A Method for Aerosol Retrieval from the Spectral Variation in the Visible and Near Infrared. Application to the MERIS Sensor.

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Abstract – The signal recorded by the sensor contains information relative both to the atmosphere and the surface. Atmospheric correction is necessary to extract the surface reflectance required within biophysical algorithms used to estimate canopy characteristics. Aerosol characteristics are the most difficult to evaluate because they vary rapidly with time and space. The objective is to develop an autonomous aerosol correction method exploiting the information content in MERIS top of atmosphere signal. We propose to use 13 MERIS bands to estimate the aerosol optical thickness, training a dedicated neural network over a database made of radiative transfer model simulations (SMAC, SAIL, PROSPECT).

Keywords: Aerosol, Atmospheric Correction, Neural Network, MERIS, AERONET, MODIS.

1. INTRODUCTION

The atmosphere affects strongly the reflectance signal as recorded by sensors aboard satellite platforms. Atmospheric correction is thus mandatory to get top of canopy reflectance values from which a number of surface characteristics could be derived. The radiative transfer in the atmosphere depends both on absorption and scattering processes.

The atmospheric pressure at the surface, which is known with a sufficient accuracy from the surface elevation or from main Meteorological Organizations such as ECMWF, allows characterizing absorption effects due to oxygen and carbon dioxide (relatively well mixed gases) and Rayleigh scattering. Ozone, water vapour and aerosols pose a problem varying rapidly and strongly with space and time. But the organizations also provide reliable estimates of water vapour at very coarse resolution. And, dedicated sensors such as TOMS (Mc Peters and al., 1998) allow getting a good estimate of the total ozone content. In addition, the most recent sensors such as MODIS and MERIS have specific bands dedicated to atmospheric water even ozone content estimations. Unfortunately, no instrument provides routinely sufficiently accurate estimates of aerosol characteristics exhaustively over the Earth's surface and at the desired temporal and spatial resolution.

Current aerosol correction methods are mainly based on the Dense Dark Vegetation (DDV, Kaufman, 1989) concept. It consists in identifying dark pixels in the image characterized by very low top of canopy reflectance values for the shorter wavelengths where aerosol contribution to the reflectance at the top of the atmosphere is the largest. The use of empirical relationships between the top of canopy reflectance in the shorter wavelengths and that at longer wavelengths (SWIR), where aerosol effects are weak, permits to increase the number of targets. This is the basis of the MODIS aerosol correction (Kaufman and al., 1997) and that developed for VEGETATION (Berthelot and Dedieu, 2000).

In the case of MERIS and SeaWiFS where no SWIR band is available, the BAER method was proposed (Von Hoyningen-Huene and al., 2002). The surface reflectance is represented as the mixture of typical vegetation and bare soil surfaces, the vegetation fraction being derived from a vegetation index. Then, the aerosol optical thickness and characteristics are iteratively varied to simulate the top of atmosphere reflectance thanks to LOWTRAN model (Kneizys and al., 1989).

Rather than using the spectral variation of the signal, alternative methods have been developed exploiting the directionality of the reflectance as observed by POLDER (Deuzé et al., 2003), ATSR (North and al., 1999) or MISR (Martonchik and al., 1998) sensors.

The objectives of this paper are to propose an autonomous atmospheric correction method based on the spectral variation of the signal. The MERIS sensor provides a good spectral sampling within the visible and near infrared domains. The exploitation of the spectral information as observed from MERIS should hopefully allow unravelling the atmosphere from the surface effects. The method proposed here is based on the training of neural networks over a learning data base made of radiative transfer model simulations.

In the following, we will first recap the main MERIS features, the ground data and the MODIS aerosol products. Then we will describe the method used with emphasis on the learning data base and design of the neural network architecture. Finally, the method will be evaluated over an extensive data set made of AERONET aerosol characteristics measurements and a comparison with the algorithm implemented on MODIS will be achieved.

2. AERONET, MERIS AND MODIS DATA

2.1 The AERONET network

AERONET is a network of automated sun-photometers (Holben and al., 1998) measuring the incoming radiation in a number of directions and bands (1020, 870, 670, 500, 440, 380 and 340nm) during the daily time course. The aerosol optical thickness is thus computed from these measurements for the set of wavebands available after a number of tests to check the reliability of the data.

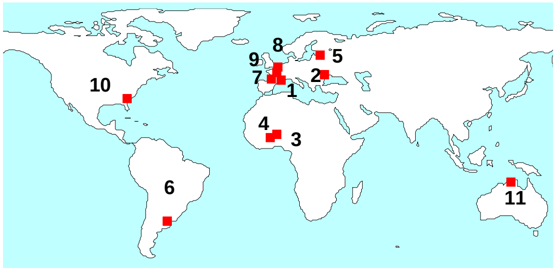

Figure 1. Location of the AERONET validation sites.

Eleven AERONET sites were used for this validation exercise. They include a wide range of situations, both in latitude, longitude (figure 1), date, distance to the sea and surface conditions. The optical thickness at 550nm was estimated by interpolating the actual AERONET AOTs thanks to the Angström power law.

2.2 The MERIS sensor and available data

MERIS aboard the ENVISAT polar sun-synchronic platform is acquiring images since 2002 (Rast et al., 1999). It measures the radiance from 800 km altitude in 15 wavebands in the visible and near infrared domain (Table A). The field of view is limited to ±34° providing a revisit frequency around 3 days at the equator. The original spatial resolution called full resolution (FR) is around 300 m while the reduced resolution (RR) corresponds to a pixel size close to 1.2 km. The MERIS products used in this study are level 1b, i.e. calibrated and geo-referenced radiance values. In addition, the 3 angles defining the view and illumination geometry are also available.

Table A. Characteristics of the 15 MERIS bands (nm).

Centre	Width	Potential Applications
412.5	10	Yellow substance and detrital pigments
442.5	10	Chlorophyll absorption maximum
490	10	Chlorophyll and other pigments
510	10	Suspended sediment, red tides
560	10	Chlorophyll absorption minimum
620	10	Suspended sediment
665	10	Chlorophyll absorption and fluo. reference
681.25	7.5	Chlorophyll fluorescence peak
708.75	10	Fluo. Reference, atmospheric corrections
753.75	7.5	Vegetation, cloud
760.62	3.75	Oxygen absorption R-branch
778.75	15	Atmosphere corrections
865	20	Vegetation, water vapour reference
885	10	Atmosphere corrections
900	10	Water vapour, land

During year 2002 and 2003 and the early 2004, 97 level 1b MERIS images were acquired over the 11 AERONET sites. They were mainly made of RR products, although 9 scenes were available at the FR. All the scenes corresponded to available and apparently valid AERONET measurements of the optical thickness. For each MERIS image, a 20×20 km² window centred on the sun-photometer was extracted.

2.3 MODIS aerosol products

MODIS (MODerate Imaging Spectrometer) aerosol data were downloaded from the on line Data Gateway web site (http://delenn.gsfc.nasa.gov). MODIS aboard the Terra satellite platform has a crossing time at descending node similar to that of MERIS. The product used is the AOT at 550nm at a resolution of 5 km of side pixels for a synthesis period of 5 minutes and calculated within the extended DDV algorithm as seen in the introduction. However, only 31 dates were available from the original list of 97. The data extracted were corresponding to a window of 20 x 20 km² such as in the MERIS case and also the same process with larger pixels will be applied to get an estimation of the AOT at 550 nm over the same AERONET sites.

3. ESTIMATION OF AEROSOL OPTICAL THICKNESS USING NEURAL NETWORKS

3.1 Overview of the method

Neural networks (NN) are recognized as universal interpolators as demonstrated by Leshno et al. (1993). This capacity will be exploited to relate the top of atmosphere reflectance data to the corresponding aerosol characteristics. This was already used with success in remote sensing in a number of studies (Danson et al., 2003). Most of the efforts in training a neural network consist in generating a proper learning data base. The learning data base should sample all the surface and atmosphere conditions that can be observed from MERIS. Ideally, the training data base should therefore be made of MERIS observations that are paired with accurate ground (AERONET) measurements of the aerosol optical thickness (AOT). However, because of the number of configurations to be used, and the possible errors in AERONET and MERIS data such as cloud occurrence or malfunctioning, it is often preferred to use physical radiative transfer model simulations.

Top of atmosphere reflectance data as measured by MERIS are simulated by coupling models describing the radiative transfer at the surface (soil, vegetation) and in the atmosphere. The top of canopy reflectance can be simulated thanks to the combination of a canopy radiative transfer model that accounts for the canopy structure and the illumination and observation geometry. This canopy radiative transfer model needs as input a description of the leaf optical properties as well as soil background reflectance.
The PROSPECT model (Jacquemoud and Baret, 1990) with the updated specific absorption coefficients proposed by Fourty and Baret (1997) provides a good description of the leaf reflectance and transmittance with a limited number of input variables. Ten reference soil spectra are used from a data base available at INRA Avignon representing a large variation of soil types, moisture, roughness and geometrical configurations (Liu and al., 2003). In addition, snow and water surfaces were also included to represent these situations that are not exceptional.
The SAIL radiative transfer model (Verhoef, 1984) is proposed to describe canopy reflectance, including the Kuusk's hot-spot formulation (Kuusk, 1994). This model is computer efficient and uses a limited number of input variables thanks to the simple approximation of canopy architecture that is considered as a turbid medium.
Among the several atmosphere irradiative transfer models, the SMAC code (Rahman and Dedieu, 1994) was selected for the good compromise it provides between the realism of the simulations, the relatively small number of inputs and the computation requirements (aerosol continental type will only considered).

46656 MERIS top of atmosphere reflectance observations were simulated, resulting from the sampling scheme based on 2 full orthogonal experimental plans : the first one for the radiative transfer at the surface (Bacour et al., 2002) and the second one for the radiative transfer in the atmosphere. The 2 plans were done separately to maximize the number of atmosphere cases since one of them must be extracted from the signal by the NN. For all the variables, the distributions selected were supposed to approach the best the actual distribution of the variables over the Earth during the yearly cycle: current information available or truncated Gaussian laws from empirical knowledge were used. Because of the lack of knowledge on the co-distributions, all the variables were simply assumed independent (Baret and al., 2004).

3.2 Representativity of the simulated data base

To evaluate the representativity of the learning data base, we compared the TOA reflectance values as observed from actual MERIS sensor to those simulated in the learning data base. We used the 97 MERIS L1b images subsets to compute the reflectance mismatch for each pixel p:

$$MISM(p) = min_{p_i \in LearningDatabase}(RMSE_{\lambda=1:13}(\rho_\lambda(p), \rho_\lambda(p_i)))$$

Where $\rho_\lambda(i)$ represents the reflectance value of the pixel p_i in the wavelength λ, i belonging to the learning data set. The reflectance mismatch is the RMSE computed between the actual MERIS spectrum and the closest one in the learning data base in the sense of quadratic distance. The averages reflectance mismatch value is about 0.01 with a maximum value of 0.03, representing respectively 1% and 3% of the reflectance value. The learning data base seems to represent well the actual MERIS data over the large range of variation considered. A closer inspection of the reflectance mismatch shows larger discrepancies in the blue bands, behaviour explained by the enhanced sensitivity to aerosol and Rayleigh scattering in the blue domain.

3.3 Architecture, training and performances of the NN

Among the 15 MERIS bands, bands 11 and 15 were not used because dedicated respectively to the oxygen and water vapour absorption. Therefore only 13 bands were actually used. In addition, the sun and view zenith angles as well as the relative azimuth between these two directions were also used as inputs. The total number of inputs amounts to 16. The output of the network is the AOT at 550nm.

Finally half of the simulations were used to train the network thanks to the Levenberg-Marquardt minimization algorithm, while one quarter was used to evaluate the hyper-specialization of the network and the remaining to test its potential performances.

The neural network applied to each case of the test data set provides relatively good performances, with a RMSE value of 0.058 for an AOT varying between 0 and 1. The residuals are distributed as a Gaussian centred on 0.0, i.e. no bias is observed. However a slight overestimation appears for the very low values of AOT. From these theoretical performances, it is concluded that the spectral information as sampled by MERIS allows retrieving the aerosol optical thickness with a reasonable accuracy. Note however, that the aerosol type was here limited to the continental one.

4. RESULTS OVER MERIS AND RELATIVE COMPARISON WITH MODIS AEROSOL PRODUCTS

4.1 Capacity to estimate the AOT with actual MERIS data

The neural network was run over the 97 actual MERIS TOA reflectance images. The AOT as measured by the sun-photometer at the ground level integrates a distance of few kilometres in the sun direction, depending on sun zenith angle (figure 2). We supposed a height of 12 kilometres of the aerosol layer and fixed the width of the zone of the instrument's view equal to the length induced by the sun zenith angle. Finally spectra of all the pixels of the zone are averaged and the resulting spectra is processed within the neural network, assuming implicitly an almost constant aerosol characteristics over the area.

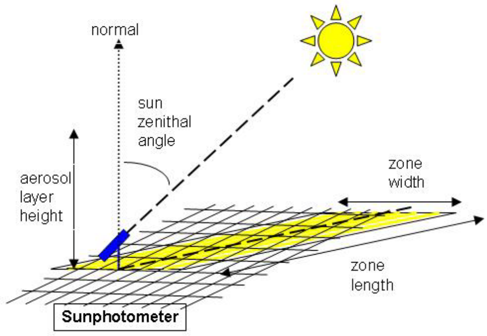

Figure 2 : Principle of a Sun-photometer measurements.

Results show that the AOT at 550 nm as estimated by the neural network from MERIS level 1b products is in good agreement with that measured at the ground level thanks to the sun-photometer. The corresponding RMSE value of 0.1042 (figure 3, left) is higher than the theoretical performances observed previously over the test data set but this accuracy is comparable to other AOT at 550 nm estimations within algorithms such as the extended DDV method. The distribution of the residuals is relatively well approached by a Gaussian distribution centred on 0.0.

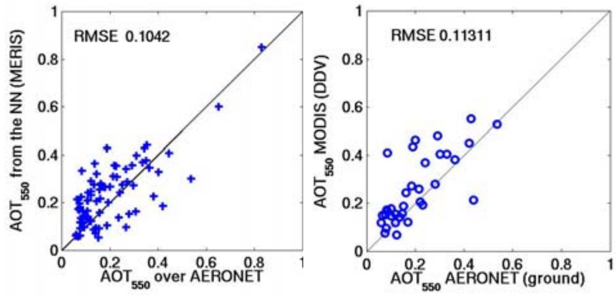

Figure 3 AOT estimations vs. ground measurements: NN based on MERIS (left) and MODIS aerosol products (right).

4.2 Relative comparison with MODIS aerosol products

This comparison was achieved over the 31 pairs of MODIS and MERIS images. The slight difference in terms of time of overpass between MERIS and MODIS was shorter than one hour, leading to an AOT difference smaller than 10% as measured by AERONET. The neural network algorithm provided a RMSE close to 0.1 with AERONET AOT measurements. Note that his value computed over the 31 scenes is quasi the same than the one observed over the 97 scenes. As compared to the MODIS AOT product, the RMSE value of 0.113 is slightly higher than that of MERIS and shows a slight overestimation.

5. CONCLUSIONS AND PERSPECTIVES

This study introduces a new concept in atmospheric correction over land surfaces. It is based on the retrieval of aerosol optical thickness using the spectral information of the signal as recorded from top the atmosphere by the MERIS sensor and radiative transfer model simulations. Despite other methods qualified as extended DDVs or the BAER one where the surface reflectance is supposed to be a linear combination of a pure bare soil and a pure vegetation components, our method allows a wide variability in the surface reflectances. The only implicit assumption used is that the surface spectral features are different enough from those associated to the atmosphere scattering and absorption. It was demonstrated that the set of radiative transfer models used were capable to simulate with a good accuracy (RMSE around 0.01) the top of atmosphere reflectance in the 13 MERIS bands considered. This justifies also the approximation introduced through the simple coupling or the radiative transfer between the surface and the atmosphere, as well as the use of a single aerosol type. Reciprocally, this result constitutes also an indication of the good absolute radiometric performances of the MERIS sensor. In addition to the good retrieval performances they proved, neural networks are very simple to implement and run within operational processing chains or toolboxes. Once the aerosol optical thickness is estimated, it is possible to complete the atmospheric correction if pressure, ozone and water vapour are known. In our case we used the simple SMAC code which is very computer efficient, but probably degrades slightly the accuracy of the whole atmospheric correction scheme as compared to 6S or MODTRAN codes.

The assumption of a unique aerosol type (continental) might limit the performances of the algorithm, particularly for the larger particles. A concurrent estimation of AOT at 550nm and the Angström coefficient would potentially improve the accuracy of the retrieval. This aspect will be further investigated. The algorithm was developed for the MERIS sensor that compensates the absence of short wave infrared bands by a better spectral sampling in the visible and near infrared domains. However, the same principles could be applied to other sensors such as SEAWIFS, VEGETATION, MODIS, as well as for higher spatial resolution instruments such as SPOT and Landsat with due attention to the adjacency effects.

6. REFERENCES

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