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

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1. INTRODUCTION

Radiative-forcing by aerosols is the most important and most uncertain of all Earth climate, direct radiative-forcing estimates [IPCC, 2001]. Reducing this uncertainty calls for the expansion of worldwide measurements and studies in order to better characterize aerosol types and sources. Aerosols can be characterized by their microstructural parameters: the aerosol size distribution (ASD) dV(r)/dlnr and complex refractive index (CRI) Z(λ) [Hansen and Travis, 1974], both of which are accurately retrieved via maximum likelihood matrix inversion of ground-based AERONET atmospheric radiance measurements I(θ,λ) using the relation [Dubovik and King, 2000]:

$$I(\theta,\lambda)=I(\ dV(r)/d\ln r,\ Z(\lambda)\ )$$

The global resolution of such data, however, is very uneven – being dense in industrialized areas and sparse elsewhere. Here, we report on the first phase of a new EU-funded project AEROMAP designed to perform this inversion using neural networks (NN) for use with satellite inputs. We present the methodology used to train and test the extrapolation potential of such NNs for the case of continental pollution at 2 sites: GSFC-Washington and MSUMO-Moscow. For this study, continental pollution was classified by the range of values: 47.0 ≤ Lidar Ratio ≤ 86.2 and 1.17 ≤ Angstrom Exponent (870nm,440nm) ≤ 1.79, and used to extract this aerosol type from the set of all available data.

3. RESULTS

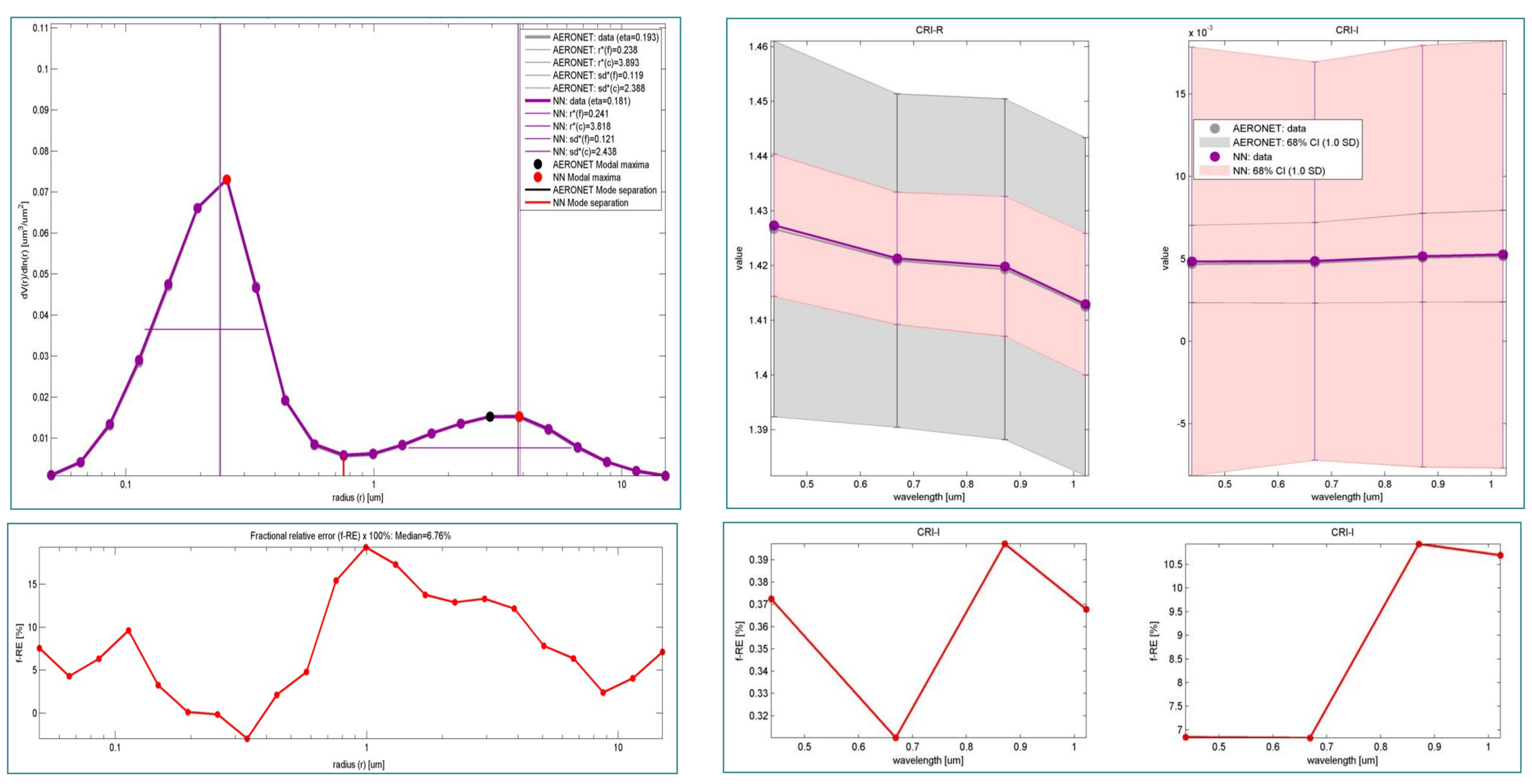
Summary statistics of the fractional relative error (f-RE) and the mean values of microstructural parameters for the four CASES I-IV considered here.

f-RE	I	II	III	IV
dV/dlnr	[-3.0%,18.0%]	[-6.0%,26.0%]	[-93.0%,62.0%]	[-72.0%,43.0%]
Median	6.8%	13.1%	32.3%	21.7%
CRI-R	[-0.3%,0.4%]	[-0.3%,0;.4%]	[-6.9%,-6.6%]	[-4.8%,-3.1%]
CRI-I	[6.5%,11.0%]	[5.5%,15.5%]	[-120.0%,-45.0%]	[-95.0%,20.0%]

	I (AERONET)	(NN)	II (AERONET)	(NN)	III (AERONET)	(NN)	IV (AERONET)	(NN)
eta	0.193	0.181	0.192	0.163	0.079	0.297	0.098	0.148
r*(f)	0.238	0.241	0.238	0.225	0.183	0.190	0.192	0.216
r*(c)	3.893	3.818	3.931	3.436	3.701	2.854	3.794	3.670
σ*(f)	0.119	0.121	0.120	0.132	0.102	0.116	0.113	0.120
σ*(c)	2.388	2.438	2.416	2.687	2.155	2.592	2.164	2.216
CRI-R	[1.414,1.428]	[1.414,1.428]	[1.417,1.432]	[1.412,1.425]	[1.480,1.482]	[1.415,1.418]	[1.464,1.480]	[1.418,1.420]
CRI-I	[0.004,0.005]	[0.004,0.005]	[0.004,0.005]	[0.004,0.005]	[0.009,0.013]	[0.005,0.006]	[0.009,0.012]	[0.005,0.006]

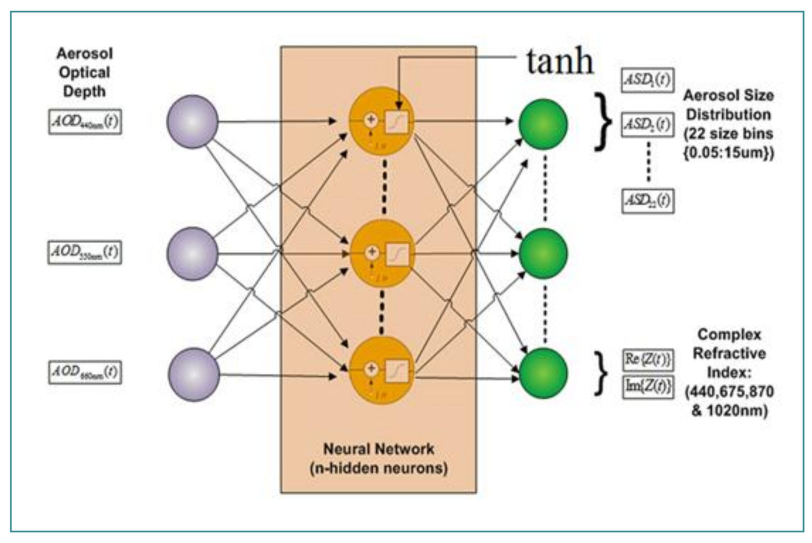
***Figure 1**: NN training: CASE I* *GSFC-Washington (AERONET)*

Microstructure parameters retrieved from the ASD include: the fine mode (f) and coarse mode (c) effective radii r*(f) and r*(c), effective standard deviations σ*(f) and σ*(c), the fine mode fraction eta=Vf /(Vf+Vc), and the mode separation point.

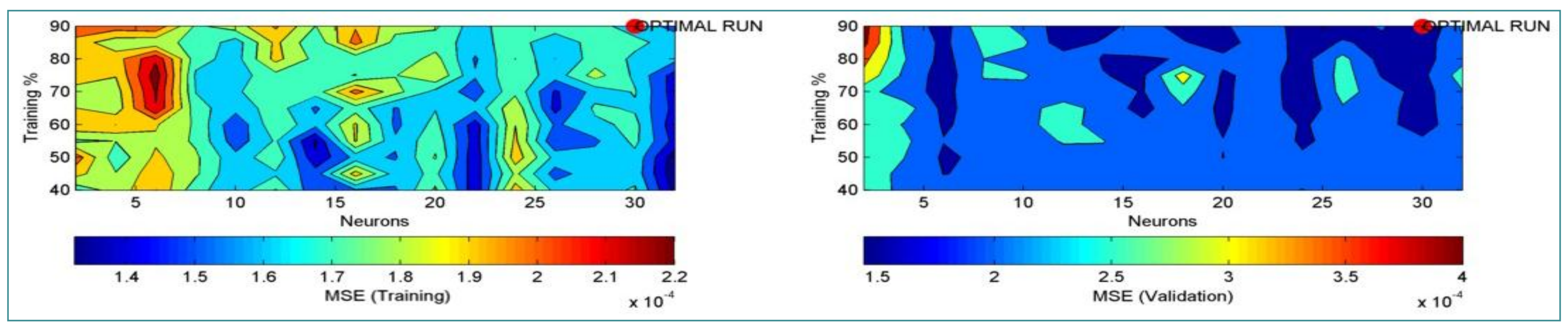


2. METHODOLOGY

MATLAB was used to generate a grid of 150 universal function approximator NN [Hornik, Stinchcombe and White, 1989] trained on AERONET Level 2.0 Inversion Products including at GSFC-Washington including: derived daily-averaged values of aerosol optical depth (AOD) at 470nm, 550nm and 660nm, dV(r)/dlnr in 22 log-radius bins spanning the aerosol size range [0.05,15]μm, and the real (Re) and imaginary (Im) parts of Z(λ) at 441nm, 673nm, 873nm and 1022nm.



The grid permuted over NN architectures such that the number of hidden nonlinear hyperbolic tangent (Tanh) neurons ranged from 2-32 (in steps of 2) and training fractions ranged from 40% to 90% (in steps of 5%). NN weights and biases were updated using the Levenberg-Marquardt backpropagation optimization algorithm until the mean-squared error (MSE) between NN outputs and AERONET targets was minimized to 1/100th of the mean variance of the target data. The optimal network had a NN V AERONET correlation value R = 0.99964, a mean error of 0.0000457, and required 30 hidden neurons with a 90%:10% training:validation data split.



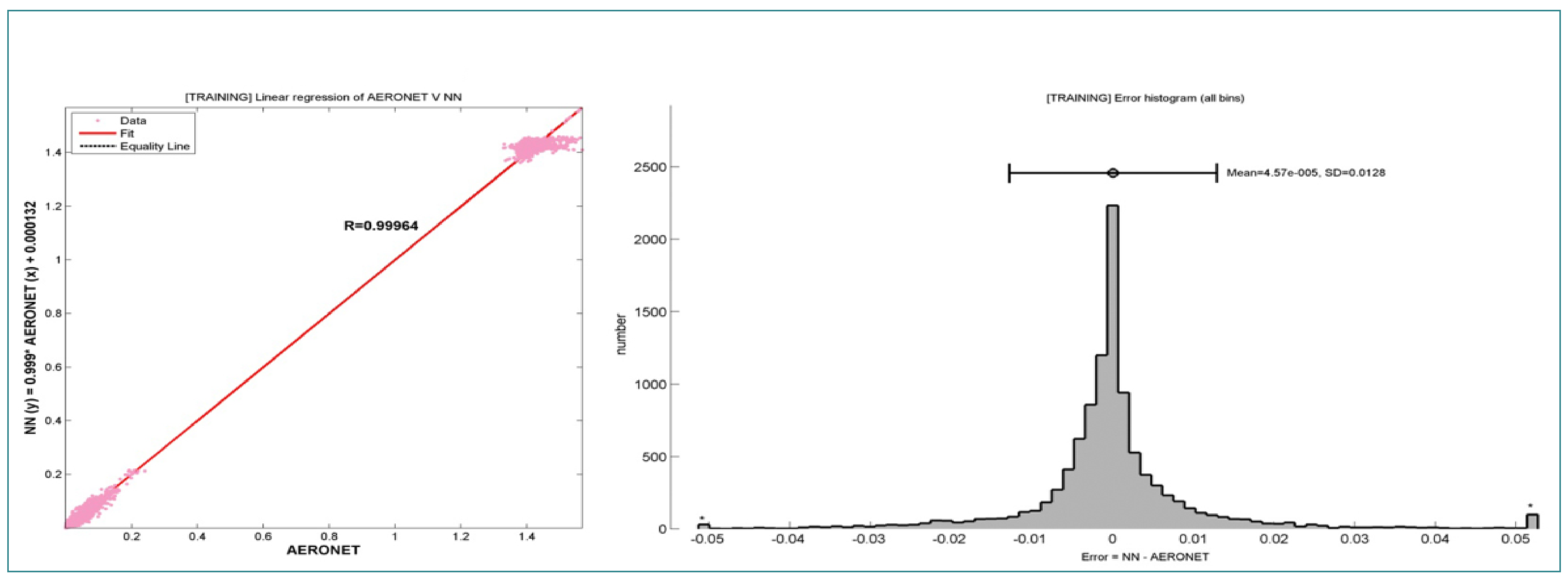
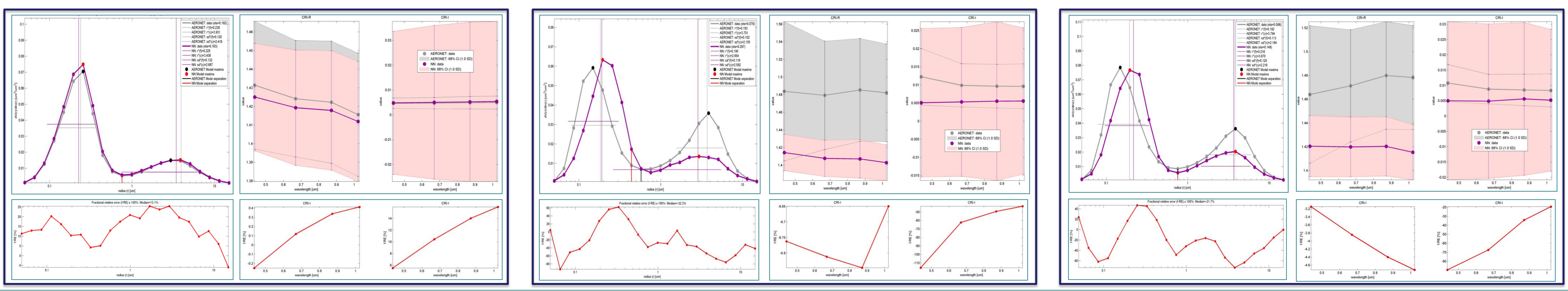


Figure 1 shows the results for ***CASE I*** (NN training at GSFC-Washington). Figure 2 presents NN simulations obtained by feeding the NN with AOD-only inputs for: ***CASE II*** (MODIS Level 3 Collection 5.1 Product-deduced AOD over GSFC-Washington), ***CASE III*** (MODIS-deduced AOD over MSUMO-Moscow), and ***CASE IV*** (AERONET-deduced AOD at MSUMO-Moscow), together with 68% confidence levels fractional relative errors (f-RE).

Figure 2**: NN simulations: (left) CASE II* *MODIS over GSFC-Washington,* ***(center) CASE III *MODIS over MSUMO-Moscow,* ***(right) CASE IV*** *MSUMO-Moscow (AERONET)*



4. DISCUSSION

The NN trained on continental pollution AERONET data at GSFC-Washington (CASE I) was able to recover the expected (ground-truth) ASD and Z well for a random subset of the training data, having a maximum f-RE=18%. When fed with collocated and synchronous MODIS satellite inputs (CASE II), the maximum f-RE=26% is higher but encouragingly, in the region of the dominant fine mode, the error was as low as 12%. Also, for the difficult to retrieve Im(Z), the error shows a tendency to increase with wavelength from f-RE=5.5% reaching a maximum of 15.5% in the infrared at 1022nm. Simulations at MSUMO-Moscow (CASES III and IV) were significantly worse as we expected and may be linked to variance in the type of continental pollution – to be investigated in the next phase of the project.

ACKNOWLEDGEMENTS

This work is supported by a Marie-Curie IEF funded project *"AEROMAP: Global mapping of aerosol properties using neural network inversions of ground and satellite based data".*

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2-7 Sep 2012
EAC-2012