AEROMAP

Satellite retrieval of dust aerosol microphysical and optical properties over Northern Africa using neural networks

M. Taylor (patternizer@gmail.com)[1], S. Kazadzis[1], A. Tsekeri[2], A. Gkikas[3], V. Amiridis[2]

[1] Institute for Environmental Research & Sustainable Development (IERSD), National Observatory of Athens (NOA), Greece.
[2] Institute for Astronomy, Astrophysics, Space Applications and Remote Sensing (IAASARS), National Observatory of Athens (NOA), Greece.
[3] Laboratory of Meteorology, Physics Department, University of Ioannina, Greece.

IERSD - NOA

1 Rationale

a. AERONET inversions are accurate but presently only occupy 368/64000 global pixels (1x1 degree)

b. SATELLITE retrievals of optical depth and columnar water vapour are ≈1/day in > 50000 pixels but microphysical parameter estimates are unreliable (Remer et al 2005)

c. **NEURAL NETWORKS can potentially learn to map inputs (SATELLITE retrievals) to outputs (AERONET inversions)**

2 Methodology

SATELLITE inputs:

Daily, gridded (1x1 degree) MODIS Level 3 aerosol optical depth at 470, 550 and 660nm plus the columnar water vapour + OMI Level 3 absorption aerosol optical depth at 500nm.

AERONET outputs:

Co-located and synchronous (with MODIS & OMI) daily-averaged Level 2 (Version 2) inversions (Dubovik et al 2000) including the aerosol volume size distribution (AVSD) and the spectral complex refractive index (CRI), single scattering albedo (SSA) and asymmetry factor. (ASYM) at 440, 675, 870 and 1020nm.

NN training & testing:

Mean global GOCART model dust AOD was used to select 7 AERONET stations in Northern Africa (Fig. 1) to train and test a grid NN models (Fig. 2).

Please see Taylor et al (2013) for details.

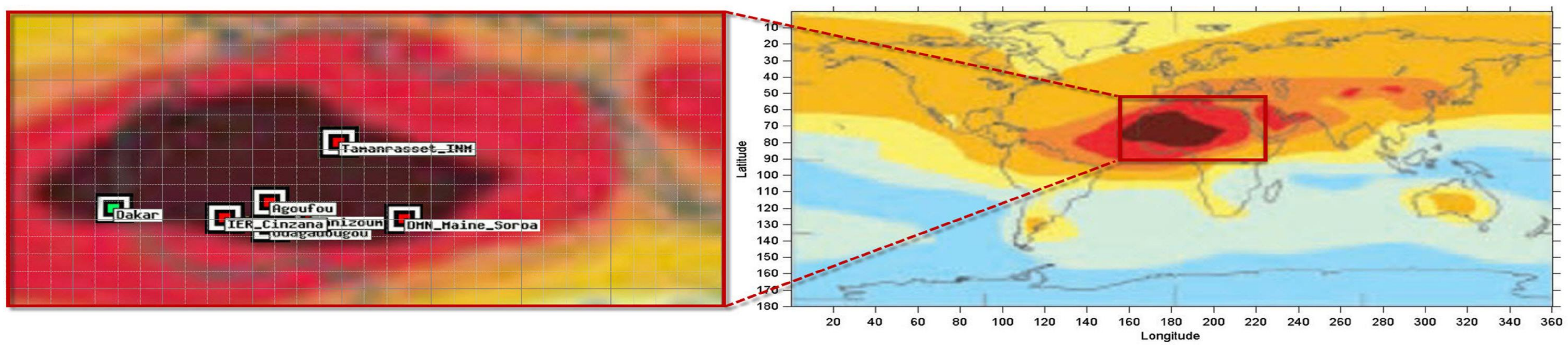


Fig. 1. Schematic showing: ***(left)*** the 7 Northern African (NAF) AERONET sites used for NN training (red) and the coastal AERONET site at Dakar used for NN testing (green) overlaid on the peak of the dust AOD extracted from the global mean (2000-2006) of the GOCART model (Chin et al., 2000) shown at ***(right)***.

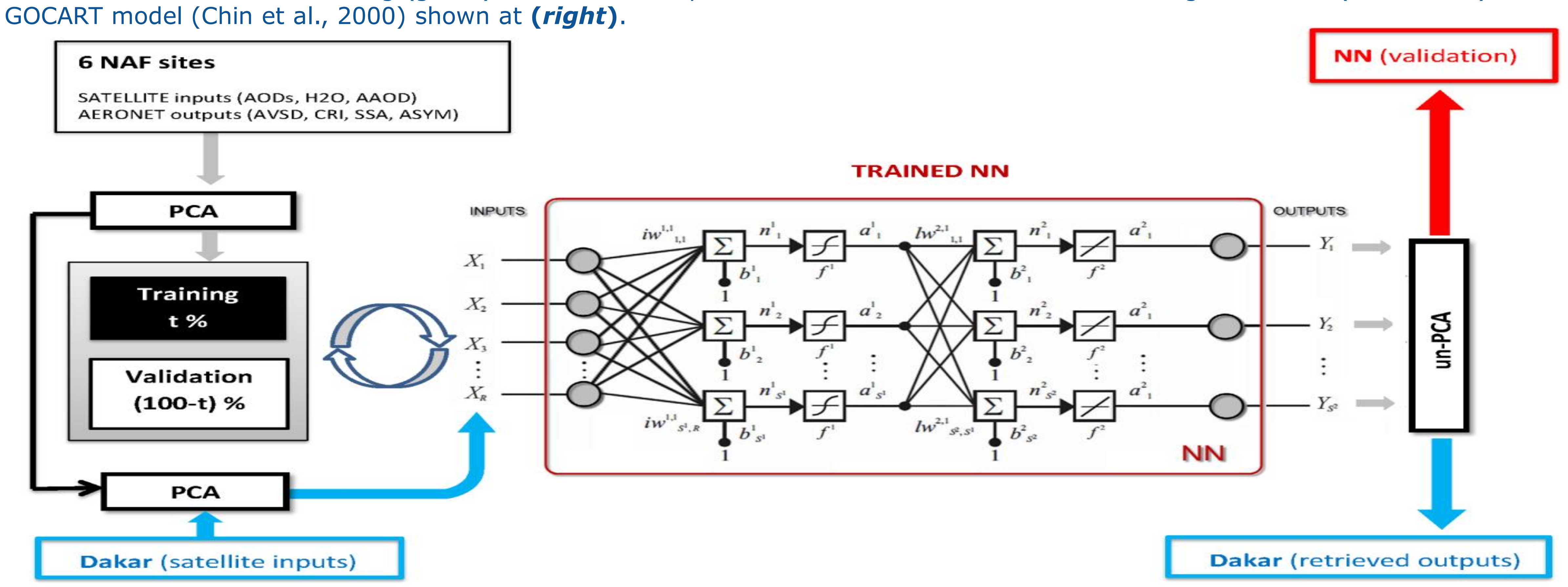
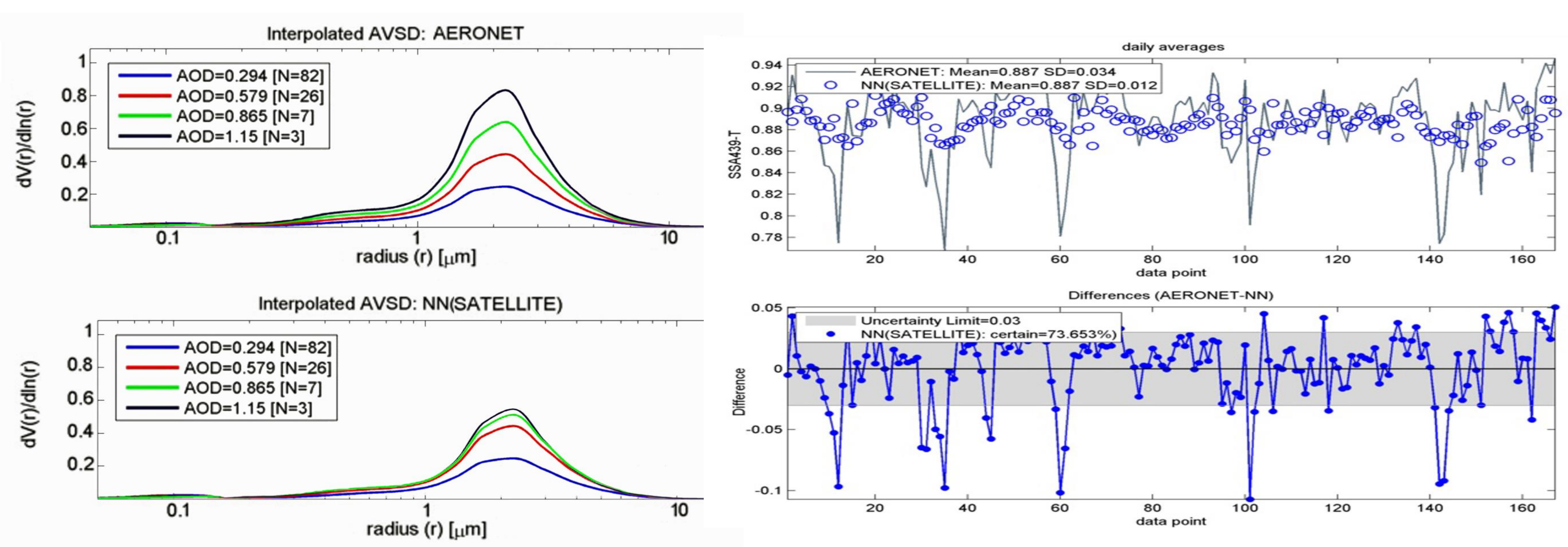


Fig. 2. A schematic of the modeling process. Principal components analysis (PCA) is applied to co-located, synchronous and normalized satellite inputs and AERONET outputs from 6 NAF sites and the PCs are used to train each NN in a grid of 100 NN architectures (varying t% and number of neurons) until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

3 Results

Table 1 shows the performance assessment of testing the optimal NN with unseen data at Dakar. The figures below show that the NN **retrieves typical daily AVSDs quite well** but that it **fails to capture well the daily variability** in the SSA.



Dakar (N=167)	Parameter	<AERONET>	<NN>	R	Uncertainty Limit	N Certain	Certainty	Assessment
Microphysics	*V(f)*	0.030	0.030	0.261	-	-	-	Poor
	V(c)	0.305	0.315	0.514	-	-	-	Very Good
	η	0.112	0.093	0.413	-	-	-	Good
	Radial Bin 15	-	-	0.486	-	-	-	Good
	<AVSD>	-	-	0.918	-	-	-	Very Good
	r(f)	0.115	0.118	-0.117	±10%	102	60.4%	Very Poor
	r(c)	1.928	1.909	0.105	±10%	58	34.3%	Very Poor
	var(f)	1.529	1.514	-0.115	±40%	169	100.0%	Very Poor
	var(c)	3.056	2.650	0.114	±40%	169	100.0%	Very Poor
	CRI-R(440)	1.472	1.457	0.344	±0.02	66	39.1%	Moderate
	CRI-R(675)	1.488	1.479	0.228	±0.02	76	45.0%	Poor
	CRI-R(870)	1.472	1.471	0.153	±0.02	76	45.0%	Poor
	CRI-R(1020)	1.459	1.460	0.139	±0.02	70	41.4%	Poor
	CRI-I(440)	0.007	0.007	0.381	-	-	-	Moderate
	CRI-I(675)	0.004	0.004	0.372	-	-	-	Moderate
	CRI-I(870)	0.004	0.004	0.373	-	-	-	Moderate
	CRI-I(1020)	0.004	0.004	0.368	-	-	-	Moderate
Optics	*SSA(440)*	0.901	0.897	0.440	±0.03	124	73.4%	Good
	SSA(675)	0.948	0.947	0.395	±0.03	115	68.1%	Moderate
	SSA(870)	0.954	0.957	0.383	±0.03	119	70.4%	Moderate
	SSA(1020)	0.956	0.959	0.373	±0.03	121	71.6%	Moderate
	ASYM(440)	0.757	0.756	0.159	-	-	-	Very Poor
	ASYM(675)	0.725	0.723	0.149	-	-	-	Very Poor
	ASYM(870)	0.726	0.724	0.094	-	-	-	Very Poor
	ASYM(1020)	0.732	0.731	0.067	-	-	-	Very Poor

Table 1. Performance assessment of the optimal (22 neuron) NN fed with 167 days of unseen satellite inputs at Dakar. Uncertainty limits are as per the target levels provided by Mishchenko et al. (2007) and comparisons are performed with respect to co-located and synchronous AERONET Version 2 Level 2.0 inversions.

4 Interpretation

➢ While a rather high percentage of NN retrievals from unseen inputs at Dakar were within acceptable uncertainty limits, low correlation coefficients suggest that more work is needed to capture the daily variability of aerosol parameters.

➢ This modeling approach allows for provision of "first guess" estimates of previously unavailable aerosol parameters from satellite data.

➢ NN retrievals of dust aerosol parameters from satellite data over Northern Africa are generally good for the AVSD, moderate for the SSA, but poor for the CRI and ASYM.

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References

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