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$\rho RC\lambda = \rho gC\lambda - \rho Ray\lambda = \rho aer\lambda + td\lambda . \rho w \lambda + \varepsilon$ (1)

MEETC2: Ocean Color Atmospheric corrections in coastal complex waters using a Bayesian latent class model and potential for the incoming Sentinel 3 - OLCI mission

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1.Context

- From the multispectral top-of-atmosphere observations, ocean colour inversion aims at separating atmosphere and water contribution. In this context, we propose a novel Bayesian model with a focus on the definition of non-homogeneous priors on the aerosol and water multispectral signatures. The considered priors are set conditionally to observed covariates, typically geometry acquisition conditions and pre-estimates by a standard algorithm. We demonstrate from numerical experiments performed for real data the relevance of our non-homogeneous Bayesian setting to retrieve geophysically-consistent ocean colour images, in particular when dealing with complex coastal waters where standard algorithms perform poorly. Using a ground truthed dataset, quantitative comparisons with operational schemes stress the overall improvement on the relative absolute error (respectively, 37% compared with the standard ESA MEGS algorithm and 9% compared with the ESA C2R neural network, for 12 bands ranging from 412 to 865 nm).

2. Method

- Ocean color inversion amounts to relate multispectral water reflectance to top-of-atmosphere satellite measurements. We consider here the Rayleigh corrected reflectance variable $\rho_{RC}(\lambda)$:

$$\rho_{RC}(\lambda) = \rho_{gC}(\lambda) - \rho_{Ray}(\lambda) = \rho_{aer}(\lambda) + t_d(\lambda).\rho_w(\lambda) + \rho_{coupl}(\lambda) + \varepsilon \qquad (1)$$

- In our scheme, the variables to be estimated are $x_w = \{h_i\}$, the coordinates of ρ_w in a Non-Negative Matrix Factorization (Lin, 2007) reference spectrum, and $x_a = \{a_i\}$ the polynomial coefficients of the aerosol models (We consider here a 3 order polynomial to model the aerosol reflectance and the coupling term). The diffuse transmittance t_d is the product of both air molecules and aerosol particles scattering.

- We consider a Bayesian model which introduces priors on the variable to be estimatedand ressort to maximizing the a posteriori likelihood (MAP criterion):

$$P(x_a, x_w | \rho_{RC}, \varphi_a, \varphi_w) \; \alpha \; P(\rho_{RC} | x_a, x_w, \varphi_a, \varphi_w) \,.\, P(x_a | \varphi_a).P(x_w | \varphi_w) \qquad (2)$$

In (2), the first likelihood term evaluates the relevance of the observed TOA measurements with respect to variables x_a and x_w. The second and third term refers to the prior on each variable, where covariates φ act as a conditioning covariates.

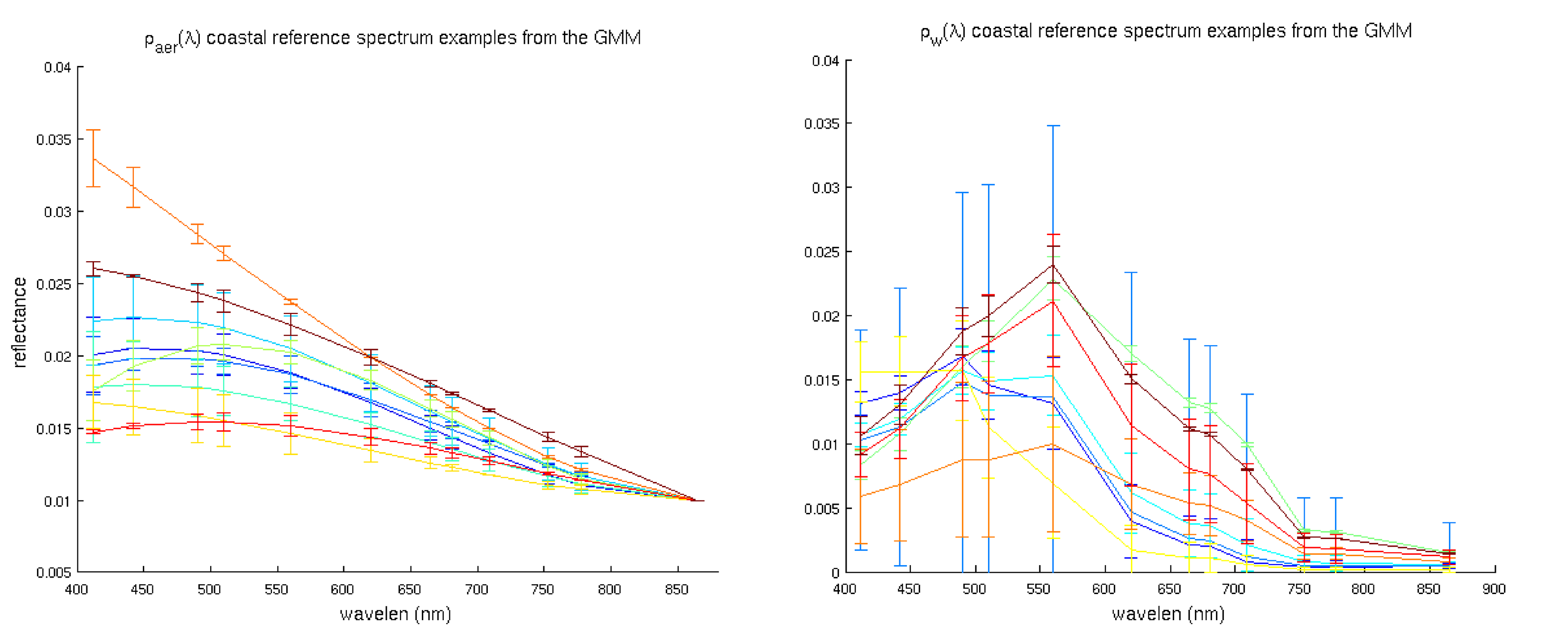
- From a physical point of view, the acquisition geometry (Θs, the sun zenith angle, Θv, the view zenith angle, and δψ, the delta azimuth) affect both the aerosol and water reflectance spectra. Besides, we argue that a preliminary analysis of the NIR part of the spectrum during the standard BPAC procedure, especially estimates of variables $\rho_{aer}(865)$ and β (aerosol's slope) and resulting $\rho_w(780)$ initial estimate, also provide valuable cues for the inversion of (1).

- We set the priors as latent class regression models derived from a Gaussian Mixture Model (GMM) of the joint distribution of extended variables $X_w = \{x_w \; \varphi_w\}$ and $X_a = \{x_a \; \varphi_a\}$ with water covariates $\varphi_w = \{\rho_w(780), \Theta_v, \Theta_s\}$ and aerosol covariates $\varphi_a = \{\rho_{aer}(865), \beta, \Theta_v, \Theta_s\}$:

$$P(x_w|\varphi_w) = \sum_i \Lambda_{x_w|\varphi_{w,i}} \, g_{\Sigma_{x_w|\varphi_{w,i}}}(x_w - \mu_{X_w|\varphi_{w,i}}) \qquad (3)$$

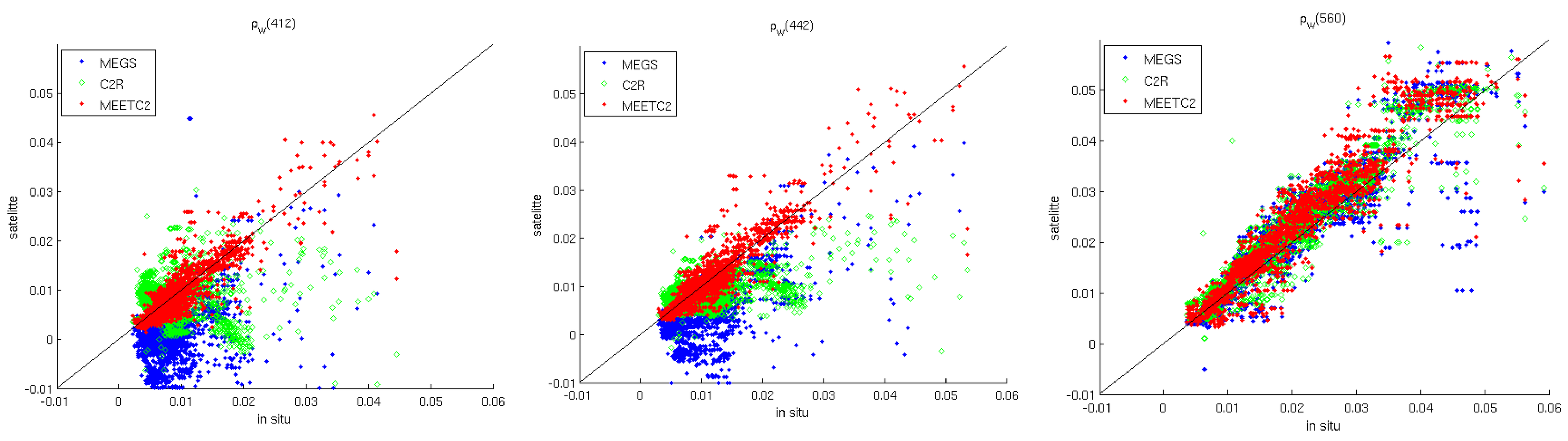
$$P(x_a|\varphi_a) = \sum_j \Lambda_{x_a|\varphi_{a,j}} \, g_{\Sigma_{x_a|\varphi_{a,j}}}(x_a - \mu_{X_a|\varphi_{a,j}})$$

- Examples of calibrated water and aerosol reflectance spectra (training dataset)

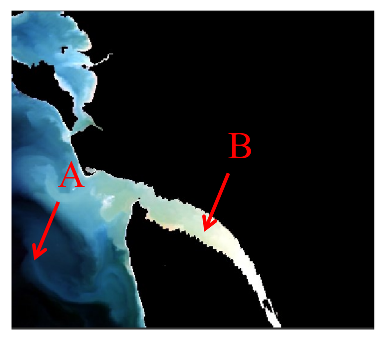


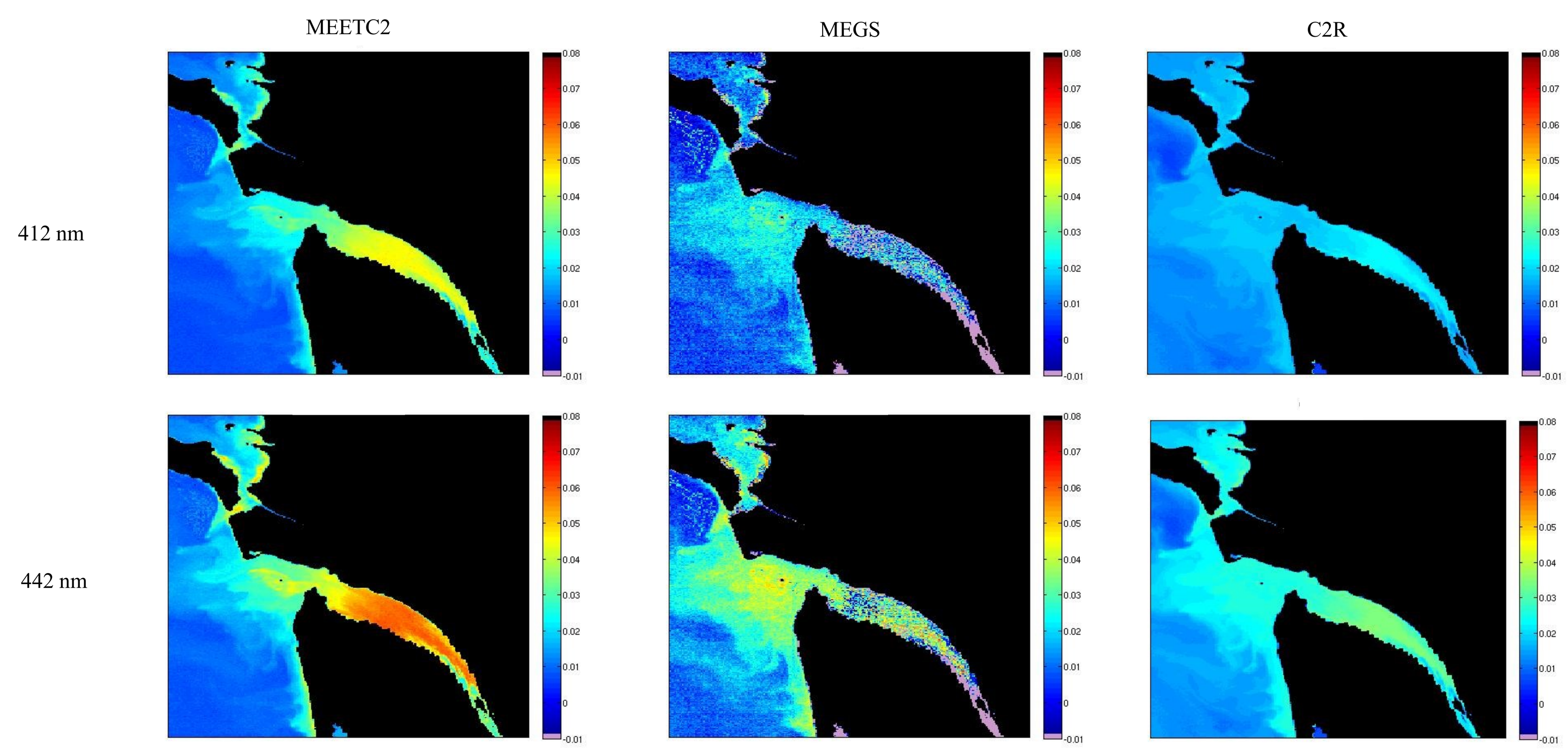
3.Numerical experiment

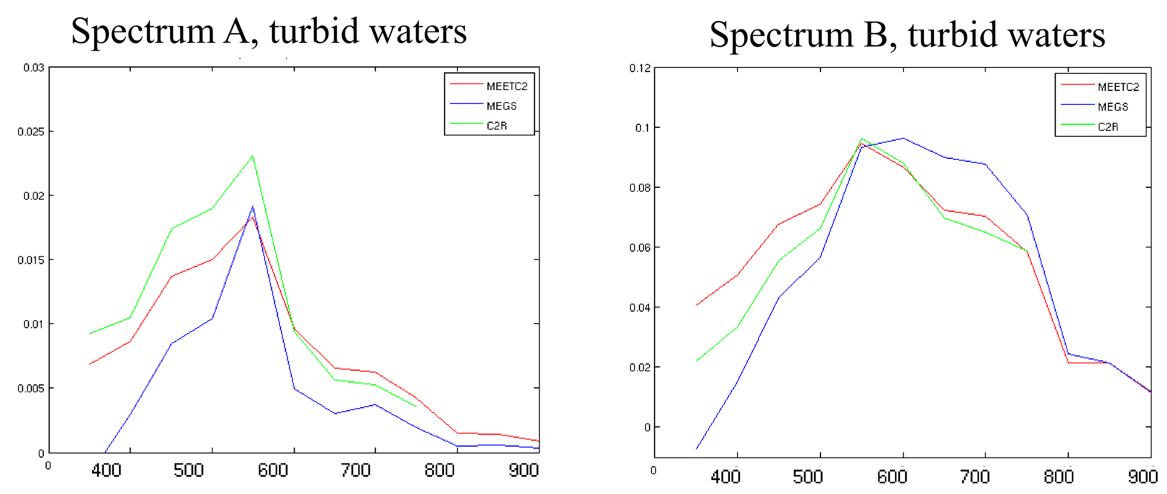
- The MERMAID (http://mermaid.acri.fr/home/home.php) in-situ matchup database is a comprehensive dataset that gathers in-situ measurements of water leaving radiances, IOPs, and MERIS TOA reflectances. To validate the proposed methodology, radiometric in-situ profile dataset have been divided randomly in two independent datasets: a training dataset (to estimate model parameters and a validation dataset.



Ocean color inversion results:
MERISFR 20090322, Gironde's Estuary

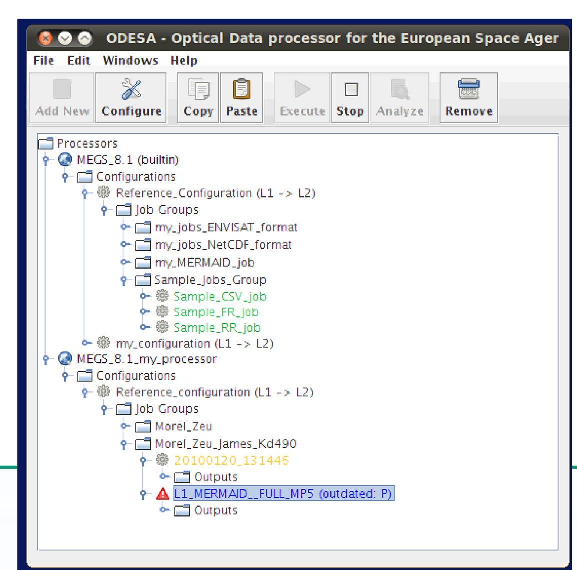






4.Towards an operational algorithm for OLCI

- The ambition of a Case1&2 algorithm to inverse operationally the OLCI water leaving reflectances: the Bayesian formalism is particularly suitable to address transitions between water types.
- An incoming training using radiative transfer simulations (coupled ocean + atmosphere) to cover the possible range of geometry, water and aerosol conditions.
- A parallelized code distributed freely in Odesa (The algorithm involves multiple initialisations and requires therefore important processing resources) **http://www.odesa-info.eu/info/.**



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