Polarimetric aerosol remote sensing using neural networks

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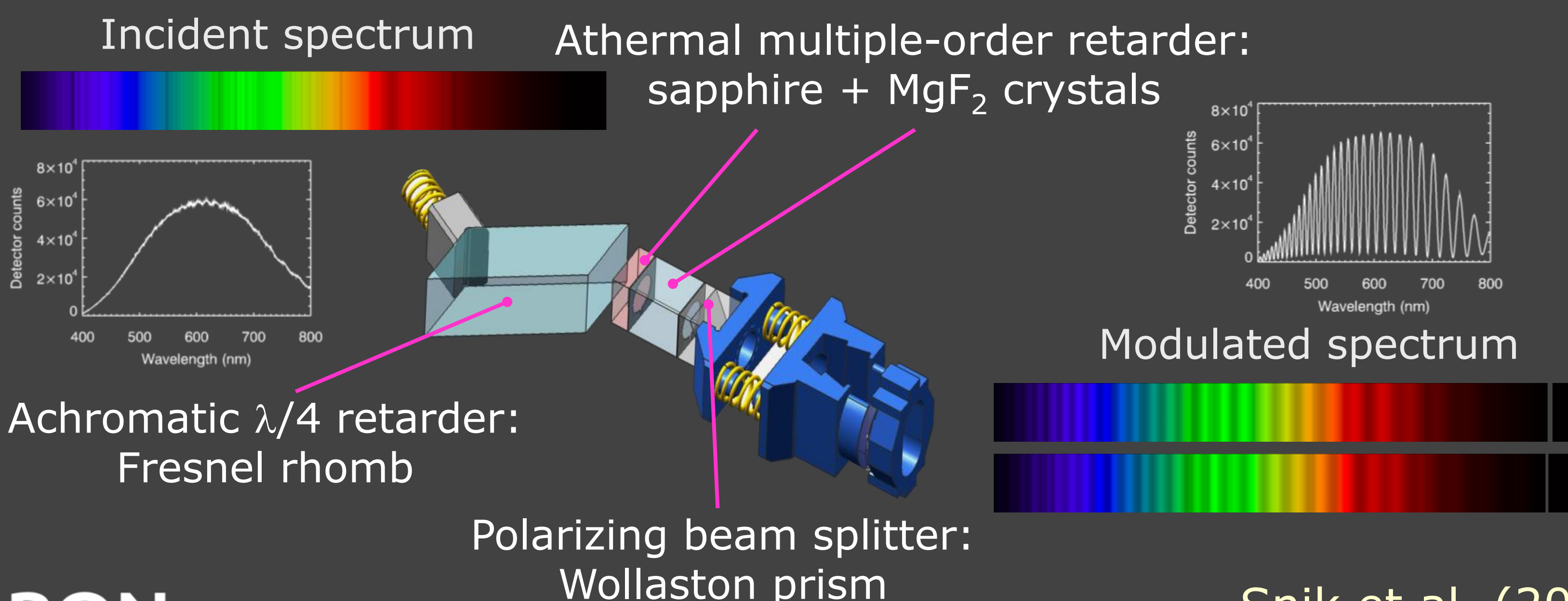
SPEX: Spectropolarimeter for planetary exploration

- Innovative measurement concept: spectral modulation
- Linear polarization parameters encoded in radiance spectrum by passive optical components

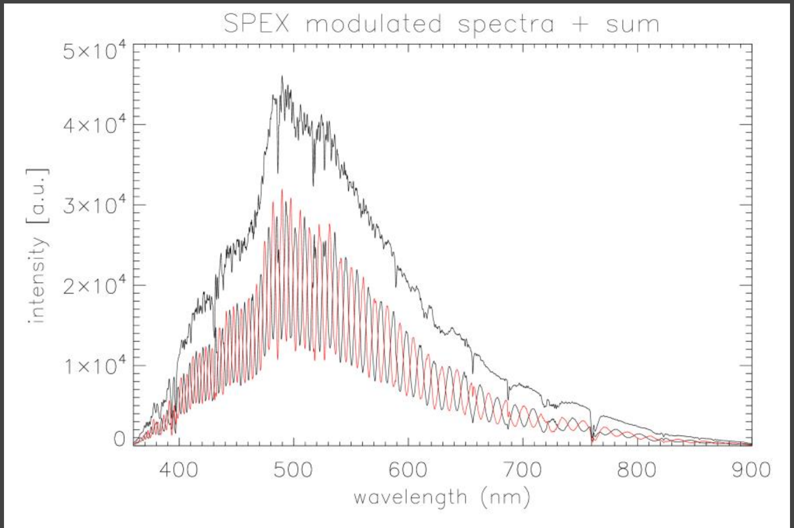
$$I(\lambda) = \frac{I_0(\lambda)}{2}\left[1 \pm P(\lambda)\cos\left(\frac{2\pi\delta(\lambda)}{\lambda} + 2\phi(\lambda)\right)\right]$$



Snik et al. (2009)

Ground based SPEX instruments

- Two SPEX exemplars developed so far
  1. Prototype operated by SRON, developed for space applications and currently operated from ground
  2. Instrument operated by RIVM/Leiden University, dedicated to ground-based observations
- Wavelength ranges: 370-850 nm for SPEX prototype, 360-900 for RIVM SPEX



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Spectropolarimetric aerosol retrievals at SRON

- Retrieval scheme developed during the last decade
- Variational retrieval based on Phillips-Tikhonov regularization

$$\hat{\mathbf{x}} = \arg\min\{[\mathbf{y} - \mathbf{F}(\mathbf{x}, \mathbf{b})]^T \mathbf{S}_\epsilon{}^{-1} [\mathbf{y} - \mathbf{F}(\mathbf{x}, \mathbf{b})] + \gamma(\mathbf{x} - \mathbf{x}_a)^T \mathbf{H}(\mathbf{x} - \mathbf{x}_a)\}$$

- Extensively applied to POLDER measurements (presentations by O. Hasekamp and A. Stap during this meeting)
- Retrieval concept extended to ground based observations (SPEX)

Retrieval concept: some details

- Iterative cost function minimization (Gauss-Newton)

$$J(\mathbf{x}) = [\mathbf{y} - \mathbf{F}(\mathbf{x})]^T \mathbf{S}_\epsilon{}^{-1} [\mathbf{y} - \mathbf{F}(\mathbf{x})] + \gamma(\mathbf{x} - \mathbf{x}_a)^T \mathbf{H} (\mathbf{x} - \mathbf{x}_a)$$
$$\mathbf{F}(\mathbf{x}_{i+1}) \approx \mathbf{F}(\mathbf{x}_i) + \mathbf{K}_i(\mathbf{x}_{i+1} - \mathbf{x}_i)$$
$$\mathbf{K}_i = \mathbf{F}'(\mathbf{x}_i)$$
$$\mathbf{x}_{i+1} = (\mathbf{K}_i{}^T \mathbf{S}_\epsilon{}^{-1} \mathbf{K}_i + \gamma \mathbf{H})^{-1} [\mathbf{K}_i{}^T \mathbf{S}_\epsilon{}^{-1} (\mathbf{y} - \mathbf{F}(\mathbf{x}_i) + \mathbf{K}_i \mathbf{x}_i) + \gamma \mathbf{H} \mathbf{x}_a]$$

- Regularization parameter γ heuristically adjusted at each iteration

- First guess provided by look-up table and also used as *a priori* $(\mathbf{x}_a)$

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LUT first guess generation

- LUT consists of about 600 aerosol models

- Each model defined by
  - Effective radius (r_{eff})
  - Effective variance (v_{eff})
  - Complex refractive index (m)
  - Fraction of spherical particles (f_{spher})

  for fine and coarse mode

- First guess generation process
  1. Find model that best matches observations
  2. Iteratively update fine and coarse mode AOT for the chosen model using the LUT as simplified radiative transfer model

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Looking for a better first guess

- Limitations of LUTs
  - Need for crude interpolations affects first guess quality
  - Need to read in LUT makes retrieval code less efficient

- First guess quality important for successful aerosol retrievals

- Idea to overcome LUTs: use neural networks
  - Fast computations
  - Do not require large memory allocation (after training)
  - Already proven good stand-alone retrieval algorithms
  - Might provide high quality first guesses for variational retrievals as well

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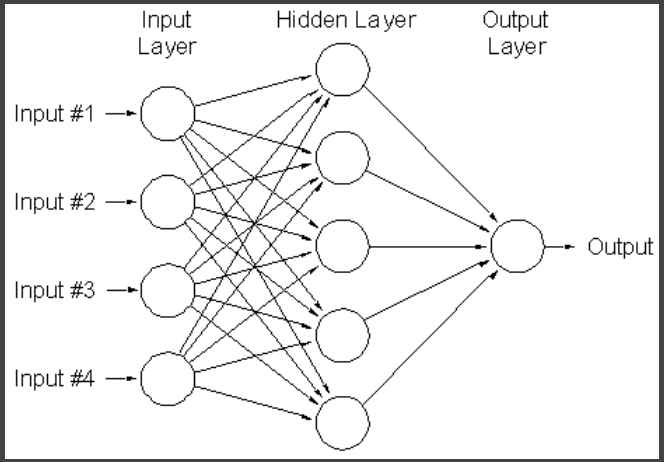
NNs in one slide (ambitious goal)

- Feedforward NN input-output function

$$y_k^{(0)} = x_k \qquad k = 1, \dots, N_{in}$$

$$y_k^{(l+1)} = \varphi^{(l+1)}\left(\sum_{j=1}^{N_l} w_{jk}^{(l)}\, y_j^{(l)} + b_k^{(l)}\right)$$

$$k = 1, \dots, N_{l+1},\ \ l = 0, \dots, N_L - 1$$



- x_k input vector, N_L number of layers, $\varphi^{(l+1)}$ nonlinear function for $l = 0, \dots, N_L - 2$, either linear or nonlinear for $l = N_L - 1$

- Goal: adjust $\{w_{jk}^{(l)}, b_k^{(l)}\}$ based on a training set $\Theta = \{(\mathbf{x}_p, \mathbf{t}_p)\}$, so as to obtain approximately correct outputs even for $\mathbf{x} \notin \Theta$

Neural network design

- Observation vector: log-reflectance and degree of linear polarization at 3 wavelengths, 6 VZA, rel. azimuth angle of 180°
- Auxiliary variables: SZA, surface pressure
- Output vector: 8 retrieved aerosol parameters + surf. albedo at 870 nm
- 7.7×10^5 input-output pairs used to train the NN
- Random Gaussian noise added to input vector
  - Log-reflectance noise std: 0.02
  - DLP noise std: 0.005
  - SZA uncertainty: 0.25°
  - Surf. pressure uncertainty: 5 hPa
- Radiometric measurements compressed via linear PCA

Validation setup

- NN retrievals validated on 1.65×10^5 independent simulations
- 3412 simulations used to compare variational retrieval schemes
  - Retrieval using the LUT as first guess
  - Retrieval using the NN as first guess
- Noise + random differences between non-retrieved quantities and assumed values → pseudo-operational scenario

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Results on noisy simulated data

Fraction of successful retrievals ($\chi^2 < 2$): LUT 21.22%, NN 58.94%

Parameter	RMSE/MAE			
	fguess-LUT	fullretr-LUT	fguess-NN	fullretr-NN
r_{eff} – fine	0.221/0.167	0.214/0.153	0.108/0.066	0.115/0.065
Re(m) – fine	0.129/0.107	0.115/0.092	0.064/0.049	0.070/0.050
Im(m) – fine	0.124/0.067	0.125/0.067	0.079/0.034	0.081/0.035
AOT – fine	0.723/0.471	0.583/0.357	0.279/0.177	0.288/0.163
r_{eff} – coarse	1.342/1.080	1.940/1.245	0.972/0.753	1.145/0.839
Re(m) - coarse	0.092/0.075	0.098/0.079	0.077/0.062	0.084/0.066
Im(m) – coarse	0.137/0.076	0.136/0.073	0.095/0.049	0.099/0.049
AOT - coarse	0.844/0.549	0.909/0.511	0.295/0.193	0.348/0.185

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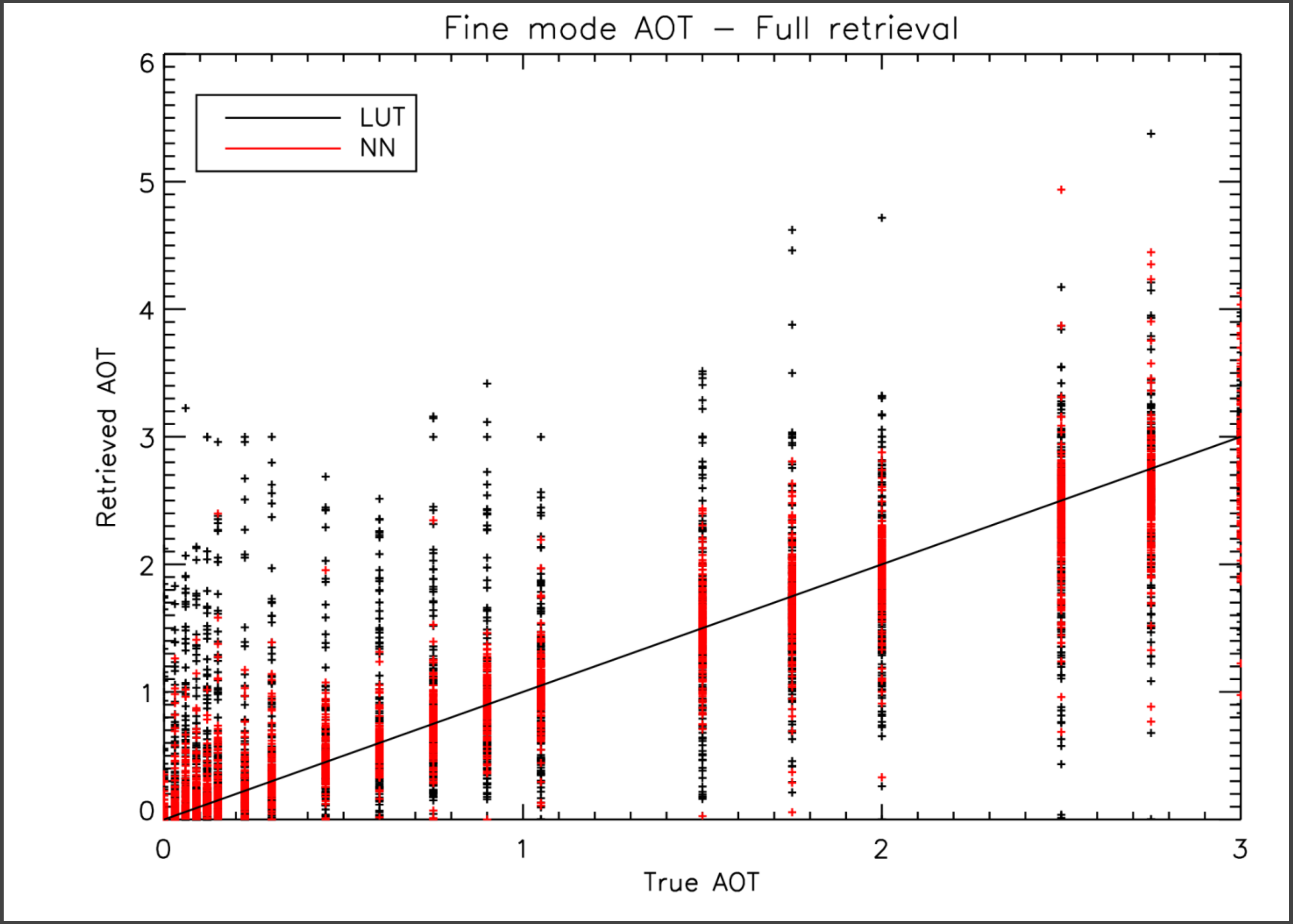
Results on noisy sim. data – successful retrievals

Fraction of successful retrievals ($\chi^2 < 2$): LUT 21.22%, NN 58.94%

Parameter	RMSE/MAE			
	fguess-LUT	fullretr-LUT	fguess-NN	fullretr-NN
r_{eff} – fine	0.168/0.118	0.146/0.087	0.096/0.059	0.100/0.055
Re(m) – fine	0.129/0.108	0.092/0.069	0.059/0.045	0.061/0.044
Im(m) – fine	0.099/0.043	0.098/0.042	0.071/0.031	0.073/0.032
AOT – fine	0.451/0.262	0.192/0.111	0.228/0.140	0.197/0.104
r_{eff} – coarse	1.300/1.048	2.225/1.322	0.944/0.728	1.086/0.807
Re(m) - coarse	0.093/0.076	0.099/0.079	0.075/0.061	0.084/0.066
Im(m) – coarse	0.139/0.076	0.136/0.073	0.100/0.053	0.103/0.054
AOT - coarse	0.394/0.240	0.218/0.121	0.223/0.145	0.206/0.115

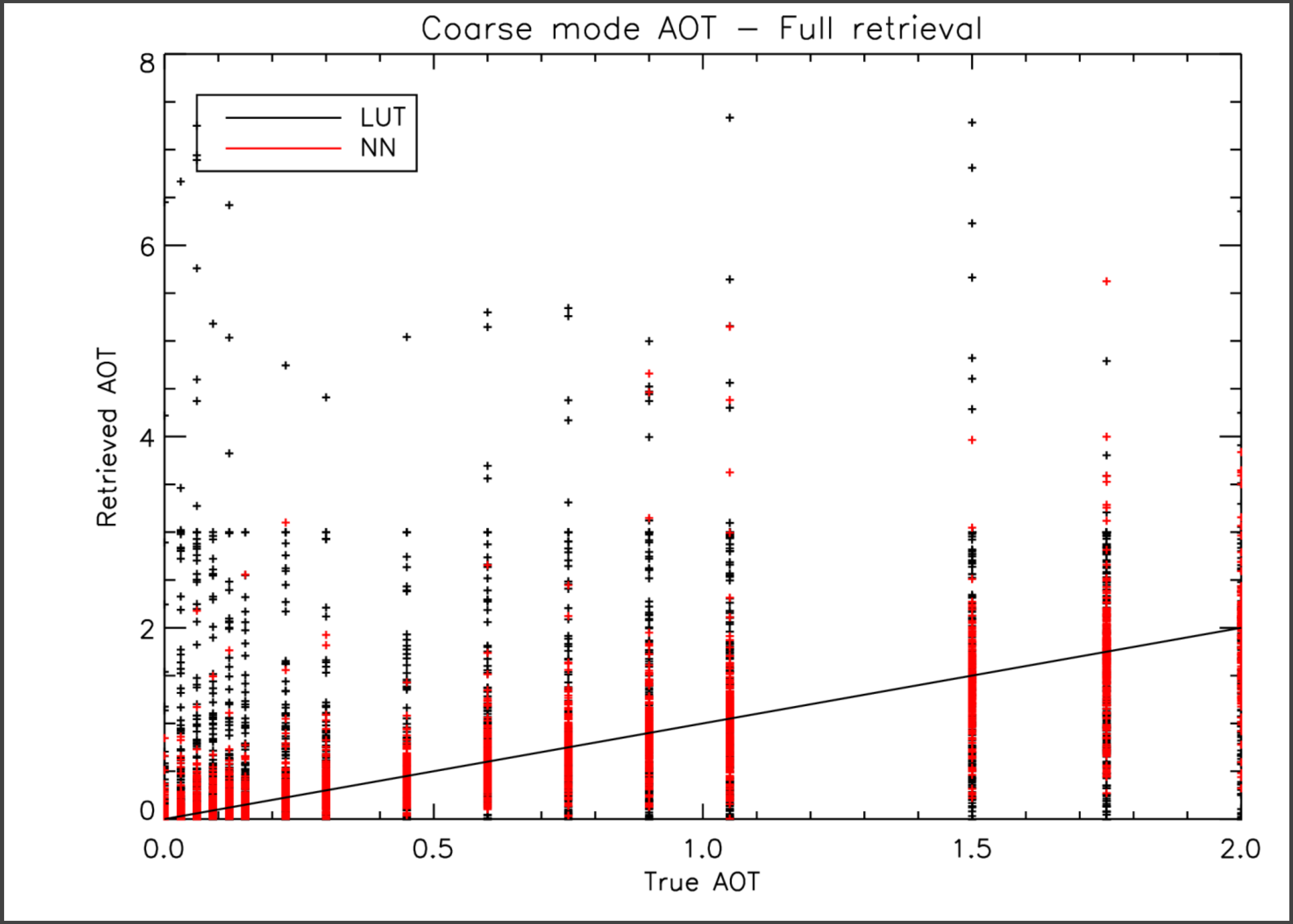
Results – Fine mode AOT

Retrieved vs true AOT – Converging + non-converging retrievals



Results - Coarse mode AOT

Retrieved vs true AOT – Converging + non-converging retrievals



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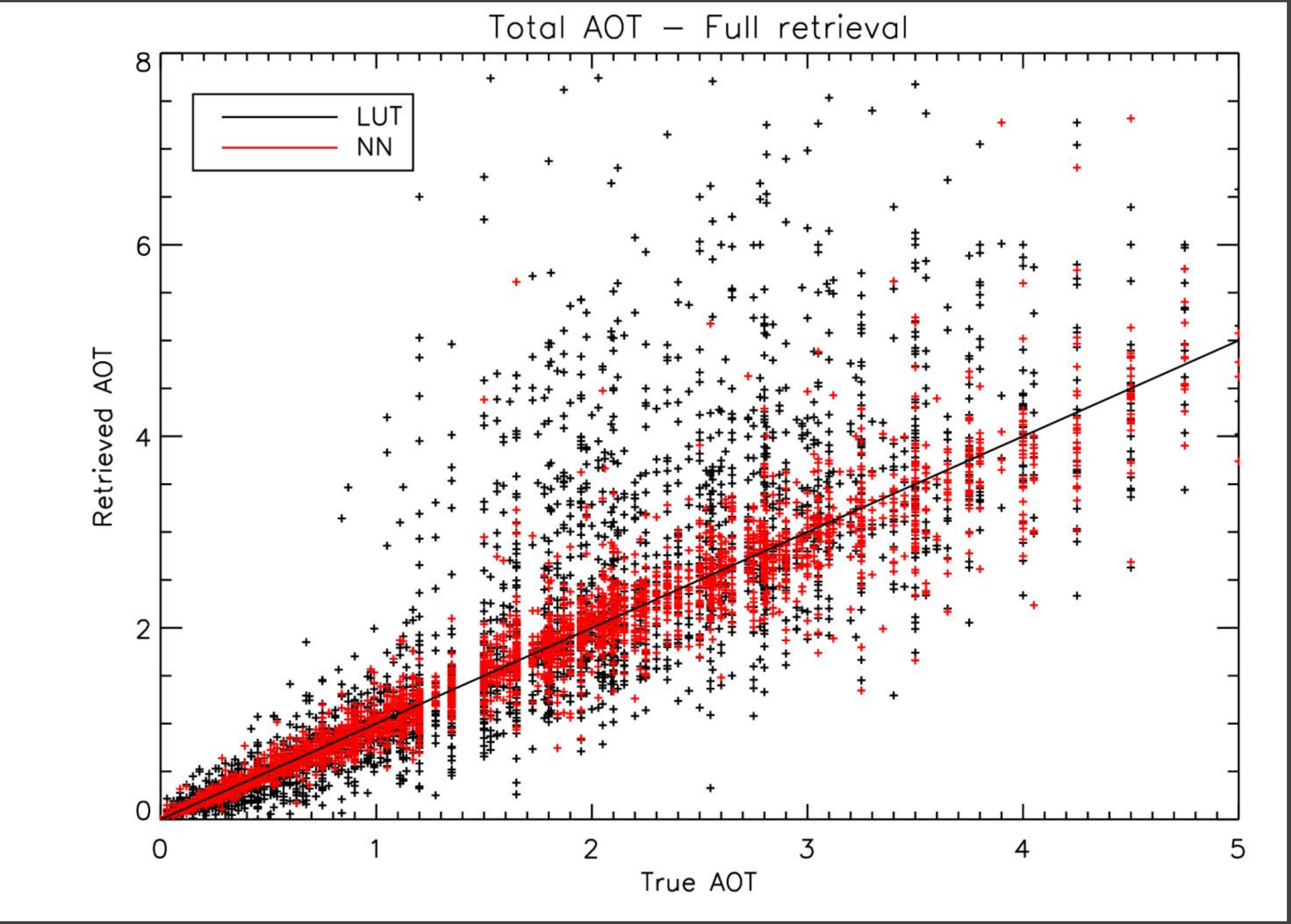
Results – Total AOT

Retrieved vs true AOT – Converging + non-converging retrievals



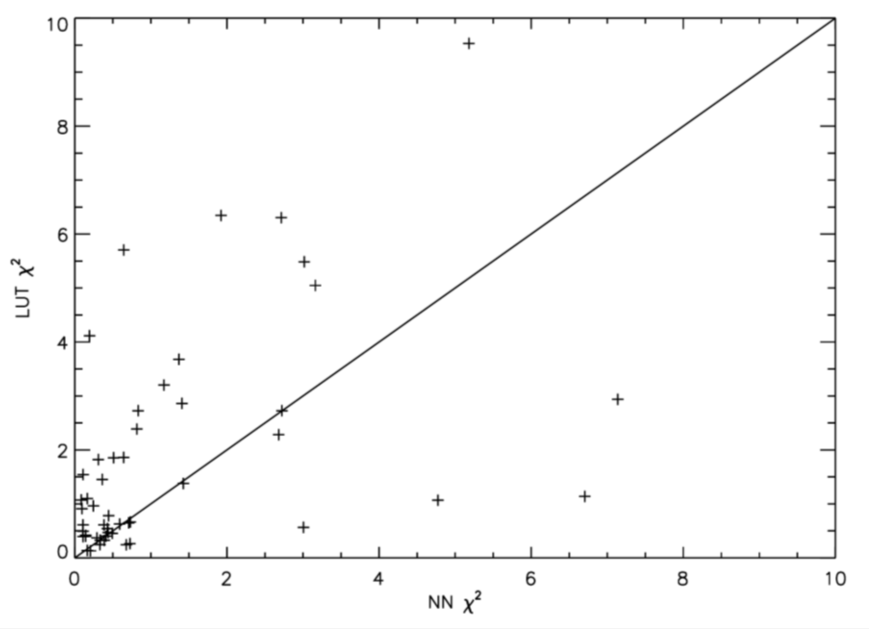
Application to RIVM SPEX measurements

- Ground-based RIVM-SPEX observations performed between 7 and 9 July 2013 at Cabauw (Netherlands)
- Intensity and degree of polarization in the principal plane at 441, 675 and 870 nm, used in the retrieval scheme
- Albedo at 870 nm fitted together with aerosol parameters

LUT vs NN first guess – SPEX retrievals

- 57 retrievals performed using LUT and NN first guess
- NN first guess yields more converging retrievals also with real measurements

N. data	LUT FG	NN FG
$\chi^2 < 1$	26 (45.6%)	36 (63.2%)
$\chi^2 < 2$	36 (63.2%)	42 (73.7%)
$\chi^2 < 5$	45 (78.9%)	49 (85.9%)



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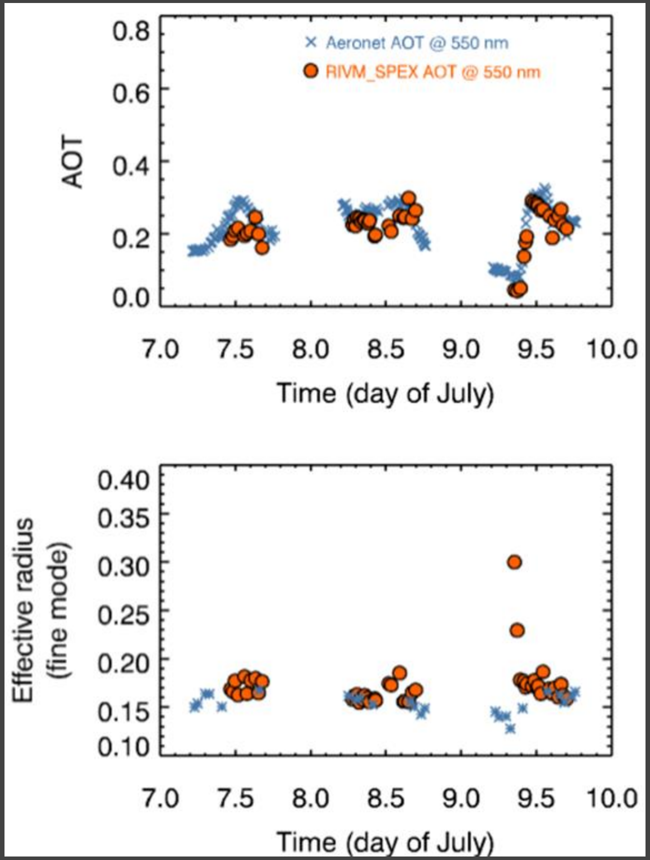
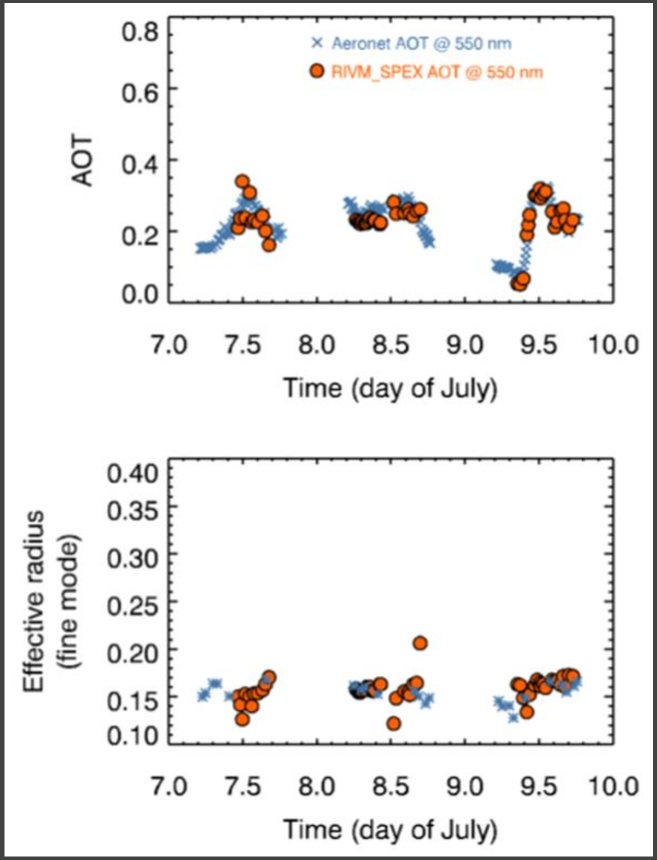
SPEX vs AERONET : AOT and effective radius

LUT first guess



NN first guess



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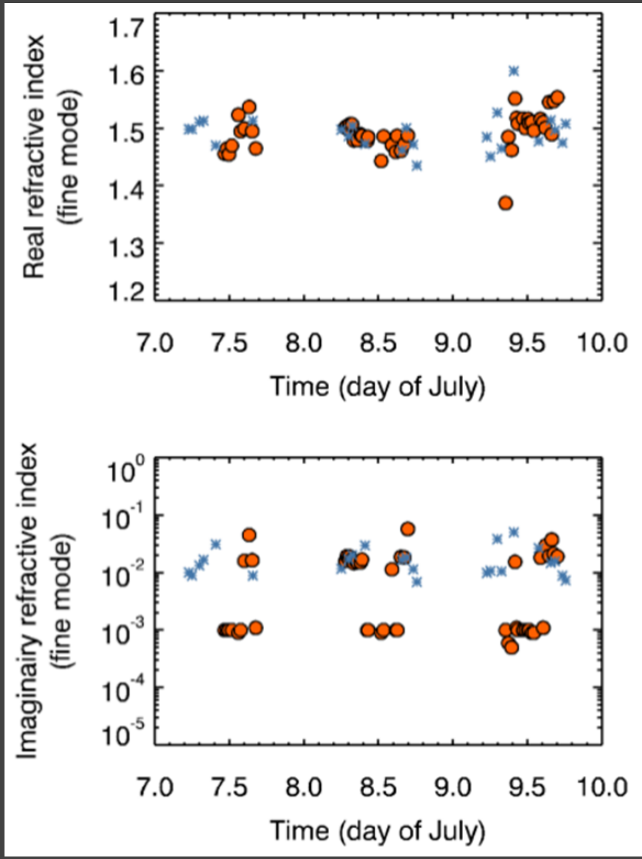
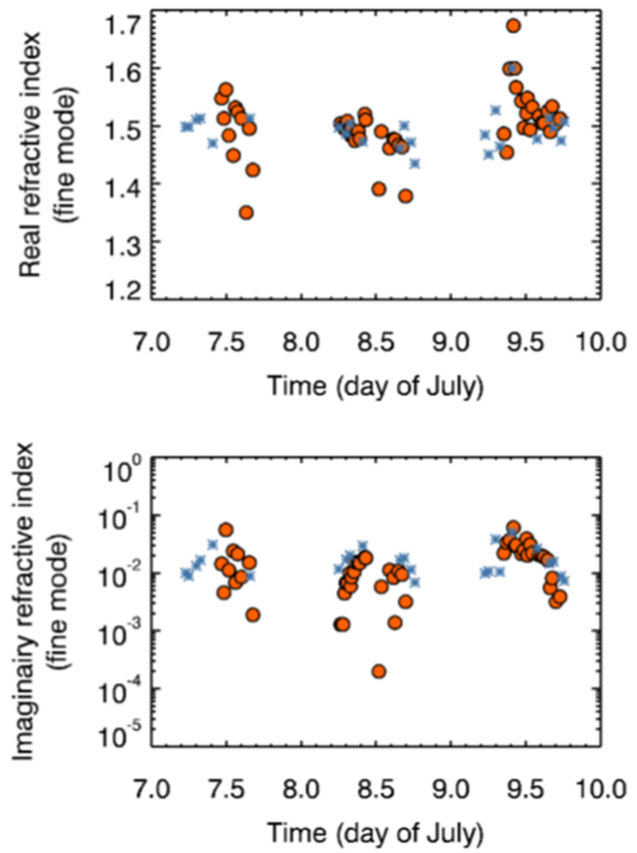
SPEX vs AERONET: refractive index

LUT first guess



NN first guess



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Conclusions

Outline

- NNs seem a good replacement for LUTs in polarimetric aerosol retrieval schemes
- Evidence with simulated data seems confirmed by first (few) preliminary experiments with real observations
- More reliable conclusions to be drawn as soon as more SPEX measurements are available

Limitations and open challenges

- Reduced input flexibility (once trained for a set of wavelengths/angles, NN needs measurements at (or close to) those wavelengths/angles)

- Difficult extension to satellite geometry in case of multiangular observations (POLDER set of viewing angles is highly variable from pixel to pixel – difficult to define an uniform observation vector for training a NN)

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