PACE simulated Data: R_{rs} simulation using Hydrolight

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The objective is to generate a synthetic hyperspectral IOPs, Rrs, and Kd data set from Hydrolight simulations

Runs will start in January/February

Spectral range from 300 to 800 nm with 5 nm resolution
(or 3 nm, but according to Cael et al. (2020) error more important than resolution, so…. 5 ok)

Good vertical resolution to be able to calculate Kd over the first attenuation depth (37% of Ed(0-))
All AOPs will be make available.

Include inelastic processes:

- Run without Raman
- Runs with Raman
- Runs with Raman+Chl fluo with a mean chlorophyll fluorescence quantum efficiency

Deep ocean (no bottom albedo), IOPs homogeneously distributed, wind speed of 5 $m.s^{-1}$

Representative of IOPs variability commonly encountered in the natural environment. The IOPs variability will be driven by $a_{phy}(440)$ (free variable) as a starting point similarly to Craig et al. (2020).

Approach for synthesizing water IOPs for COART:

$$b_b(\lambda) = b_{bw}(\lambda) + b_{b-ph}(\lambda) + b_{b-dm}(\lambda)$$

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

synthesized

constants

From measurements

and,

$$a_y(\lambda) = a_y(440)e^{-S_y(\lambda-440)};\quad a_y(440) = p_1 \times a_{ph}(440)$$

$$a_d(\lambda) = a_d(440)e^{-S_d(\lambda-440)};\quad a_d(440) = p_2 \times a_{ph}(440)$$

$$b_{b-ph}(\lambda) = 0.01 \times \left(c_{ph}(\lambda) - a_{ph}(\lambda)\right) \qquad c_{ph}(\lambda) = p_3 \times \left(\frac{440}{\lambda}\right)^{p_4}$$

$$b_{b-dm}(\lambda) = p_5 \times \left(\frac{440}{\lambda}\right)^{p_6}$$

Do these constraints conform with observations ?

From Craig et al., 2020

0.57

0.766

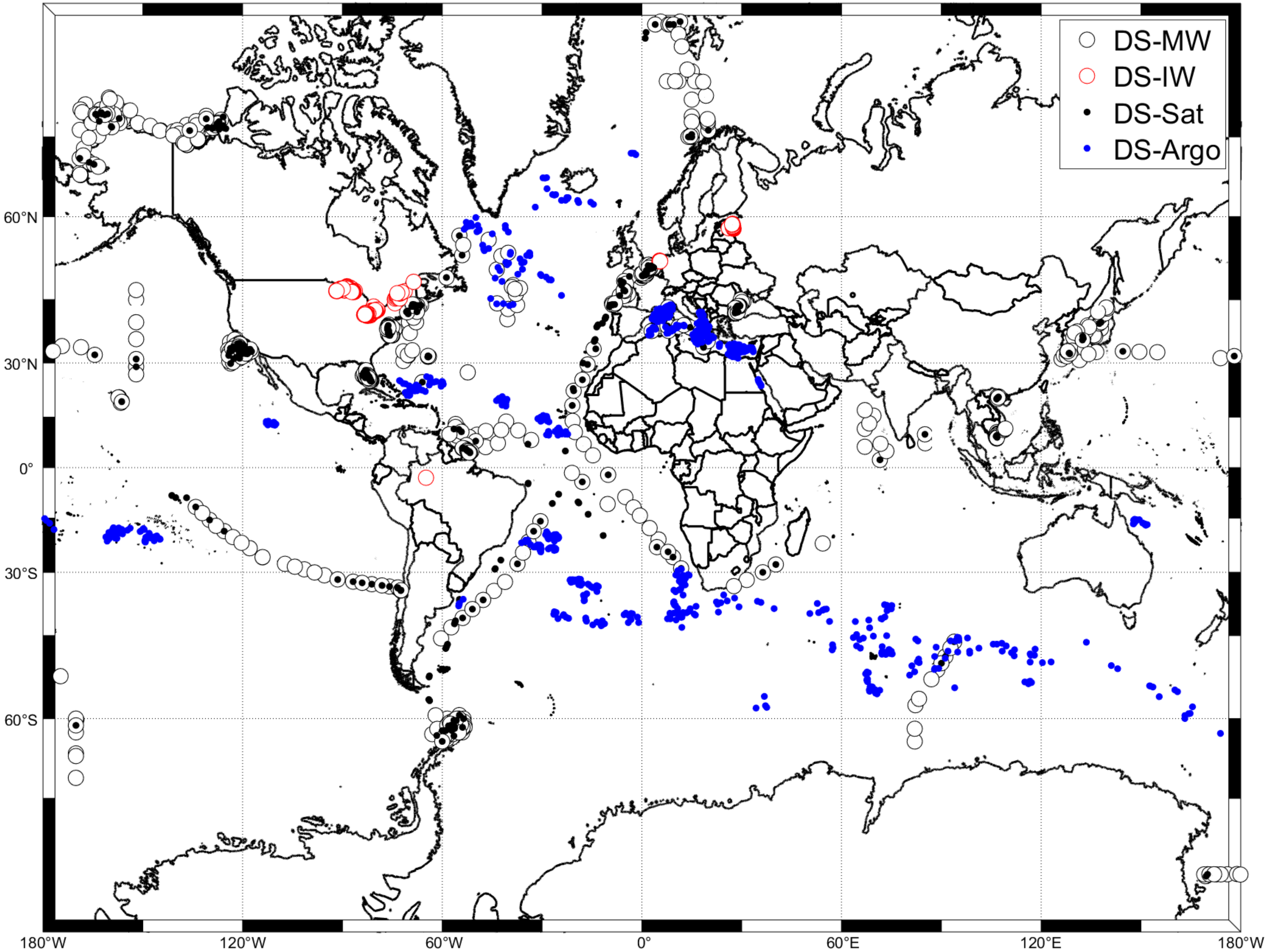
$$b_{b-ph}(\lambda) = 0.01 \times \left(c_{ph}(\lambda) - a_{ph}(\lambda)\right)$$

$$c_{ph}(\lambda) = p_3 \times \left(\frac{440}{\lambda}\right)^{p_4}$$

$$b_{b-dm}(\lambda) = p_5 \times \left(\frac{440}{\lambda}\right)^{p_6}$$

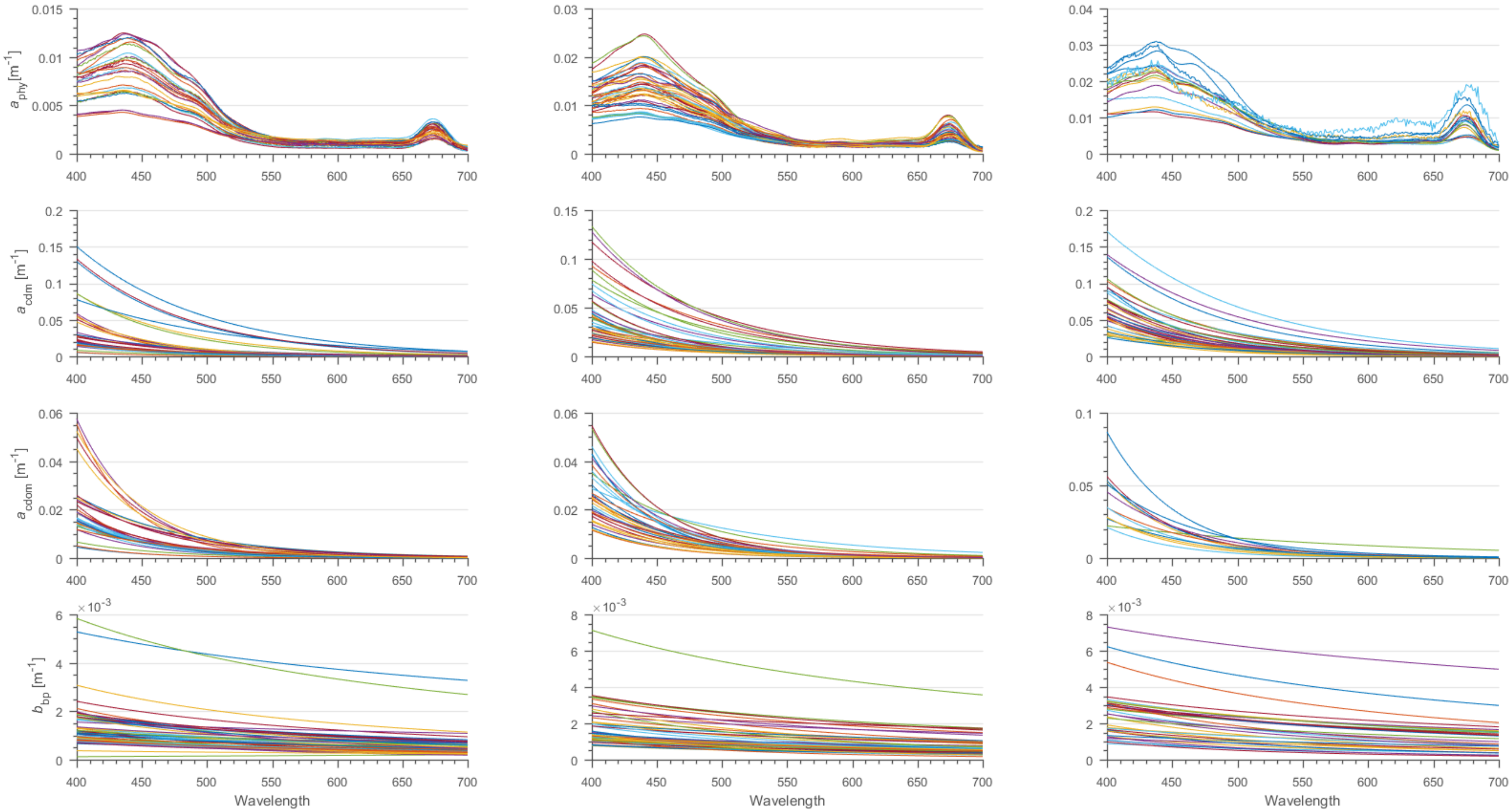
p5=(0.6-0.06).*
random(between 0 and 1)
+0.06;

p3=(0.6-0.06).*
random(between 0 and
1) +0.06;

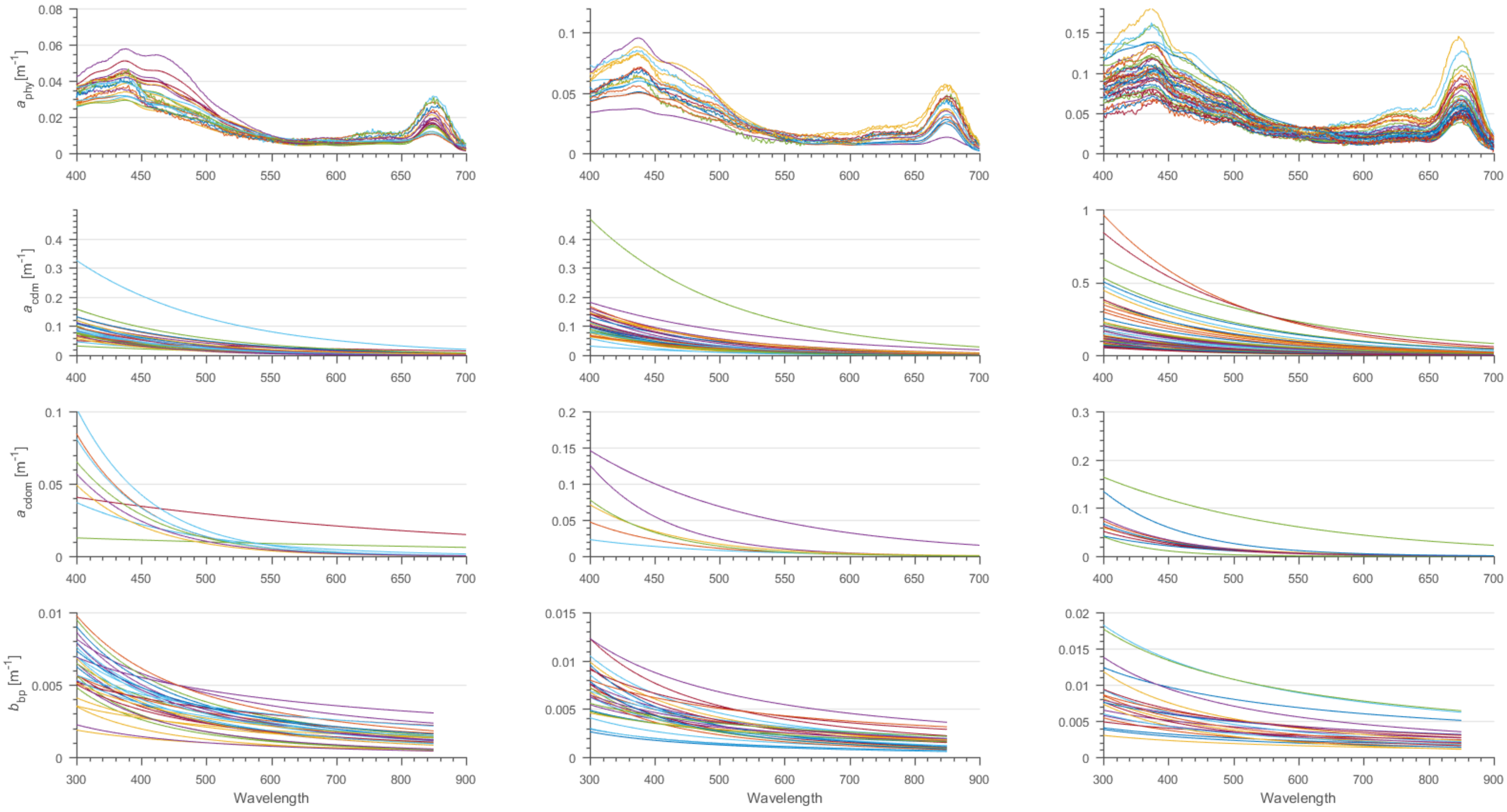


DS-MW
DS-IW
DS-Sat
DS-Argo
60°N
30°N
0°
30°S
60°S
180°W
120°W
60°W
0°
60°E
120°E
180°W

IOP in situ

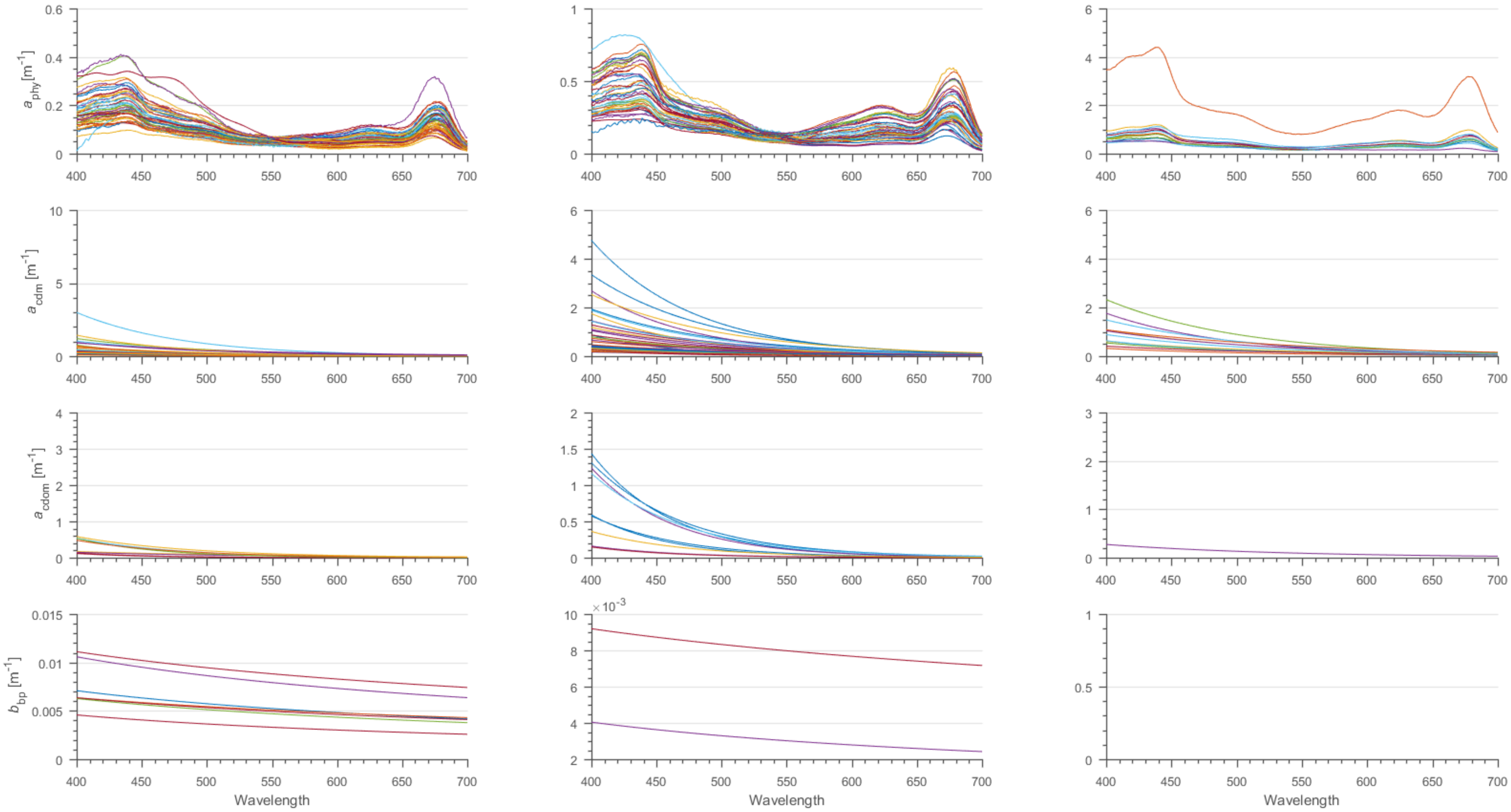


IOP in situ



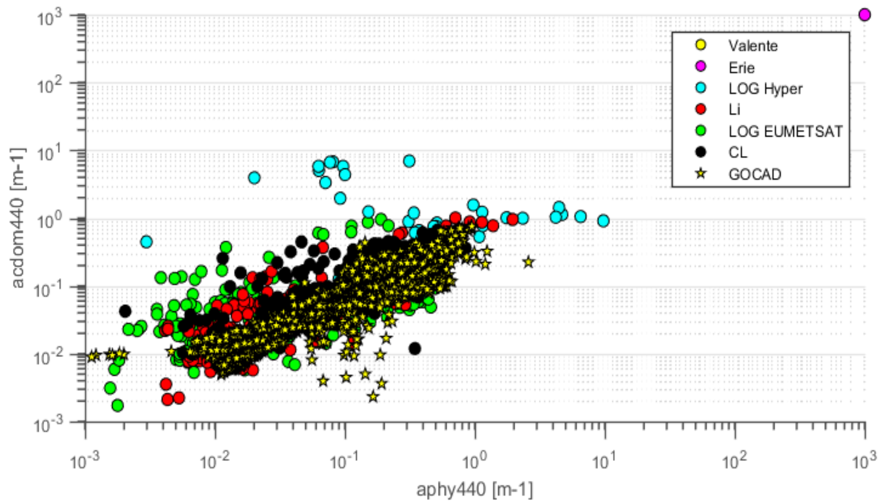
a_{phy} [m^{-1}]
a_{cdm} [m^{-1}]
a_{cdom} [m^{-1}]
b_{bp} [m^{-1}]
Wavelength
Wavelength
Wavelength

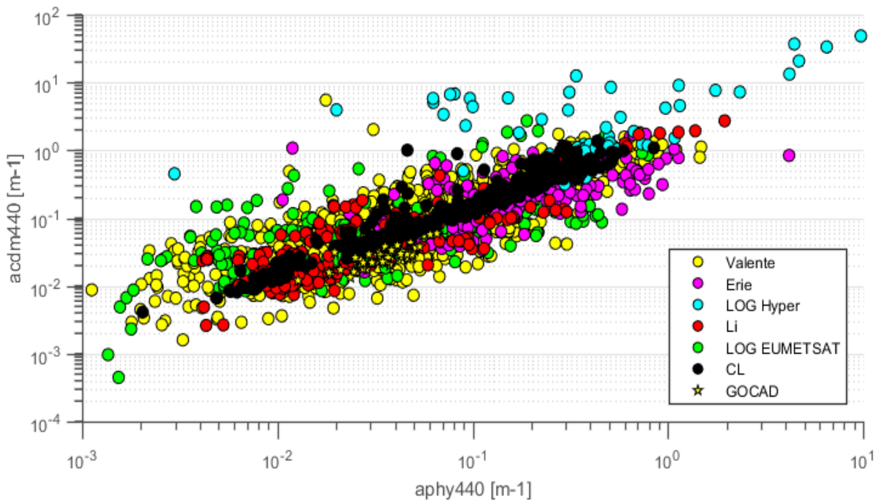
IOP in situ



a_{phy} [m^{-1}]
a_{cdm} [m^{-1}]
a_{cdom} [m^{-1}]
b_{bp} [m^{-1}]
$\times 10^{-3}$
Wavelength
Wavelength
Wavelength

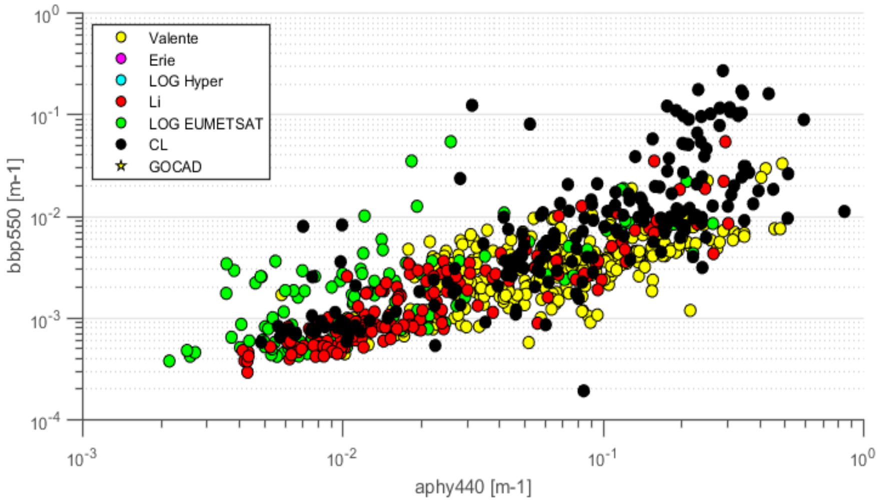
Representativity of the in situ data set



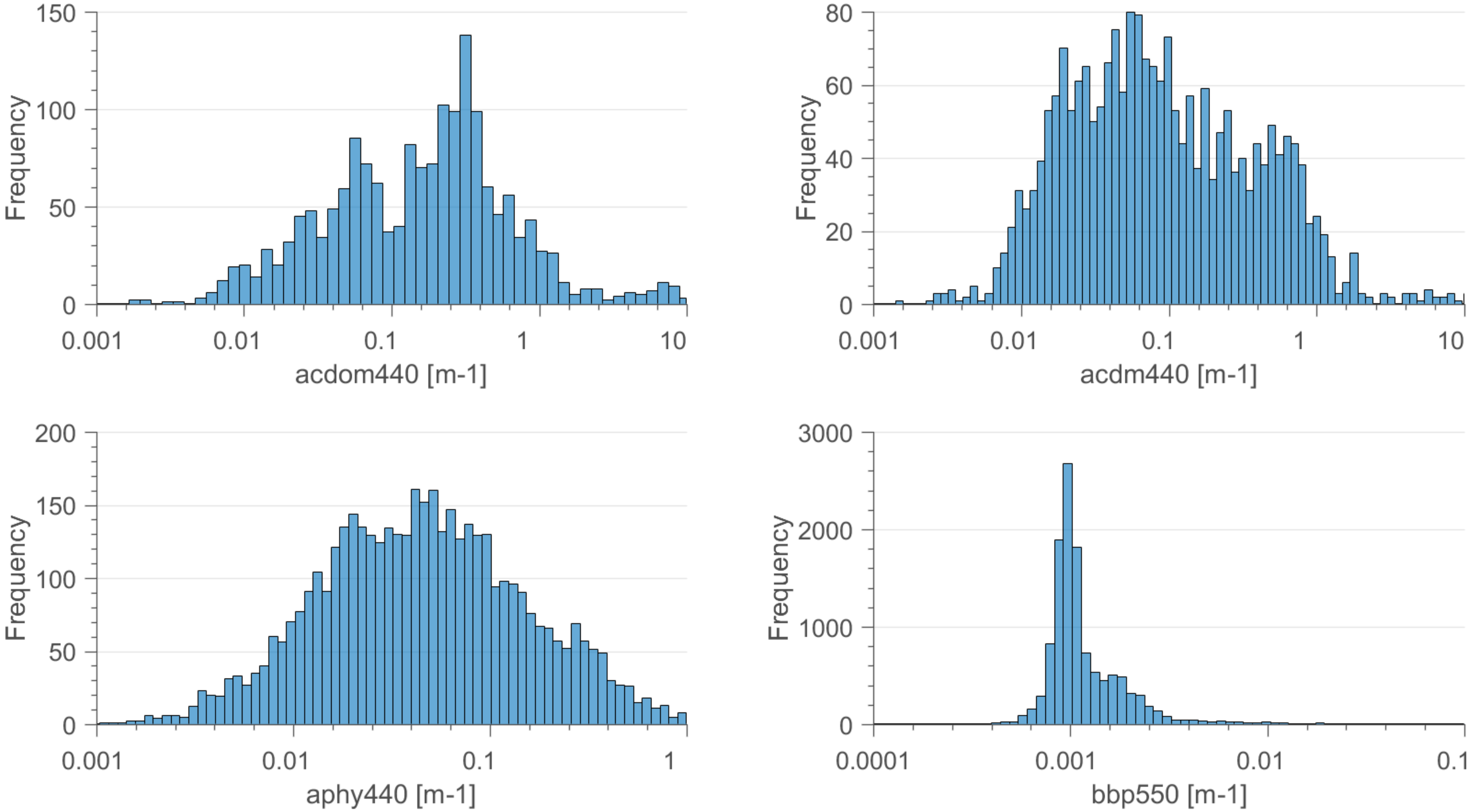


First condition: the generated IOPs will have, at least, to cover the scatter observed from the in situ data set, using the previous parameterizations.

Note that in situ data for which b_{bp}, a_{phy}, a_{NAP}, a_{cdom} are available will also be included.

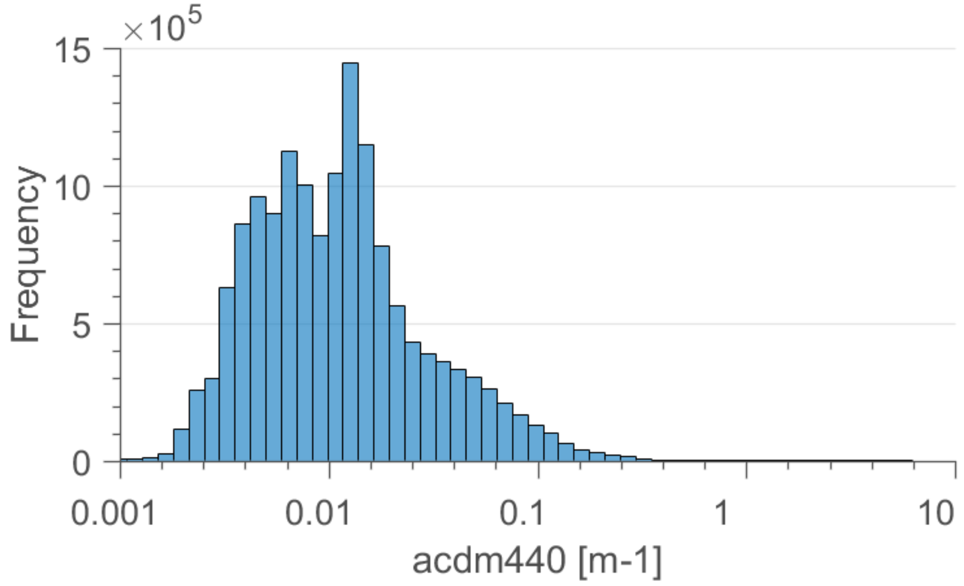


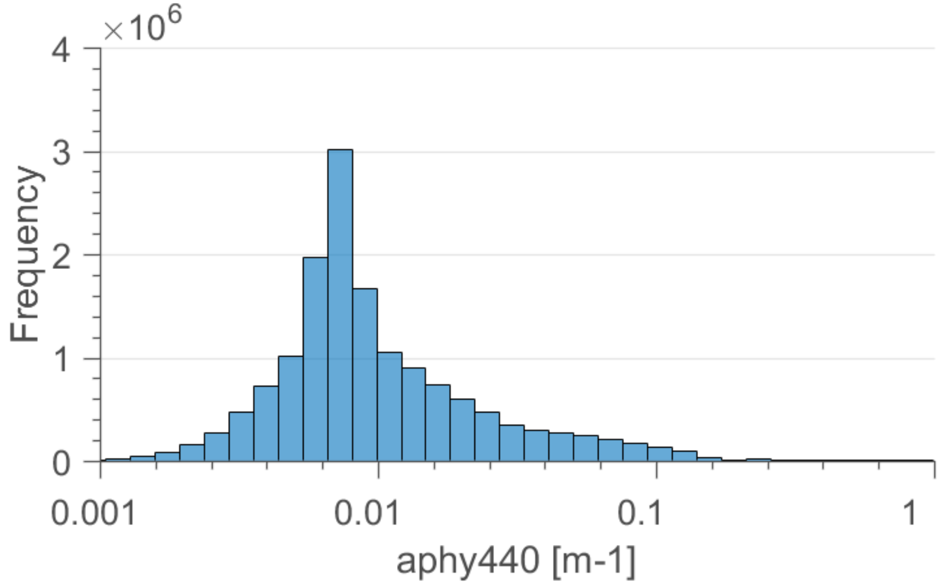
Distribution of in situ IOP

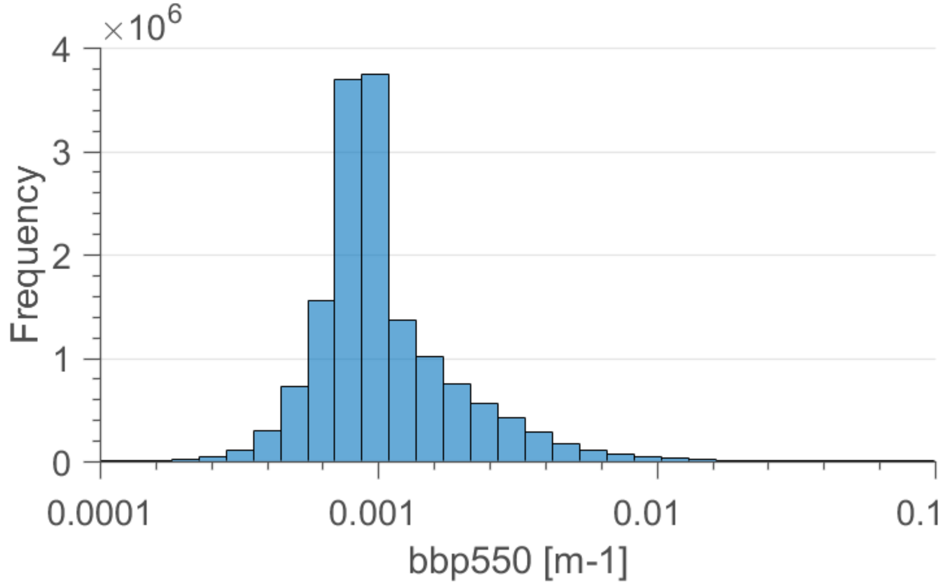


Distribution of IOP as estimated from OCR (2SAA)

Second condition: the distribution of the IOPs used for the simulations will have to cover, at least, the variability observed at global scale from satellite.







IOP in situ
vs
IOP sat