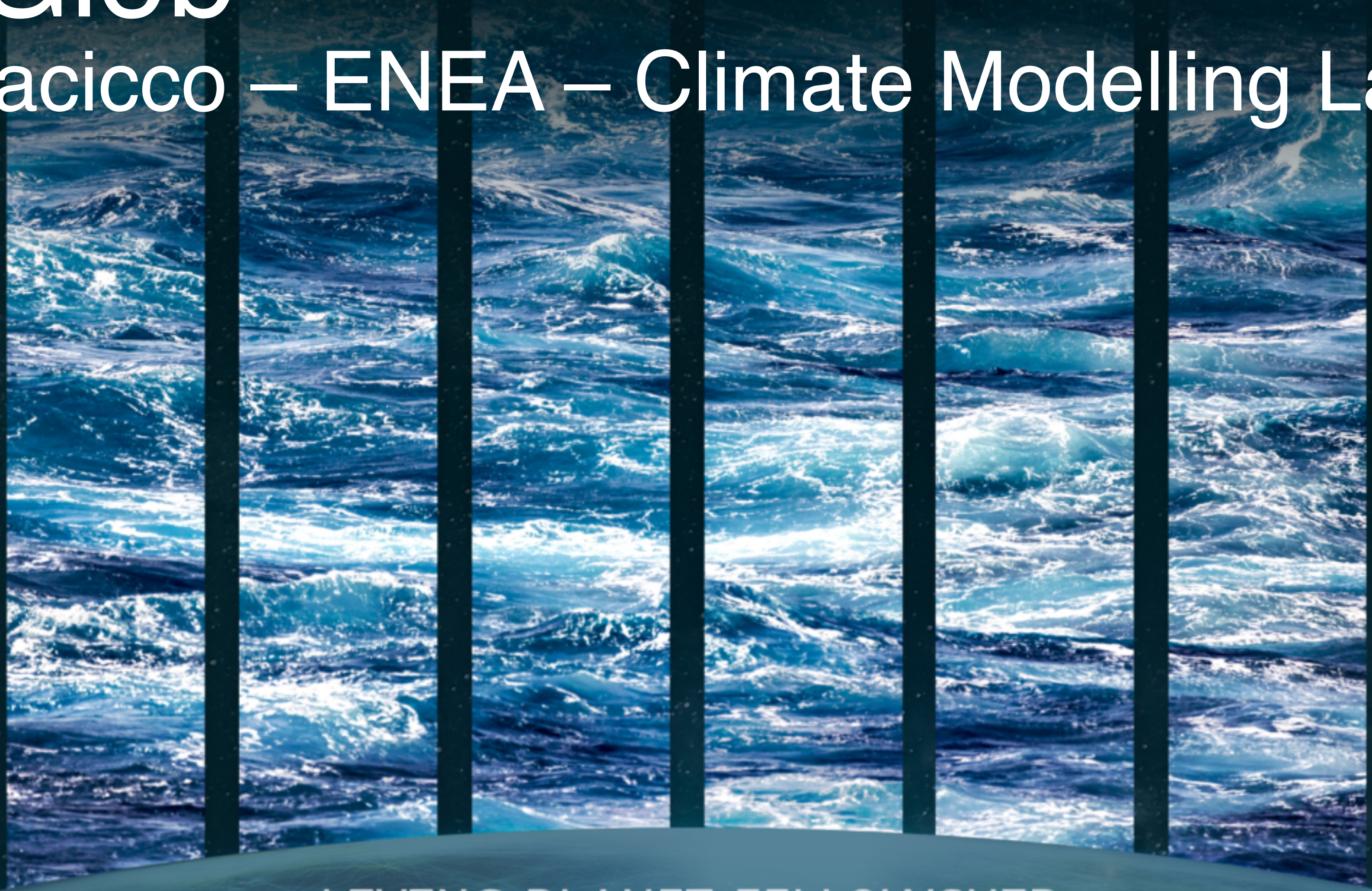
PhysioGlob

Marco Bellacicco – ENEA – Climate Modelling Laboratory

esa



LIVING PLANET FELLOWSHIP

HYDROSPHERE

General Context

Assessing the inter-annual **Physio**logical response of phytoplankton to **Glob**al warming using long-term satellite observations

Why is important study phytoplankton from space?

- Phytoplankton produces ~50% of the **primary production** of the Earth
- Phytoplankton are basis of oceanic trophic chain through the photosynthesis process: fundamental actress in the **global carbon cycle**
- Phytoplankton are **sentinels** of **changes** in the ocean because they rapidly respond to environment perturbations

Scientific objectives

Goals:

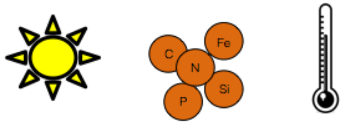
- Which is the physiological response – in terms of temporal oscillations – of phytoplankton to global warming/climate change on both global and regional scales?

- Which are the main drivers of the phytoplankton decreasing and physiological temporal oscillations?

Scientific objectives

What is the physiological response and how we can detect it from space?

Light, nutrients and temperature are the most important variables that drive the phytoplankton production and define the so-called "*Integrated Growth Environment*" (*Behrenfeld et al.*, 2008)



Phytoplankton cells respond to fluctuations in light and nutrients with physiological strategies that enhance the efficiency of light capturing and photosynthetic capacity, growth and persistence

Photoadapation

Changes that might happen at the genotype level, and are expected to occur on a long evolutionary time-scale

(*Moore et al.*, 2006)

Photoacclimation

Phenotypic response at the cellular level:
1) Regulation of the pigment amounts (e.g. chlorophyll-*a*)
2) Other components of the photosynthetic machinery (such as, electron transport chain, photosystem I and II, and their efficiency)

(*Dubinsky and Stambler*, 2009)

The most important and easily observable effect due to photoacclimation is the variation of the cellular concentration of photosynthetic pigment such as chlorophyll-*a* (Chl).

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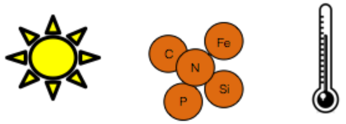

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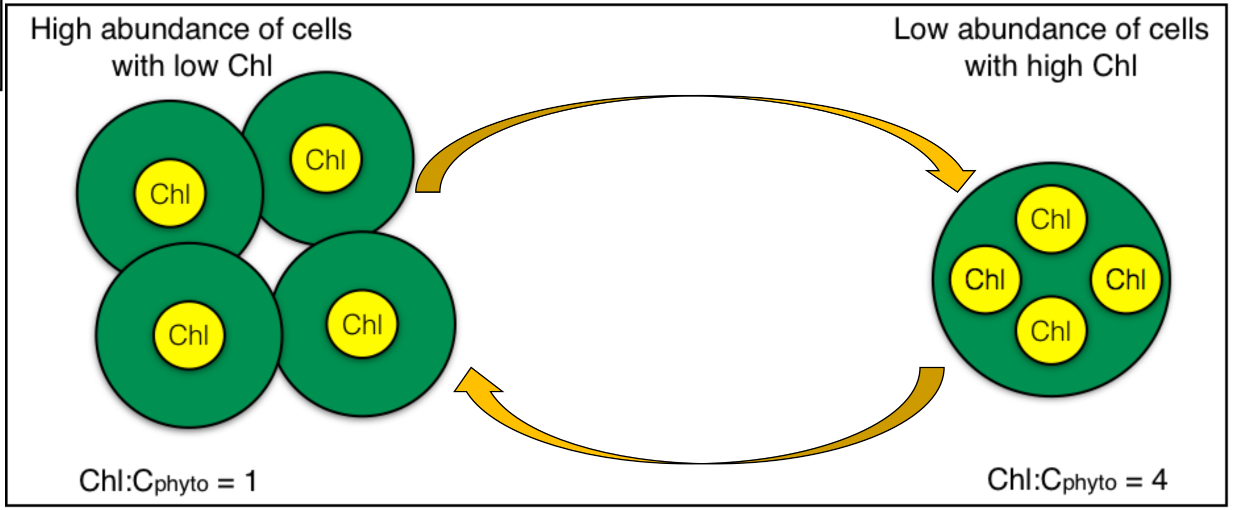
The most important and easily observable effect due to photoacclimation is the variation of the cellular concentration of photosynthetic pigment such as chlorophyll-*a* (Chl).

Satellite chlorophyll cannot distinguish between community and intra-cellular dynamics



Alternative index to define algal biomass concentration in terms of phytoplankton carbon (C_{phyto}; in mg m^{-3}) based on particulate backscattering coefficient, b_{bp}.
A direct index of phytoplankton physiology is provided through changes in chlorophyll-carbon ($Chl{:}C_{phyto}$) ratios

Scientific objectives

Backscattering-based phytoplankton carbon - C_{phyto} - from space

$$C_{phyto} = [b_{bp}(\lambda) - b^{k}_{bp}(\lambda)] \cdot SF$$

C_{phyto} = phytoplankton carbon biomass [mg C m^{-3}]

b_{bp} is the total particulate backscattering retrieved by satellite [m^{-1}]

b^{k}_{bp} is the *background* contribution of non-algal particles to total b_{bp} (*i.e.* heterotrophic bacteria, viruses, particles aggregates)

SF is a scaling factor equal to 13000 mg m^{-2} taken from literature (*Behrenfeld et al.*, 2005)

What we have:
- Daily Chl from OC-CCI at 4 km resolution (1997-today) v4.0
- Daily R_{rs} from OC-CCI at 4 km resolution (1997-today) v4.0
- In-situ C_{phyto} data for validation (*Martinez-Vicente et al.*, 2017)

What we want:
Daily C_{phyto} from space at 4 km resolution (1997- today)

Backscattering-based phytoplankton carbon - C_{phyto} - from space

$$C_{phyto} = [b_{bp}(\lambda) - b^{k}_{bp}(\lambda)] \cdot SF$$

C_{phyto} = phytoplankton carbon biomass [mg C m^{-3}]

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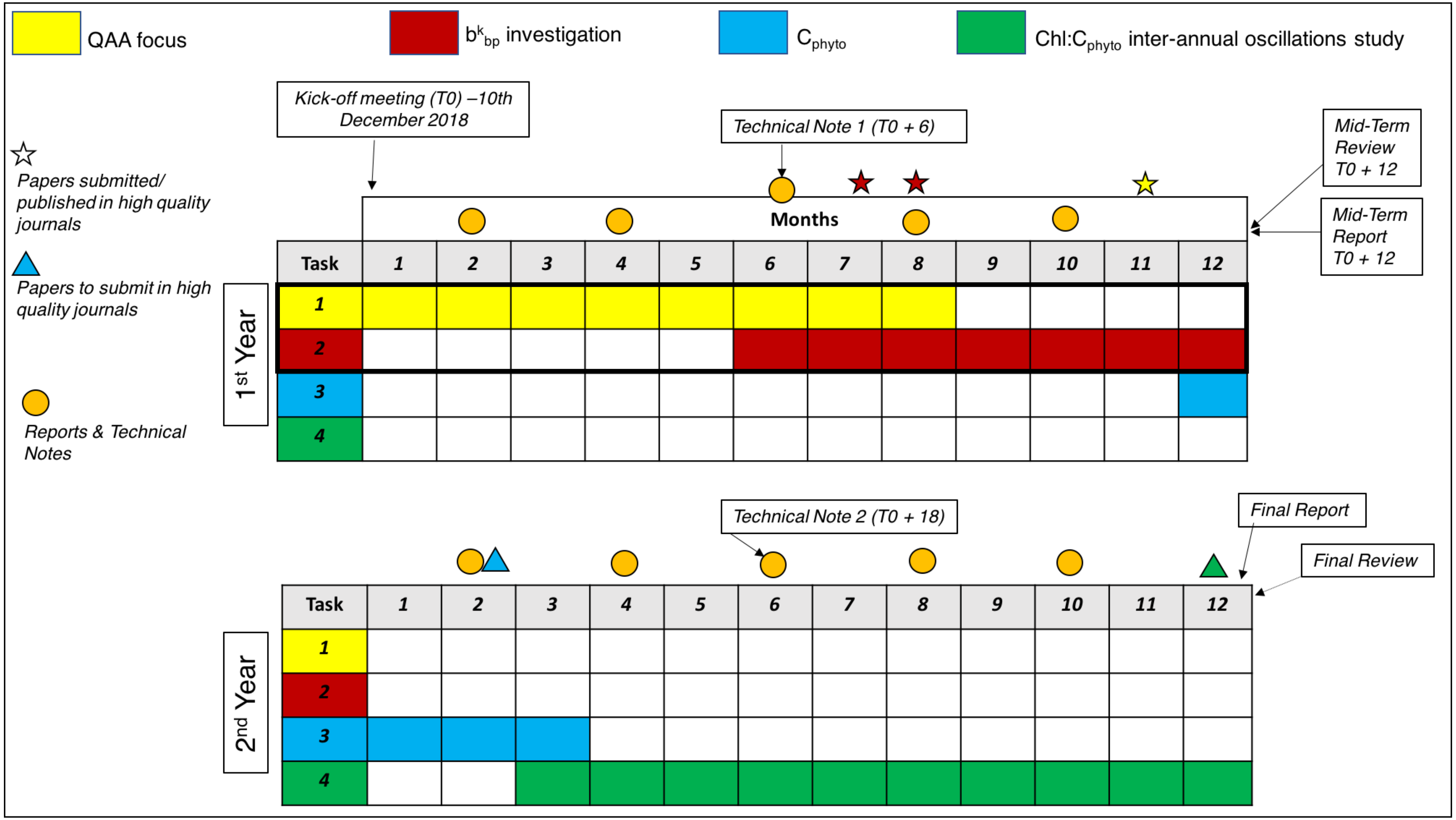
SF is a scaling factor equal to 13000 mg m^{-2} taken from literature (*Behrenfeld et al.*, 2005)

Is Quasi-Analytical Algorithm (QAA) - used in OC-CCI - a good algorithm to retrieve b_{bp} from R_{rs}? Can we improve it?

Does b^{k}_{bp} varies in space and time or not? Which is the best method for its computation?

Status @MTR


QAA focus
b^k_{bp} investigation
C_{phyto}
Chl:C_{phyto} inter-annual oscillations study
Kick-off meeting (T0) –10th December 2018
Technical Note 1 (T0 + 6)
Mid-Term Review T0 + 12
Mid-Term Report T0 + 12
Papers submitted/ published in high quality journals
Papers to submit in high quality journals
Reports & Technical Notes
Months
1st Year
Task
1
2
3
4
5
6
7
8
9
10
11
12
Technical Note 2 (T0 + 18)
Final Report
Final Review
2nd Year

Main sub-goals :

- R_{rs} Raman-Correction inclusion: how does change the b_{bp} retrievals?
    - In-situ $R_{rs}(\lambda)$ → QAA algorithm → b_{bp}→ comparison with in-situ b_{bp} data at the different λs available <u>*with*</u> *and* <u>*without*</u> Raman-Correction (not used in CCI context);
- Evaluation of η by using an in-situ independent dataset;
- Validation of OC-CCI $R_{rs}(\lambda)$ vs in-situ $R_{rs}(\lambda)$;
- OC-CCI $R_{rs}(\lambda)$ → QAA algorithm → satellite b_{bp} → comparison with in-situ data at different λs including the Raman-Correction

Quasi-Analytical Algorithm (QAA) in OC-CCI Framework

Step	Formula	
0	$r_{rs}(\lambda) = R_{rs}(\lambda)(0.52 + 1.7R_{rs}(\lambda))$	
1	$u(\lambda) = \frac{-g_0 + \sqrt{g_0^2 + 4g_1 r_{rs}(\lambda)}}{2g_1}$ $\quad with\ g_0 = 0.089\ g_1 = 0.1245$	
2	if $r_{rs}(671) < 0.0015\ sr^{-1} \rightarrow \lambda_0 = 551\ nm$	else $\rightarrow \lambda_0 = 671\ nm$
	$\chi = \log\left(\frac{r_{rs}(443) + r_{rs}(486)}{r_{rs}(551) + 5\frac{r_{rs}(671)}{r_{rs}(486)}r_{rs}(671)}\right)$	$a(\lambda_0) = a_w(\lambda_0) + 0.39\left(\frac{R_{rs}(671)}{R_{rs}(443) + R_{rs}(486)}\right)^{1.14}$
	$a(\lambda_0) = a_w(\lambda_0) + 10^{h0 + h1\chi + h2\chi^2}$	
3	$b_{bp}(\lambda_0) = \frac{u(\lambda_0)a(\lambda_0)}{1 - u(\lambda_0)} - b_{bw}(\lambda_0)$	
4	$\eta = 2.0\left(1 - 1.2\exp\left(-0.9\frac{r_{rs}(443)}{r_{rs}(551)}\right)\right)$	
5	$b_{bp}(\lambda) = b_{bp}(\lambda_0)\left(\frac{\lambda_0}{\lambda}\right)^{\eta}$	
6	$a(\lambda) = (1 - u(\lambda))(b_{bw}(\lambda) + b_{bp}(\lambda))/u(\lambda)$	
7	$\zeta = 0.74 + \frac{0.2}{0.8 + r_{rs}(443)/r_{rs}(551)}$	
8a	$S = 0.015 + \frac{0.002}{0.6 + r_{rs}(443)/r_{rs}(551)}$	
8b	$\xi = \exp(S(442.5 - 415.5))$	
9a	$a_{dg}(443) = \frac{a(412) - \zeta a(443)}{\xi - \zeta} - \frac{a_w(412) - \zeta a_w(443)}{\xi - \zeta}$	
9b	$a_{dg}(\lambda) = a_g(443)\exp(-S(\lambda - 443))$	
10	$a_{ph}(\lambda) = a(\lambda) - a_{dg}(\lambda) - a_w(\lambda)$	

Lee et al., (2011)

Pitarch et al., (2019; submitted)

Results @MTR – Task #1

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5	$b_{bp}(\lambda) = b_{bp}(\lambda_0)\left(\frac{\lambda_0}{\lambda}\right)^{\eta}$	
6	$a(\lambda) = (1 - u(\lambda))(b_{bw}(\lambda) + b_{bp}(\lambda))/u(\lambda)$	
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Lee et al., (2011)

Pitarch et al., (2019; submitted)

Results @MTR – Task #1

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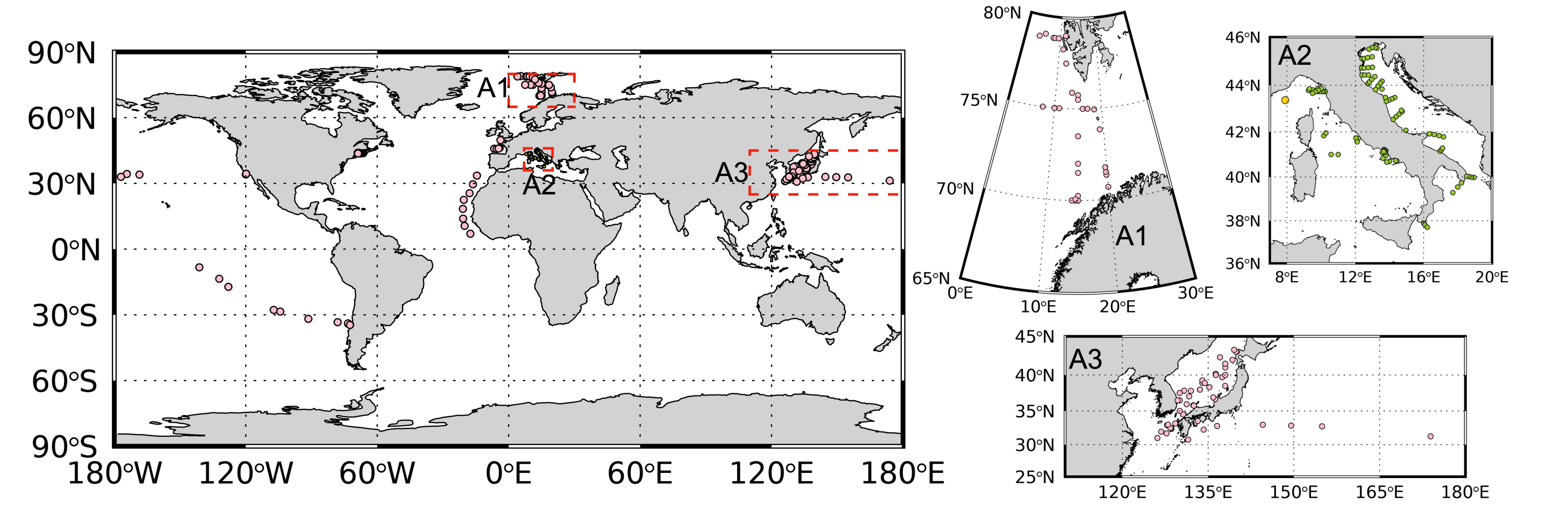
Quasi-Analytical Algorithm (QAA) in OC-CCI Framework



- Big in-situ $R_{rs}(\lambda)$ and $b_{bp}(\lambda)$ dataset on a global scale (N=2881)
- Satellite OC-CCI $R_{rs}(\lambda)$ v4.0

Pitarch et al., (*2019; submitted*)

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Lee et al., (2011)

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10	$a_{ph}(\lambda) = a(\lambda) - a_{dg}(\lambda) - a_w(\lambda)$

Lee et al., (2011)

$$R_{rs,corr}(\lambda) = \frac{R_{rs}(\lambda)}{1 + F(\lambda)}$$

$$F(\lambda) = \alpha(\lambda)\frac{R_{rs}(443)}{R_{rs}(555)} + \beta_1(\lambda)R_{rs}(555)^{\beta_2(\lambda)}$$

else → $\lambda_0 = 671\ nm$

$$a(\lambda_0) = a_w(\lambda_0) + 0.39\left(\frac{R_{rs}(671)}{R_{rs}(443) + R_{rs}(486)}\right)^{1.14}$$

Pitarch et al., (2019; submitted)

Results @MTR – Task #1

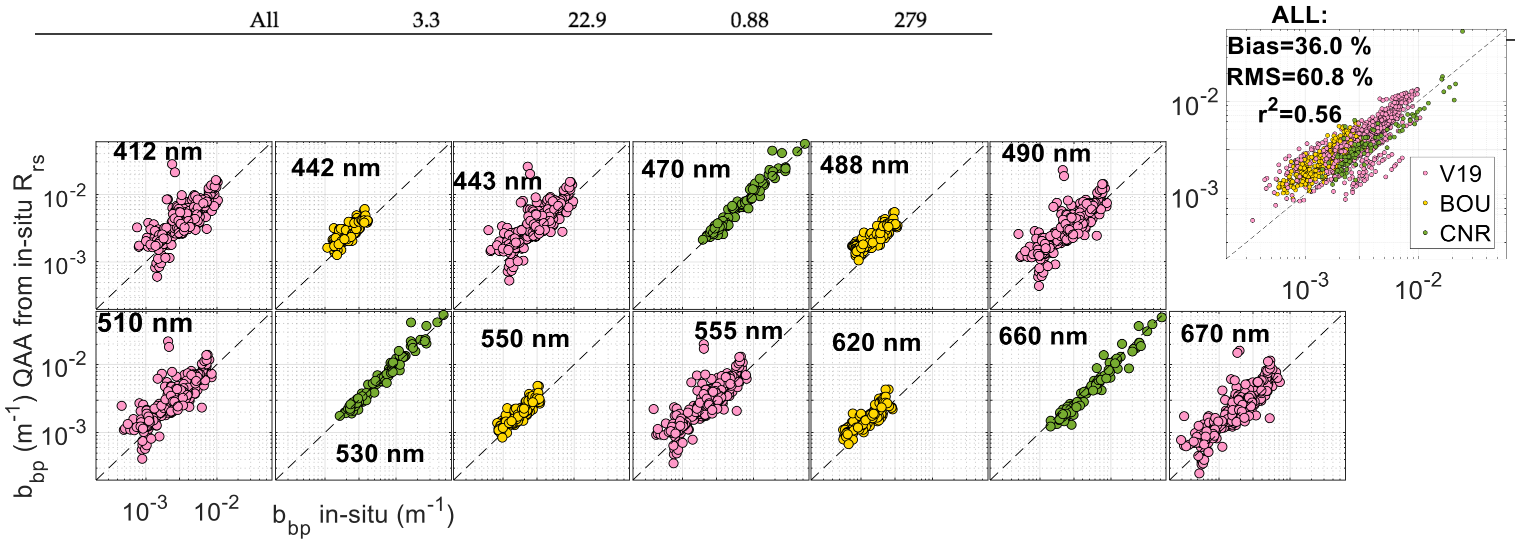
Table 1. Statistical descriptors of the difference between the QAA-derived b_{bp} and in-situ b_{bp} for each dataset, without Raman Scattering compensation.

	Band (nm)	Bias (%)	RMS (%)	r^2	N
V19	412	40.3	128.4	0.35	319
	443	42.7	129.4	0.37	319
	490	44.5	127.8	0.41	319
	510	45.0	127.1	0.42	319
	555	45.2	124.2	0.44	319
	670	43.1	114.2	0.47	319
	All	43.4	125.3	0.43	1914
BOU	442	44.5	50.7	0.73	172
	488	71.3	79.2	0.73	172
	550	29.0	36.5	0.78	172
	620	52.0	60.2	0.73	172
	All	49.2	58.7	0.75	688
CNR	470	11.8	25.1	0.88	93
	530	7.7	22.8	0.89	93
	660	-9.6	20.7	0.93	93
	All	3.3	22.9	0.88	279

Raman-Correction on in-situ $R_{rs}(\lambda)$

Table 2. Statistical descriptors of the difference between the b_{bp}-QAA derived and in-situ b_{bp} for each datas with Raman Scattering compensation.

	Band (nm)	Bias (%)	RMS (%)	r^2	N
V19	412	28.5	94.6	0.45	319
	443	30.7	95.0	0.47	319
	490	32.2	93.4	0.50	319
	510	32.6	92.8	0.51	319
	555	32.7	90.4	0.52	319
	670	30.7	83.1	0.54	319
	All	31.2	91.6	0.52	1914
BOU	442	33.0	40.1	0.73	172
	488	57.2	64.8	0.73	172
	550	18.2	27.1	0.78	172
	620	39.0	47.8	0.73	172
	All	37.0	47.0	0.75	688
CNR	470	6.5	22.6	0.88	93
	530	2.5	21.3	0.89	93
	660	-14.2	23.0	0.93	93
	All	3.3	22.9	0.88	279



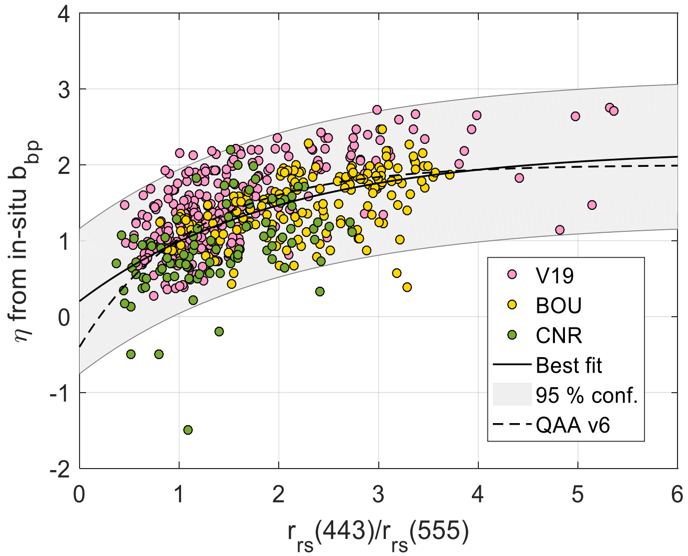
Raman-Correction on R_{rs} significantly reduces matchup errors with respect to in-situ b_{bp} (Bias and RMS lower than 10-30% with respect the non-application)

Pitarch et al., (2019; submitted)

Results @MTR – Task #1

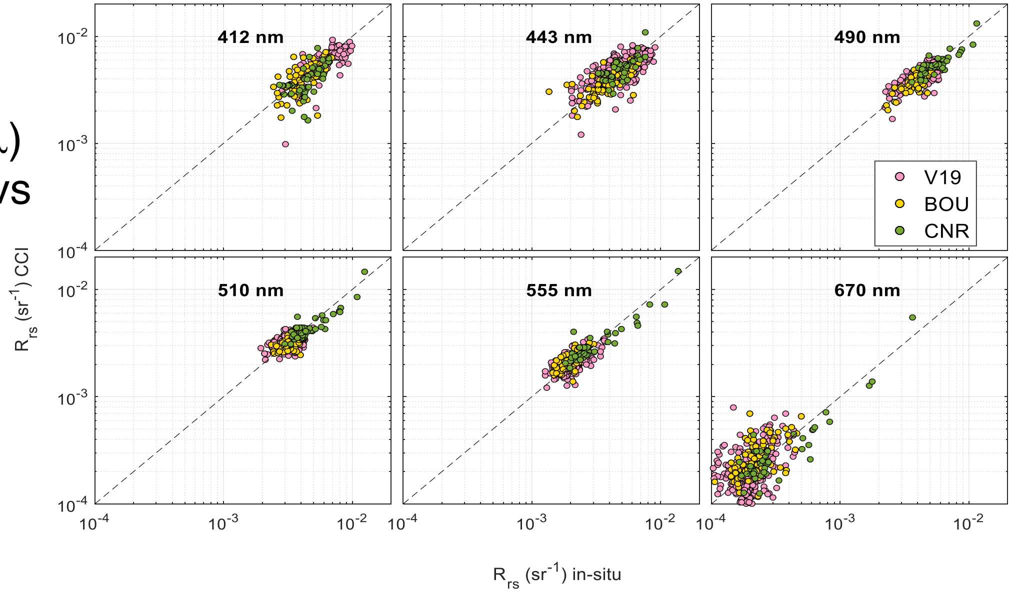
η evaluation with independent in-situ dataset

Excellent comparison between best fit and *Lee et al.*, (2002, 2014) by using an independent in-situ dataset

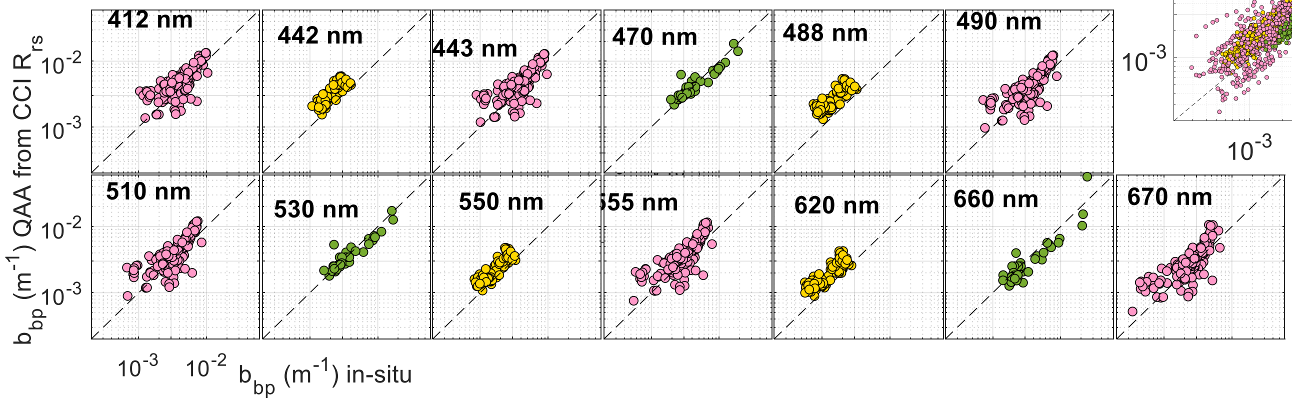


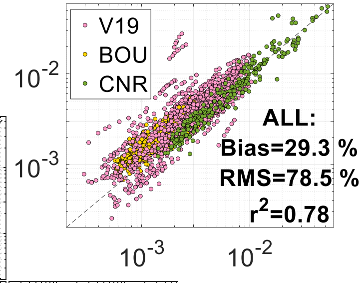
Validation of ESA OC-CCI $R_{rs}(\lambda)$

Good agreement between $R_{rs}(\lambda)$ from satellite vs in-situ data



$R_{rs}(\lambda)$ Raman-Corrected





Notwithstanding these results, there is the necessity to increase the amount and spatial coverage of high-quality in-situ b_{bp} observations

Pitarch et al., (*2019; submitted*)

Status @MTR

$$C_{phyto} = [b_{bp}(\lambda) - b^{k}_{bp}(\lambda)] \cdot SF$$

Resume of work tasks:

1. Focus on QAA algorithm for detection of b_{bp} from space: a possible update?
2. Does b^{k}_{bp} varies in space and time or not?
3. Estimation of a refined C_{phyto} from space and validation with in-situ data
4. Extraction and study of the main oscillatory modes of the physiological signal ($Chl:C_{phyto}$) in relation to physical and climate forcing agents on a global ocean scale by using long-term satellite observations (from 1997 up to today)

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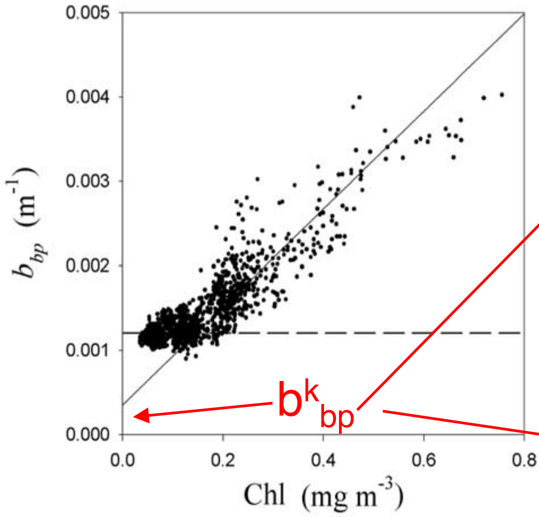
Background backscattering coefficient of NAP (b^k_{bp})

Linear Model:

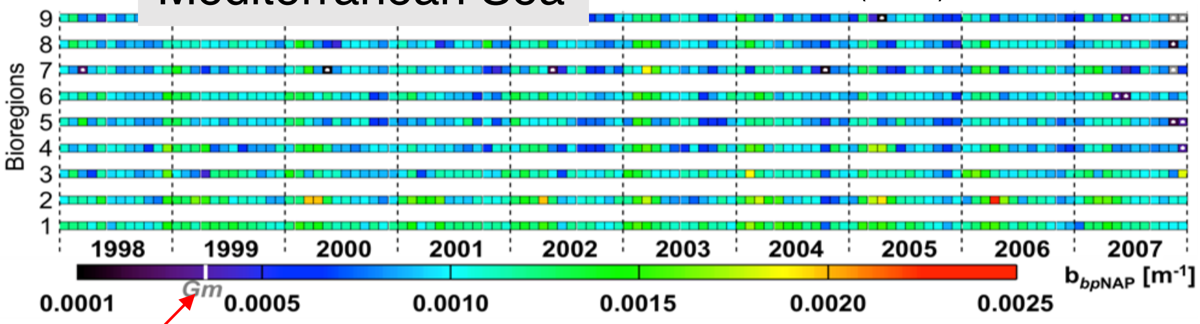
- *Behrenfeld et al.*, (2005)
- *Bellacicco et al.*, (2016)
- *Bellacicco et al.*, (2018)

$$b_{bp} = k \cdot Chl + b^k_{bp}$$

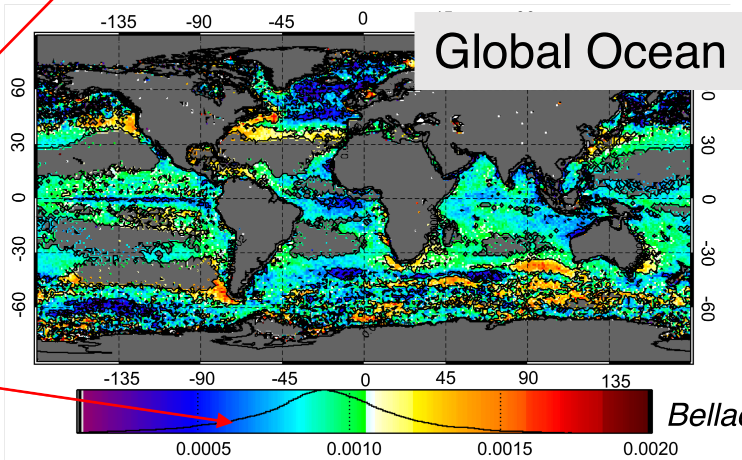


Mediterranean Sea

Bellacicco et al., (2016)



Global Ocean

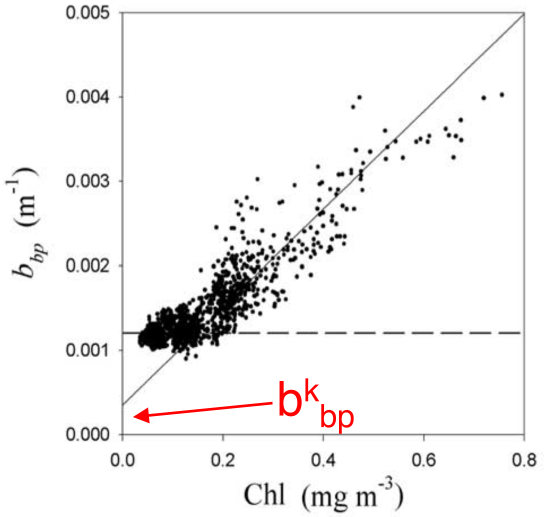


Bellacicco et al., (2018)

Background backscattering coefficient of NAP (b^k_{bp})

Linear Model:
- *Behrenfeld et al.*, (2005)
- *Bellacicco et al.*, (2016)
- *Bellacicco et al.*, (2018)

$$b_{bp} = k \cdot Chl + b^k_{bp}$$



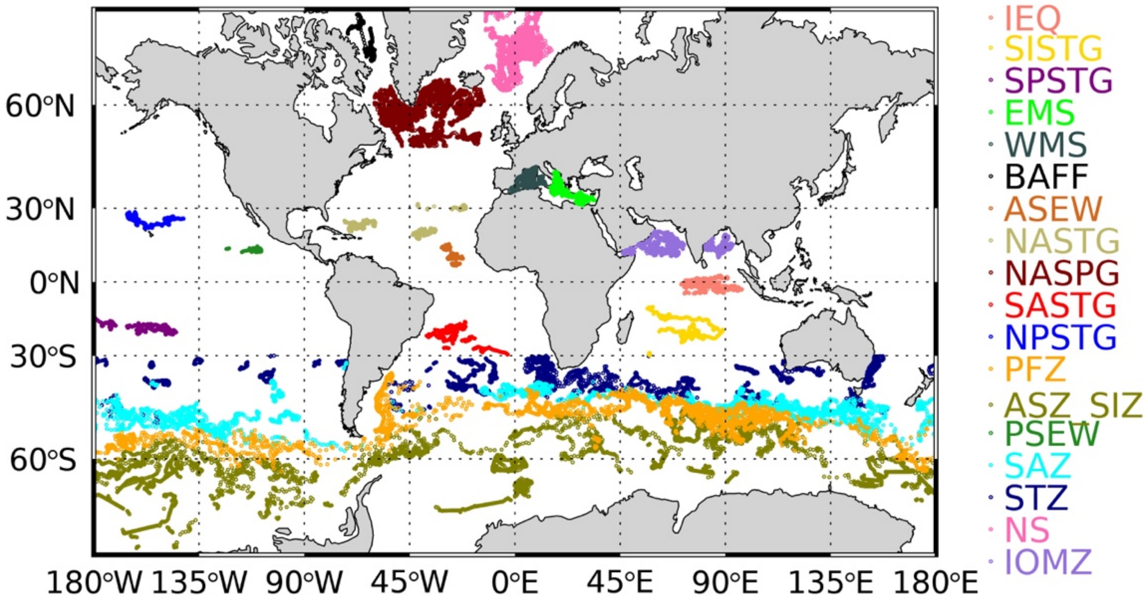
Non-Linear Model:
Brewin et al., (2012)

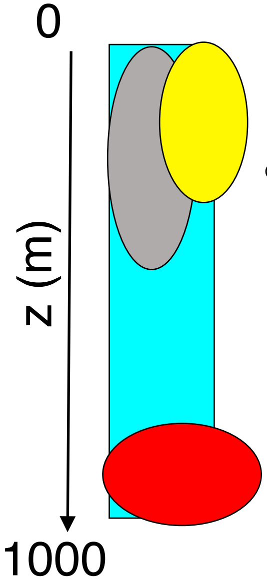
$$b_{bp} = k \cdot Chl + c \cdot [1 - e^{(-d\ Chl)}] + b^k_{bp}$$

Why?
- The model takes into account phytoplankton populations (small and large phytoplankton cells (say *c* and *d* coefficients);
- The model overcomes the limits of a simple linear correlation between the Chl and b_{bp};
- The model works also in case of oligotrophic waters (low Chl; the subtropical gyres).

Results @MTR – Task #2

Bellacicco et al., (2019; GRL)





In-situ Dataset:

- BGC-Argo global dataset of Fluorescence-Chlorophyll-*a* (converted to Chl) and b_{bp} (700nm);

"satellite" layer (first optical depth)

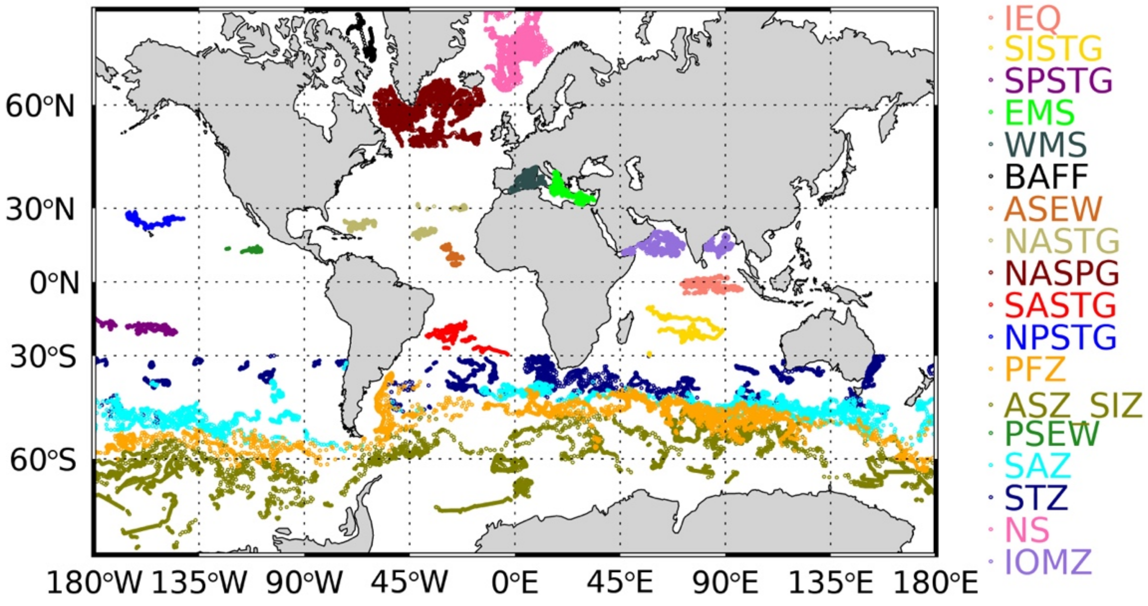
euphotic layer

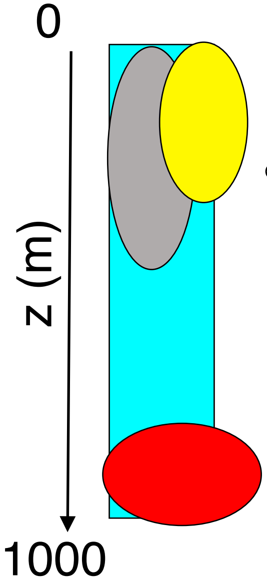
deeper layer, 950-1000 meters of depth (Chl is 0; $b_{bp} = b^{k}_{bp}$

Bellacicco et al., (2019; GRL)

Results @MTR – Task #2

Bellacicco et al., (2019; GRL)





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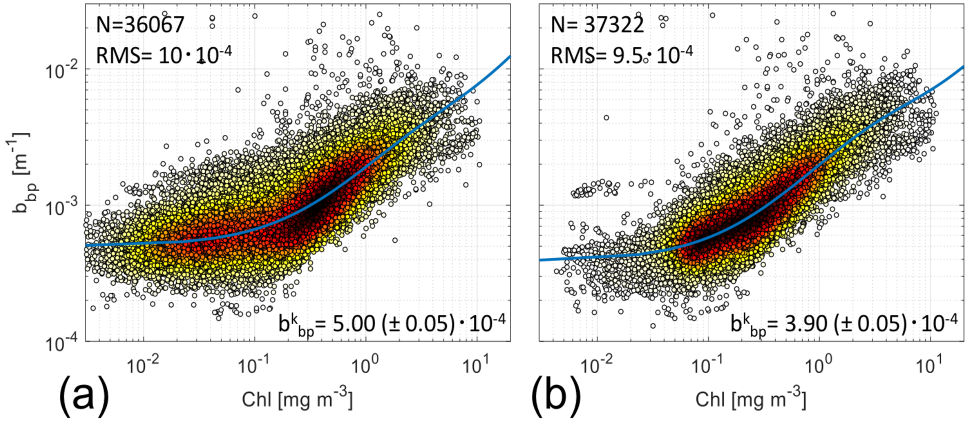
deeper layer, 950-1000 meters of depth (Chl is 0; $b_{bp} = b^{k}_{bp}$

Satellite layer   Euphotic layer

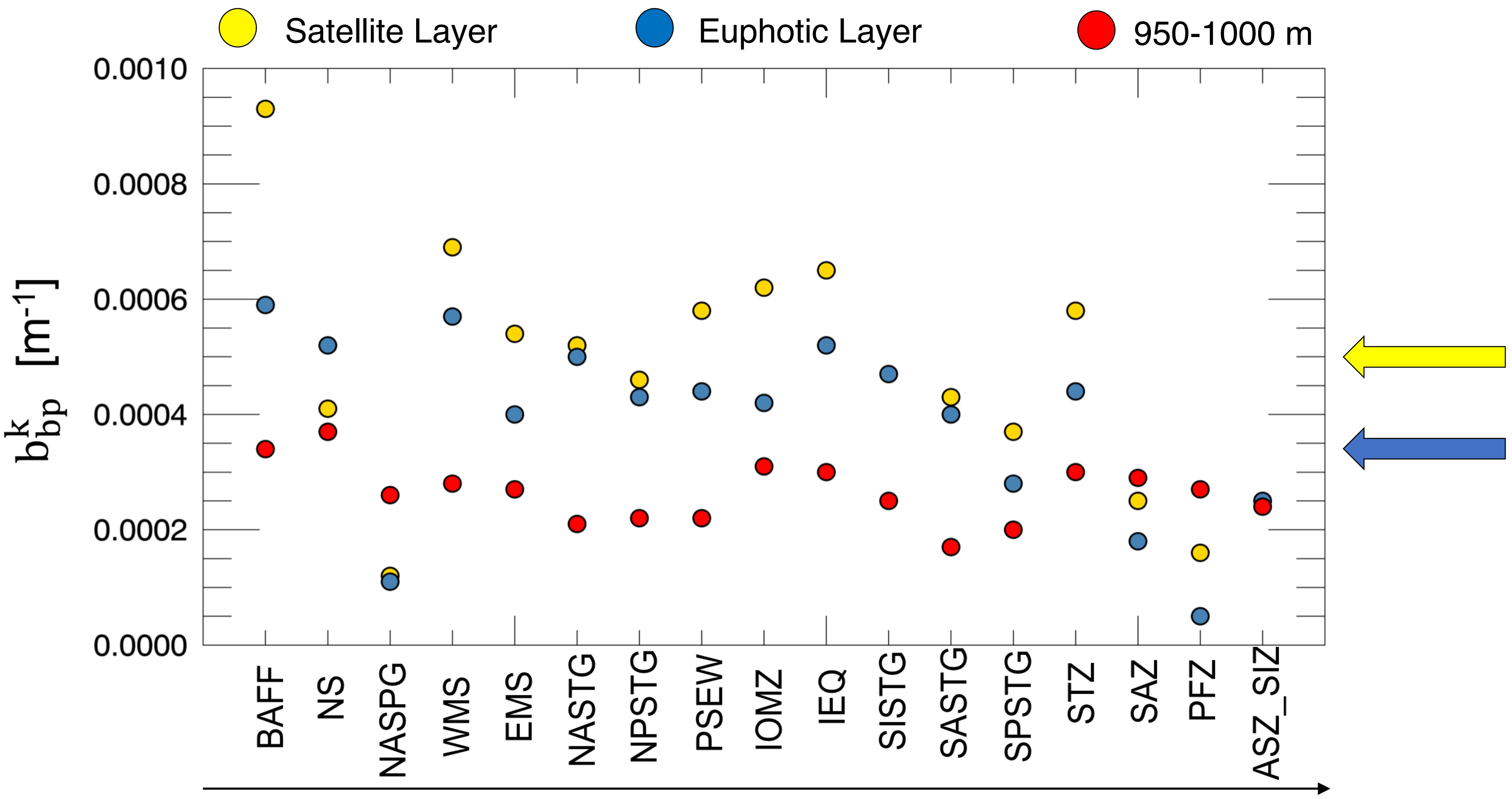


b^{k}_{bp} all points

- This is the first assessment of b^{k}_{bp} in different layers;
- The b^{k}_{bp} shows a different value in respect to what currently used by oceanographic community (0.00035 m^{-1}).

Bellacicco et al., (2019; GRL)

Results @MTR – Task #2

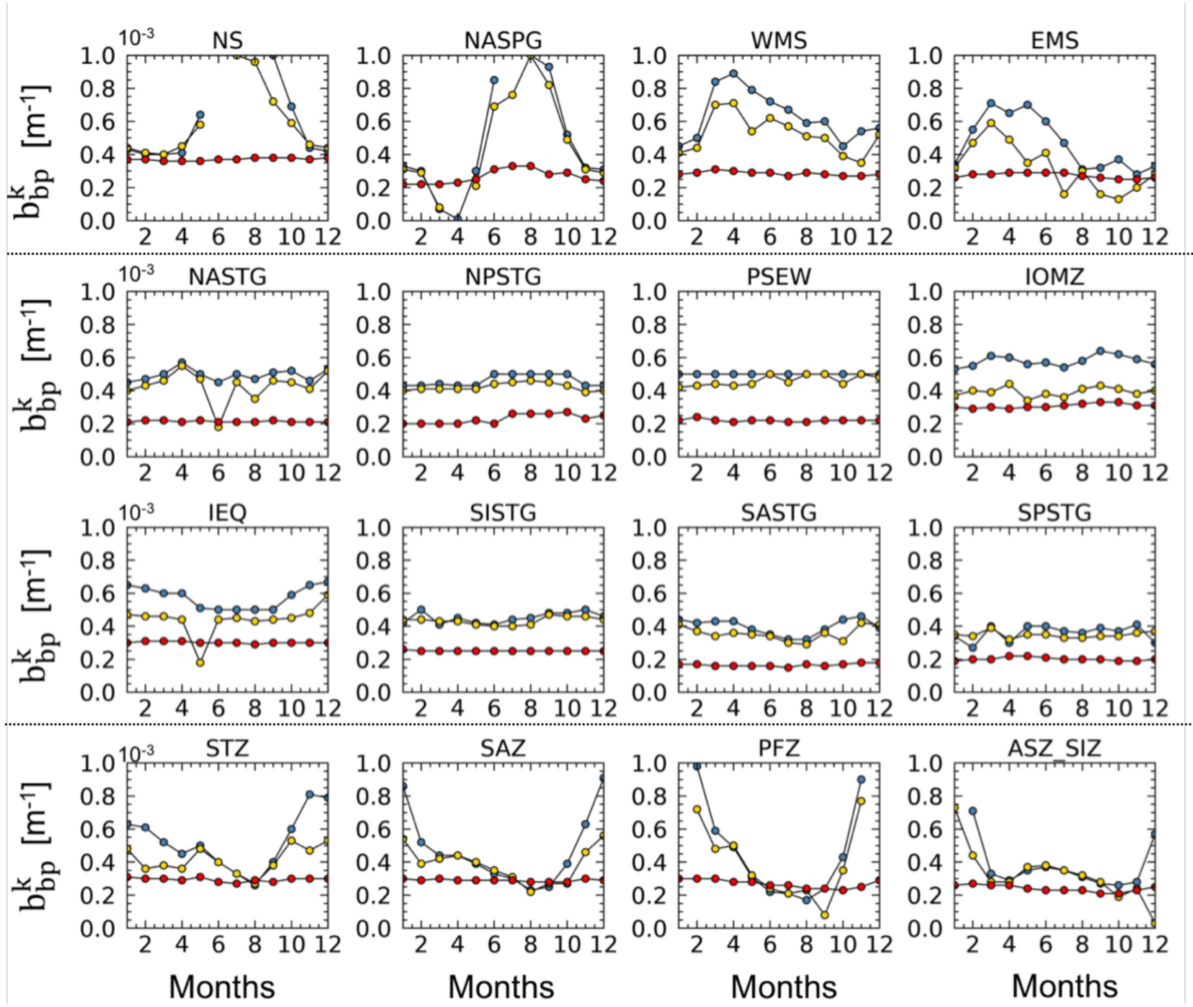


b^k_{bp} all points

b^k_{bp} spatially-resolved

Bellacicco et al., (2019; GRL)

b^k_{bp} spatially and temporal resolved



Northern hemisphere

Subtropical gyres & equatorial areas

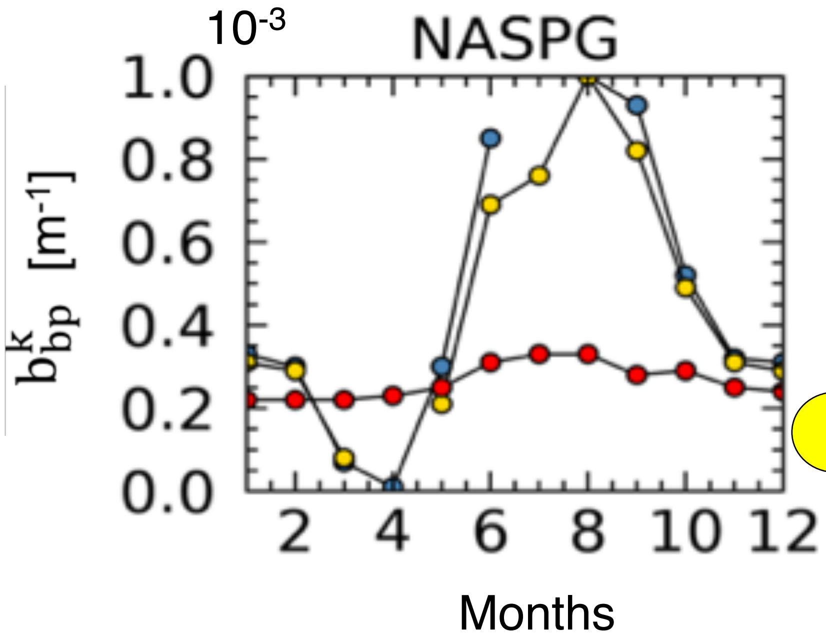
Southern Hemisphere

Bellacicco et al., (2019; GRL)

Results @MTR – Task #2

b^k_{bp} spatially and temporal resolved

North-Atlantic Sub-Tropical Gyre

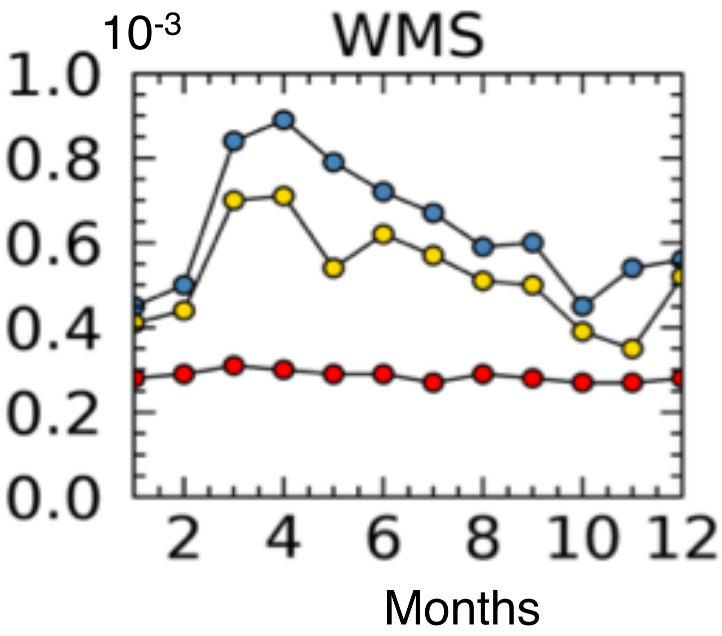


b^k_{bp} spatially resolved

b^k_{bp}-all points

b^k_{bp} spatially resolved

Western Mediterranean Sea



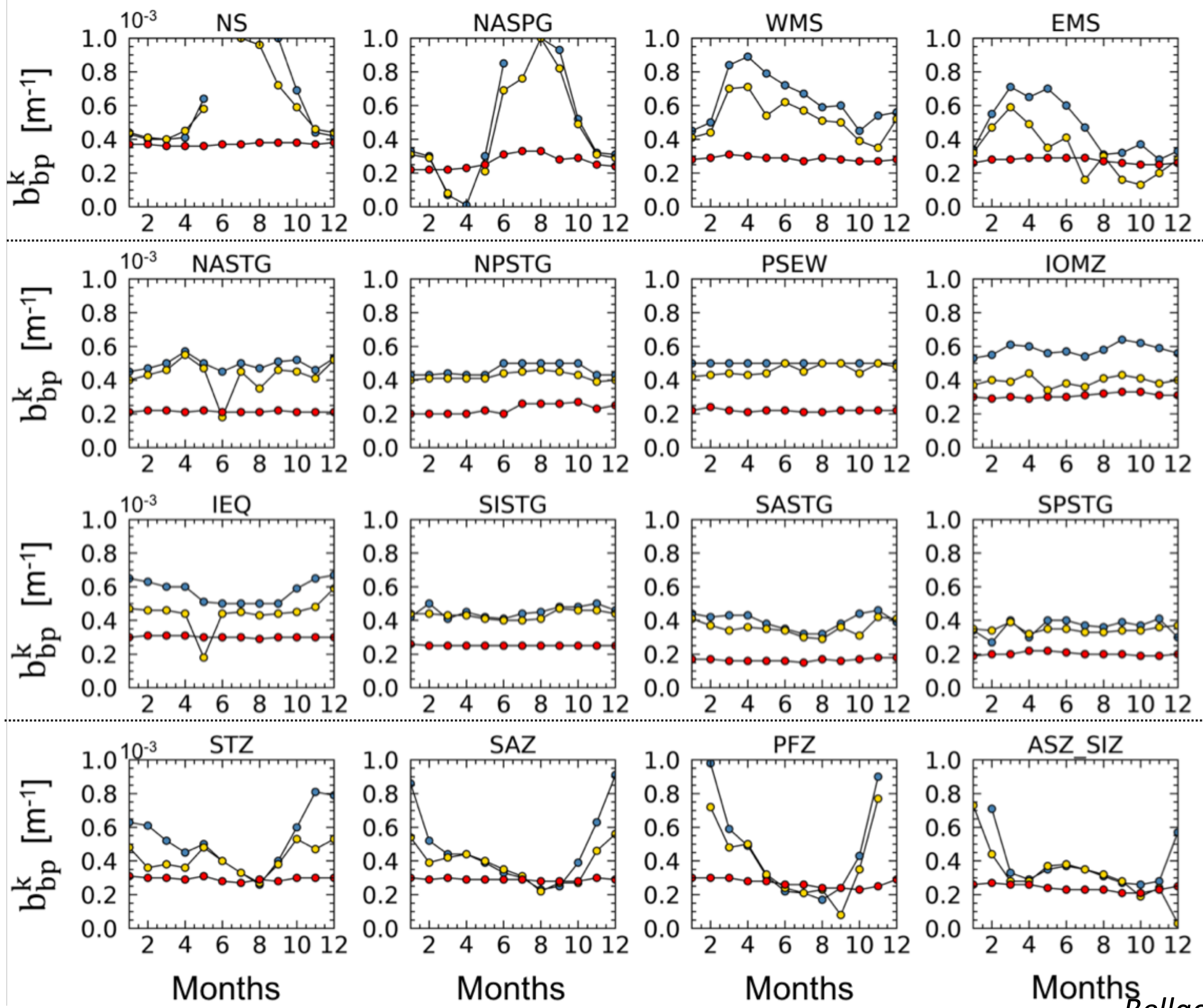
Bellacicco et al., (2019; GRL)

Results @MTR – Task #2

b^k_{bp} spatially and temporal resolved

b^k_{bp} varies in space and time capturing seasonal cycle at mid- and high latitudinal regions

Inclusion of its spatio-temporal variability in C_{phyto} is mandatory



Northern hemisphere

Subtropical gyres & equatorial areas

Southern Hemisphere

Bellacicco et al., (2019; GRL)

Status @MTR

$$C_{phyto} = [b_{bp}(\lambda) - b^{k}_{bp}(\lambda)] \cdot SF$$

Resume of work tasks:

1. Focus on QAA algorithm for detection of b_{bp} from space: a possible update? Raman Correction inclusion
2. Does b^{k}_{bp} varies in space and time or not?
3. Estimation of a refined C_{phyto} from space and validation with in-situ data
4. Extraction and study of the main oscillatory modes of the physiological signal ($Chl:C_{phyto}$) in relation to physical and climate forcing agents on a global ocean scale by using long-term satellite observations (from 1997 up to today)

Status @MTR

$$C_{phyto} = [b_{bp}(\lambda) - b^{k}_{bp}(\lambda)] \cdot SF$$

Resume of work tasks:

1. Focus on QAA algorithm for detection of b_{bp} from space: a possible update? Raman Correction inclusion ✓
2. Does b^{k}_{bp} varies in space and time or not? $b^{k}_{bp}(\lambda)$ = f (lat, lon, time) by using a non-linear model between Chl and b_{bp} ✓
3. Estimation of a refined C_{phyto} from space and validation with in-situ data
4. Extraction and study of the main oscillatory modes of the physiological signal ($Chl{:}C_{phyto}$) in relation to physical and climate forcing agents on a global ocean scale by using long-term satellite observations (from 1997 up to today)

Next Steps (2nd year) – Task #3

$$C_{phyto} = [b_{bp}(\lambda) - b^{k}_{bp}(\lambda)] \cdot SF$$

HOW???

Next Steps (2^{nd} year) – Task #3

$$C_{phyto} = [b_{bp}(\lambda) - b^k_{bp}(\lambda)] \cdot SF$$

- **Data:**
  - ✓ ESA OC-CCI daily Chl and $R_{rs}(\lambda)$ v4.0 time-series at 4 km resolution for the period 1997-2018
- **Algorithms**:
  - ✓ Application of QAA to $R_{rs}(\lambda)$ for b_{bp} retrievals including the Raman-Correction on $R_{rs}(\lambda)$

For each pixel and day → C_{phyto} (lat, lon, day) = [b_{bp} (lat, lon, day) – b^k_{bp} (lat, lon, day)] · SF (equal to 13000)

where:

- b^k_{bp} is computed using (2N+1) days centered at each single day &
- the choice of N is based on trade-off between the need of having enough data for the non-linear regression fit between Chl and b_{bp} and to remain as close as possible to the central day

→ Sensitivity Analysis: which is the best N to minimize errors in the C_{phyto} validation?

Next Steps (2nd year) – Task #3

$$C_{phyto} = [b_{bp}(\lambda) - b^k_{bp}(\lambda)] \cdot SF$$

- **Data:**
  - ✓ E
- **Algorithm**
  - ✓ A

For each pixel a

- b^k_{bp} is co
- the choic [...] gression fit between [...]

From one constant value to more than 8000 satellite daily b^k_{bp} fields at 4 km resolution for C_{phyto} space-borne estimations

Sensitivity Analysis: which is the best N to minimize errors in the C_{phyto} validation?

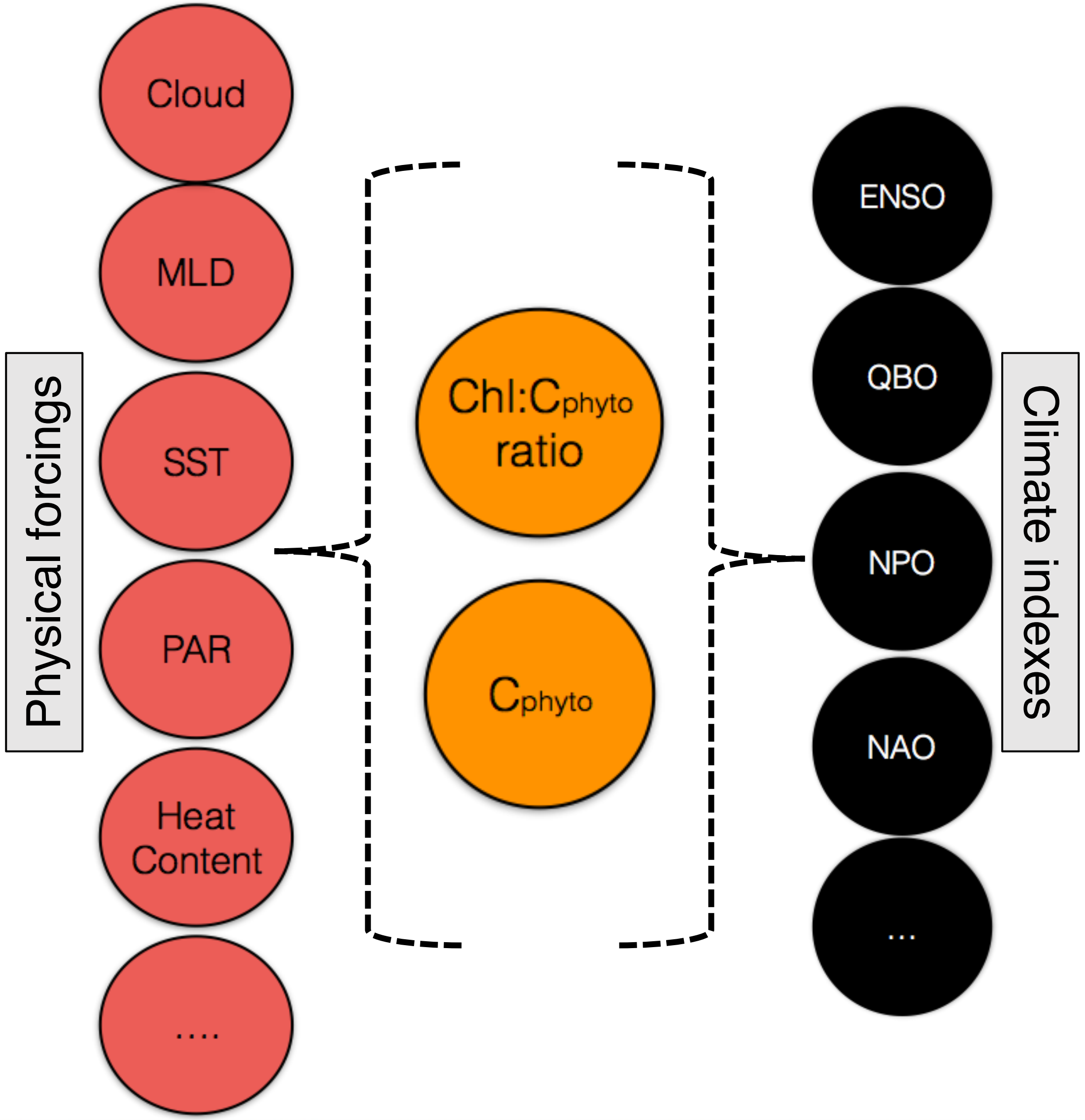
Next Steps (2nd year) – Task #4

Main sub-goals:

- to classify components of single, and coupled, time series into trends, oscillatory patterns, and noise;
- to evaluate similarities among the inter-annual variabilities of parameters;
- to understand the spatio-temporal structure associated with oscillatory modes in the biological/physiological proxies and global ocean physical fields following *Ghil et al.,* (2002), *Marullo et al.,* (2011) and *Groth et al.,* (2017).

How?

Application of advanced statistical methods for time-series analysis such as SSA, M-SSA, Wavelet Analysis



Conclusions @MTR

1. Assessment of QAA for b_{bp} retrievals with in-situ and satellite data

2. Evaluation of which is the best model for b^k_{bp} computation: linear vs non-linear approaches

3. Demonstration of b^k_{bp} spatio-temporal variability and importance of its inclusion in C_{phyto} computation → b^k_{bp} is thus not a single constant value but will be a series of daily maps at 4 km resolution.

4. Production of daily b_{bp} (443 nm, 555 nm) time-series at 4 km resolution with Raman Correction on R_{rs} included.

Expected Outputs & Papers for 2nd year

1. Daily C_{phyto} satellite product, validated with in-situ dataset after the selection of the best method for daily b^k_{bp} satellite fields at 4 km resolution from 1997 until today → *it can be very important tin order o complement Chl data in phytoplankton studies from space*

2. Chl:C_{phyto} time-series → *it can be potentially impactful also for operational biogeochemical model where Chl:C_{phyto} is usually a single constant value thus not taking into account its variability*

3. One paper about the C_{phyto} dataset (*e.g.* Earth System Science Data or Remote Sensing of Environment, similar) and al least one paper on inter-annual Chl:C_{phyto} oscillations modes in relation to physical forcings (*e.g.* temperature, heat content, nutrients, clouds, MLD, etc...) and climate indexes (*e.g.,* QBO, NAO, NPO, ENSO).

4. Conferences: Ocean Sciences Meeting @San Diego (USA); Ocean from Space @Venice (Italy); Ocean Optics @Norfolk (USA)

Publications – 1st year

PhysioGlob papers published/submitted:

- **Bellacicco, M.,** Vellucci, E., Scardi, M., Barbieux, M., Marullo, S and D'Ortenzio, F. (2019). Quantifying the impact of linear regression model in deriving bio-optical relationships: the implications on ocean carbon estimations. *Sensors*, 19, 3032.

- **Bellacicco, M.**, Cornec, M., Organelli, E., Brewin, R., Neukermans, G., Volpe, G., Barbieux, M., Poteau, A., Schmechtig, C., D'Ortenzio, F., Marullo, S. Claustre, H. and Pitarch, J. (2019). Global variability of optical backscattering by non-algal particles from a Biogeochemical-Argo dataset. *Geophysical Research Letters*, 46 (16), 9767-9776.

- Pitarch, J., **Bellacicco, M.,** Organelli, E, Volpe, G., Colella, S., Vellucci, V and Marullo, S. Retrieval of particulate backscatter using field and satellite radiometry: assessment of the QAA algorithm (*submitted*).

Other papers published/submitted/in preparation:

- **Bellacicco, M.,** Vellucci, V., D'Ortenzio, F. and Antoine, D. (2019). Discerning dominant temporal patterns of bio-optical properties in the northwestern Mediterranean Sea (BOUSSOLE site). *Deep-Sea Research: Part I*, 148, 12-24.

- Mansour, K., Decesari, S., **Bellacicco, M.,** Marullo, M., Santoleri, R., Bonasoni, P., Facchini, M.C., Ovadnevaite, J., Ceburnis, D., O'Dowd, C. and Rinaldi, M. Particulate methanesulfonic acid over the central Mediterranean Sea: relationship with phytoplankton activity and source region identification (*submitted*).

- Mansour, K., Decesari, S., **Bellacicco, M.**, Marullo, M., Santoleri, R., Bonasoni, P., Facchini, M.C., Ovadnevaite, J., Ceburnis, D., O'Dowd, C. and Rinaldi, M. Linking Oceanic Biological Activity to Aerosol Chemical Composition and Cloud-Relevant Properties over the North Atlantic (*in preparation*).

THANKS FOR THE ATTENTION!

Collaborations with:

marco.bellacicco@enea.it

ISMAR NIOZ LOV OBSERVATOIRE OCEANOLOGIQUE VILLEFRANCHE/MER PML Plymouth Marine Laboratory Università di Roma Tor Vergata