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).

We consider a Bayesian model which introduces priors on the variable to be estimated and resorted to maximizing the a posteriori likelihood (MAP criterion).

\[
P(x, \{\rho_{\text{at}}(\lambda), \phi_L(\lambda), \rho_w(\lambda)\}) = P(x|\{\rho_{\text{at}}(\lambda), \phi_L(\lambda), \rho_w(\lambda)\})P(\{\rho_{\text{at}}(\lambda), \phi_L(\lambda), \rho_w(\lambda)\}) \tag{2}
\]

In (2), the first likelihood term reveals the relevance of the observed TOA measurements with respect to variables \(x_\text{a}\) and \(x_\text{w}\). The second and third term refer to the prior on each variable, where covariates \(\phi\) act as a conditioning covariates.

From a physical point of view, the acquisition geometry (\(\Omega_\text{s}\), the sun zenith angle, \(\Omega_\text{v}\), the view zenith angle, and \(\delta_{\phi}\), 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 \(\rho_{\text{at}}(865)\) and \(\beta\) (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 \(X_\text{a} = \{x_\text{a}, \phi_L(\lambda), \rho_w(\lambda)\}\) with water covariates \(\phi_L(\lambda)\) (with water radiances, \(\phi_L(\lambda)\) and aerosol covariates \(\phi_{\text{at}} = \{\rho_{\text{at}}(865), \delta_{\phi}\}\)) and initial estimate, also provide valuable cues for the inversion of (1).

\[
P(x_\text{a})(\lambda) = \sum_{j=1}^{k} \pi_j \mathcal{N}(x_\text{a}^{(j)}(\lambda) - \mu_j, \Sigma_j) \tag{3}
\]

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