# AEROMAP: Satellite retrieval of dust aerosol microphysical and optical parameters using neural networks

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We constructed a neural network which uses satellite measurements to retrieve dust aerosol microphysical and optical properties in the atmosphere. The satellite data comprised the aerosol optical depth at 470, 550 and 660nm plus the columnar water vapour from the MODIS/Aqua Level 3 data product and the estimated absorption aerosol optical depth at 500nm from the OMI Level 3 data product. The neural network was trained to retrieve AERONET Level 2.0 (Version 2) Inversion Product retrievals including the aerosol size distribution and its refractive index, the single scattering albedo and the asymmetry factor. For training and validation of the neural network, we used data from AERONET stations known to be affected by high dust concentrations. More specifically, we trained the neural network with data from stations in North Africa and tested its performance using data from the station at Dakar. The daily-averaged values of the aerosol size distribution, the imaginary part of the complex refractive index and the spectral single scattering albedo were obtained with the neural network with moderate precision (correlation coefficients in the range $0.368 \leq R \leq 0.514$). It appears that neural networks provide daily-averaged retrievals of aerosol properties that were not accessible from satellite data until now.

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# 1 Introduction

A global characterization of aerosols in the atmosphere is vital to correctly estimate their effect on climate. Aerosol properties are most routinely monitored by the ground-based aerosol robotic network (AERONET). However, while there is a high density of AERONET instruments in populated areas and megacities, the most dominant sources of aerosol originate from often uninhabited regions like the planet's deserts, oceans and ice-caps where few instruments exist. There is therefore a lack of knowledge of the overall global spatial and temporal variation of aerosol (Hansen et al. 2005) and hence a substantial uncertainty in the magnitude of their contribution to the perturbation of the radiation budget of the Earth-Atmosphere system. The size of the uncertainty has been estimated and found to be unacceptably large (Schwartz, 2004). In response to this, aerosol scientists have outlined a set of retrieval accuracy requirements for remote-sensing instruments in space to be able to detect changes in planetary aerosol radiative-forcing over the next two decades (Mishchenko et al. 2007):

- radius of the fine and coarse particle modes, *r(f)* and *r(c)* (±10 %)
- variance of the fine and coarse particle modes, *var(f)* and *var(c)* (±40 %)
- spectral behaviour of the real part of the complex refractive index, CRI-R (±0.02)
- spectral behaviour of the single-scattering albedo, SSA (±0.03)

AERONET retrieves the latter two parameters and also the aerosol volume size distribution (AVSD) from which it is possible to estimate modal radii, variances and concentrations (see Appendix A of Taylor et al. 2013) from inversion of direct sun and sky radiance measurements (Dubovik and King 2000) to high precision but at local sites. In contrast, space-borne satellite instruments like the moderate resolution imaging spectroradiometer (MODIS) instrument onboard the twin polar orbiting satellites Terra and Aqua, can sample the atmospheric column of the whole Earth, but their retrieval algorithms are not currently able to provide reliable proxies that give information on the mean particle size of fine and coarse aerosol, the complex refractive index and particle shape – all necessary for a full understanding of aerosol microphysics (Remer et al., 2005) and a global characterization of different aerosol sources (Tanré et al., 1996). Therefore, in order to exploit the full-Earth viewing potential of space-bound measurements, new algorithms are required to deduce these key parameters. This is the principal aim of the AEROMAP project (http://apcg.meteo.noa.gr/aeromap), a two-year EU-funded project that began in March 2012 and hosted by IERSD-NOA. In this short paper, we describe how neural network (NN) models developed by AEROMAP can be used to retrieve daily estimates of aerosol microphysical and optical parameters from satellite measurements, and we present results for an extensive region, Northern Africa (NAF), where the dust global aerosol optical depth (AOD) has its peak (Chin et al. 2000).

The NNs are trained with satellite measurements as input variables and co-located and synchronous AERONET microphysical and optical parameters as the target output variables, and are then validated with unseen AERONET data. Until now, estimates of aerosol properties from space have made use mainly of look-up tables to match aerosol properties to corresponding light measurements on a case by case (and day by day) basis. The NN calculation of the inverse function (between satellite inputs and AERONET outputs) may require considerable time due to the need for run and optimize a grid of trained NN models (see below) but, once complete, the NN solution is instantaneous and simultaneously retrieves target output variables in a single step – without having to re-calculate each day. Such NN retrieval schemes therefore (potentially) have the capacity to produce real-time retrievals for large datasets on the global scale.

# 2 Data and Methodology

## 2.1 Data

This work draws on four different data sources. Satellite inputs comprising over eight years of daily measurements (2004-2013) of the AOD at 470, 550, 660nm and the columnar water vapour content $H_2O$ from the MODIS Aqua Level 3 Collection 5.1 together with the absorption AOD at 500nm from the Ozone Measuring Instrument (OMI) Level 3 OMAERUV algorithm have been derived at a spatial resolution of 1×1 degree. In conjunction with this, co-located (in the same pixel) and synchronous daily-averaged ground-based target outputs including the AVSD retrieved in 22 logarithmically-equidistant radial bins spanning the range of particle radii from 0.05 to 15μm, the real and imaginary parts of the complex refractive index CRI-R(λ) and CRI-I(λ), the SSA(λ) and the asymmetry parameter ASYM(λ) centered at λ = 440, 675, 870 and 1020nm are provided from the AERONET Level 2.0 Version 2 inversion algorithm. Finally, mean global extinction AOD data spanning the years 2000-2006 from the global ozone chemistry aerosol radiation and transport (GOCART) model (Chin et al. 2000) is used for selection of 7 dust-dominated ( >84.8% ) AERONET sites in Northern Africa (NAF) shown in Fig. 1.

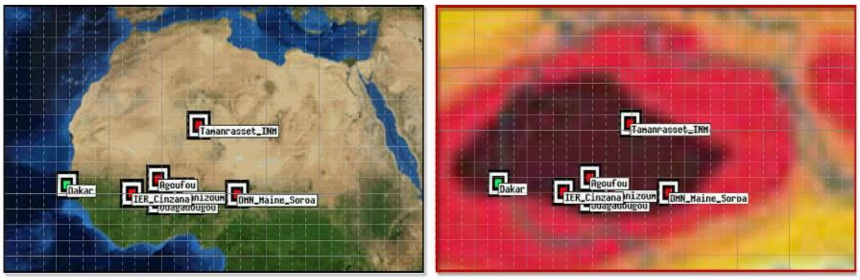


**Fig. 1**. Left: A satellite map showing the location of the 6 Northern African (NAF) AERONET sites used to train the NN models (red) and the Dakar (green) site used for NN testing. Right: An overlay of the same sites on the peak of dust AOD for the study region extracted from GOCART.

## 2.2 Methodology

The AEROMAP approach is based on NN models since feed-forward NNs, having at least one layer of intermediary neurons whose activation functions are nonlinear hyperbolic tangent (Tanh) functions or sigmoidal functions, have been proved to operate as universal function approximators (Hornik et al. 1989). This means that given enough neurons and training data, such NNs are (potentially) capable of learning the numerical relation between satellite inputs and output aerosol parameters. We developed a new automated procedure to detect the optimal architecture based on permuting the number of intermediary neurons and the proportion of data used for training (t%), and then selecting the NN having the lowest mean squared error *MSE* between network outputs and AERONET targets (see Taylor et al. 2013 for details). NNs having Tanh activation functions, and learning by back-propagating errors with the Levenberg-Marquardt algorithm (Levenberg 1944; Marquardt 1963), were coded in MATLAB script and the optimal trained NN was found by: 1) normalizing all input and output variables, 2) applying principal components analysis (PCA) to inputs and outputs separately to exclude redundant variability, 3) looping through a grid of 100 NNs of varying numbers of hidden neurons (4–24 neurons in steps of 2) and proportions of training data (40–90% in steps of 5 %), and 4) selecting the NN having the minimum MSE between its outputs and the target AERONET outputs. A schematic of the learning process is shown in Fig. 2. The number of co-located (satellite-ground) and synchronous (daily) complete available NAF

AERONET records used to train the NN were 139 days, and 169 days of complete co-located and synchronous records at Dakar were used to test the optimal NN.

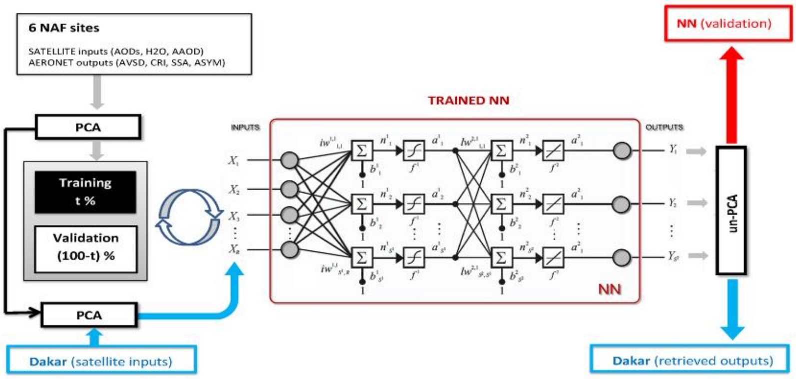


**Fig. 2.** A schematic of the modeling process. PCA is applied to co-located and synchronous, normalized satellite inputs and AERONET outputs from 6 North Africa (NAF) sites and the PCs are used to train each NN in a grid of 100 NN architectures (varying t% and number of neurons) until the MSE between NN PC outputs and PC target outputs is minimized. Real-space outputs of the optimal NN are obtained by transformed back with reverse principal components ("un-PCA"). To test the optimal trained NN, new ("unseen") satellite inputs at Dakar are presented to the optimal trained NN and used to retrieve daily co-located and synchronous aerosol parameters.

## 3 Results

The optimally-trained NN is able to retrieve the magnitude of aerosol parameters (their mean values) but also importantly their variability on the daily timescale – required for real-time monitoring. As an illustration, Fig. 3 shows the NN retrieval of SSA(440) obtained from satellite inputs over Dakar and compares it with collocated and synchronous daily-averaged values obtained by AERONET.

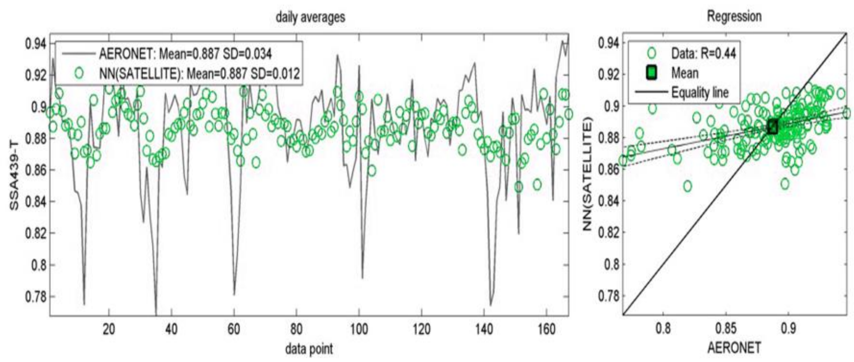


**Fig. 3.** The retrieval of the daily-averaged SSA at Dakar using the NN trained on input-output data at 6 sites in the vicinity.

The mean of the NN retrieval of this parameter and the AERONET retrieval are equal to 3 decimal places. However, the NN retrieval does not exhibit the same variability as the AERONET data as reflected by its lower standard deviation – suggesting that the training data set does not include enough low SSA records for the NN to capture this behaviour. Note that this NN model also simultaneously retrieves the SSA together with the AVSD, the CRI and ASYM parameters. An analysis of the number of NN retrievals that fall within the suggested levels of acceptable uncertainty laid out by Mishchenko et al. (2007) are shown in Table 1.

**Table 1.** Uncertainty analysis using the target levels of Mishchenko et al. (2007). Results are shown for unseen satellite inputs at Dakar on the daily timescale fed to an optimal NN having 22 intermediary neurons, trained on 90% of the NAF data and validated on the remaining 10%.

| Aerosol Parameter | Uncertainty (Mishchenko et al. 2007) | <AERONET> | <NN> | *N* Certain | % of sample falling within the uncertainty limits |
|---|---|---|---|---|---|
| *r(f)* | ±10% | 0.115 | 0.118 | 102 | 60.4% |
| *r(c)* | ±10% | 1.928 | 1.909 | 58 | 34.3% |
| *var(f)* | ±40% | 1.529 | 1.514 | 169 | 100.0% |
| *var(c)* | ±40% | 3.056 | 2.650 | 169 | 100.0% |
| CRI-R(440) | ±0.02 | 1.472 | 1.457 | 66 | 39.1% |
| CRI-R(675) | ±0.02 | 1.488 | 1.479 | 76 | 45.0% |
| CRI-R(870 | ±0.02 | 1.472 | 1.471 | 76 | 45.0% |
| CRI-R(1020) | ±0.02 | 1.459 | 1.460 | 70 | 41.4% |
| SSA(440) | ±0.03 | 0.901 | 0.897 | 124 | 73.4% |
| SSA(675) | ±0.03 | 0.948 | 0.947 | 115 | 68.1% |
| SSA(870 | ±0.03 | 0.954 | 0.957 | 119 | 70.4% |
| SSA(1020) | ±0.03 | 0.956 | 0.959 | 121 | 71.6% |

While the width (variance) of the fine and coarse modes in the AVSD is certain and the mean radius of the fine mode is found with some 60% certainty, the mean radius of the coarse mode is of low certainty. This is now understood to result from AERONET over-predicting the location of the mode separation point used to calculate secondary microphysical parameters (Taylor et al. 2013b). The daily SSA retrieval is fine but the CRI is retrieved with moderate (≈ 40%) certainty.

## 4 Conclusions

In the case of Saharan desert region presented here, the NN retrievals are generally good for the AVSD, moderately accurate for the SSA, but poor for the CRI and ASYM parameters. This new modeling approach is opening up a window on aerosol properties in previously inaccessible regions of the planet where no surface measurements are available and, it is hoped, will allow for a quasi-real time global monitoring of aerosols from space.

**Acknowledgments** MT was supported by a FP7-PEOPLE-2011-IEF grant for the project "AEROMAP: Global mapping of aerosol properties using neural network inversions of ground and satellite based data". MT would like to thank the members of IERSD-NOA for excellent training in the field, and for their kind and ongoing hospitality.

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