Uncertainty estimation of case2 water IOP products of OLCI using artificial neural networks

- Technical Note -

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Revisions:

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<th>Issue</th>
<th>Date</th>
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<td>1</td>
<td>20190630</td>
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1 Content of this TN

This document describes the procedures using artificial neural networks (NN) to estimate the uncertainties of the Inherent Optical Properties (IOPs) of water constituents, which are derived from top of atmosphere (TOA) radiance data of the Ocean Land Colour Imager (OLCI) on board the earth observing satellite Sentinel 3.

The description and test results of this document is related to the system of NNs, which are listed in annex A.

2 Introduction and Overview

All procedures used to determine IOPs or concentrations of water constituents from reflectance spectra at top of atmosphere produce a variable degree of uncertainty. This has two major reasons:

- The inverse relationship between IOPs and reflectance spectra is an under determined system, i.e. the information content of reflectance spectra is much lower than the number of factors, which determine the reflectances.
- The natural variability of the properties of all components, which determine reflectance spectra is extremely large. This includes the optical properties of the water constituents and its vertical distribution as well as the optical properties of aerosols and its vertical distribution, furthermore properties of the air-sea interface.

Consequently any algorithm is a simplification of the system and works only properly within its scope, which is defined by the underlying model, which describes the relationship between the IOPs and the corresponding reflectance spectrum.
In order to acknowledge these facts it is necessary

- to determine if a measured spectrum is within the scope of the model / algorithm
- and, if accepted, estimate the uncertainty of the result, i.e. of the IOPs or concentrations.

For the European satellite instruments MERIS on ENVISAT, OLCI on Sentinel 3 and MSI on Sentinel 2, algorithms have been developed to determine IOPs of constituents of particular coastal and inland waters, which are based on artificial neural networks, which have been trained using a large number of simulated cases including water and atmosphere (for OLCI s. ATBD, Doerffer, 2010).

These neural networks have been complemented with NNs to determine spectra, which are out of scope, and with NNs to estimate the uncertainties of the IOPs and concentrations. All of these NNs are based on the same training data set and have the same scope.

This scope is defined by the bio-optical model, which describes the IOPs of the water constituents, its ranges and co-variances, a wind driven rough water surface, and the atmosphere with different surface pressures and aerosols.

### 3 Training and test data set

#### 3.1 Bio-optical model

The training and test data sets are based on simulations. Core is the bio-optical model (version of May 2019). It consists of 5 components, which have been defined by an analysis of data of the NOMAD data set (Werdell & Bailey, 2005) and of further published and unpublished data (Lefering et al, 2014, 2018, Röttgers & Gehnke, 2012, Röttgers & Doerffer, 2007, Röttgers et al, 2007, Röttgers, pers. comm.). It is important to realize that such a reduction and simplification implies already an uncertainty, which may easily lead to errors in the order of factor 2.

The spectral properties of these 5 optical components, which represent a variety of IOPs of water constituents, were normalized at 443 nm (s. Fig. 2). Furthermore, range, frequency distribution and co-variances between the components were defined.

These properties are shown in figures 4 - 6. For the pigment absorption component the mean absorption spectrum of different algae species was used (Fig. 3, Fig. 4a, Röttgers & Gehnke, 2012).

The absorption spectrum of detritus and dissolved humic substances (gelbstoff, CDOM, defined by the pore size of a filter of 0.47 or 0.2 µm) is very similar. It follows an exponential decrease with increasing wavelength, which can be described by a spectral exponent. Measurements of this exponent show a large range with a broad overlap between CDOM and detritus (Fig. 1).

Thus the two components - gelbstoff or CDOM ag and detritus ad - are not clearly defined by two different substances, but are used to encompass the spectral variability of humic substances in general. The final OLCI product adg is just the sum of ag and ad.
The absorption and scattering spectrum as well as the spectral refractive index of pure water is computed for different temperatures and salinity using the water model (Röttgers et al. 2016). The absorption coefficient of pure water (Fig. 4c) is based on the measurements by Mason et al., 2016). Note, that previous NNs for OLCI are based on older measurements of Pope and Fry, which show a higher absorption at wavelengths < 450 nm and which have introduced an error in the calculation of reflectances of clear water at the OLCI bands at 400 nm and 412 nm.

| detritus ad: 0.0039 | particle scattering bp: 1.87 |
| gelbstoff ag: 0.016  | white scatterer bw: 0.0    |

*Tabelle 1: Spectral exponents of the 4 components of water constituents*
The bio-optical model

**Fig. 2**: Reduction of the multitude of water constituents to 5 IOPs and to 3 products of OLCI and MERIS 4th reprocessing (Doerffer, 2015)
In Vivo Absorption Spectra of Marine Phytoplankton

Normalized Absorption of Phytoplankton

Fig. 3: The absorption spectra of 9 representative phytoplankton species, normalized 443 nm

Data courtesy of Steffen Gehnke, GKSS
Fig. 4: (a) Mean normalized absorption spectrum of 9 phytoplankton species, (b) normalized absorption and scattering spectra of CDOM, detritus, and scattering spectra of particles and white particles and (c) absorption spectrum of pure water (log scale)
Fig. 5: Range and frequency distribution of the IOPs of the 5 basic water constituents and of adg, atot and btot

Most critical for the reduction of uncertainty is the co-variance between the 5 components. If they are randomly varied without any co-variance the ambiguities and thus the uncertainty of the result increase because of the similarity of the spectral shapes. In contrast, if the co-variance is too high the scope of the algorithm decreases. Thus, one has to find a trade-off. The co-variances shown in Fig. 6 used for training of the present NNs are based on an analysis of IOP data of the North Sea, which comprise a large variety of optical water types, and on the NOMAD data set. Ranges and co-variances have been extended to clearest case 1 water.
Fig. 6: Co-variances of the IOPs (a) \text{apig} (pigment absorption) / \text{btot}, (b) \text{ad} (detritus) / \text{btot}, (c) \text{ag} (CDOM) / \text{btot}, (d) \text{bp} (particles scattering) / \text{btot}, (e) \text{bw} (white scatterer) / \text{btot} and (f) \text{adg} (detritus+CDOM absorption) / \text{apig}. The green line indicates the 1by1-relationship.

3.2 Model of the Atmosphere

The model of the atmosphere has been developed by Aznay & Santer, 2009, Zagolski et al., 2007. It is based on AERONET data of coastal stations. The results of a large number of simulations with variations of aerosol properties, surface pressure and wind speeds (for the specular reflectance at a rough sea surface) are stored in look-up tables for 15 spectral bands and various sun and viewing angles. An interpolation program is then used to produce TOA reflectance spectra for different combinations of these input parameters. The aerosol properties are described by the aerosol optical thickness (AOT) at 560 nm and a spectral shape parameter like an angstrom coefficient.

For the training data set the input parameters for the present NN system are:

<table>
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<tr>
<th>Parameter</th>
<th>Range</th>
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<tbody>
<tr>
<td>AOT560</td>
<td>[0.002 - 0.4]</td>
</tr>
<tr>
<td>angstrom coefficient</td>
<td>[0.0 - 2.2]</td>
</tr>
<tr>
<td>wind speed</td>
<td>[0.1 - 9 m s^{-1}]</td>
</tr>
<tr>
<td>surface pressure</td>
<td>[930-1040 hPa]</td>
</tr>
<tr>
<td>water temperature</td>
<td>[0.0 - 36 degC]</td>
</tr>
<tr>
<td>salinity</td>
<td>[0.0 - 43]</td>
</tr>
<tr>
<td>solar zenith angle</td>
<td>[0-75 deg]</td>
</tr>
<tr>
<td>viewing zenith angle</td>
<td>[0-60 deg]</td>
</tr>
<tr>
<td>azimuth difference</td>
<td>[0-180 deg]</td>
</tr>
</tbody>
</table>
3.3 The simulation procedure

All NNs of a C2R generation are based on the same training data set, which includes IOPs, water temperature, salinity, aot560, angstrom coefficient, wind, pressure, solar and viewing angles.

The simulation uses a combined system of two different radiative transfer models: Hydrolight 5 for water (based on Mobley 1994) and the C2R atmosphere simulation program (Zagolski et al., 2007). For the pure water properties a special program based on WOPP3 (Röttgers et al., 2016), is used, which includes the effects of water temperature and salinity on refractive index and absorption and scattering coefficients (Röttgers et al, 2014). The pure water absorption coefficients are from Mason et al., 2016. The radiative transfer programmes have been modified to include the bio-optical model as described above. All variables are varied randomly within the described ranges and co-variances. The IOPs are varied on a logarithmic scale.

For the present version 3.9 Mio cases have been simulated. The data set consists of 80000 combinations of the 5 IOPs, sun zenith angle, wind speed, water temperature and salinity. For each of these cases 7 viewing angles are selected randomly and for each of these 560000 cases 7 different atmospheres are added with variable AOT560, angstrom coefficient and surface pressure.

The effect of gasesous absorption of water vapour and ozone is corrected outside the NN system when it is applied to real satellite data.

4 System of neural networks

4.1 Overview

The overall procedure to determine IOPs of water constituents and kd490, kd_min and z90 uses 9 neural nets, which are shown in Fig. 8. A further NN is used to determine the uncertainties of $adg$, $btot$, $kd490$ and $kd_min$. 
The system consists of 3 parts.

(1) Preprocessing of the data (radiances) to compute gaseous corrected TOA reflectances, \( \rho_{\text{toa}} \).

(2) Processing of \( \rho_{\text{toa}} \) with NNs to identify out-of-scope reflectances, path radiance reflectances, transmittances and radiance reflectances of water (\( \rho_{\text{w}} \)).

(3) Processing of \( \rho_{\text{w}} \) to compute IOPs and \( k_{\text{ds}} \), normalized \( \rho_{\text{wn}} \), uncertainties and the conversion of IOPs to concentrations.

The NN based atmospheric correction part can be replaced by the standard atmospheric correction, as it was requested by ESA.

Details are described in the ATBD (Doerffer, 2010, to be updated).

In this document we focus on NNs for the identification of spectra, which are out of scope, and on NNs for the determination of uncertainties.
4.2 Neural networks for identifying out of scope cases

As described above, the optical models of water and atmosphere cannot cover all possible cases, which might happen in nature. Thus, we have to expect TOA spectra, which are not covered in the training data set. Such spectra would then lead to large errors or meaningless results.
To identify spectra, which are out of scope, two methods are applied.

The TOA reflectance spectra are tested with an auto-associative neural network (aaNN). Such a network has the TOA reflectances as input and output. Further inputs are the sun and viewing angles, surface air pressure, water temperature and salinity. The architecture of the NN includes a bottle-neck layer with a number of neurons, which is just large enough to reproduce the TOA reflectances with a defined uncertainty, i.e. of $< 1\%$ (s. Fig. 9a). TOA spectra, which are out of scope, produce then a larger uncertainty. A threshold is set, to decide, whether rho_toa is out of scope. The following procedure is used

$$nn_in = \{\text{sun_zeni}, x, y, z, \text{temperature}, \text{salinity}, \text{alti_press}, \text{log_rtosa}\};$$  // NN input

$$\text{log_rtosa_aann} = \text{nnhs_ff(nn_rtosa_aan, nn_in)};$$  // run the NN

$$\text{abs_diff_log_rtosa} = \text{abs(log_rtosa - log_rtosa_aann)};$$  // compute out of scope

$$\text{abs_diff_log_rtosa_max} = \max(\text{abs_diff_log_rtosa});$$  // parameter

$$\text{if abs_diff_log_rtosa_max > thresh Absd_log_rtosa} \text{ then}$$

$$\text{rtosa_oos_flag=1;}$$  // set flag if ratios outside thresholds

Water leaving radiance reflectance spectra are tested with a different technique. In this case the IOPs, which are the results of the rho_w->IOP NN are input to a forward NN, which produces rho_w' from IOPs. This rho_w' is compared to rho_w, which is the output of the rho_toa->rho_w NN (Fig. 9b). But in contrast to the aaNN procedure for rho_toa, here 2 spectral slopes, s1 and s2, are compared. Then again a threshold is used to decide whether rho_w is out of scope.

// test out of scope of rho_w by combining inverse and forward NN
// compute the test and set rho_w out of scope flag

$$s1\_mess = \text{abs(log_rw(6) - log_rw(3))};$$  // s1_mess and s2_mess are the spectral band ratios of rho_w

$$s2\_mess = \text{abs(log_rw(7) - log_rw(6))};$$

$$s1\_nn2 = \text{abs(log_rw_nn2(6) - log_rw_nn2(3))};$$  // s1_nn2 is the band ratios of rho_w'

$$s2\_nn2 = \text{abs(log_rw_nn2(7) - log_rw_nn2(6))};$$

$$s1\_test = \text{abs(s1\_nn2 - s1\_mess)};$$  // relative deviation for band ratio 6/3

$$s2\_test = \text{abs(s2\_nn2 - s2\_mess)};$$  // relative deviation for band ratio 7/6

$$s12\_test\_a(ipix) = \max([s1\_test s2\_test]);$$  // maximum deviation of both slopes

$$\text{if s12\_test\_a(ipix) > thresh rwlogslope then}$$

$$\text{rho_w_oos_flag=1;}$$

Fig. 9: Networks to identify out of scope spectra, a) auto-associative NN for rho_toa, b) combination of inverse and forward NN for rho_w, details s. algorithms above
4.3 Neural networks for determining uncertainties

The neural network to determine the uncertainties of the retrieved IOPs and concentrations are trained with the errors of the rho_w->iop NN for determining IOPs from rho_w. This error is the difference between the output of this NN and the (true) simulated IOPs for each of the training cases. These 'true' errors, which are defined as $\text{abs}(\log_{10}\text{IOP}_{\text{train}} - \log_{10}\text{IOP}_{\text{model}})$, are used to train a neural network with the IOPs as input and uncertainties as output. The absolute operator is necessary to get only positive numbers for training of the NN.

The uncertainty in absolute IOP units is then $\exp(\text{abs\_diff\_log\_iop})*\text{IOP}$, the relative uncertainty in % is $(\exp(\text{abs\_diff\_log\_iop})-1)*100$.

The NN treats all 5 IOPs at once. Input are the 5 IOPs, output the corresponding 5 uncertainties. The uncertainty product are the absolute uncertainties. However, the positive or negative direction is lost due to the abs operation.

Two different versions are trained: (1) training with the IOPs, which are the output of the rho_w->iop NN with the modelled rho_w as input and (2) training with the IOPs, with the rho_w as input, which is the output of the rho_toa->rho_w NN. Thus, the latter version includes the uncertainties due to the atmosphere, and, thus, produces a much larger uncertainty of the IOPs.

The present uncertainty product is computed with the first version, i.e. without the effect of the atmosphere. Reason was the option to perform the atmospheric correction for case2 water with the standard atmospheric correction procedure.

Fig. 10: Scheme of the training process for determining uncertainties of IOPs with and without atmospheric correction (courtesy of C. Brockmann)

5 Test of the NN using simulated data

The test of the NNs using simulated data is the basis for training of the uncertainty NNs. The following figures show the relationship between the simulated IOPs and the corresponding output of the NN, (1) derived from the simulated rho_w as well as (2) from rho_w, which is the output of
the atmospheric correction NN as described in Fig. 10. The figures include the 1by1 line and the regression line together with the regression function and standard deviation.

\[
apig_{nn} = 1.0046 \times \text{apig\_simu} + 0.0064, \quad \text{sig}=0.014
\]

\[
apig_{nn} = 0.94 \times \text{apig\_simu} - 0.075, \quad \text{sig}=0.357
\]

Fig. 11: Scatter plot between the simulated and NN-derived absorption coefficients of pigments at 443 nm. (a) derived from the simulated rho_w, (b) derived from rho_w, which is the outcome of the rho_tosa->rho_w NN, i.e. after the atmospheric correction

Fig. 12: Frequency distribution of the absolute error of the absorption coefficient of pigments, (a) derived from simulated rho_w, (b) derived from rho_w, which is the output of rho_tosa->rho_w NN.
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\[
b_{\text{tsm}} = 1.0025 \times b_{\text{tsm\_nn}} + 0.0055, \quad \text{sig}=0.032
\]
\[
b_{\text{tsm}} = 0.92 \times b_{\text{tsm\_nn}} + 0.0047, \quad \text{sig}=0.269
\]

Fig. 13: Scatter plot between the simulated and NN-derived scattering coefficients of \( b_{\text{tsm}} = b_{\text{part}} + b_{\text{white}} \) at 443 nm. (a) derived from simulated \( \rho_w \), (b) derived from \( \rho_w \), which is the outcome of \( \rho_{\text{tosa}} \to \rho_{\text{w}} \) NN, i.e. after the atmospheric correction.

\[
b_{\text{tsm}} = 0.99 \times b_{\text{tsm\_nn}} + 0.011, \quad \text{sig}=0.012
\]
\[
b_{\text{tsm}} = 1.02 \times b_{\text{tsm\_nn}} - 0.043, \quad \text{sig}=0.152
\]

Fig. 14: Scatter plot between the simulated and NN-derived scattering coefficients of \( b_{\text{tslm}} = b_{\text{part}} + b_{\text{white}} \) at 443 nm for AOT < 0.3. (a) derived from simulated \( \rho_w \), (b) derived from \( \rho_w \), which is the outcome of \( \rho_{\text{tosa}} \to \rho_{\text{w}} \) NN, i.e. after the atmospheric correction.
Fig. 15: Scatter plot between the simulated and NN-derived scattering coefficients of $b_{tsm} = b_{part} + b_{white}$ at 443 nm, derived from $\rho_w$, which is the outcome of the $\rho_{tosa} \rightarrow \rho_w$ NN, i.e. after the atmospheric correction. (a) for an atmosphere with AOT > 0.1 and (b) < 0.03

Fig. 16: Frequency distribution of the absolute error of the scattering coefficient of particles ($b_{tsm} = b_{part} + b_{white}$), (a) derived from simulated $\rho_w$, (b) derived from $\rho_w$, which is the output of the $\rho_{tosa} \rightarrow \rho_w$ NN.
6  Comparison of the true errors with the uncertainties from the NN

In this chapter we compare the directly computed absolute errors, i.e. the difference between the 'true' (=simulated) IOP and the output of rho_w->IOP NN as a function of the IOP, with the uncertainty using the uncertainty NN.

The absolute error, which is used for comparison with the NN derived absolute error, is computed as

\[
\text{iop\_abs\_direct\_error} = (\sqrt{\exp(\text{abs}(\log(\text{iop\_nn})-\log(\text{iop\_sim}))))-1)\times\text{iop}
\]
The uncertainty NN determined error is computed as:
\[ \text{iop\_abs\_nnunc\_error} = (\exp(\text{nn\_iop\_unc}) - 1) \times \text{iop} \]

The two different versions of uncertainty NNs (s. above) are (a) starting with simulated rho\_w and (b) starting with simulated rho\_toa (i.e. including atmospheric correction).

Due to the impact of the atmosphere and the introduced ambiguities and masking effects by aerosol scattering and specular reflectance at the air/sea interface, also the determination of the uncertainties shows more scatter, both for the direct computation as well as the NN determined.

**Fig. 19:** Scatter of (a) directly computed and (b) NN derived absolute error of apig as a function of apig, both without atmospheric correction, starting from simulated rho\_w.
Fig. 20: Scatter of (a) directly computed and (b) NN derived absolute error of apig as a function of apig, both with atmospheric correction, starting from simulated rho_toa.

![Scatter of (a) directly computed and (b) NN derived absolute error of apig](image)

Fig. 21: Scatter of (a) directly computed and (b) NN derived absolute error of b_tsm as a function of b_tsm, both with atmospheric correction, starting from simulated rho_toa.

![Scatter of (a) directly computed and (b) NN derived absolute error of b_tsm](image)

Fig. 22: Scatter of (a) directly computed and (b) NN derived absolute error of kd_min as a function of kd_min, both with atmospheric correction, starting from simulated rho_toa.

![Scatter of (a) directly computed and (b) NN derived absolute error of kd_min](image)

7 Conversion of IOPs into mass concentrations

The conversion of IOPs into concentrations produces a further increase of uncertainties because of
(1) the reduction of the manifold of water constituents to 5 components and (2) the variability of the relationship between absorption or scattering coefficients and mass concentrations.

As an example, the relationship between the absorption coefficient of phytoplankton and the chlorophyll concentration of the NOMAD data set (Fig. 23 a) shows that the uncertainty is in the order of factor 2. A similar scatter (Fig. 23b) exists for the relationship between the particle scattering coefficient \(bp_{440}\) and the total suspended matter (TSM) dry weight, based on measurements of the North Sea (Röttgers, unpublished data). The uncertainty of in situ measurements are also discussed in Röttgers et al., 2014 and Lefering et al., 2016 and 2018. Also, both slopes and, thus, the conversion factors differ from those, which are used in the present processor. However, these uncertainty components are not included in the present algorithm. Since the NOMAD data set is a compilation of measurements from different researchers, who handle samples and measurements in different ways, so that the uncertainties of these data set are partly caused by methodological differences. Thus, a simple addition of this uncertainty to the uncertainty product of the NN is questionable.

\[
\text{b)} \quad \text{Chl} = 32.33 \cdot \text{apig}_4^{1.203}, \quad \text{stdv: 0.262 on log10 scale, n=425}
\]

(b) \(TSM = 1.35 \cdot bp_{440}^{1.076}, \quad n=412\)

\[
\text{Relationship between } \log_{10} \text{bp}_{440} \text{ and TSM}
\]

\[
\log_{10} \text{bp}_{440} \text{[m}^{-1}] \\
\text{log}\_\text{bp}_{440} \text{[m}^{-1}]
\]

\[
f(x) = 1.076 \cdot x + 0.130 \\
R^2 = 0.780
\]

\[8\]

**Application to OLCI data**

As an example, the out-of-of-scope parameters for rho_toa and rho_w are presented as well as the uncertainties for chlorophyll, TSM, adg and kd_min with atmospheric correction. An OLCI scene (Sentinel 3b) of 20190401 has been selected, which covers part of the North Sea and the Baltic Sea, to include a large variety of case 2 waters.
Fig. 24: Sentinel 3b OLCI L1b RGB scene
S3B_OI_1_ERR_20190401T094916_20190401T103321_20190401T120225_2645_023_350

Fig. 25: Out-of-scope indicator for (a) rho_toa without cloud mask and (b) rho_w with cloud mask
a) Chlorophyll concentration

b) uncertainty from rho_toa (with atmospheric correction)

Fig. 26: Chlorophyll distribution (a) and its uncertainty (b), version which includes the atmospheric correction

a) TSM concentration

b) TSM uncertainty

Fig. 27: Total suspended matter (TSM) distribution (a) and its uncertainty (b), version, which includes the atmospheric correction
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Fig. 28: adg (=ad+ag) distribution (a) and its uncertainty (b), version, which includes the atmospheric correction

Fig. 29: kd_min distribution (a) and its uncertainty (b), version, which includes the atmospheric correction

Fig. 30: Uncertainty of chlorophyll concentration without (a) and with the influence of the atmosphere (b)
Summary, conclusions and outlook

This document describes procedures to identify spectra, which are out of scope of the neural network algorithms, as well as procedures to determine the uncertainty of the IOP-products. The procedures are based on models of the water and atmosphere and radiative transfer simulations and are valid only within the scope of their definition by all cases of water and atmosphere constituents and their variability and vertical distribution.

Thus, the basic idea is first to test if a measured spectrum is sufficiently in agreement with the model, which is used to train the neural network, and then to determine the remaining uncertainty.

The comparison between the direct computation of errors case by case and the determination of the uncertainties using the NN shows that the NN determined case by case uncertainty is in agreement with the square root of the absolute difference between the true (=simulated) and the NN determined IOP.

Two options for determining uncertainties have been studied and implemented in the form of neural networks: (1) the difference between the true (simulated) IOPs and the IOPs, which are determined using the rho_w->IOP NN, and (2) with rho_w as input, which is the output of the rho_toa->rho_w NN, i.e. which includes the uncertainties caused by the atmosphere.

These two types of uncertainties differ significantly. Presently option (1) is implemented in the OLCI case2 water processor, because of the requirement to use the standard atmospheric correction alternatively to the rho_toa->rho_w NN.

However, because option (2) is more realistic, it is recommended to replace the NNs accordingly, which is easily possible without changing the code.

Future work has to focus on tuning the thresholds for both out-of-scope flags and to compare the IOP uncertainties with measured uncertainties.

10 References


Doerffer, R.: Sentinel-3 OLCI Ocean Colour Turbid Water ATBD, REFERENCE S3-L2-SD-03-C11-GKSS-ATBD, 15 July 2010, access: https://sentinel.esa.int/web/sentinel/user-guides/sentinel-3-olci/document-library/-/asset_publisher/hkf7sg9Ny1d5/content/sentinel-3-olci-ocean-colour-turbid-water-atbd?redirect=https%3A%2F%2Fsentinell.esa.int%2Fweb%2Fsentrinel%2Fuser-guides%2Fsentrinel-3-olci%2Fdocument-library%3Fp_p_id%3D101_INSTANCE_hkf7sg9Ny1d5%26p_p_lifecycle%3D0%26p_p_state%3Dnormal%26p_p_mode%3Dview%26p_col_id%3Dcolumn-1%26p_p_col_count%3D1

note: updates of this ATBD is in preparation

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uncertainties in PSICAM and reflective tube absorption meters, Opt. Express 26(19) 24384-24402


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11 Appendix

11.1 Used neural networks

This document is based on the following neural networks:

iop->rw: 55x55x55_173.7.net
iop->unciop: 77x77x77_68400.6.net
iop->uncsumiop_unckd: 77x77x77_46381.2.net
rtosa->aann: 55x7x55_112.8.net
rtosa->rpath: 55x55x55_269.1.net
rtosa->rw: 160x160x160x160x160_75051.5.net
rtosa_trans: 55x55x55_27144.9.net
rw->iop: 55x55x55_3005.6.net
rw->kd: 55x55x55_37.0.net

### 11.2 Conversion IOP -> concentrations

\[
\text{tsm} \ [g \ m^{-3}] = bp*1.73 + bw*3.1
\]

\[
\text{chlorophyll} \ [mg \ m^{-3}] = 21.0*apig^{1.04}
\]

Note: these conversion factors can be changed when using SNAP for adaption to local / seasonal conditions.

Also:

\[
b_{\text{tsm}} = bp+bw
\]

\[
\text{adg} = ad+ag
\]