

Uncertainties of inherent optical properties in the Dutch Lakes

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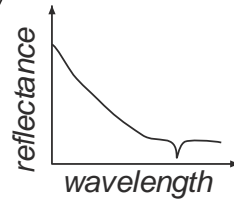
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- Acknowledgement

Concept

The primary measurement of EO data over water is the visible light leaving the water column

In inland and coastal waters, this water leaving radiance is strongly affected by different materials, e.g. terrigenous particulate and dissolved materials, re-suspended sediment or highly concentrated phytoplankton bloom

sensor's instantaneous field of view



observed reflectance by the sensor at a pixel size

direct and diffuse incident sun light



scattering and absorption by atmospheric constituents

adjacent reflectance

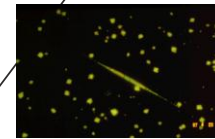
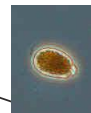
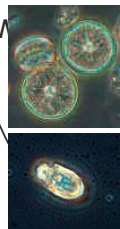
surface reflectance

water leaving reflectance

scattering, absorption and remittance by water constituents

suspended particles

Phytoplankton



bidirectional substrate reflectance

Challenges

Remote sensing of inland and coastal waters is quite challenging due to the complicated signals from turbid water, substrate reflectance and adjacent land surfaces



What you see is not what you get!

Requirements and objective

Consistent EO-estimates of water quality parameters in inland and coastal waters requires three components:

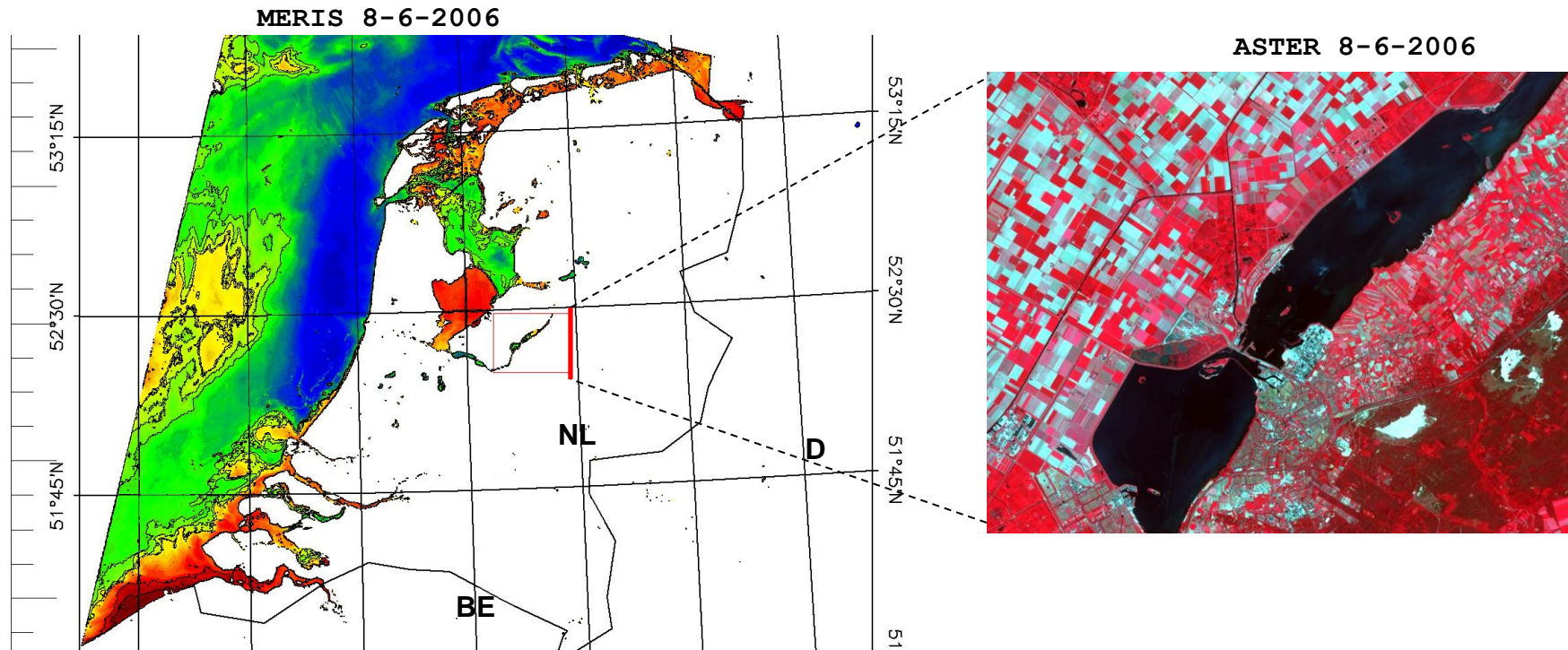
- (i) a reliable atmospheric correction method;
- (ii) an accurate retrieval algorithm and
- (iii) an objective method to estimate the uncertainty budget based on their sources

The objective :

- Applying and adapting state of the art retrieval algorithms
- Quantifying the uncertainties on the retrieved parameters and the relative contribution of each fluctuation to the total error budget

Data sets

- In situ measurements Eagle2006 and (A. Dekker): Dutch Lakes
- EO data: ASTER, MERIS, and AHS: Dutch Lakes
- NOMAD-match-ups
- Simulated data, IOCCG (Lee 2006)



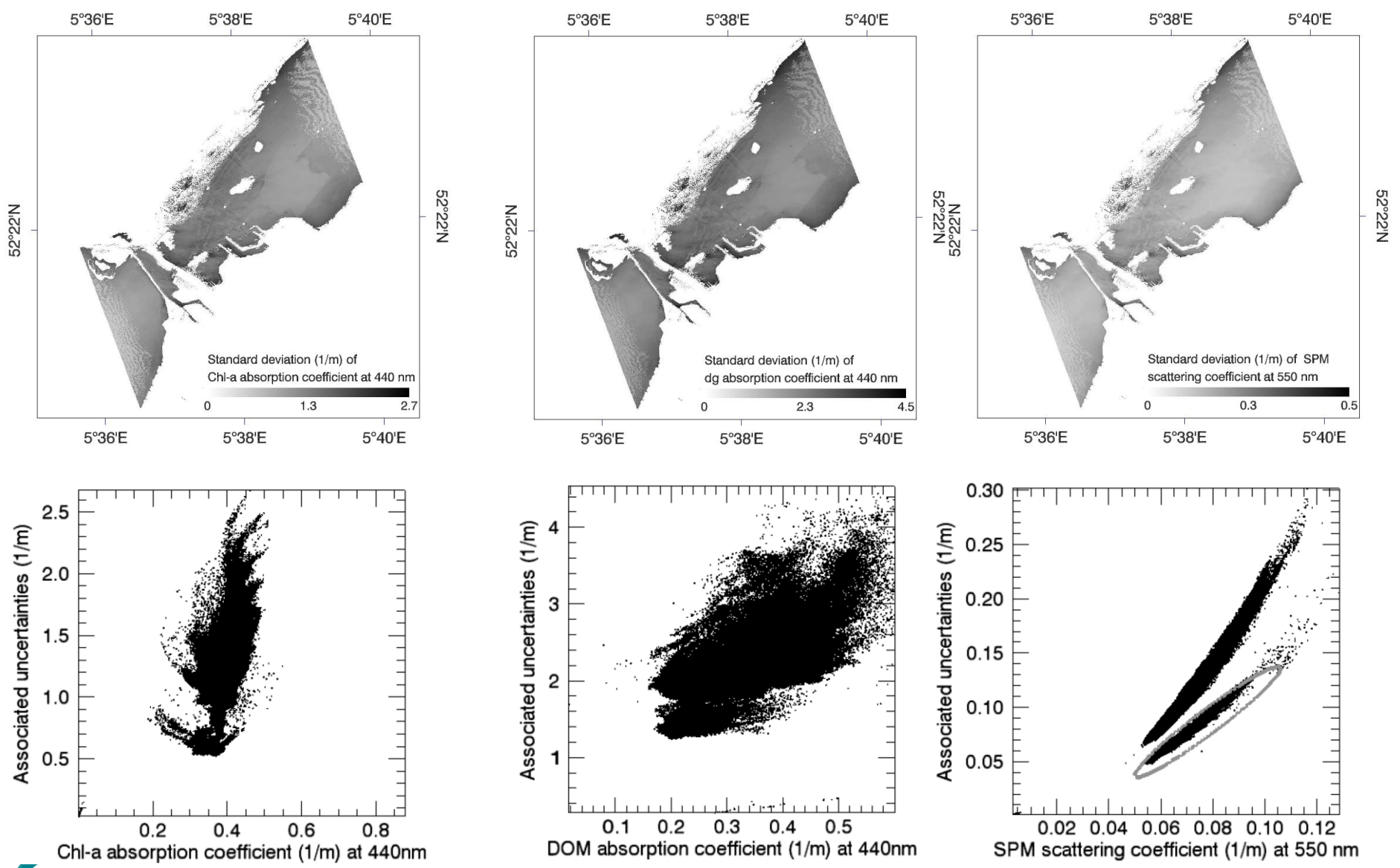
Semi-analytical ocean color models

Semi-analytical ocean color models are based on approximations that link remote sensing reflectance and the inherent optical properties. The general form of most of these models is that water remote sensing reflectance is proportional to the backscattering coefficient and inversely proportional to the absorption coefficient

Example, the GSM model (Maritorena et al. 2002)

$$R_{rs}(\lambda) = f \sum_{i=1}^2 g_i \left(\frac{b_b(\lambda)}{b_b(\lambda) + a(\lambda)} \right)^i$$

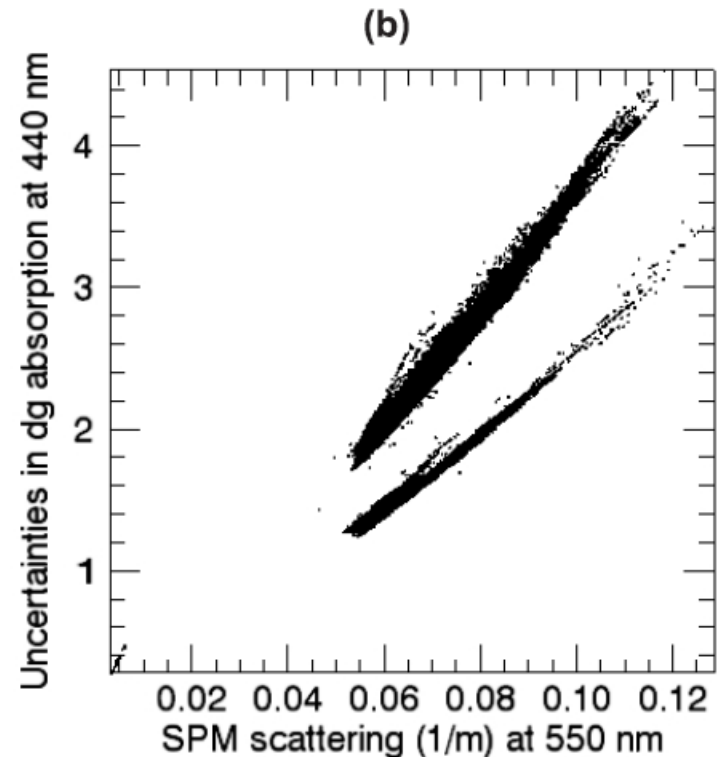
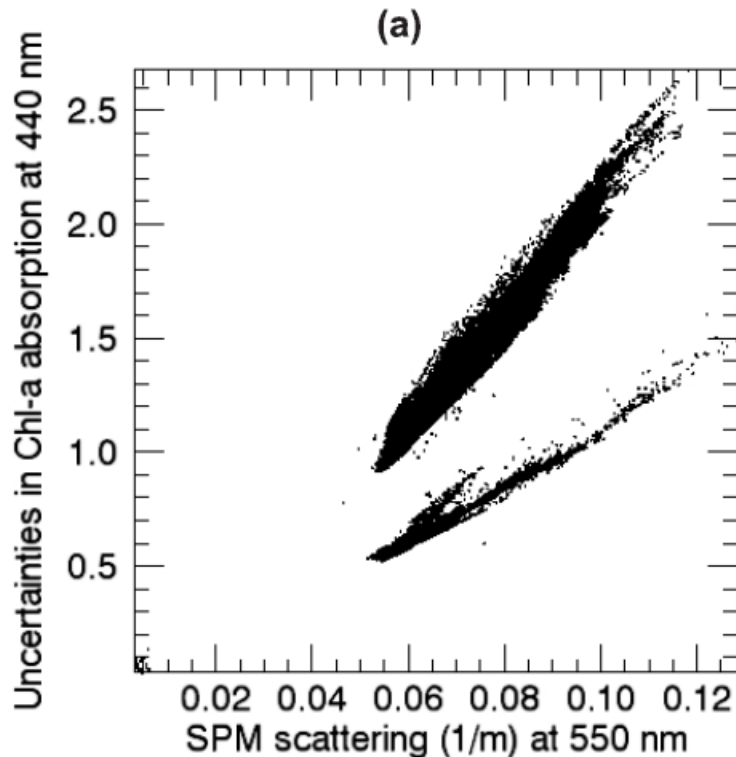
Uncertainties due to model inversion: standard



Bates and Watts 1988, Salama 2003, Maritorna et al. 2005, Wang et al. 2005, Salama et al. 2009

Uncertainties due to model inversion: standard

- In this specific case all inversion-uncertainties seem to be related to water turbidity



Inversion-uncertainty of derived IOPs is proportional to water turbidity and is not representative of our confidence about the derived products from remote sensing data

Sensitivity of ocean color model

- We can use Taylor expansion as

$$Rrs(\mathbf{iop}) = Rrs(\mathbf{iop}_0) + \sum_{n=1}^{\infty} \frac{1}{n!} Rrs^{(n)}(\mathbf{iop}_0)(\mathbf{iop} - \mathbf{iop}_0)^n$$

- In our case Rrs is observed radiance, $Rrs^{(n)}$ is the n th partial derivative of R w.r.t each of the \mathbf{iop}
- \mathbf{iop} is the real IOPs which are unknowns
- \mathbf{iop}_0 is the derived IOPs from ocean color radiances
- If we truncate Taylor series to leave the first term we will have

$$Rrs(\mathbf{iop}) - Rrs(\mathbf{iop}_0) = f'(\mathbf{iop}_0)(\mathbf{iop} - \mathbf{iop}_0)$$

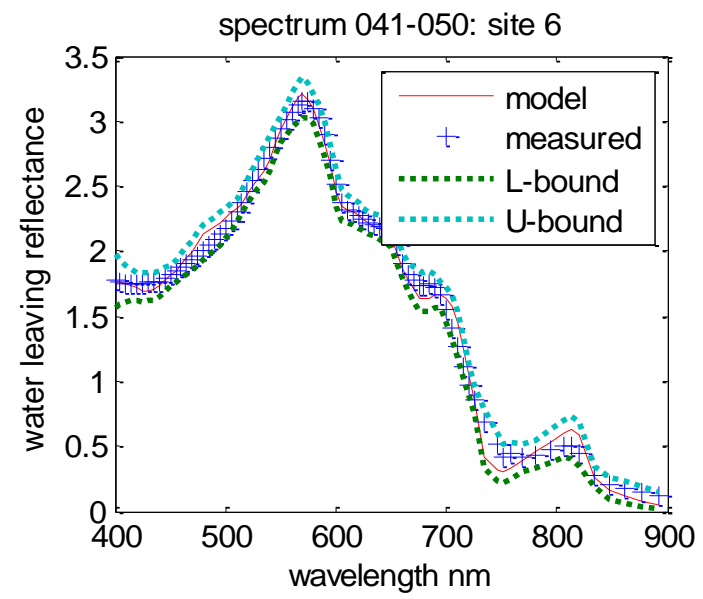
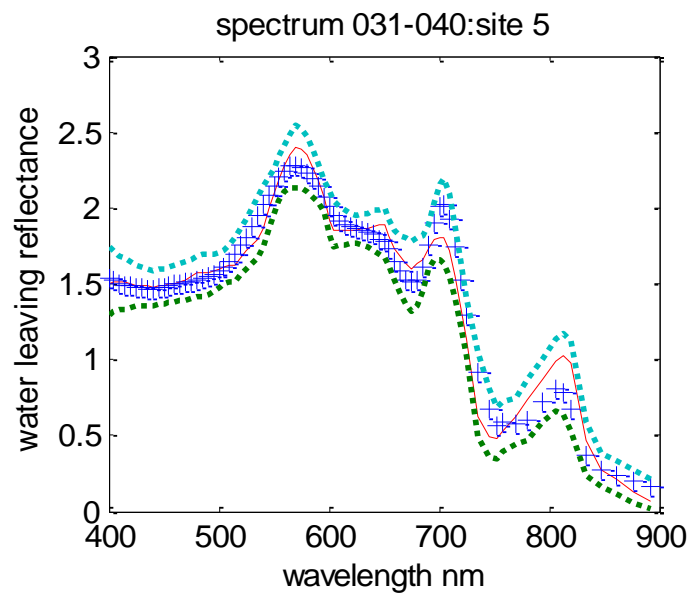
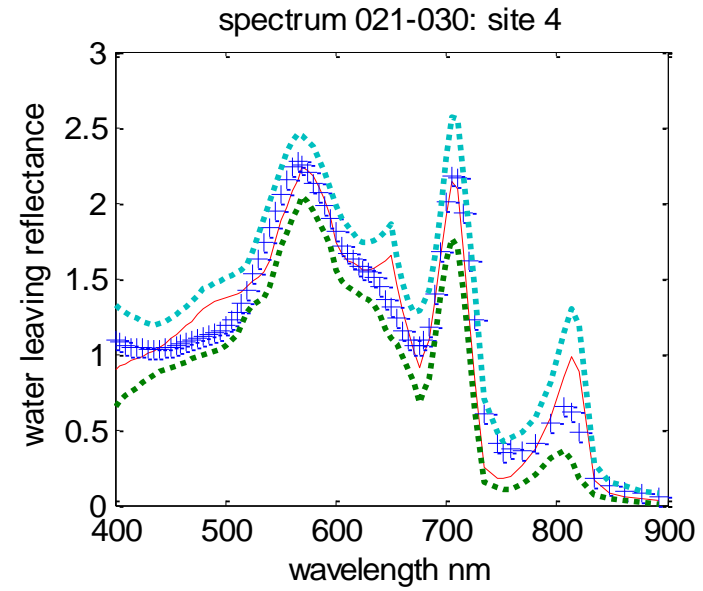
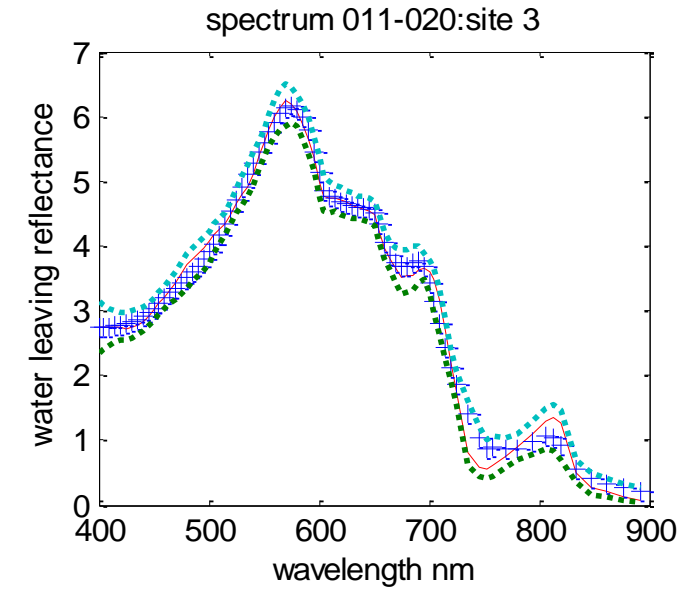
$$\Delta \mathbf{iop} = \frac{\Delta Rrs}{Rrs'(\mathbf{iop}_0)}$$

Radiometric errors are needed to estimate the uncertainties of derived IOPs

Radiometric uncertainty estimation: proposed

- Atmospheric fluctuations are estimated from the two bounding aerosol models: optical thickness and type (Gordon and Wang 1994). NIR water signal is accounted (Salama and Shen, 2010b)
- Fluctuations due to sensor's noise are derived from known data on sensor's Noise Equivalent Radiance (NER), e.g. Doerffer 2008 for MERIS
- Estimate the confidence interval around model predictions and sensor's observation

Radiometric uncertainty estimation: proposed



Uncertainty estimation of IOPs; prior

- Derive the plausible range of IOPs from the upper and lower spectral bounds

Now we have three sets of IOPs:

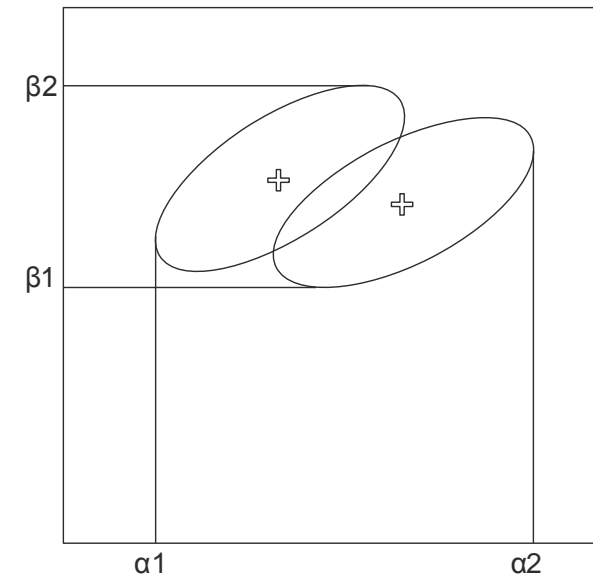
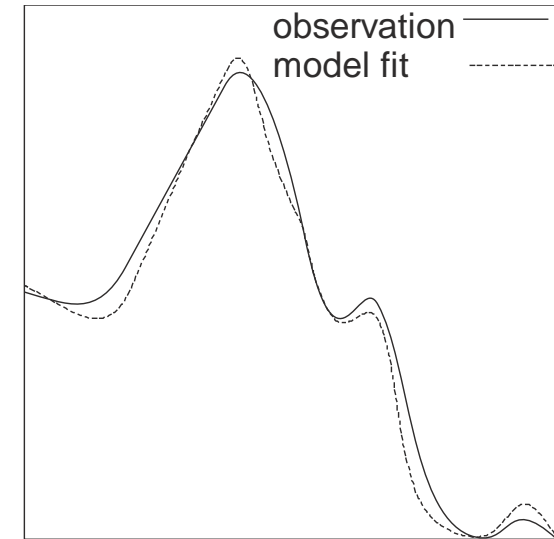
- u_IOP derived from upper bound
- l_IOP : derived from the lower bound
- m_IOP : derived from actual observation

We call it IOP-triplet

- The standardized variate of a quantity x is simply

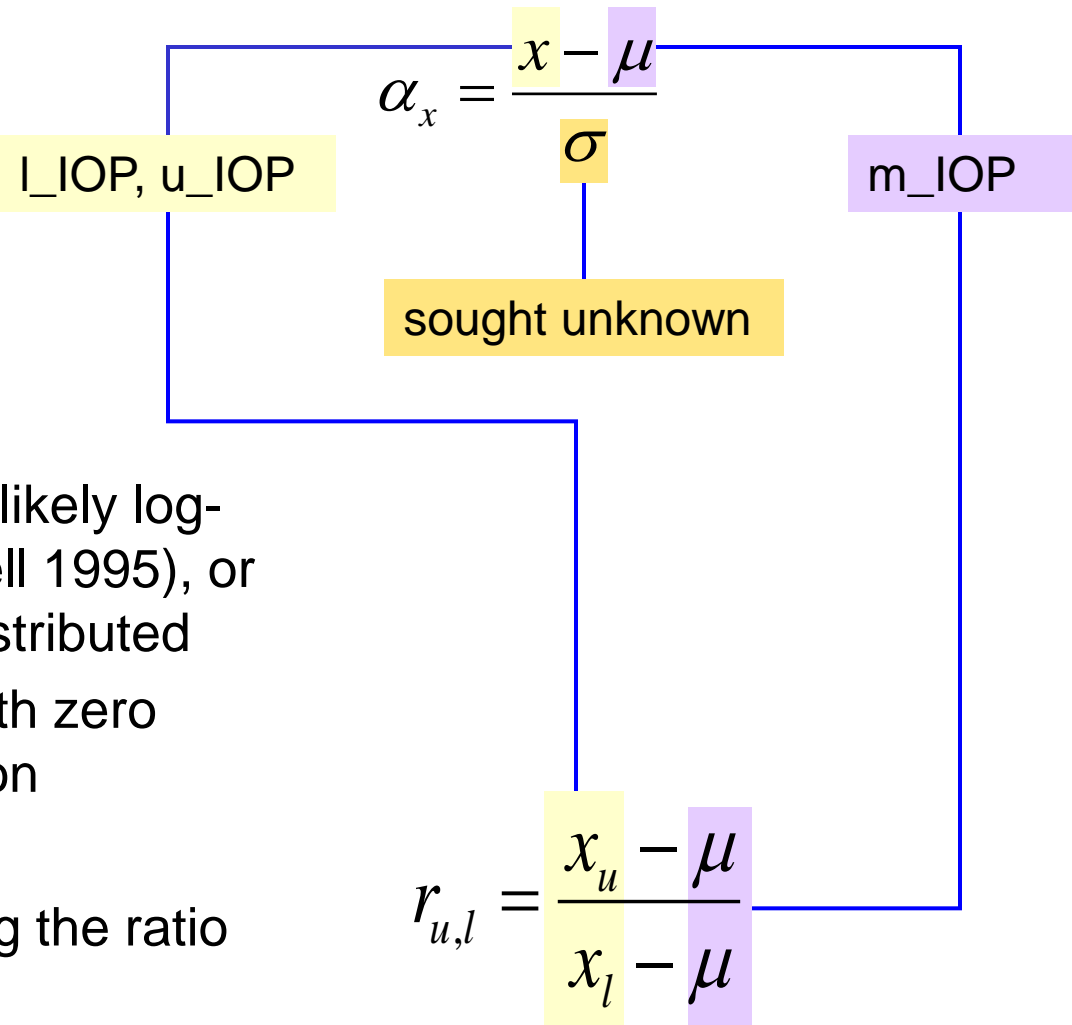
$$\alpha_x = \frac{x - \mu}{\sigma}$$

The diagram shows the components of the standardized variate equation $\alpha_x = \frac{x - \mu}{\sigma}$. The numerator $x - \mu$ is highlighted in yellow. The denominator σ is highlighted in yellow and labeled "sought unknown" in a yellow box below it. The term x is linked to a yellow box containing "l_IOP, u_IOP". The term μ is linked to a purple box containing "m_IOP".



Uncertainty estimation of IOPs; prior

- Standardize variate have:
zero mean and unity standard deviation
- We know that IOPs are most likely log-normally distributed (Campbell 1995), or the log of IOPs is normally distributed
- Generate normal numbers with zero mean and 1 standard deviation
- Get red of σ by taking the ratio



In your generated numbers make sure that each ratio has a unique pair of variates

Uncertainty estimation of IOPs; posterior

- Form the IOP-triplet compute the ratio and compare it to the already generated look up table of random numbers
- Now we can estimate the standard deviation,
- We call it prior standard deviation because the lower and upper IOPs in the IOP-triplet may not represent the actual range of IOPs.

- Use Bayesian-like updating to get a better estimate of sigma

- It is an iterative process that

minimizes our uncertainty about the uncertainty

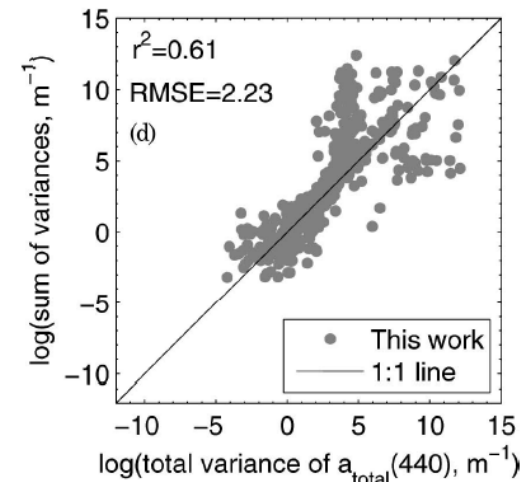
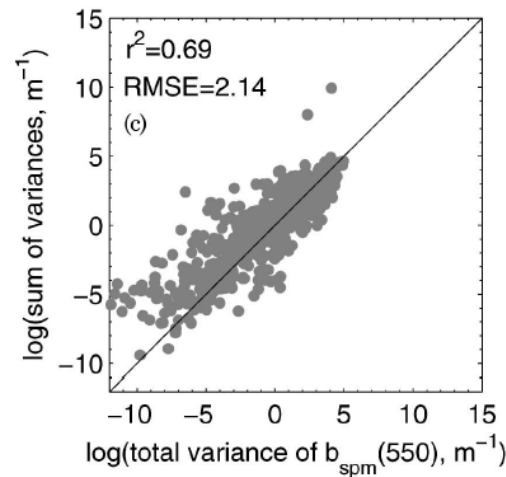
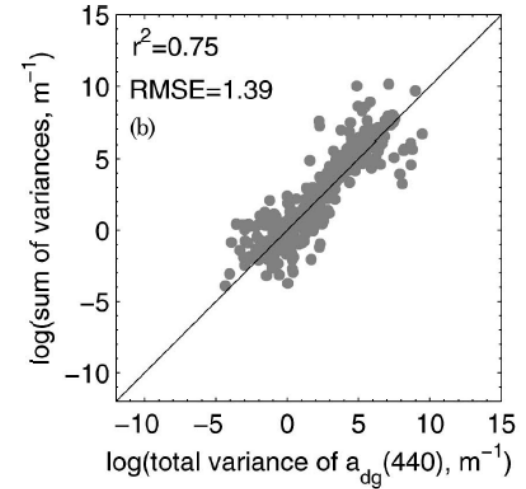
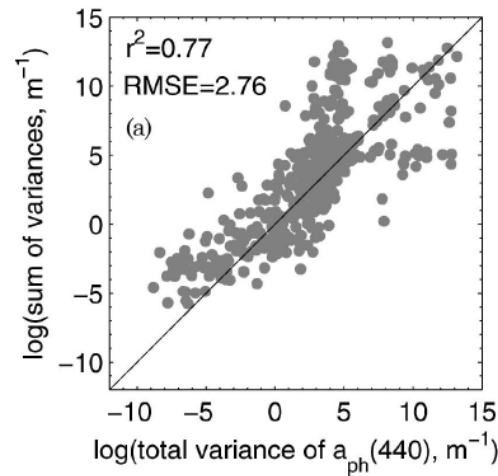
Uncertainty decomposition

- The total uncertainty in derived IOPs is the sum of three error component:

- atmosphere correction residuals
- sensor noise
- model inversion

$$\sigma_t^2 = \sigma_{atm}^2 + \sigma_{noise}^2 + \sigma_{inv}^2$$

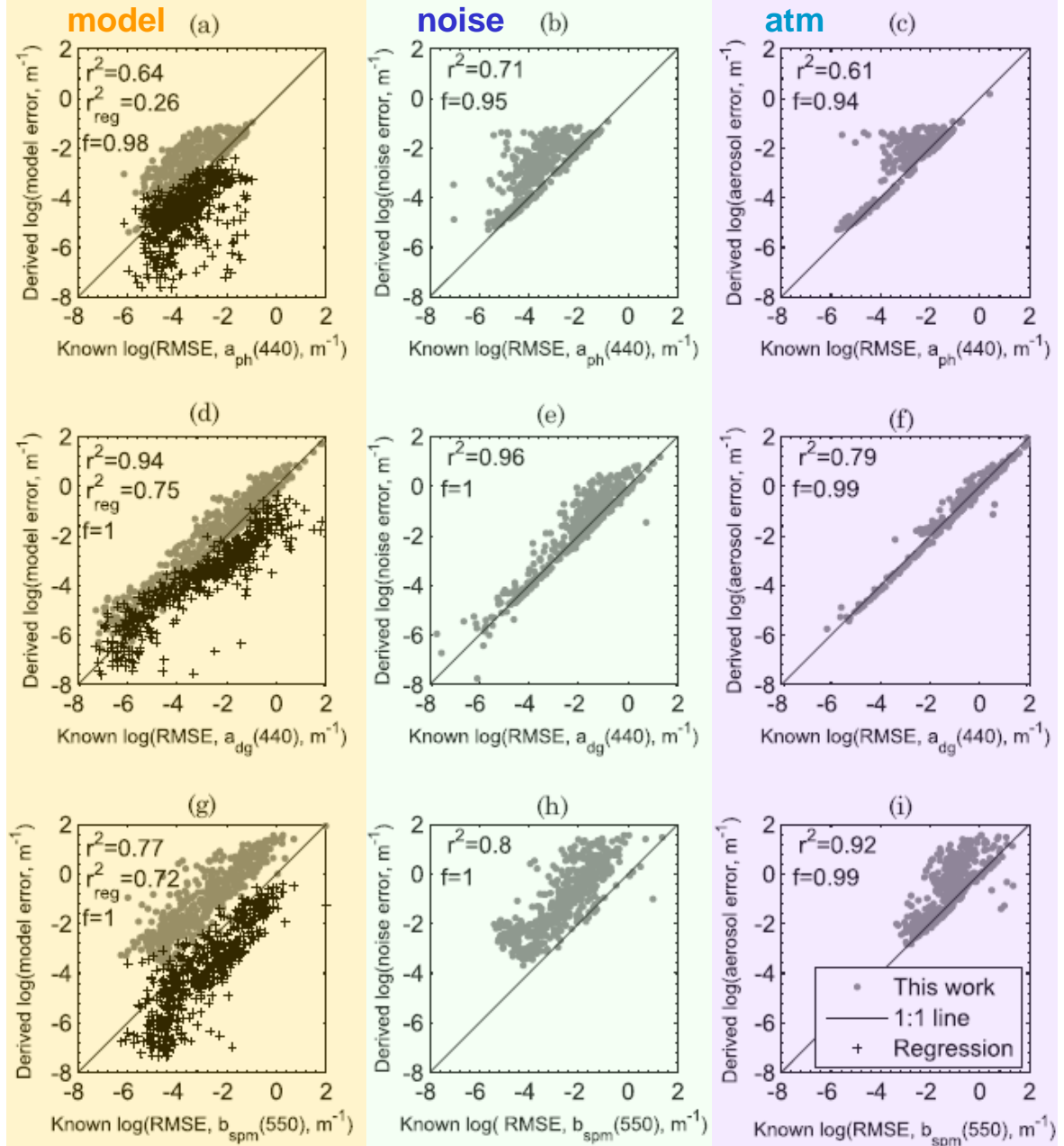
- The effect of this simplification is tested for ICCOG data (Lee 2006)



Validation with simulated data

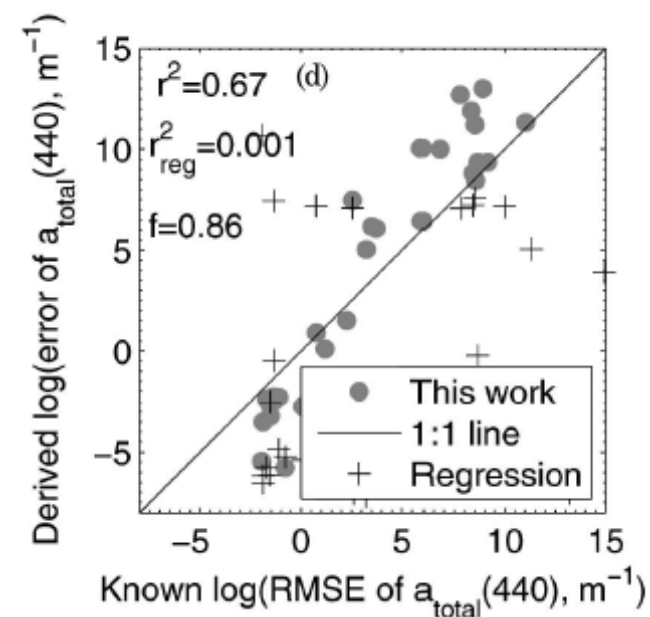
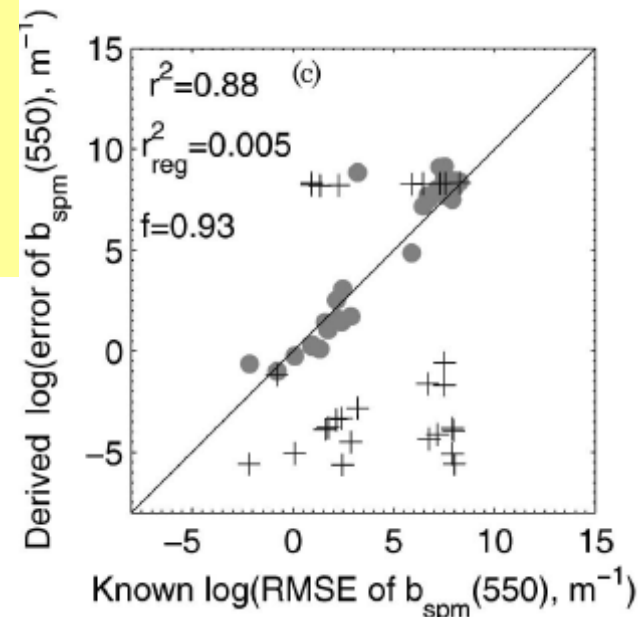
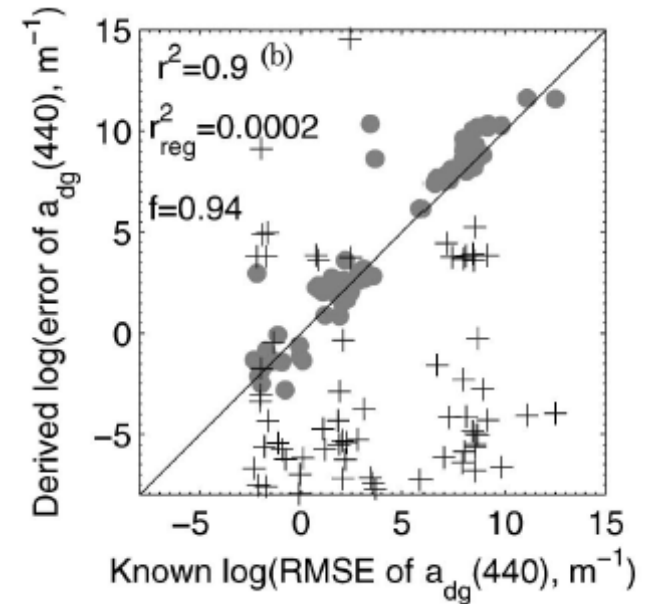
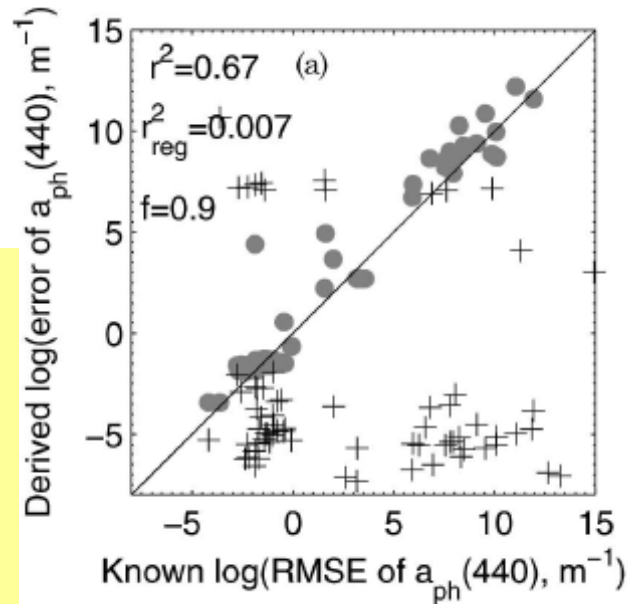
Derived versus known errors (dot symbols) of the IOPs estimated from the **IOCCG** data set

Nonlinear regression errors are also superimposed on derived model errors as plus symbols



Validation with EO-in-situ match ups data

Derived versus known errors (dots) of IOPs estimated from **SeaWiFS** spectra of the **NOMAD** data set
Nonlinear regression results are also superimposed as plus symbols

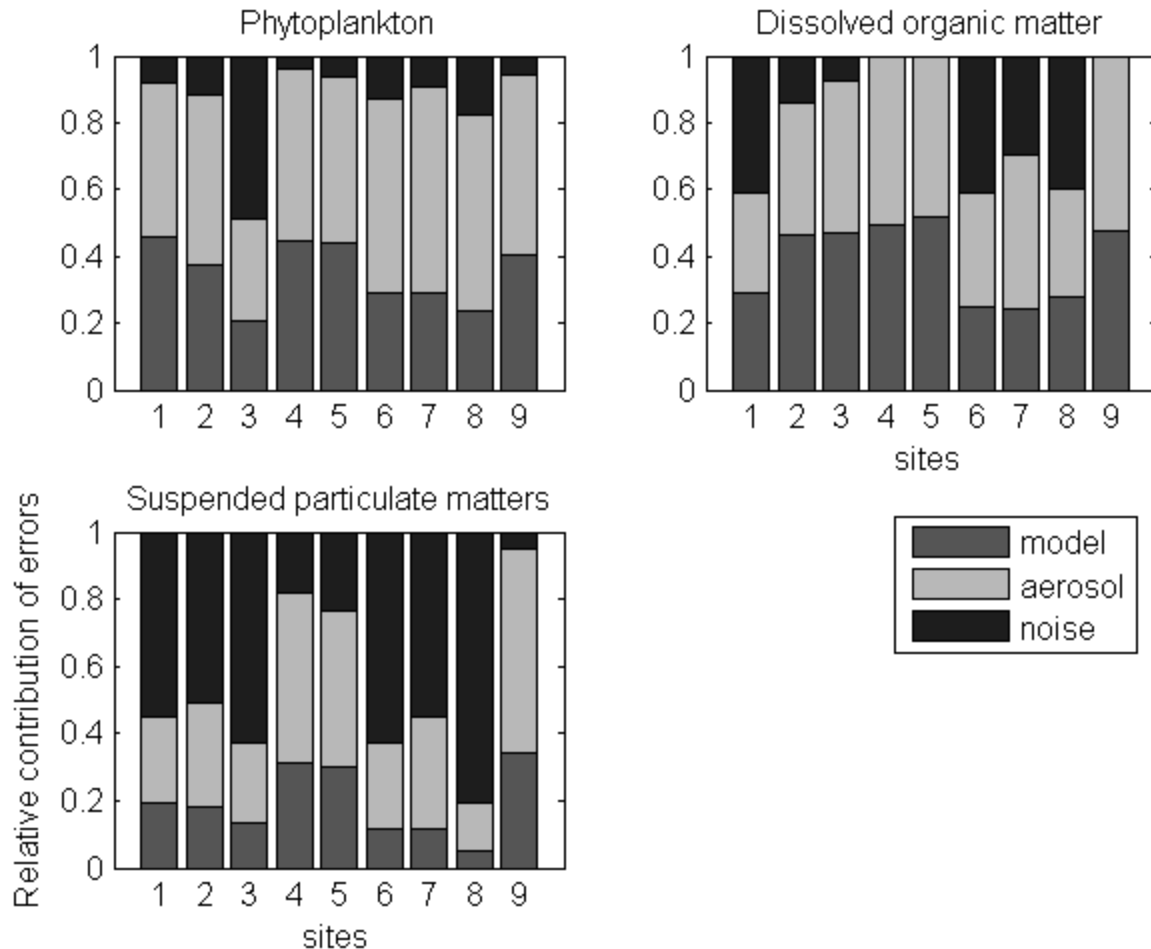


Application to measured data

- Quantify and partition the source of fluctuation:
 - Sensor noise
 - Model approximation and parameterization
 - Atmospheric correction

We used stochastic modeling and Bayesian updating

- The right panel shows the contribution of model approximations, imperfect atmospheric correction and sensor noise to the total error budget of the retrieved water quality indicators



Model-sensor error table

- For a specific “small” region with known range of IOPs ,model uncertainty can be estimated
- Update NER table of EO sensor enables the evaluation of noise induced errors
- From the above two quantities we can have an estimate of the atmospheric error: assuming that it constant for this “small” region

Conclusions

- Inversion-uncertainty of derived IOPs is proportional to water turbidity and is not representative of our confidence about the derived products from remote sensing data
- Errors due to atmospheric correction are the major source of errors in the derived IOPs. Imperfect atmospheric correction, due to the variability of aerosol optical thickness, is responsible for more than 50% of the total error and up to 82%.
- One fifth of the total errors on derived IOPs (except for the SPM scattering: one tenth) is attributed to noise error
- Model error has the lowest contribution ($\approx 7\%$) to the total error on derived SPM scattering, but it has a significant contribution ($\approx 16\%$) to y , the spectral dependency of SPM scattering
- A specific error table to the MERIS sensor is constructed. It shows that the main uncertainty is due to atmospheric and noise-induced errors for $aph(440)$ and $bspm(550)$, while model inversion is the main source of error to $adg(440)$ in this data

Thanks to

- NASA Ocean Biology Processing Group and individual data contributors for maintaining and updating the SeaBASS database;
- IOCCG and all individuals contributors for providing well documented reports and data sets
- the Management Unit of the North Sea Mathematical Models (MUMM, Belgium) for maintaining the Aeronet sunphotometer site
- ESA: for funding the research and providing EO data access
- GEOSS group for inland and coastal waters for giving me the chance to speak up

At your service, ITC, salama@itc.nl



Willamette River