Calculation of aerosol microphysical properties by neural network inversion of ground-based AERONET data

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Radiative-forcing by aerosols is the most important and most uncertain of all Earth climate, direct radiative-forcing estimates (IPCC Report, 2001). Reducing this uncertainty calls for the expansion of worldwide aerosol measurements and studies in order to characterize different types of aerosols and sources. Aerosols are characterized by their microphysical properties (AMPs): the aerosol size distribution a_i (in each i^{th} size bin) and complex refractive index Z (Hansen and Travis, 1974), which are accurately retrieved from ground-based instruments (Holben et al., 1998). Unfortunately, their global resolution is very uneven – being densely-situated in industrialized areas and sparsely-located elsewhere.

We report on the initial phase of *AEROMAP* - a new EU-funded project designed to map the global distribution of aerosol microphysical and optical properties (AOPs) by capitalising on the full-Earth coverage provided by satellite remote sensing instruments like MODIS in conjunction with the accuracy provided by ground-based AMP and AOP retrievals provided by AERONET. Figure 1 shows the 5 steps adopted for implementation of *AEROMAP*.

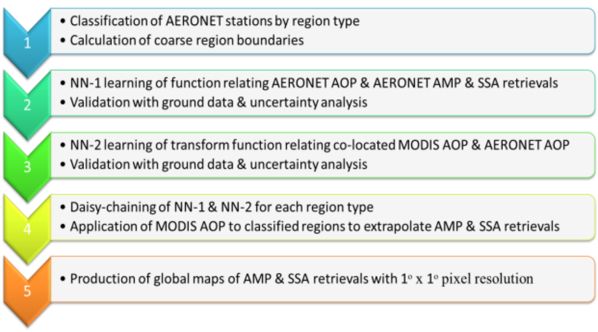

Figure 1. The stepwise implementation of *AEROMAP*.

In step 1, data pre-processing involves the application of a cluster analysis algorithm (Omar et al 2000) to AERONET data and the use of Gobbi coordinates (Gobbi et al., 2007) to classify aerosol regions by type. A nearest neighbour algorithm is used to establish regional boundaries. In step 2, multiple-input multiple-output (MIMO) universal function-approximating artificial neural networks (NN) are trained at selected sites for each aerosol region type. The NN inputs include: the aerosol optical depth (*AOD*) at four wavelengths in the visible wavelength range, the Ångström Exponent (*AE*) at visible wavelengths, and the fine mode fraction (η). The NN outputs include the AMP and SSA retrievals. An indicative NN architecture is shown in Figure 2. To train the NN, AERONET level 2 AOP and AMP products are used, as this data is cloud-screened and available daily.

NNs trained for each aerosol region type are evaluated by: a) analysing uncertainties using the AERONET AMP and SSA retrievals for the training periods, b) validating NN-derived AMPs and SSA for non-training periods using the corresponding AERONET products, c) validating NN results against AERONET products at different sites of the same aerosol type. The results allow assessment of the potential of such NN-derived AMP and SSA retrievals for each aerosol region type.

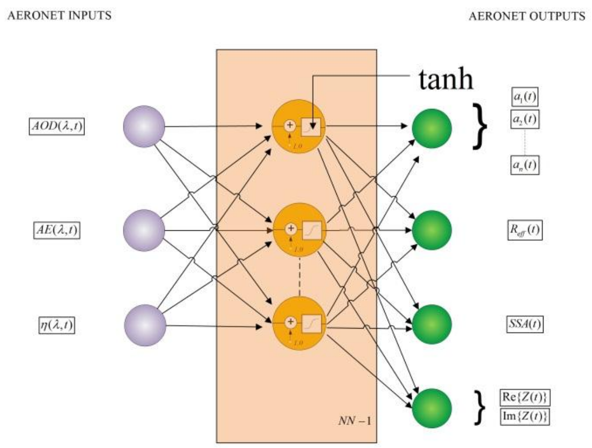

Figure 2. The architecture of the NN in step 2.

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