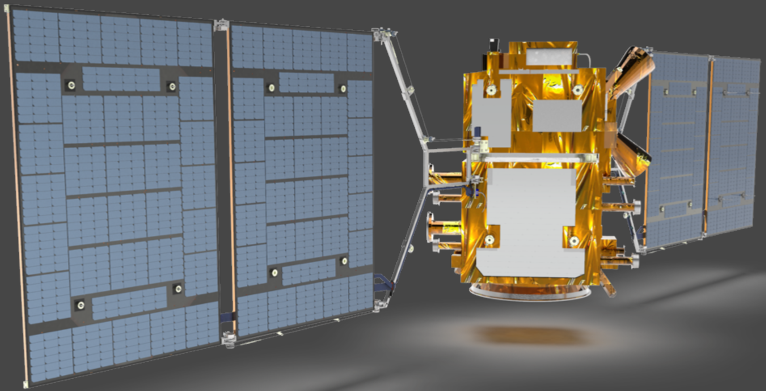
Mission Critical Design Review



SABIA-Mar Project

SECTION: 7D

L1 & L2 Error Budget

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CONAE

Ministerio de Ciencia, Tecnología e Innovación
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Related documentation

- **SB-04030500000000-AN-00002-A**: Uncertainty analysis for SABIA-Mar.
- **SB-040000-RQ-00400-C**: L1 and L2A Requirements Baseline Document.

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Uncertainty sources for L1B product

The uncertainty sources for Level 1B products are:

- Satellite pointing error uncertainty sources are:
  - AOCS sensor uncertainties
  - Camera pointing axis to cube.
  - Camera cube to Star tracker cube
  - Orbital position
- Satellite geolocalization error uncertainty sources are:
  - Star Tracker bias, noise after filtering
  - Mean thermoelastic deformation (detector deformation and among cubes)
  - Misalignment between cubes, optical and geometrical axis.

L1 Product Error Budget

Product	Uncertainty
Pixel geolocation	It shall be less than 200 meters on earth surface
Sensor and Solar Angles	Pointing error shall be less than 60 arc-sec
TOA Radiance	It shall be less than 0.5 %

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L2 products uncertainty requirements

Product	Uncertainty
Normalized Water Leaving Radiance (L_w)	It shall be less than 5% at bands B0, B1, B2, B3, and less than 15% at bands at B4, in oligotrophic deep case 1 waters.
Chlorophyll-a concentration (Chl_a)	It shall be less than 40% in oligotrophic deep case 1 waters.
Diffuse Attenuation coefficient at 490nm (Kd490)	It shall be less than 25% in oligotrophic deep case 1 waters.
Daily mean Photosynthetic Available Radiation (PAR)	It shall be less than 20%.
Turbidity (T)	It shall be less than 35% in turbid waters.

Uncertainty sources I

The uncertainty sources for every ocean color product is given by three independent components:

- Systematic uncertainty:
  - Also called *instrument artifacts* and they are involved in the process to convert voltage difference to radiance units.
  - They are reproducible.
  - Absolute gain, Non-linearity, Crosstalk, Stray light, Polarization sensitivity, Temporal response, Temperature correction, Dark offset, Relative spectral response, Inter-pixel relative response.
- Random uncertainty:
  - This source of error comes from the instrument noise.
  - For every new measure, a new different error could be obtained.

Uncertainty sources II

- Model uncertainty:
  - Assumptions in the mathematical model.
  - Auxiliary data error.
  - Algorithmic implementation.
  - Numerical error.

Total uncertainty, σ_{total}, is defined as the root sum square of geophysical algorithm (model), systematic, and random uncertainty:

$$\sigma_{total} = \sqrt{\sigma^2_{systematic} + \sigma^2_{random} + \sigma^2_{model}}$$

How do TOA reflectance error propagate to the surface reflectance error ?

Objetive: Studying how an error percentage of 0.5% in ρ_{TOA} propagates to ρ_w, and to the other science products (Chl-a, KD490, PAR and T).

Water leaving radiance

- To simulate this TOA uncertainty we add a random perturbation to simulated TOA reflectance with OSOAA Radiative Transfer Code, i.e.,

$$\hat{\rho}_{\mathrm{TOA}} = \rho_{\mathrm{TOA}} + N(\mu = 0, \sigma = 0.0025\rho_{\mathrm{TOA}})$$

The procedure was done as follows:

- Set atmospheric conditions (AOT)
- Set ocean conditions for Oligotrophic waters
- Simulate with OSOAA the TOA reflectance and surface reflectance
- Add Gaussian noise with SABIA-Mar expected error to each band and perform AC
- Compare $\hat{\rho}_w^{SMAC}$ and ρ_w^{SMAC}.

ρ_{TOA} Chl $0.1 mg/m^3$, RH 75%, τ 0.1, wind 5m/s

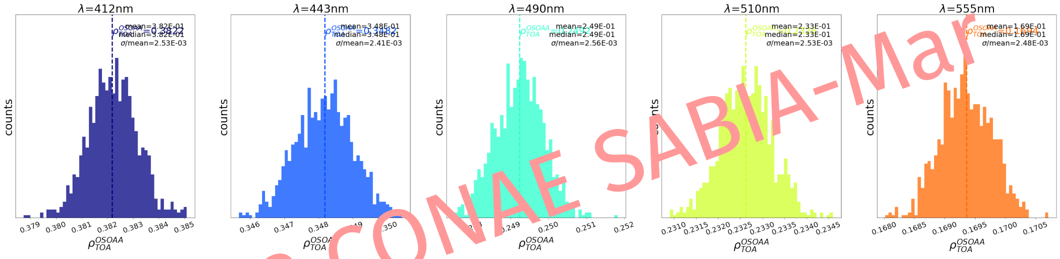

Figure: ρ_{TOA} with a Gaussian noise

ρ_w Chl $0.1 mg/m^3$, RH 75%, τ 0.1, wind 5m/s

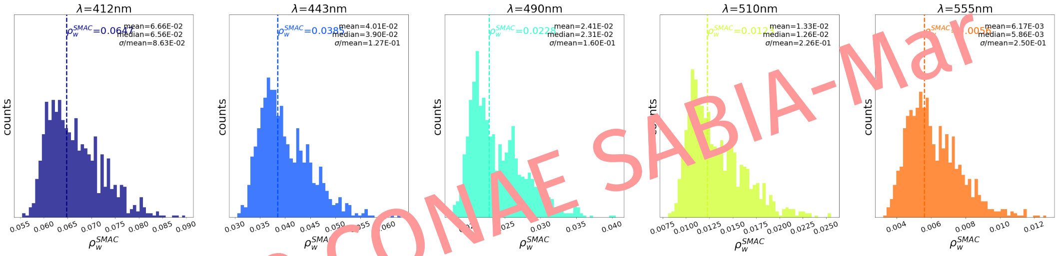

Figure: ρ_w of the ρ_{TOA} with noise ($\hat{\rho}$)

Relative differences Chl $0.1 mg/m^3$, RH 75%, τ 0.1, wind 5m/s

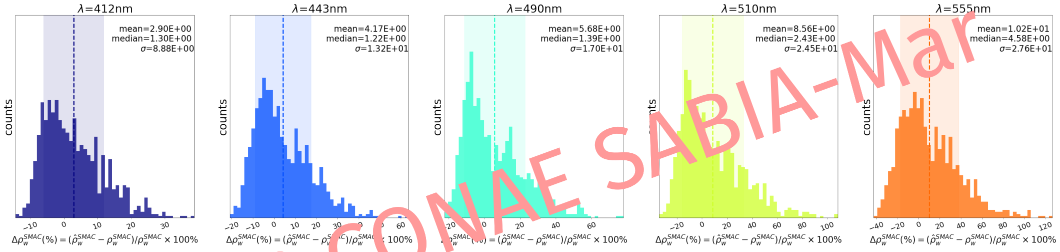

Figure: Relative difference between $\hat{\rho}_w$ and ρ_w (both from SMAC)

Simulated conditions

The following conditions were used for the simulations up to the moment:

- Lines: [0, 1, 2, 3, 4, 5]
- Pixels: [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23]
- Chl-a: [0.05]
- AOT: [0.05, 0.1, 0.2]
- RH: [75, 90]
- Wind speed: [5]

Distribution of Random Error for Oligotrophic waters

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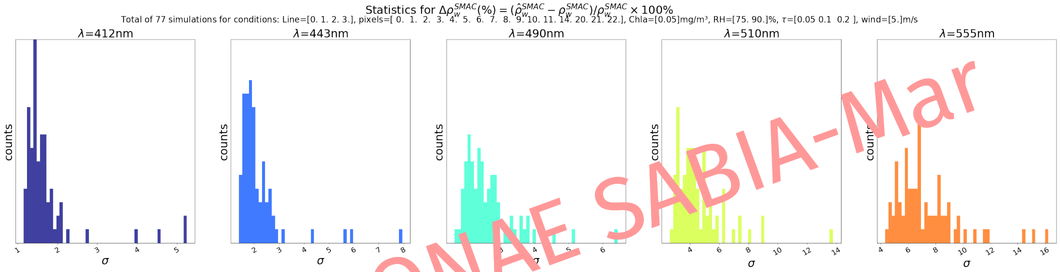

λ	mean	median	σ	$p_{25\%}$	$p_{75\%}$
412	1.73	1.52	0.81	1.36	1.74
443	2.17	1.89	1.03	1.65	2.24
490	2.61	2.40	0.80	2.11	2.82
510	4.66	4.25	1.73	3.44	5.20
555	7.36	6.76	2.40	5.87	8.13

Total uncertainty on ρ_w

- σ^2_{model} was obtained with the comparison between ρ_w^{SMAC} and ρ_w^{OSOAA} simulations.

λ(nm)	σ^2_{model}	$\sigma^2_{systematic} + \sigma^2_{random}$	σ_{total}(%)
412	11.22	2.99	3.77
443	2.31	4.71	2.65
490	0.56	6.81	2.71
510	1.66	21.72	4.84
555	3.1	54.17	7.57

Table: Statistic of relative uncertainty ρ_w

Chl-a, KD490, PAR and T

- Same procedure must be implemented to estimate σ^2_{random} for these products.
- In order to estimate σ^2_{random} it will be implemented a propagation in terms of partial derivatives for each product,

$$\Delta g(x_1, \ldots, x_n) = \sqrt{\sum_{i=1}^{n} \left(\frac{\partial g}{\partial x_i} \right)^2 \Delta x_i^2}, \tag{1}$$

where Δx_i is the uncertainty of variable (or measured quantity) x_i.

Example: Chl-a case

As an example, let us consider the case for Chlorophyll-a and the OC4 algorithm,

$$log_{10}([\text{Chl-a}]) = \sum_{i=0}^{4} a_i log_{10}\left(\frac{R_{rs}(\lambda_b)}{R_{rs}(\lambda_g)}\right)^i, \quad (2)$$

where λ_b and λ_g are the blue and green spectral bands, respectively. We can rewrite the OC4 algorithm as

$$[\text{Chl-a}](R_{rs}(\lambda_b), R_{rs}(\lambda_g)) = 10^{f(R_{rs}(\lambda_b),R_{rs}(\lambda_g))}, \quad (3)$$

where

$$f(R_{rs}(\lambda_b), R_{rs}(\lambda_g)) = \sum_{i=0}^{4} a_i log_{10}\left(\frac{R_{rs}(\lambda_b)}{R_{rs}(\lambda_g)}\right)^i. \quad (4)$$

Example: Chl-a case

$$\Delta[\text{Chl-a}] = \sqrt{\left(\frac{\partial[\text{Chl-a}]}{\partial R_{rs}(\lambda_b)}\right)^2 \Delta R_{rs}(\lambda_b)^2 + \left(\frac{\partial[\text{Chl-a}]}{\partial R_{rs}(\lambda_g)}\right)^2 \Delta R_{rs}(\lambda_g)^2} \quad (5)$$

$$= \sqrt{\left(\frac{\partial[\text{Chl-a}]}{\partial f}\frac{\partial f}{\partial R_{rs}(\lambda_b)}\right)^2 \Delta R_{rs}(\lambda_b)^2 + \left(\frac{\partial[\text{Chl-a}]}{\partial f}\frac{\partial f}{\partial R_{rs}(\lambda_g)}\right)^2 \Delta R_{rs}(\lambda_g)^2} \quad (6)$$

$$= \frac{\partial[\text{Chl-a}]}{\partial f}\sqrt{\left(\frac{\partial f}{\partial R_{rs}(\lambda_b)}\right)^2 \Delta R_{rs}(\lambda_b)^2 + \left(\frac{\partial f}{\partial R_{rs}(\lambda_g)}\right)^2 \Delta R_{rs}(\lambda_g)^2}. \quad (7)$$

Once we compute the AC algorithm uncertainty, we would know the values of $\Delta R_{rs}(\lambda_j)$ and finally compute the uncertainty on Chlorophyll-a. The same should be done for the others algorithms.

Questions?