Brewin, R.J.W., et al., The Ocean Colour Climate Change Initiative: III. A round-robin comparison on in-water bio-optical algorithms, Remote Sensing of Environment (2013), http://dx.doi.org/10.1016/j.rse.2013.09.016

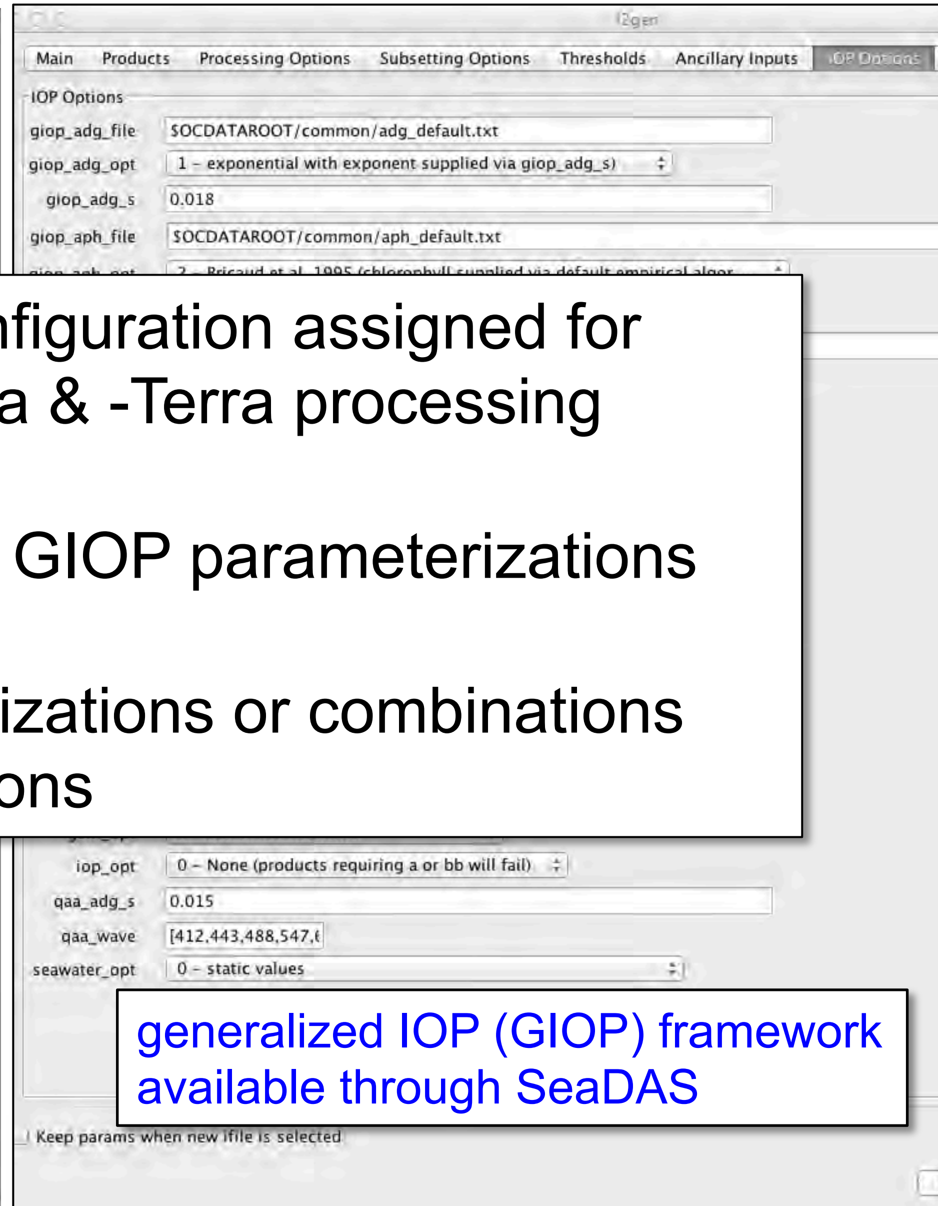
state of the art



Generalized ocean color inversion model for retrieving marine inherent optical properties

Ocean color measured from satellites provides daily, global estimates of marine inherent optical properties (IOPs). Semi-analytical algorithms (SAAs) provide one mechanism for inverting the color of the water observed by the satellite into IOPs. While numerous SAAs exist, most are similarly constructed and few are appropriately parameterized for all water masses for all seasons. To initiate community-wide discussion of these limitations, NASA organized two workshops that deconstructed SAAs to identify simi-

1 April 2013 / Vol. 52, No. 10 / APPLIED OPTICS 2019



default, global GIOP configuration assigned for operational MODIS-Aqua & -Terra processing

end-user can customize GIOP parameterizations

- test new parameterizations or combinations
- regional configurations

first comprehensive evaluation of SAA similarities/differences

generalized IOP (GIOP) framework available through SeaDAS

presentation outline

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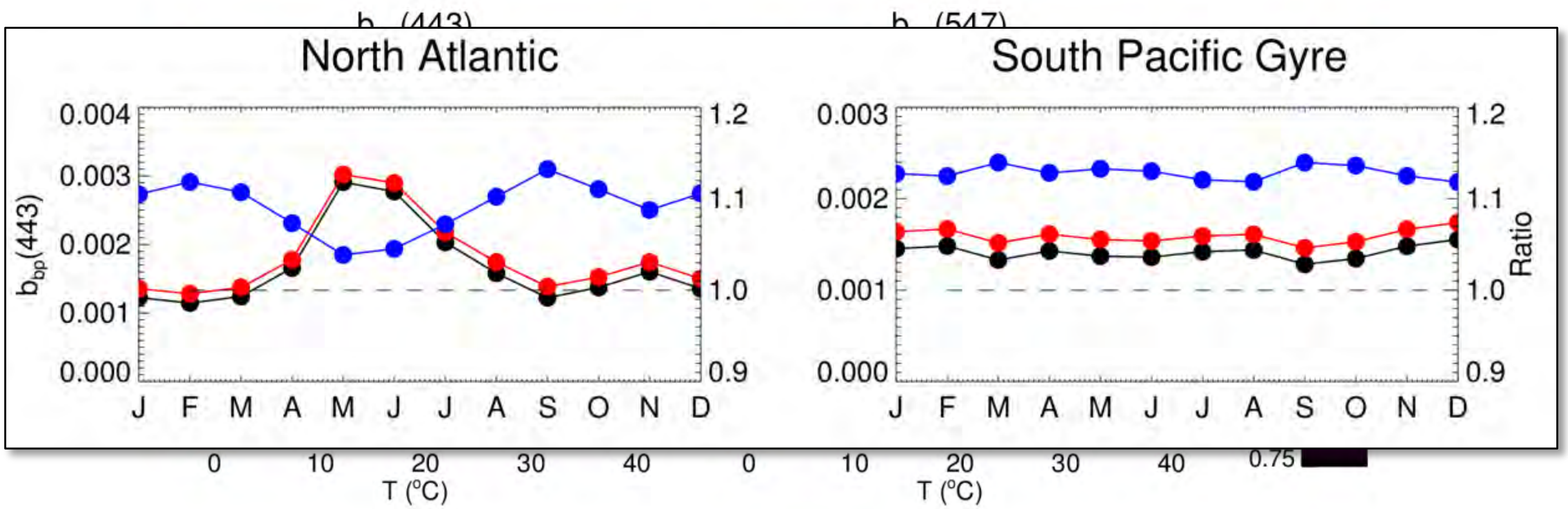
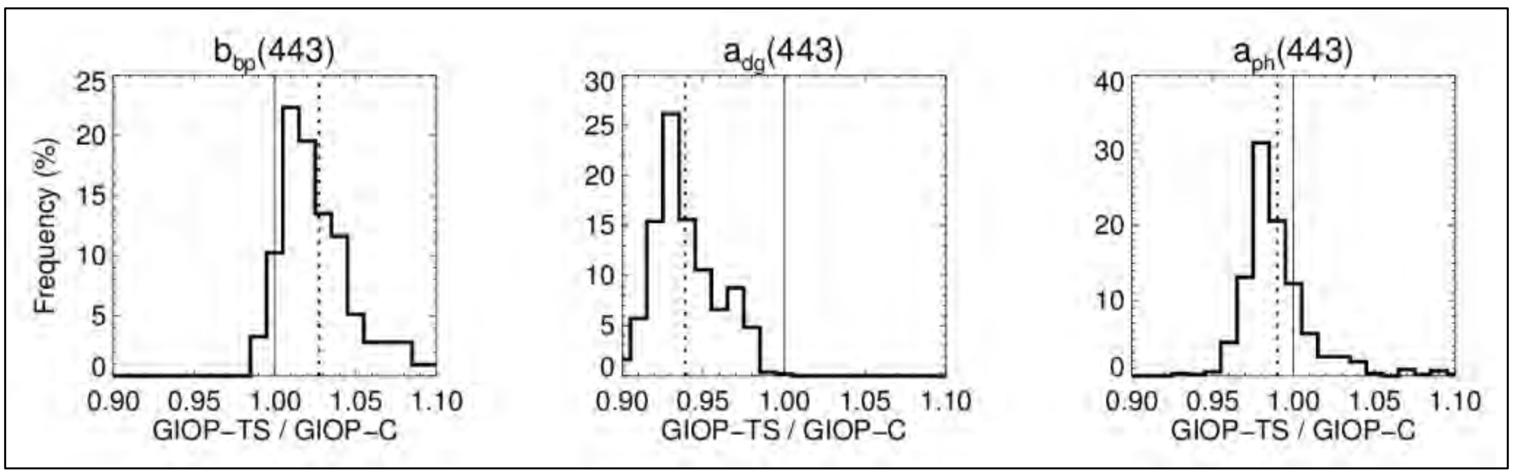
future plans - general

temperature & salinity dependence of pure seawater





future plans - general

temperature & salinity dependence of pure seawater

inelastic scattering
Raman effects (Westberry et al. 2013)
phytoplankton fluorescence ???

reduction of spectral shape assumptions
one size rarely fits all
optical water types (Moore et al. 2009)
ensemble methods (Wang et al. 2005, Brando et al. 2012)

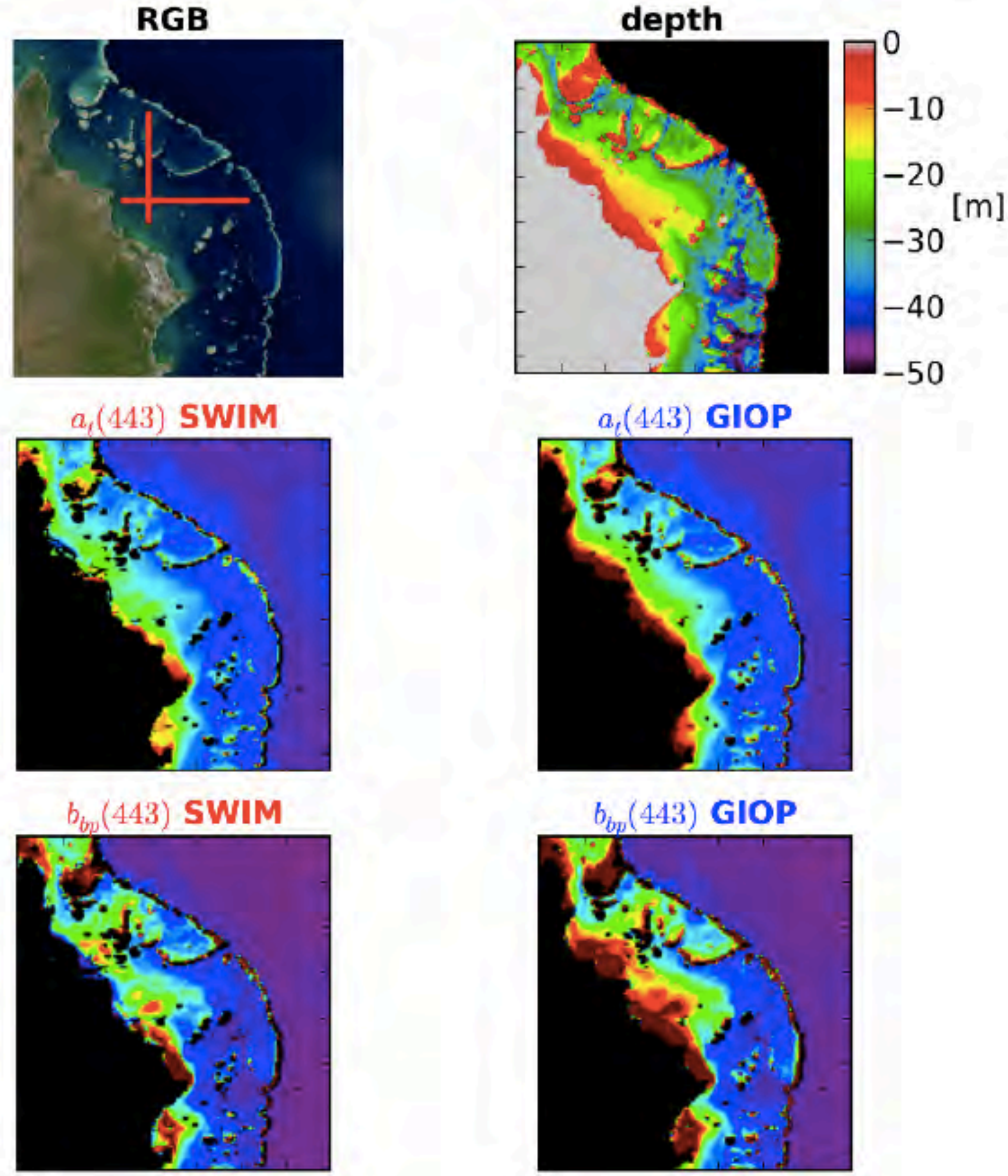
inversion approaches
statistical cost functions, uncertainties
the relationship between AOPs and IOPs (spectral G)
expanded wavelength suites

future plans - shallow water

optically shallow water
where sunlight reflected off the seafloor is seen by the satellite

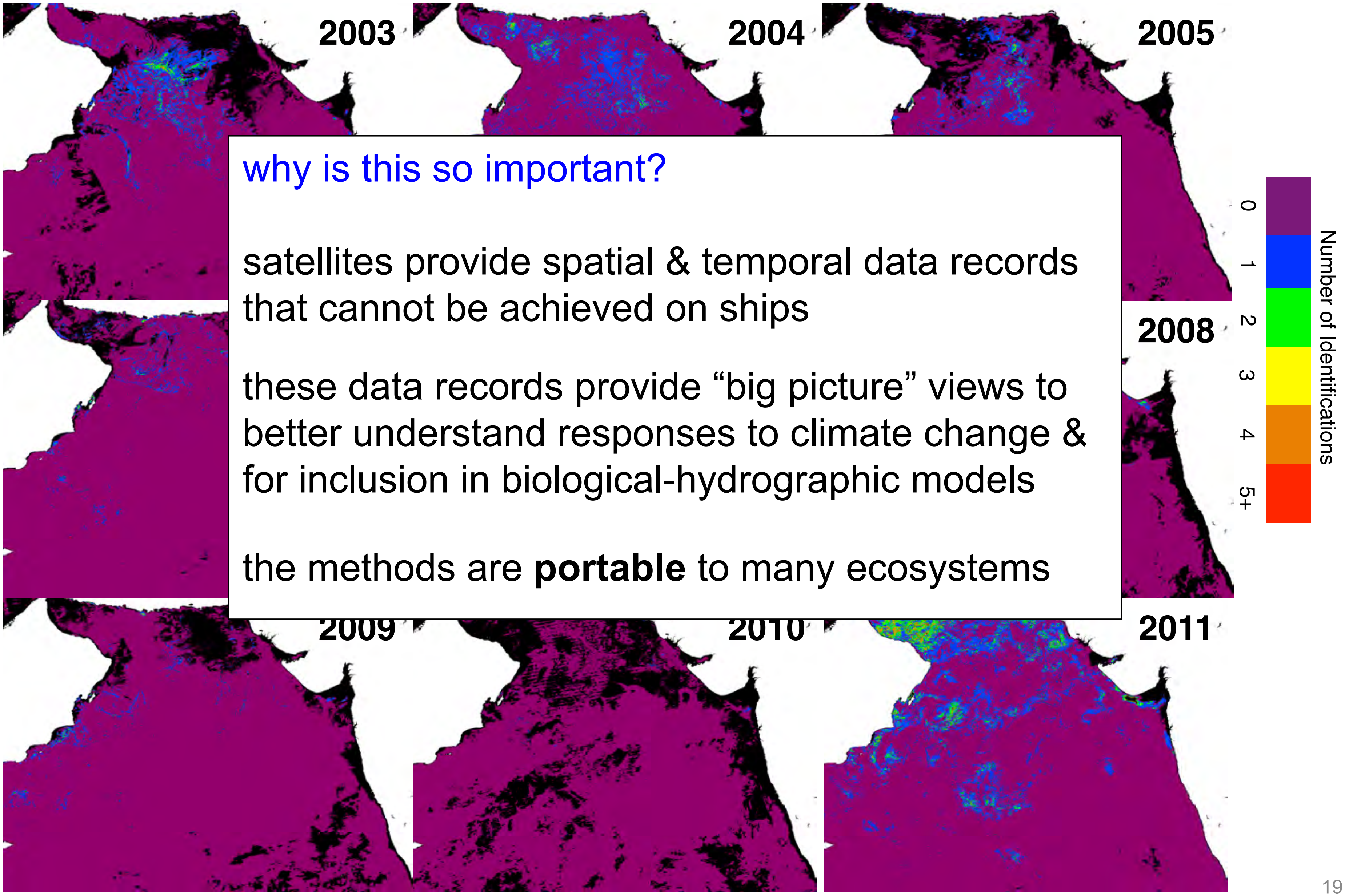
SWIM model
GIOP-like SAA extended to account for shallow water reflectances

Great Barrier Reef
McKinna et al. (2014)



again … why study marine IOPs from space?

Noctiluca identified during the NEM using MODISA



why is this so important?

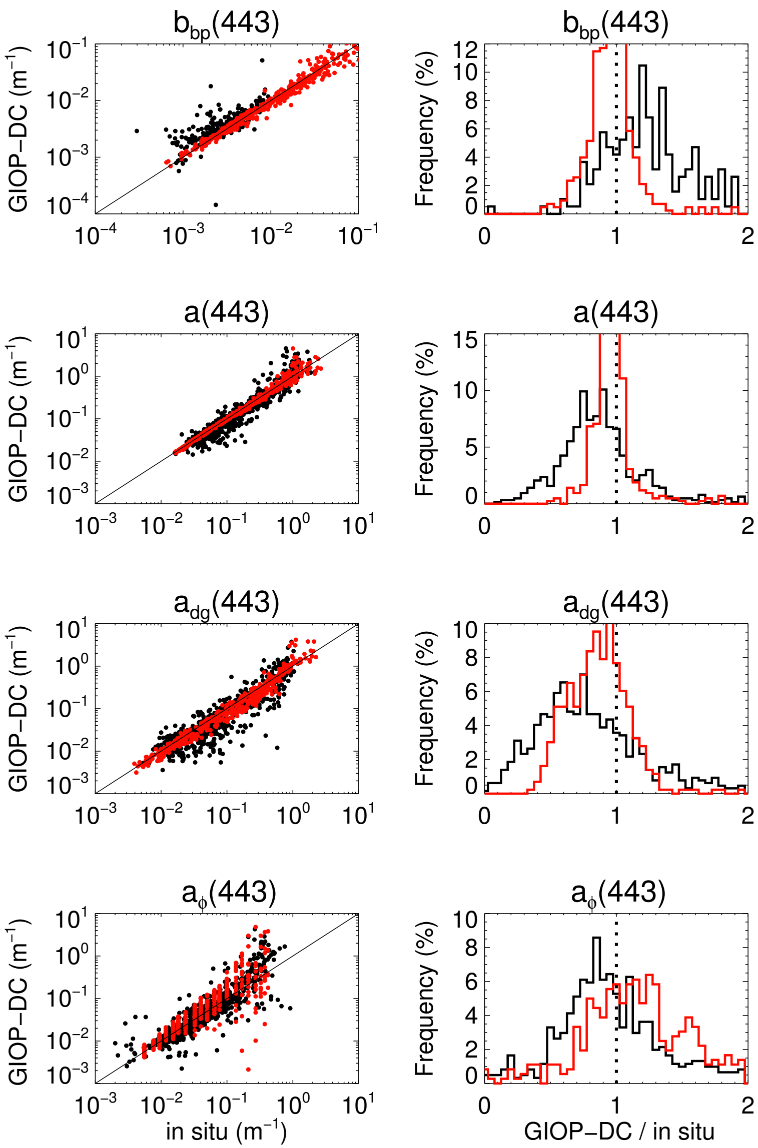
satellites provide spatial & temporal data records that cannot be achieved on ships

these data records provide “big picture” views to better understand responses to climate change & for inclusion in biological-hydrographic models

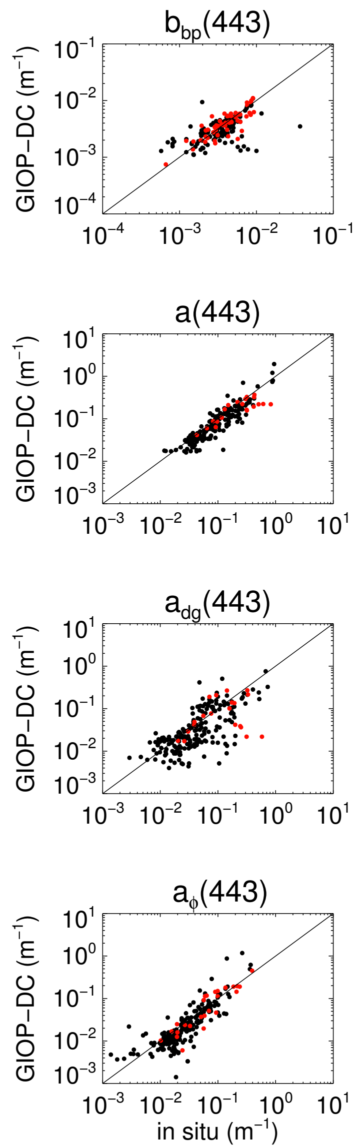
the methods are **portable** to many ecosystems thanks

a generalized IOP (GIOP) inversion model

in situ (NOMAD) & synthesized (IOCCG) data



SeaWiFS & MODISA data



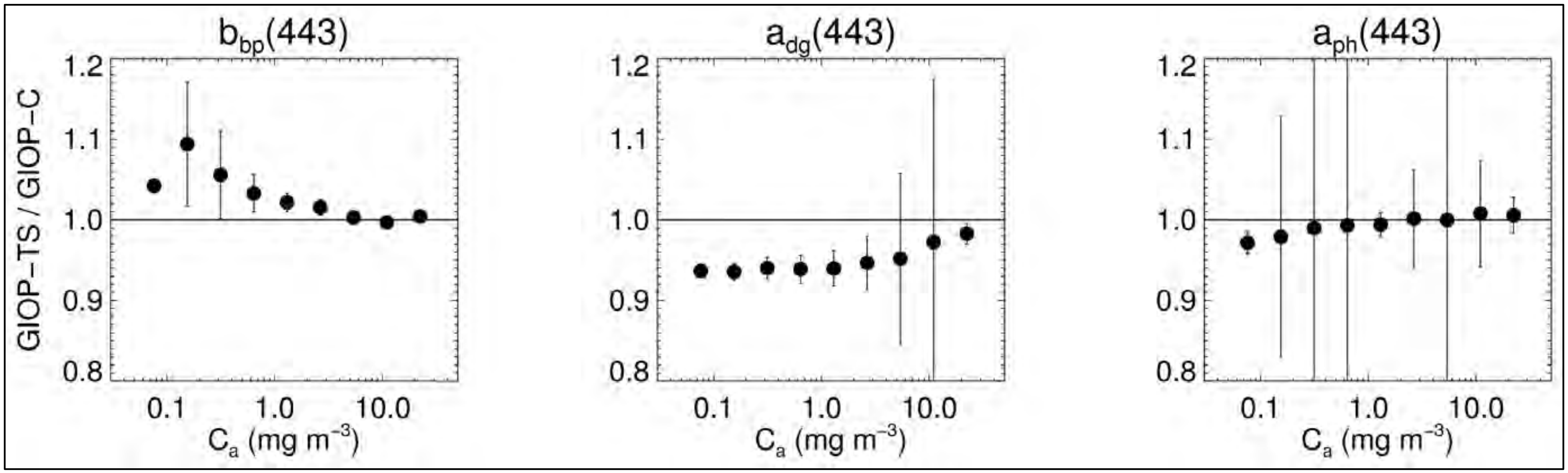
a generalized IOP (GIOP) inversion model

Table 1. Summary of Eigenvectors Available for Use in GIOP (as of March 2011)[a]

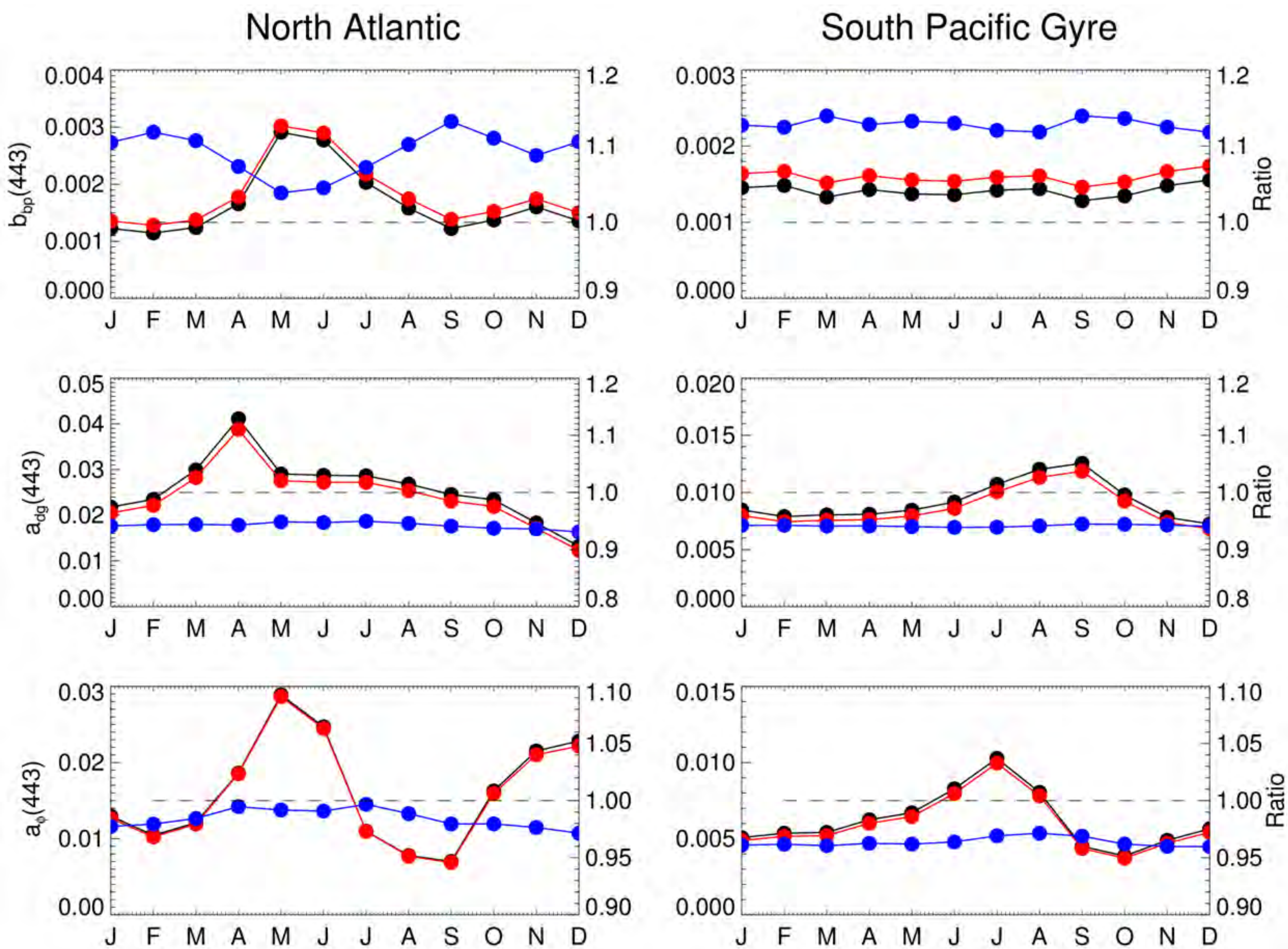
Eigenvector	Description	Reference
$a^*_\phi(\lambda)$	User-provided $a^*_\phi(\lambda)$	
	Maritorena *et al.* (2002) tabulated $a^*_\phi(\lambda)$	[8]
	Bricaud *et al.* (1998)-derived $a^*_\phi(\lambda)$ using OC-derived C_a	[14]
	Ciotti and Bricaud (2006)-derived $a^*_\phi(\lambda)$ using user-provided size fraction	[17]
$a^*_{dg}(\lambda)$	**Eq. (5) with user-provided S_{dg}**	
	Eq. (5) with Lee *et al.* (2002)-derived S_{dg}	[7]
	Eq. (5) with Franz and Werdell (2010)-derived S_{dg}	[13]
	User-provided $a^*_{dg}(\lambda)$	
$b^*_{bp}(\lambda)$	Eq. (8) with user-provided S_{bp}	
	Eq. (8) with Hoge and Lyon (1996)-derived S_{bp}	[4]
	Eq. (8) with Lee *et al.* (2002)-derived S_{bp}	[7]
	Eq. (8) with Ciotti *et al.* (1999)-derived S_{bp}	[15]
	Eq. (8) with Morel and Maritorena (2001)-derived S_{bp}	[22]
	Eq. (8) with Loisel and Stramski (2000)-derived S_{bp}	[6]
	User-provided $b^*_{bp}(\lambda)$	
	Loisel and Stramski (2000)-derived $b^*_{bp}(\lambda)$	[6]
	Lee *et al.* (2002)-derived $b^*_{bp}(\lambda)$	[7]

[a]Boldface indicates the eigenvector used in GIOP-DC.

temperature & salinity dependence of $b_{bw}(\lambda)$



temperature & salinity dependence of $b_{bw}(\lambda)$



GIOP-C, GIOP-TS, ratio of GIOP-TS to GIOP-C

temperature & salinity dependence of $b_{bw}(\lambda)$