ATMOSPHERIC CORRECTION OF MERIS IMAGERY ABOVE CASE-2 WATERS *)

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ABSTRACT/RESUME

This paper describes an atmospheric correction algorithm designed for the Medium Resolution Imaging Spectrometer (MERIS) with special emphasis to case-2 waters based on inverse modeling of radiative transfer calculations by using artificial neural network techniques. The presented correction scheme is implemented as a direct inversion of spectral top-of-atmosphere (TOA) radiances into spectral remote sensing reflectances at mean sea level, with additional output of the aerosol optical thickness (AOT) at 4 wavelengths for validation purpose. In this work we apply the inversion algorithm to 8 MERIS Level 1b data tracks of the year 2002 and 2003 covering the North and Baltic Sea region. A validation of the retrieved AOTs is performed with coincident in situ sunphotometer measurements of the Aerosol Robotic Network (AERONET) from Helgoland Island. The overall root mean square error (RMSE) of the retrieved AOTs at 440, 550, 670 and 870 nm is 0.05 when using Rayleigh corrected TOA radiances and 0.073 without prior Rayleigh and ozone correction.

1 INTRODUCTION

A water classification scheme into case-1 and case-2 water types was first introduced by [1]. In contrast to case-1 waters, in which the optical properties are determined solely by phytoplankton and their degradation products and the water itself, the spectral signatures of case-2 waters are influenced additionally by colored dissolved organic matter (CDOM) and suspended particulate matter (SPM). In this optically complex water type all water constituents can vary independently from each other. For an accurate retrieval of water constituents from remotely sensed images one needs to remove the effects that result from scattering and absorption in the atmosphere and from reflection at the sea surface from the measured TOA radiances. Such procedures are called atmospheric corrections. Standard atmospheric correction algorithms, which assume the ocean color as black in the near infrared spectral region (\(\lambda > 700\) nm), often fail above these water type, due to the influence of highly scattering water constituents or bottom up effects. Non zero water-leaving radiances in the near infrared will lead to an overestimation of the AOT with the consequence of an over-correction in the visible spectral region which often results in negative water-leaving radiances. By setting up a multi-band algorithm based on artificial neural networks we try to overcome the problems in atmospheric correction above case-2 waters.

2 ALGORITHM DESCRIPTION

2.1 Forward and inverse model

As forward model we used a radiative transfer code based on the matrix-operator method to generate two large databases which are used as data pools for the neural network training [2],[3]. The first database was generated with azimuthally resolved upward radiances in the MERIS channels just above the sea surface and at TOA for a variety of sun and observing geometries. All simulations are based on a U.S. Standard atmosphere with a constant ozone loading of 344 DU and were performed for a mixture of maritime [4], continental [5] and \(\text{H}_2\text{SO}_4\) [5] aerosol types as outlined in Tab. 1. As shown from the normalized spectral extinction coefficients of Fig. 1 no absorbing aerosols were taken into account. The optical properties of these aerosols used as input for the radiative transfer simulations were derived prior from Mie calculations. Moreover, a rough sea surface characterized by wind speeds of 1.5 and 7.2 m/s and surface air

pressure variations of 980 and 1040 hPa were considered. The ocean of the model is characterized by varying concentrations of water constituents, typically found in European coastal waters, namely chlorophyll (CHL), SPM and CDOM as tabulated in Tab. 2. The inherent optical properties required as input to the simulations, such as the absorption and scattering of pure sea water, CDOM, SPM and phytoplankton were taken from published measurements or parameterizations. The absorption of the sea water is modeled as a sum of the absorption coefficients of pure sea water itself, pigments (chlorophyll-a + phaeophytin), CDOM and SPM. The total scattering coefficient is modeled as a sum of pure sea water and total particulate matter (exogenous+endogenous). We computed the absorption coefficient of phytoplankton according [6]. The scattering coefficient of total particulate matter according to [7]. The absorption coefficient of pure water is taken from [8] and [9] while the pure sea water scattering coefficient is taken from [10]. The CDOM is assumed to be totally absorbing and is taken from [7]. The scattering phasefunction of pure water was taken from [10]. Moreover, a new model of the backscattering probability in case-2 waters was applied from [11]. It relates the backscattering of marine particles to the wavelength and the ratio of CDOM absorption to SPM concentration and was derived by reconciling radiative transfer simulations of the hemispherical reflectance just below the sea surface with the corresponding values contained in the COASTLOOC data set. The second database was generated by additional simulations for a pure Rayleigh atmosphere (AOT=0) and an ozone loading of 344 DU above a black ocean.

The neural networks serving as inversion models are fully connected feedforward networks trained by the backpropagation algorithm [12]. Their task is to perform non linear function approximations. All networks consist of three layers: an input layer, a hidden layer and an output layer. While the number of neurons for the input and output layer is fixed by the problem under investigation the optimum number of neurons for the hidden layer has to be found by training different networks. Since there is no rule in finding the optimum architecture, it has to be found by varying the number of neurons in the hidden layer.

For the training of the atmospheric correction networks two subsets of each 100 000 training vectors with Rayleigh corrected and uncorrected TOA radiance spectra were extracted randomly from the simulated databases. One input vector consists of a complete simulated MERIS spectrum (except band 8, 11, 15), the sun and observing geometry, the surface pressure and the wind speed information. We did not use MERIS band 8 (681 nm) because chlorophyll fluorescence was not considered in the model. Moreover MERIS band 11 (760 nm) was not taken into account because it is affected by oxygen absorption and MERIS band 15 (900 nm) was not considered due to the influence of the water vapor absorption. Signal dependent Gaussian noise was added to all training vectors according to the assumed uncertainty of the associated parameters. A principal component transformation (PCA) was used to decorrelate all input dimensions to the network. The generalization power of the network was controlled with a test dataset not being used for the network training. Output of the atmospheric correction networks is the remote sensing reflectance at mean sea level (MSL) for band 1-7 and 9 with additional AOT at 440, 550, 670 and 870 nm.

To apply a Rayleigh-Ozone correction to real MERIS data, a Rayleigh-Ozone network was trained to calculate the Rayleigh-Ozone path radiance at TOA for the MERIS bands mentioned above. This network was trained with 12000 randomly chosen vectors from the second database containing pure Rayleigh-Ozone simulations. For this network an input vector is composed of a wind speed, a surface pressure and the sun and observation geometries. The associated output is the TOA Rayleigh-Ozone path radiance spectrum.

Tab. 1: The 8 aerosol assemblages used for the proposed atmospheric correction algorithm.

<table>
<thead>
<tr>
<th>Set 1</th>
<th>Rel. Humidity [%]</th>
<th>AOT @550 nm Boundary Layer (BL) 0-2 km</th>
<th>AOT @550 nm Troposphere 2-12 km</th>
<th>AOT @550 nm Stratosphere 12-50 km</th>
</tr>
</thead>
<tbody>
<tr>
<td>70, 80, 95, 99</td>
<td>Maritime [4]</td>
<td>0.03, 0.1, 0.3, 0.5, 1.0</td>
<td>H2SO4 [5]</td>
<td>Mixing Ratio 5% of BL</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.005</td>
</tr>
<tr>
<td>Set 2</td>
<td>Rel. Humidity [%]</td>
<td>AOT @550 nm Boundary Layer (BL) 0-2 km</td>
<td>AOT @550 nm Troposphere 2-12 km</td>
<td>AOT @550 nm Stratosphere 12-50 km</td>
</tr>
<tr>
<td>70, 80, 95, 99</td>
<td>Maritime [4]</td>
<td>0.03, 0.1, 0.3, 0.5, 1.0</td>
<td>H2SO4 [5]</td>
<td>Mixing Ratio 25% of BL</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.005</td>
</tr>
</tbody>
</table>

Tab. 2: Concentration ranges of the oceanic constituents used for the simulations

<table>
<thead>
<tr>
<th>Constituent</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>CHL</td>
<td>0.05</td>
<td>50.0</td>
<td>mg m-3</td>
</tr>
<tr>
<td>SPM</td>
<td>0.05</td>
<td>50.0</td>
<td>g m-3</td>
</tr>
<tr>
<td>CDOM</td>
<td>0.005</td>
<td>1.0</td>
<td>m-1</td>
</tr>
</tbody>
</table>

Fig. 2: Normalized spectral extinction of the aerosols of Tab. 1.
2.2. Data processing

When introducing real MERIS data to the networks, two normalizations have to be applied to be consistent with the simulation world. First, the TOA radiances need to be normalized to the actual spectral solar constant values contained in the Level 1b data file. Second, the TOA radiances have to be normalized to an ozone loading of 344 DU used in the radiative transfer simulations. Therefore, the direct ozone transmission for the simulation with 344 DU and for the ozone amount at the time of the MERIS overpath have to be calculated. The total ozone amount at the time of the MERIS measurement is taken from the resampled ECMWF data of the annotation dataset while the spectral ozone extinction coefficients are taken from [13].

When applying a Rayleigh correction to the MERIS measurements first, the atmospheric correction is performed by two consecutive networks. First, the Rayleigh-Ozone network calculates the TOA Rayleigh-Ozone path radiances for the actual pressure and an ozone loading of 344 DU for each pixel. This output is used to correct the normalized TOA radiances for Rayleigh scattering and ozone absorption and is then processed by the atmospheric correction network. If no Rayleigh-Ozone correction is applied to the TOA radiances only one network will do the atmospheric correction. Output of both networks consists of the remote sensing reflectances at mean sea level for 8 bands and the AOT at 4 wavelengths.

3 RESULTS AND VALIDATION

Validation of atmospheric correction algorithms is performed with the help of coincident in situ measurements of the marine reflectance and the spectral aerosol optical thickness. Due to the lack of marine reflectance measurements, a validation of the proposed algorithm is achieved solely with the help of coincident CIMEL sunphotometer measurements of the Aerosol Robotic Network (AERONET) [14] from the Helgoland Island (Fig. 2). Helgoland Island is located at 7.89°E longitude and 54.18°N latitude about 70 km off mainland in the German Bight. In the frame of this work, 8 MERIS tracks from the years 2002 and 2003 were processed with the outlined neural network atmospheric correction algorithms. From a 20 x 20 pixel box centered at Helgoland Island, the median values of the retrieved neural network AOTs for an inversion with Rayleigh correction are compared with the median values of the sunphotometer measurements of a 2 hour time window (Fig. 3). MERIS overpath time for the selected tracks is calculated to be between 10 and 10:30 UTC.

![Fig. 2: Helgoland Island](image)

![Fig. 3: Median of the neural network retrieved aerosol optical thickness (black) compared with the median of in situ sunphotometer measurements from Helgoland Island (red). Black error bars represent the standard deviation for a 20x20 Pixel box. Red error bars represent the standard deviation for the 2 hour time window of the in situ measurements.](image)
Therefore the time window for the AERONET data was selected between 9 and 11 UTC. Land pixels were rejected with the help of the Level 1b data flags. Moreover we applied an own cloud mask based on simple thresholds, sufficient enough for ocean color purpose. For better intercomparison of all 8 days the median AERONET values were interpolated on 550 nm and scatter plotted versus the neural network results (Fig. 4). For AOTs less than 0.2 the network retrieved AOTs show better results for an inversion with Rayleigh and ozone correction. The overall RMSE for the Rayleigh and ozone corrected inversion is with 0.05 lower compared to the uncorrected with 0.073 RMSE. Fig. 4 suggests better performance for the Rayleigh and ozone corrected network, but if one compares the results for the derived AOT fields at 440 nm shown in Fig. 5, the Rayleigh-Ozone network produces artificial patches in the lower left of the image which can be seen in the RGB composite as structures from the water and not from the atmosphere. Therefore it is helpful for the validation of the AOT not only to look at RMSE values but also at the derived structures of the AOT fields. Even though the Rayleigh and ozone uncorrected network has a higher overall RMSE, it is leading to more reliable AOT structures. Along the coastlines both networks achieved good results, which means that the retrieved AOTs are not influenced by sediments.

Due to the lack of in situ data the network derived remote sensing reflectances could not be validated. But sample spectra taken at 4 locations marked in Fig. 6 look reliable when comparing them with spectra taken from literature [15]. The spectra of location 1 and 3 are typical for waters with moderate chlorophyll and sediment concentrations. While the spectra of location 2 and 4 are typical for moderate sediment and gelbstoff concentrations with some phytoplankton. Moreover the structures of the reflectances at 442.5 nm and 560.0 nm of Fig. 6 look feasible. Along the coastline the reflectance at 560.0 have higher values compared with 442.5 nm due to the sediments and the gelbstoff. In general, the correlation between the path reflectance and derived remote sensing reflectance at MSL should be low after applying the atmospheric correction. The correlation analysis of both reflectances for the West-to-East transact of Fig. 8 yields a low correlation of $r=0.299$ at 442.5 nm and a higher correlation of $r=0.839$ at 560.0 nm. The path reflectances were calculated with an approximation of the diffuse transmittance given by [16].
4 CONCLUSION

We proposed an atmospheric correction scheme for MERIS data above case-2 waters based on artificial neural networks and applied the algorithm to 8 MERIS Level 1b data tracks covering the German Bight. The fast and robust inversion algorithm derives the remote sensing reflectance at mean sea level and the aerosol optical thickness at 4 wavelengths. An overall RMSE of 0.05 between 440 nm and 870 nm could be derived in comparing the spectral AOTs of an atmospheric correction network with prior Rayleigh and ozone correction with in situ AERONET data from Helgoland Island. A slightly higher overall RMSE of 0.073 was achieved by a network without Rayleigh and ozone correction. Although this network is less accurate, a better separation of atmospheric and oceanic structures could be obtained from this network. Further validation data are needed to analyze the differences between the network computed spectral AOTs and AERONET. Other aerosol models like the suggested blue aerosol model may help to improve the AOT retrieval at shorter wavelengths. For the future in situ measurements of the marine reflectance like from SIMBADA are needed for validation of the neural network remote sensing reflectance.
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