Optical classification in contrasted coastal waters for monitoring water masses and improving the assessment of ocean color products

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Ocean color applications in coastal waters

Inversion algorithms (empirical or semi-analytical)

Satellite information (reflectance) -> Biogeochemical parameters

General relationships are not valid in the coastal ocean

- High biogeochemical and optical complexity of coastal ecosystems
- Large dispersion around general relationships
1rst Approach: Regional inversion algorithms

**Advantage:**
Convenient to develop

**Inconvenients:**
- Depends strongly on the data set used
- Might be inadequate even for a define area and season due to the various high frequency processes occurring in coastal waters

![Graph showing Chl.a vs max(Rrs443,490,510)/Rrs555](graph1.png)

![Graph showing Chla in-situ vs Chla computed from 3 algorithms](graph2.png)
2nd approach: Classification-based algorithms

Explicitly takes into account the optical characteristics of each pixel within the development of the bio-optical algorithms

In practice:

1) Determine the main patterns of optical variability (reflectance spectra classes)
2) Develop Class specific bio-optical algorithms
3) Identify the optical characteristics (classes) of each pixel
4) Apply Class-specific algorithm (empirical or semi-analytical)

Advantage:

Independent of the location/period
→ More « universal » approach

Requirements:

➢ Cover the diversity of the spectra gathered from satellite measurements
➢ Associate the RS spectra to the proper in situ optical class
➢ Derive relevant bio-optical algorithms
Data set

\[ N_{\text{tot}} = 167 \]

French Guiana

North Sea (MUMM, Belcolour)

Optical (Rrs, IOPs: absorption and backscattering) and biogeochemical (Chla, SPM, POC...) data collected in different coastal waters encompassing large biogeochemical and bio-optical variability, from bloom conditions to sediment-loaded waters:

- **Chla**: 0.06 - 41 mg.m\(^{-3}\)
- **SPM**: 0.1-120 mg.l\(^{-1}\)
- **\(a_{\text{CDOM}}(355)\)**: 0.019 - 3. m\(^{-1}\)
- **\(b_{bp}/b_p\)**: 0.002- 0.05
$R_{rs}$ in situ variability: Hyperspectral Data

Ascendant hierarchical clustering (Ward’s algorithm) on normalised $R_{rs}$ spectra

→ 4 classes (coherence with Lubac and Loisel, 2007)
→ Spectra from different time periods and locations
Spectral Classes Characteristics

**Class 1:**
- $b_{bp}/b_p = 0.014$
- $a_{phy} / a_p = 64\%$
- $a_{cdom}/a_{tot} = 53\%$

Mixed class

**Class 2:**
- $b_{bp}/b_p = 0.013$
- $a_{phy} / a_p = 86\%$
- $a_{cdom}/a_{tot} = 53\%$

Mixed class (more phytoplankton dominated)

**Class 3:**
- $b_{bp}/b_p = 0.019$
- $a_{phy} / a_p = 10\%$
- $a_{cdom}/a_{tot} = 0.1\%$

No CDOM and dominated by non-algal particles (sediments and detritus)

**Class 4:**
- $b_{bp}/b_p = 0.009$
- $a_{phy} / a_p = 97\%$
- $a_{cdom}/a_{tot} = 84\%$

Phytoplankton dominated and high Colored Dissolved Organic Matter
French Guiana

Classes Distribution

Turbid waters

10 Oct 2002

9 Oct 1999

Mean Spectra SeaWiFS

Novelty Detection technique
Application:

Does the class-based approach improve the SPM retrieval?

Water reflectance: $\rho_{w}(670)$
Performance of class-based algorithm for SPM retrieval

In situ data only

In situ data only
### Classes RMS

**Not Classified**

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<th>Classes</th>
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<th>RMS Not Classif</th>
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<td>&lt;10 mg.l⁻¹</td>
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Application to MODIS Data, French Guiana

**MODIS:**
A global data set providing a 9-year time series of a consistent, well calibrated, ocean colour record.

**Period:**
June 2002 - November 2010
(102 monthly data)

**Grid:**
1x1 km

**Product:**
L2 (processing 2009.1, OBPG/NASA)

Improved detection between clouds and turbid waters (Nordkvist et al., 2009)
Strong trends (up to 6%/yr) in TSM concentration over the MODIS time period

→ Alternation between increasing and decreasing TSM areas

→ TSM variability reflects mudbanks migration over the French Guiana coastal domain
Mudbanks migration

Allison and Lee, 2004

Mudbank

2002

2010
Mud banks migration

A: back of the mud bank in 2002
B: front of the mud bank in 2010

Bank area $\approx$ 225-300 km$^2$

Mud bank migration rate $\approx$ 2 to 3 km yr$^{-1}$ $\rightarrow$ Gardel and Gratiot, 2005
Mud banks migration

Time series decomposition

Census X-11 procedure
Vantrepotte et al., 2011, GRL
Vantrepotte and Mélin, 2011, DSR

→ Abrupt shifts in TSM concentrations
→ Presence of low frequency processes inducing peak events in TSM
Classification of the $R_{rs}$ data has allowed to identify 4 distinct classes characterised by different bio-optical environments.

The 4 in situ $R_{rs}$ classes depict almost all the satellite identified turbid waters (SeaWiFS).

Benefits for improving inversion algorithms (i.e. SPM retrieval).

→ These results suggest that the establishment of class-specific AOPs, IOPs-BC relationships has a meaning.

→ Ocean color TSM estimates as a good proxy for monitoring mudbanks dynamics over the French Guiana coastal waters.
What next?

Optical classes global distribution

ANR GlobCoast
THANK YOU!

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