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TAKING THE PULSE OF OUR PLANET FROM SPACE

The QAA-RGB: A universal three-band absorption and backscattering retrieval algorithm for high resolution satellite sensors. Development and implementation in ACOLITE

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Outline

Cited By (2)

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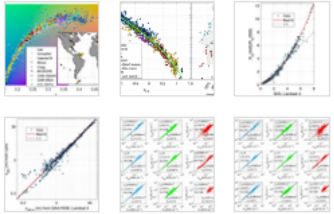

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The QAA-RGB: A universal three-band absorption and backscattering retrieval algorithm for high resolution satellite sensors. Development and implementation in ACOLITE

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Highlights

- The popular QAA is adapted for high resolution sensors like Landsat and Sentinel 2.
- We name it the QAA-RGB because it ingests only three bands (red/green /blue).
- Bulk IOPs, diffuse attenuation and Secchi disk depth are retrieved.
- Inter-sensor consistency is ensured and demonstrated.
- The QAA-RGB has been included as a module in the ACOLITE processor.

In brief: what is the QAA-RGB?

- It is not a yet-another-algorithm
- It is an adaptation of a well-known and validated algorithm for high-resolution sensors (Landsat, Sentinel 2, WorldWiew, etc…)

Motivation: there is high entropy in water quality modeling for coastal and inland waters

TABLE VI
ALGORITHMS OF WATER TRANSPARENCY ESTIMATION WITH TM BANDS REFLECTANCE DATA

Author	Algorithm	a_1	a_2	a_3	a_4	b	R^2
Proposed algorithm	$b\cdot(TM2)^{-a1}$	1.82 ± 0.12	–	–	–	4.5 ± 1.2	0.80
Allan *et al.* [5]	$b-a_1\cdot(TM4)$	0.24 ± 0.04	–	–	–	1.27 ± 0.15	0.70
Wu *et al.* [32]	$\exp[b-(a_1\cdot TM1)-(a_2\cdot TM3)]$	0.27 ± 0.05	0.65 ± 0.06	–	–	1.3 ± 0.2	0.77
Cozar *et al.* [33]	$b-(a_1\cdot TM1)-(a_2\cdot TM3)-(a_3\cdot TM4)$	0.16 ± 0.05	0.35 ± 0.07	0.09 ± 0.04	–	2.17 ± 0.19	0.76
Olmanson *et al.* [6]	$\exp[(a_1\cdot TM1/TM3)-(a_2\cdot TM1)-b]$	2.2 ± 0.2	1.10 ± 0.09	–	–	0.58 ± 0.14	0.80
Lavery *et al.* [34]	$b-(a_1\cdot TM3)-(a_2\cdot TM1/TM3)$	0.56 ± 0.07	0.42 ± 0.13	–	–	2.5 ± 0.3	0.60
Mancino *et al.* [10]	$b-(a_1\cdot TM3/TM2)+(a_2\cdot TM1/TM2)-(a_3\cdot TM1)+(a_4\cdot TM2/TM1)$	2 ± 1	3.6 ± 0.8	0.67 ± 0.07	0.04 ± 0.09	1 ± 1	0.80
Allan *et al.* [5]	$\exp[b-a_1\cdot \ln TM3]$	1.73 ± 0.15	–	–	–	0.51 ± 0.16	0.79
Allee *et al.* [8]	$b-(a_1\cdot TM3)+(a_2\cdot TM3^2)-(a_3\cdot TM3^3)$	5.4 ± 0.4	1.59 ± 0.19	0.15 ± 0.02	–	6.2 ± 0.3	0.90

a_i and b are the regression coefficients, R^2 is the fit goodness, $N = 50$ and all algorithms presented p-values <0.001.

Doña et al. (2017)

Table 2
Performance comparison of different SDD estimation models used in previous studies.

Models	*a*	*b*	*c*	*d*	*e*	RMSE (m)	R^2	Ref.
$SDD=a*(TM2)^b$	0.009	−1.69	/	/	/	1.15	0.68	(Dona et al., 2014)
$SDD= a*TM4+b$	−22.67	2.55	/	/	/	1.70	0.20	(Allan et al., 2011)
$SDD=\exp[a*TM1+b*TM2+c]$	2.67	−24.24	1.61	/	/	1.35	0.62	(Wu et al., 2008)
$SDD=a*TM1+b*TM3+c*TM4+d$	1.32	−29.05	−3.23	3.55	/	1.42	0.44	(Cózar et al., 2005)
$SDD=a*TM3/TM2+b*TM1/TM2+c*TM1+d*TM2/TM1+e$	−2.48	2.78	−25.07	−2.44	5.78	1.16	0.63	(Mancino et al., 2009)
$SDD=a*TM3^3+b*TM3^2+c*TM3+d$	−3725.31	1326.00	−153.14	6.67	/	1.20	0.60	(Allee and Johnson 1999)
$SDD=a*TM1/TM2+b$	6.48	−3.96	/	/	/	1.64	0.25	(Doron et al., 2011)
$SDD=a*TM1/(TM1+TM2+TM3)+b$	13.15	−3.43	/	/	/	1.49	0.39	(Harma et al., 2001)
$Ln(SDD)=a*(TM1/TM3)+b*TM1+c$	1.37	−13.42	−1.02	/	/	0.67	0.67	(Olmanson et al., 2008)
$\ln(SDD) = a*TM3+b$	−22.13	1.23	/	/	/	0.70	0.64	(Wu et al., 2009)
$\ln(SDD) =a* \ln(TM3/TM2)+b$	−5.03	3.4	/	/	/	0.80	0.54	(Duan et al., 2009)
$\ln(SDD) = a* \ln(TM3/TM1)+b$	−3.49	2.87	/	/	/	0.73	0.61	(Duan et al., 2009)
$SDD= a*(TM1/TM3) + b(TM3) +c$	1.99	−14.76	0.08	/	/	1.26	0.56	(Guan et al., 2011)
$SDD=a*TM1/TM3+b*TM1+c$	2.29	−16.39	−0.14	/	/	1.24	0.57	(Olmanson et al., 2015)
$SDD=a*TM3+b$	−29.72	3.53	/	/	/	1.42	0.44	(Mccullough et al., 2013)
$\ln(SDD) = a*\ln(TM3)+b$	−1.25	−3.97	/	/	/	0.63	0.71	(Dekker and Peters 1993)
$SDD = a*Rrs(550)^3 + b*Rrs(550)^2 + c*Rrs(550)+d$	−2975.89	1314.35	−184.34	8.61	/	1.14	0.64	(Binding et al., 2015)
$SDD = a*(TM3)^b$	0.0046	−1.26	/	/	/	0.63	0.73	Our model

a, *b*, *c*, *d*, and *e* are the coefficients of the adjusted models used in regression analysis.

Zhang et al. (2021)

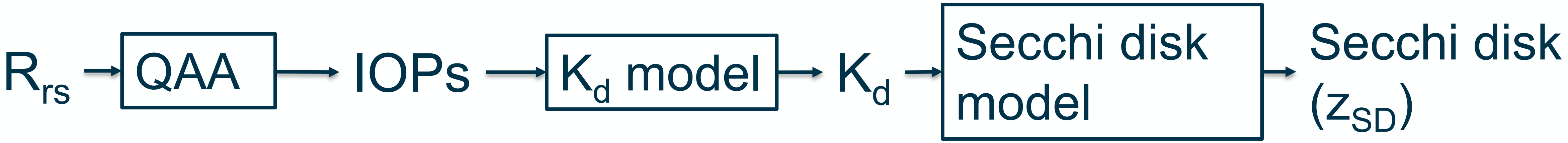
Research questions

- Can we retrieve IOPs (and K_d, Secchi…) from high-resolution sensors such as Landsat and Sentinel 2?
- Can we overcome the limitation caused by the low number of bands?
- Can we do it despite the coarse spectral resolution?
- Can we obtain an unbiased algorithms across with different band configurations?

Let's find an algorithm of broad applicability

The QAA (Lee et al. (2002))

- Semianalytical
- Most tested and validated algorithm
- Easy and modular



Perfect!!

….but we lack the required bands

This is why this approach did not exist before

How does the QAA-RGB work?

Original QAA: two blue, one green and one red band to estimate absorption from reflectance

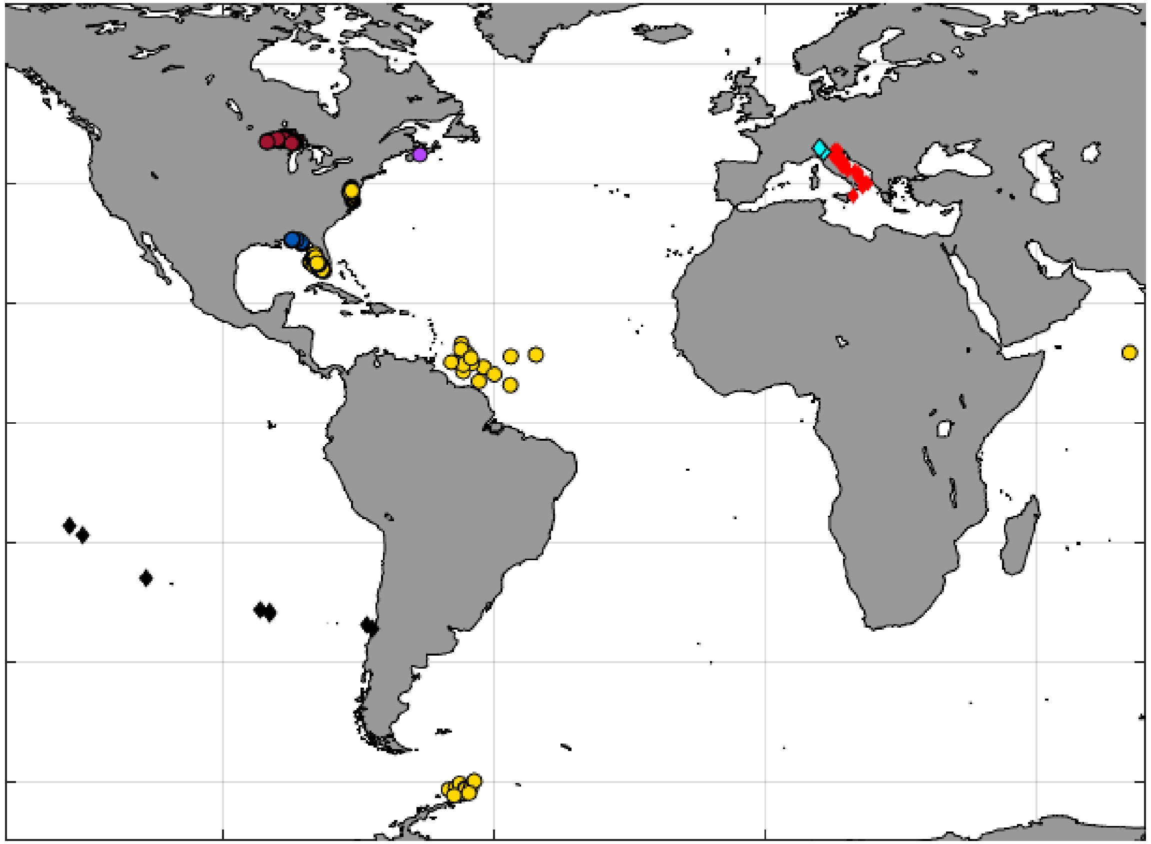
$$\chi = \log_{10}\left(\frac{r_{rs}(443) + r_{rs}(490)}{r_{rs}(555) + \frac{5 r_{rs}(670)^2}{r_{rs}(490)}}\right) \qquad \log_{10}[a_{nw}(555)] = \sum_{k=0}^{N}(p_k \chi^k)$$

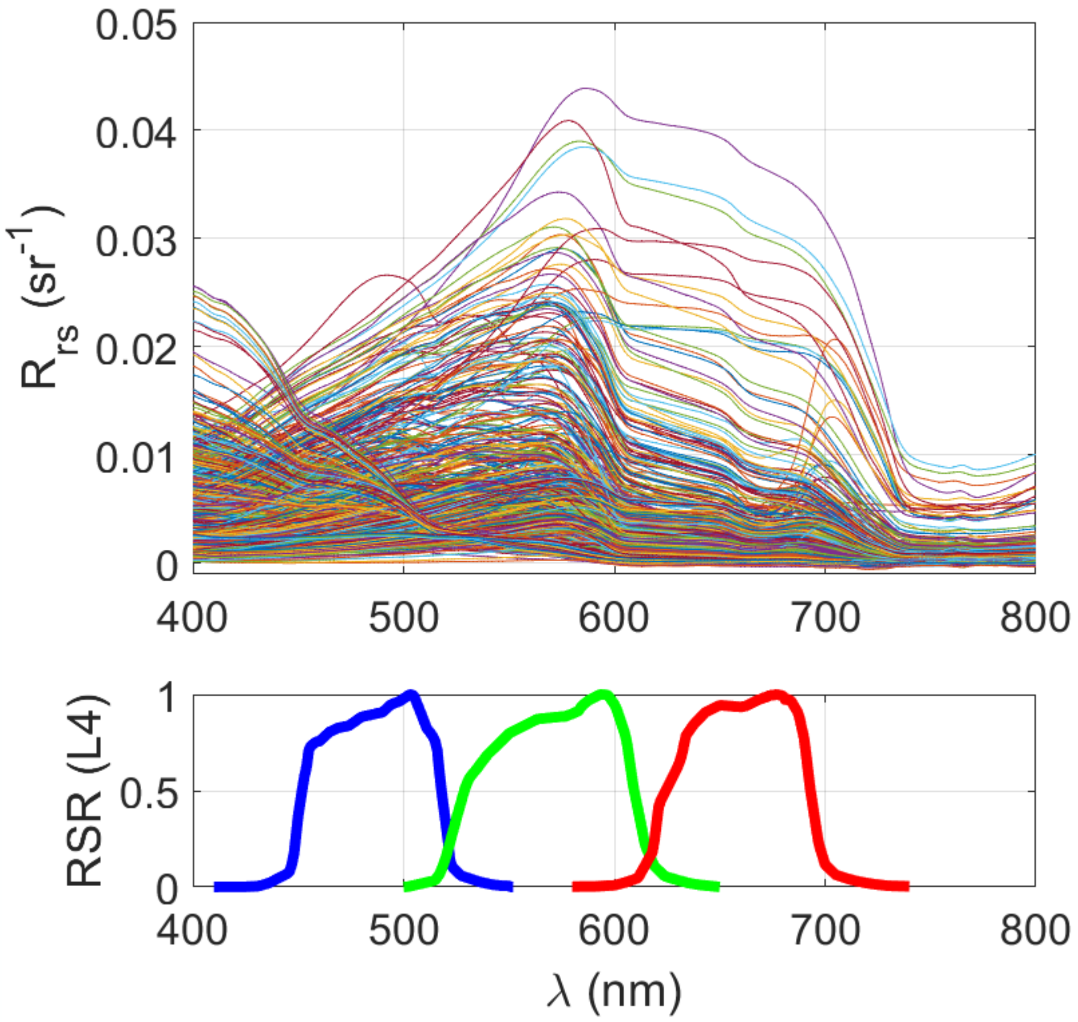
In high resolution sensors, we only have one blue (B), one green (G) and one red (R) band in this range

$$\chi = \log_{10}\left(\frac{2B}{G + \frac{5R^2}{B}}\right) = \log_{10}(2) - \log_{10}\left[\frac{G}{B} + 5\left(\frac{R}{B}\right)^2\right]$$

…essentially, a balance between a G/B and a R/B ratio

Need in situ $a_{nw}(555)$ & hyperspectral R_{rs} to calibrate

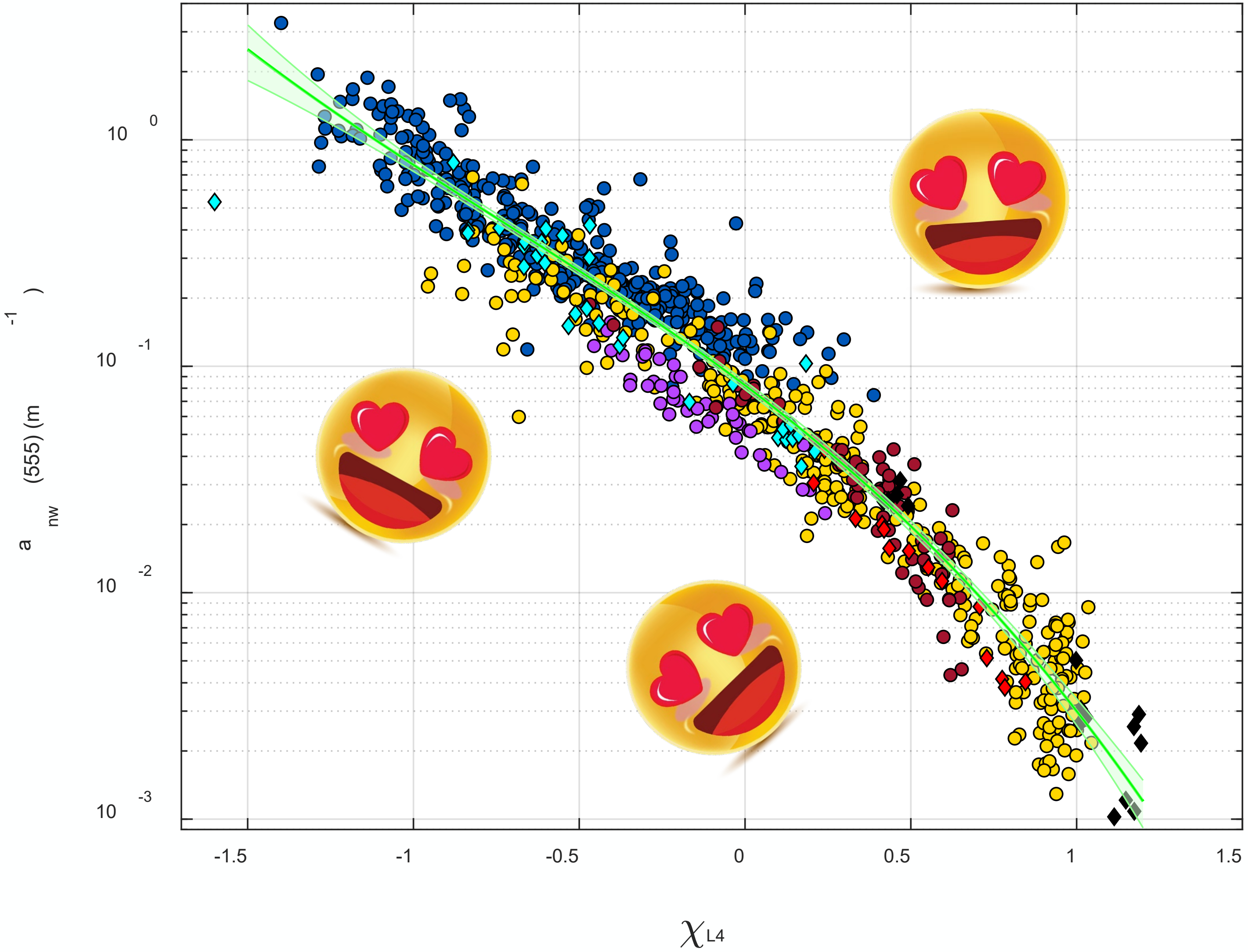




Thanks to:

- PACE team
- ZP Lee
- Valente et al.
- C. Giardino & M. Bresciani
- My CNR-ISMAR colleagues

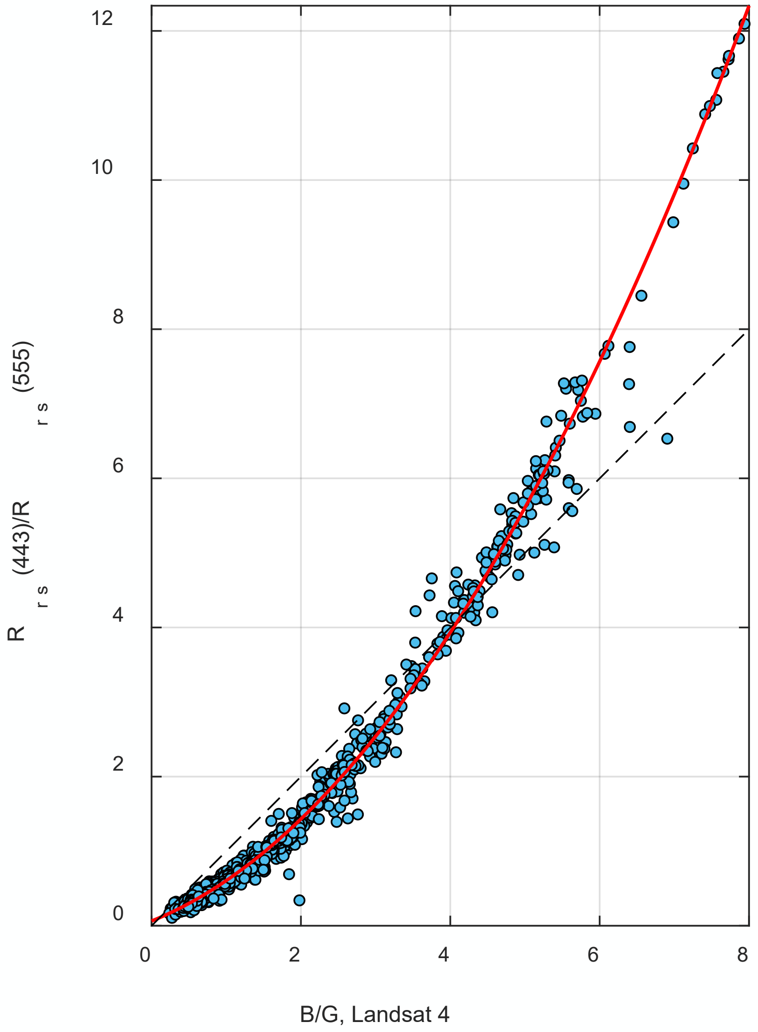
Calibration of absorption from R_{rs}



- We can do it!
- We can estimate $a_{nw}(555)$ from high resolution R_{rs} satellites with a deviation σ~ 50 %
- Once this is done, everything else is a sequence of analytical steps

One example: replace QAA's 443-to-555 ratio

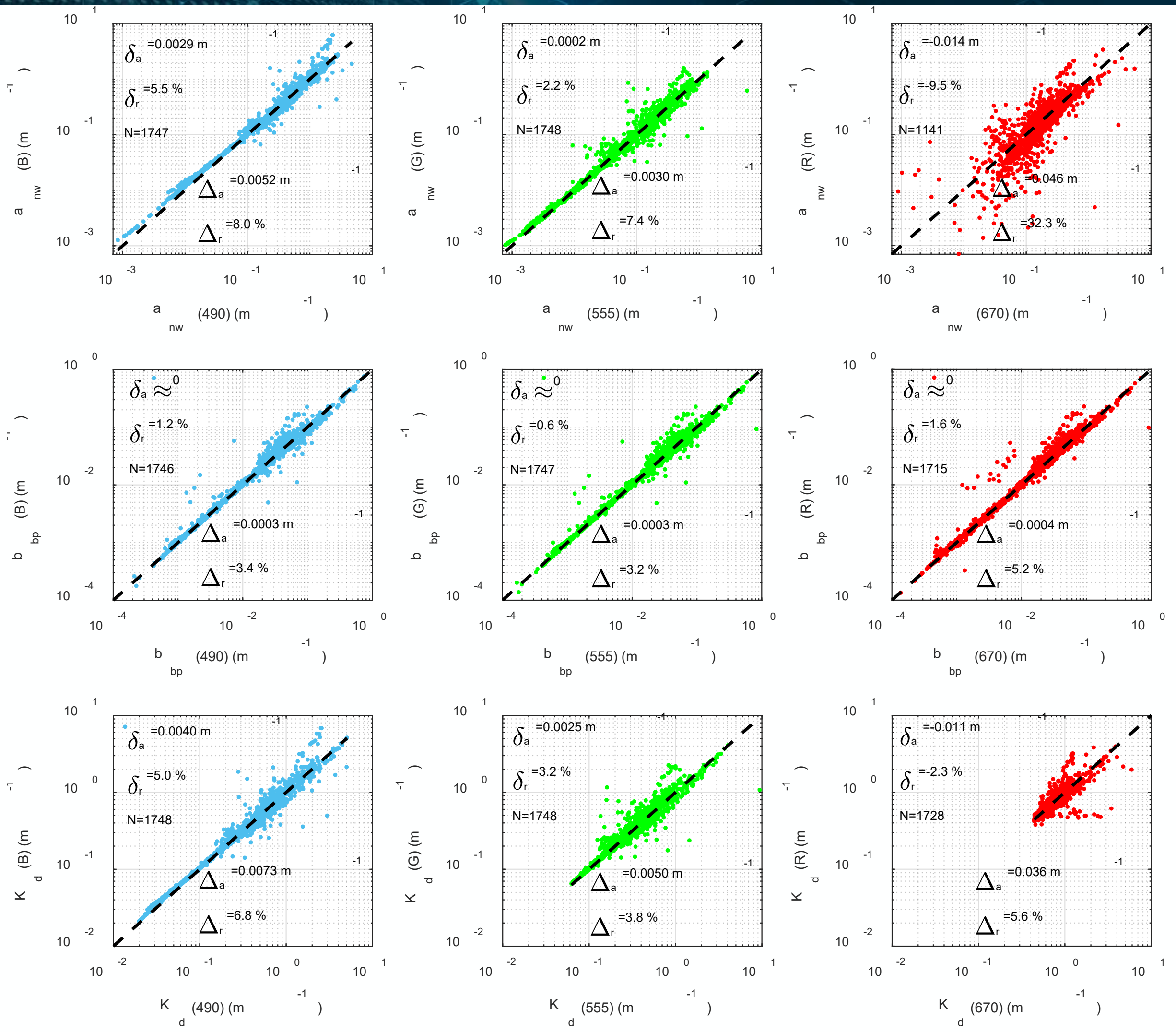
Needed for:
→ the b_b spectral slope (η)
→ an estimate of Raman scattering



In summary:
→ Tracking and compensating every bias that is caused by different sensor response functions

Validation (1): QAA-RGB vs. QAA

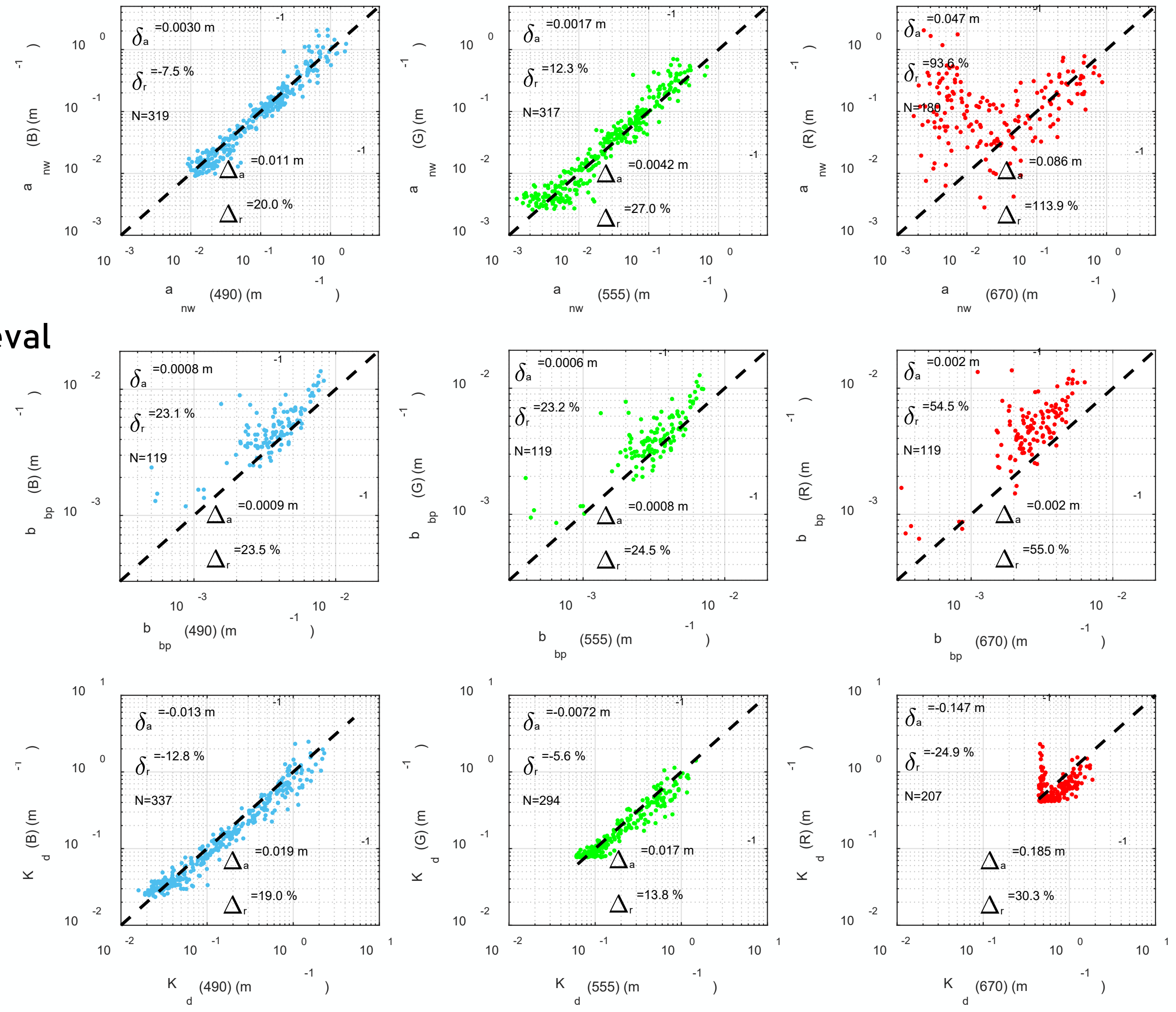
QAA retrieval



QAA-RGB retrieval (Sentinel-2A)

Validation (2): QAA-RGB vs. in-situ data

QAA-RGB retrieval (Landsat 4)



In situ data (Valente et al.)

The QAA-RGB is available, ready-to-use!

esa

- Incorporated in the ACOLITE multi-sensor processor

README.md

About ACOLITE

ACOLITE combines the atmospheric correction algorithms for aquatic applications of Landsat and Sentinel-2 developed at RBINS. This repository hosts the (more) generic version of ACOLITE with the aim of bringing together the processing of all different sensors. This new generic version was started 4 February 2021, and was released to the public on 21 April 2021. Binary releases from 20210802.0 onward are based on this codebase. Please contact Quinten via email/ACOLITE Forum/GitHub if you find any issues. The settings files are largely compatible with previous versions, but it is recommended to create a new settings file configuring only the settings you want to change.

https://github.com/acolite

- Stand-alone MATLAB code

zenodo

December 6, 2021 Software Open Access

MATLAB code of the QAA-RGB algorithm for IOP retrieval from high-resolution sensor data

Jaime Pitarch

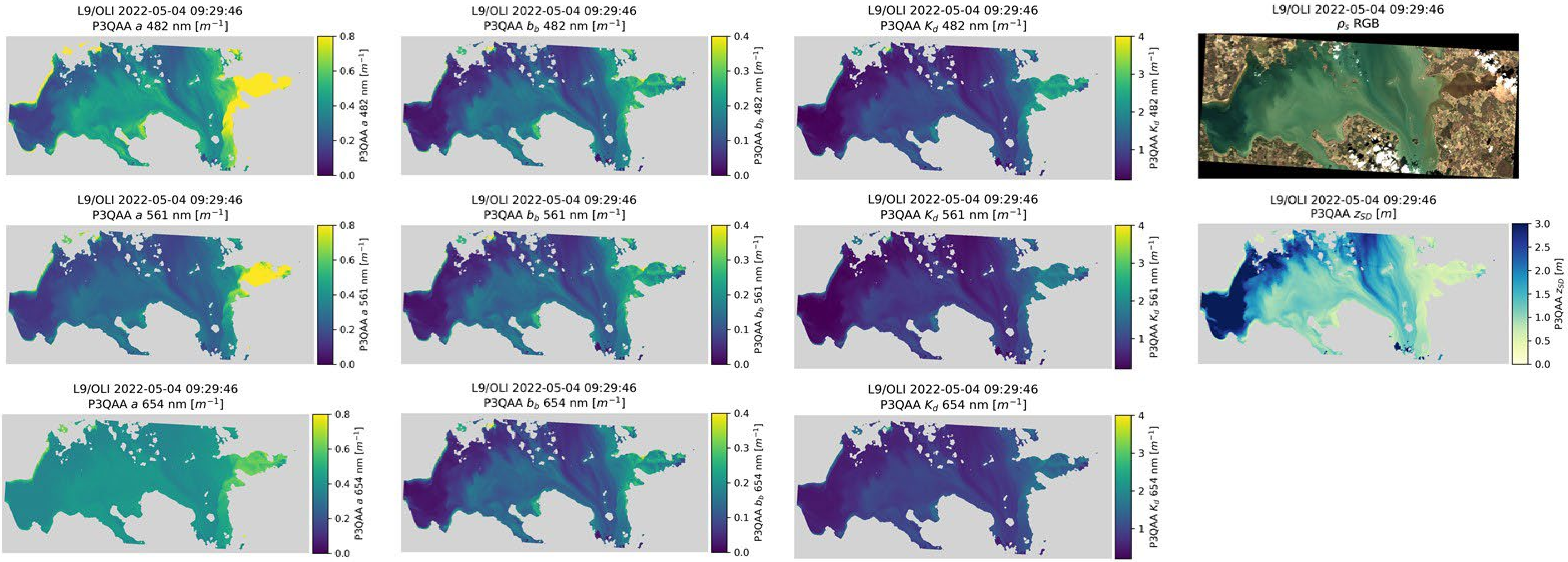
This is a code implementation of the "QAA-RGB", able to retrieve total absorption, particle backscattering, as well as the diffuse attenuation coefficient and the Secchi disk depth, from eighteen metre and decametre satellite sensors, including present and heritage Landsat data, Sentinel-2 at 10 m and an array of commercial sensors such as PlanetScope, Pléiades or Worldview. The QAA-RGB is a minimal version of the Quasi-Analytical Algorithm (QAA), and therefore keeps its robustness and general validity across different water types. It ingests remote-sensing reflectance (R_{rs}) at only three bands, i.e. centred on red, green and blue wavelengths. Retrieval is found to be robust based on in situ datasets, with a retrieval accuracy (s ~ 50% for non-water absorption at 555 nm, ($a_{t-w}(555)$) of s ~ 50% up to $a_{t-w}(555) < 2\ m^{-1}$.

https://doi.org/10.5281/zenodo.5761818

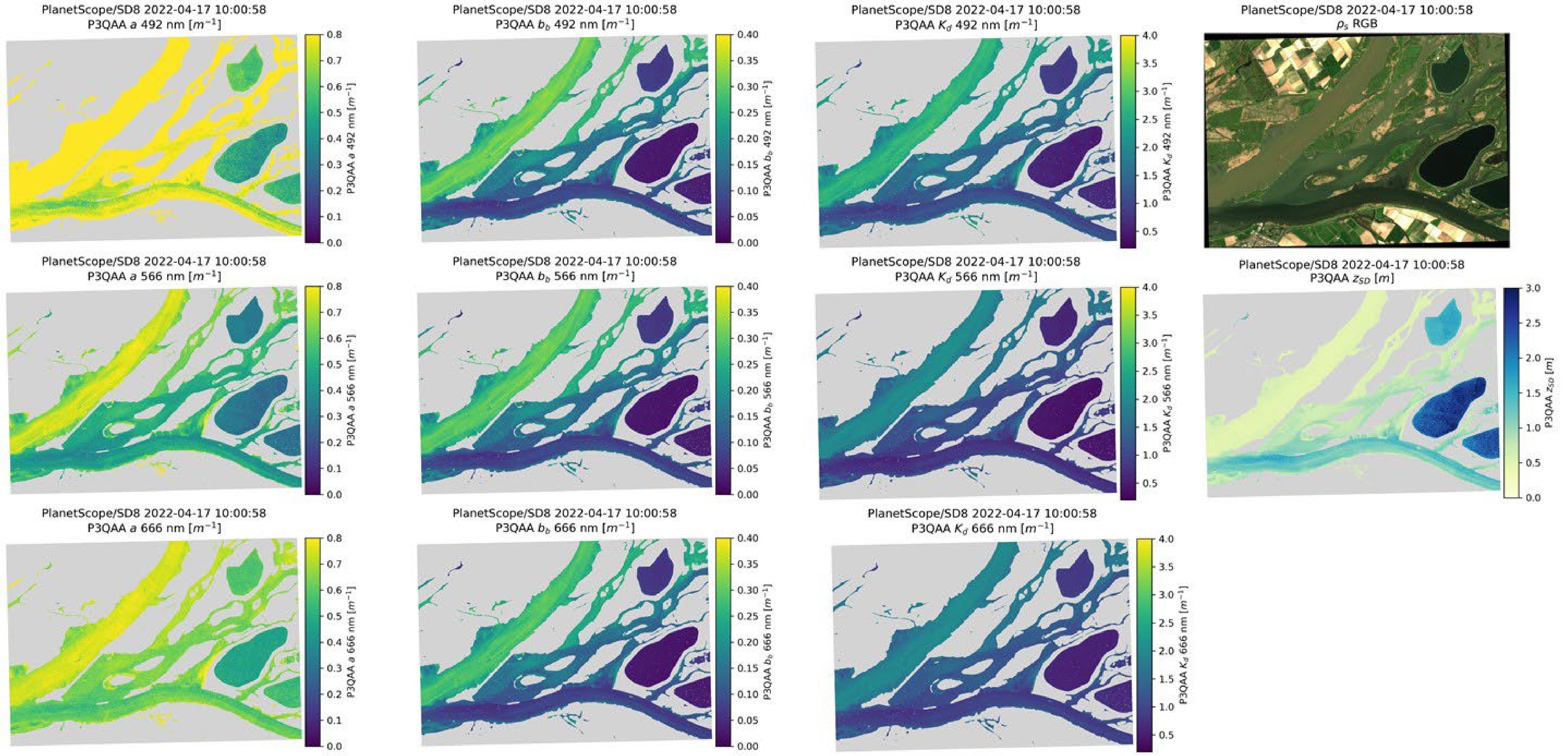
Exhaustive sensor list

Landsat 4	PlanetScope 0c
Landsat 5	PlanetScope 0d05
Landsat 7	PlanetScope 0d06
Landsat 8	PlanetScope 0e
Landsat 9 NEW!	PlanetScope 0f
Sentinel 2A	PlanetScope 22
Sentinel 2B	RapidEye
Pléiades 1A	Worldview2
Pléiades 1B	WorldViev3
	VENµS_VSSC

ACOLITE Landsat 9 image over Matsalu N.P. (Estonia)



ACOLITE PlanetScope/SD8 image over De Biesbosch N.P. (Netherlands)



Conclusions & future lines

- QAA-RGB: three band (B,G,R) retrieval of a, b_b, K_d, z_{SD} at high and very high spatial resolution
- Built on the reliable medium-resolution sensor QAA
- Careful calibration using the RSRs: negligible biases across sensors
  - Applicability to very long multi-sensor series
- Wide and tested applicability limit ($a_{nw}(555)<2\ m^{-1}$)
- Implemented in ACOLITE: user-friendly software including AC
- Future upgrade: use a NIR band: likely increasing upper limit an order of magnitude

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