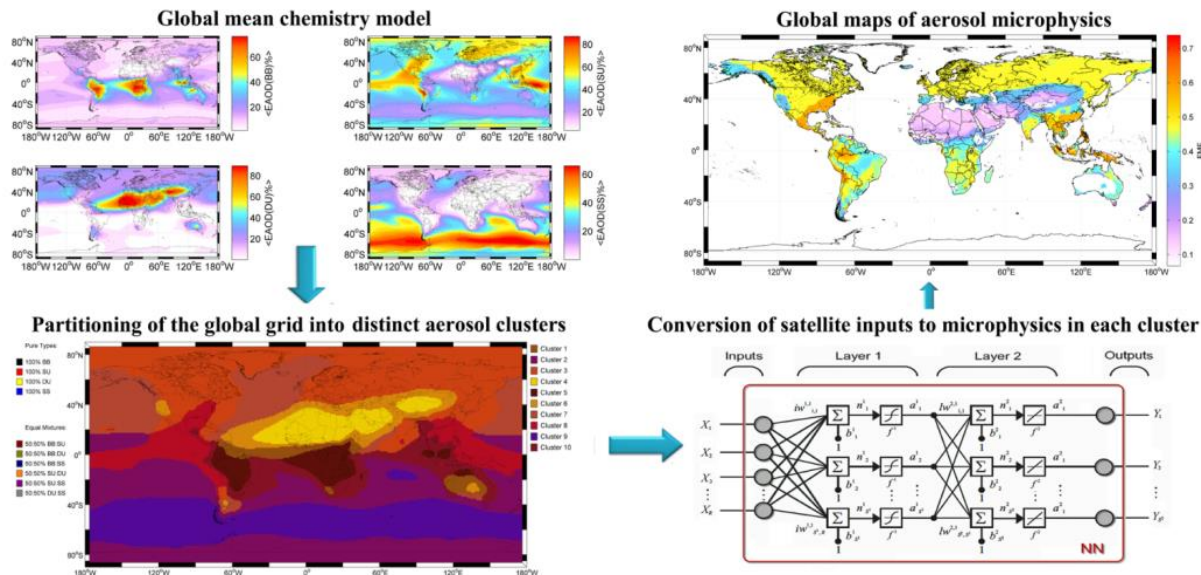


# How a synergy of GOCART, MODIS and AERONET data can be used to train neural networks for producing global aerosol volume size distributions from space

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2nd Gregory G. Leptoukh Online Giovanni Workshop:  
November 13th, 2014 (Day 3): 10:00-11:00 (UTC/GMT-5)



- **Rationale** – to train neural networks (NNs) to invert satellite measurements to retrieve daily aerosol size distributions and associated microphysics globally at 1x1 degree
- **Prototype** – a NN model trained and tested for Saharan dust aerosol in Northern Africa
- **Global aerosol model** – a 3-step approach:
  - STEP 1) application of **cluster analysis** to mean global GOCART aerosol optical depth data (per aerosol type) and identification of the composition & spatial distribution of aerosol mixtures at 1x1 degree
  - STEP 2) train a NN to invert satellite measurements for each aerosol mixture/region to produce global maps of size distributions
  - STEP 3) multimodal fitting & analysis of size distributions for determination of characteristic aerosol size & volume information
- **Case study** - quasi-realtime monitor (4-day average) of the Karthala volcanic eruption 12-23 January, 2007

A challenging experiment conducted on a single 16Gb RAM, quad-core PC with MATLAB:

From GIOVANNI 3 @NASA/GES-DISC: <http://gdata1.sci.gsfc.nasa.gov>

- Aqua/MODIS (Level 3 Collection 5 daily global 1x1 gridded values): 16 parameters x 360 degrees x 180 degrees x 3575 days [34.4Gb]
- Aura/OMI (Level 3 daily global 1x1 gridded values): 4 parameters x 360 degrees x 180 degrees x 3362 days [9.7Gb]

From GIOVANNI 4 @NASA/GES-DISC: <http://giovanni.gsfc.nasa.gov/giovanni/>

- GOCART (Version 4): 5 parameters x 2.5 x 2 gridded values (interpolated to 1x1) x 7 years x 12 months

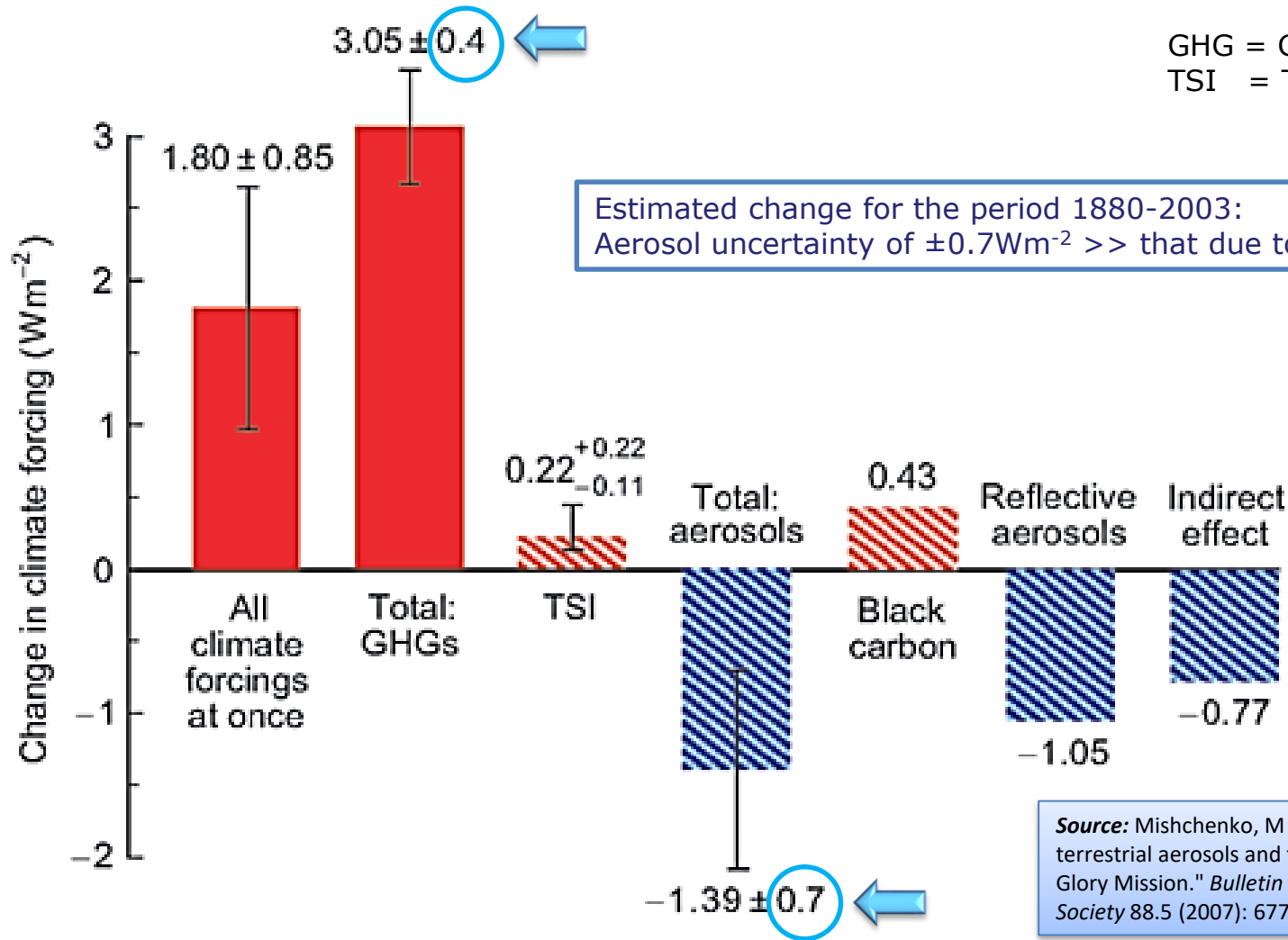
From AERONET: <http://aeronet.gsfc.nasa.gov>

- 160 aerosol optical & microphysical parameters (Levels 1.5 and 2.0/Version 2 Inversion Products) x 715,288 records (969 sites) [7.2Gb]

...which would not have been possible without the generous provision of open data by NASA/GES-DISC and the pioneering efforts of Gregory G. Leptoukh and co-workers to advance data interfacing, accessibility & visualization.

# **RATIONALE**

# CONTEXT: *There is a need to reduce uncertainty in aerosol climate forcing*



**Source:** Mishchenko, M et al (2007) "Accurate monitoring of terrestrial aerosols and total solar irradiance: introducing the Glory Mission." *Bulletin of the American Meteorological Society* 88.5 (2007): 677-691.

# CONTEXT: Reducing uncertainty requires better aerosol characterization

Year 2000 Emissions Tg yr <sup>-1</sup> or TgS yr <sup>-1</sup>	Anthropogenic NMVOCs		Anthropogenic Black Carbon		Anthropogenic POA		Anthropogenic SO <sub>2</sub>		Anthropogenic NH <sub>3</sub>		Biomass Burning Aerosols	
	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
Total	98.2	157.9	3.6	6.0	6.3	15.3	43.3	77.9	34.5	49.6	29.0	85.3

Source: IPCC/AR5 (2013)

Source	Natural Global	
	Min	Max
Sea spray	1400	6800
Mineral dust	1000	4000
Terrestrial PBAPs	50	1000
Dimethylsulphide (DMS)	10	40
Monoterpenes	30	120
Isoprene	410	600
SOA production from all BVOCs	20	380

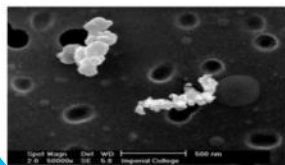


Dominant emissions are from deserts & oceans

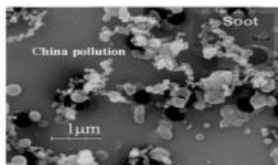
Characterization =  $f$  (**size**, **volume**, shape, composition, source)

## Anthropogenic

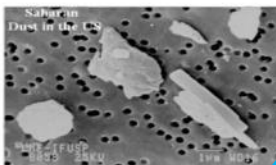
### Smoke



### Urban

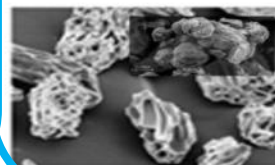


### Mineral Dust

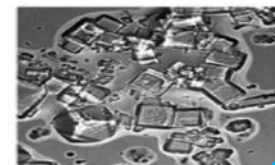


## Natural

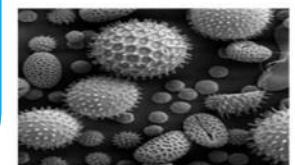
### Volcanic



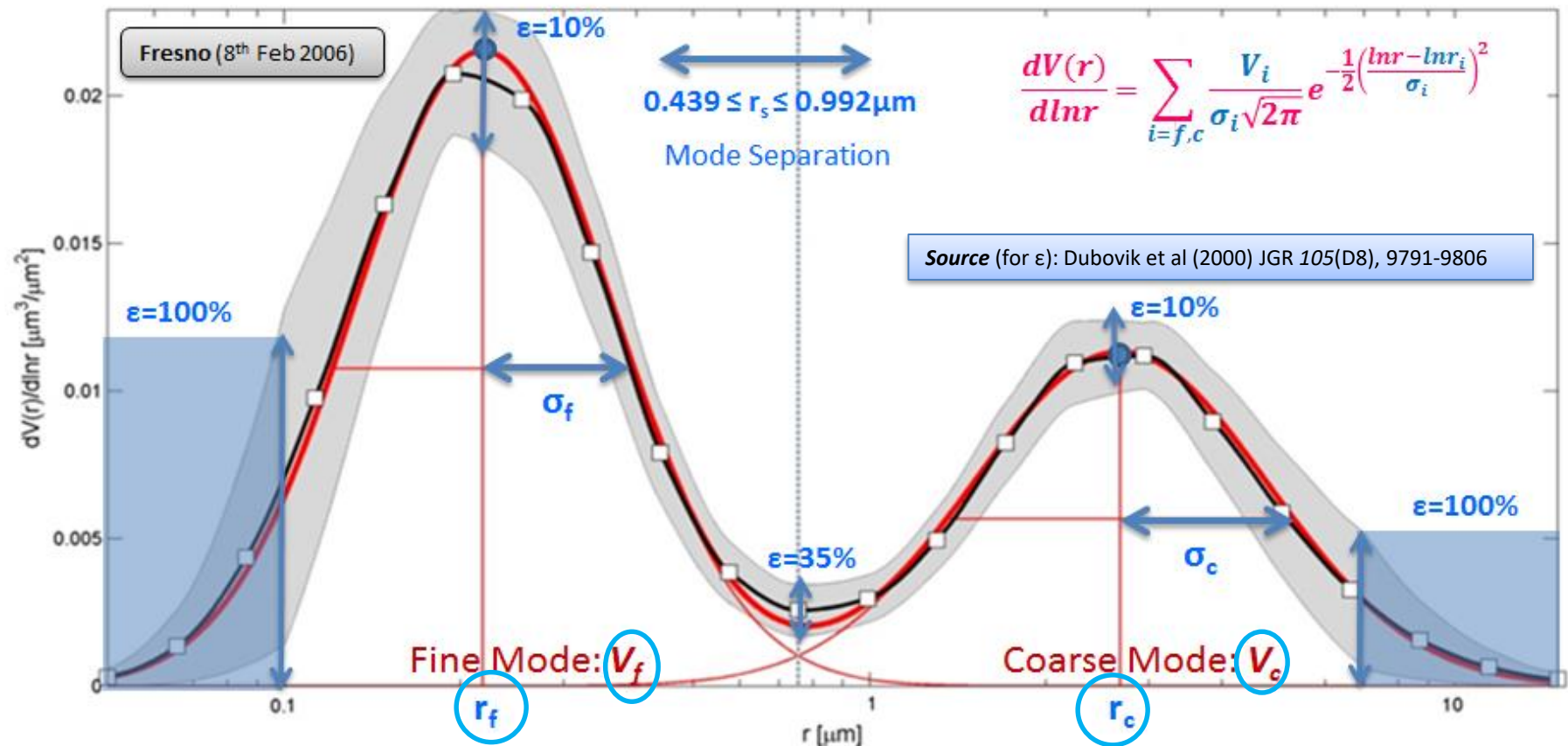
### Sea Salt



### Biogenic







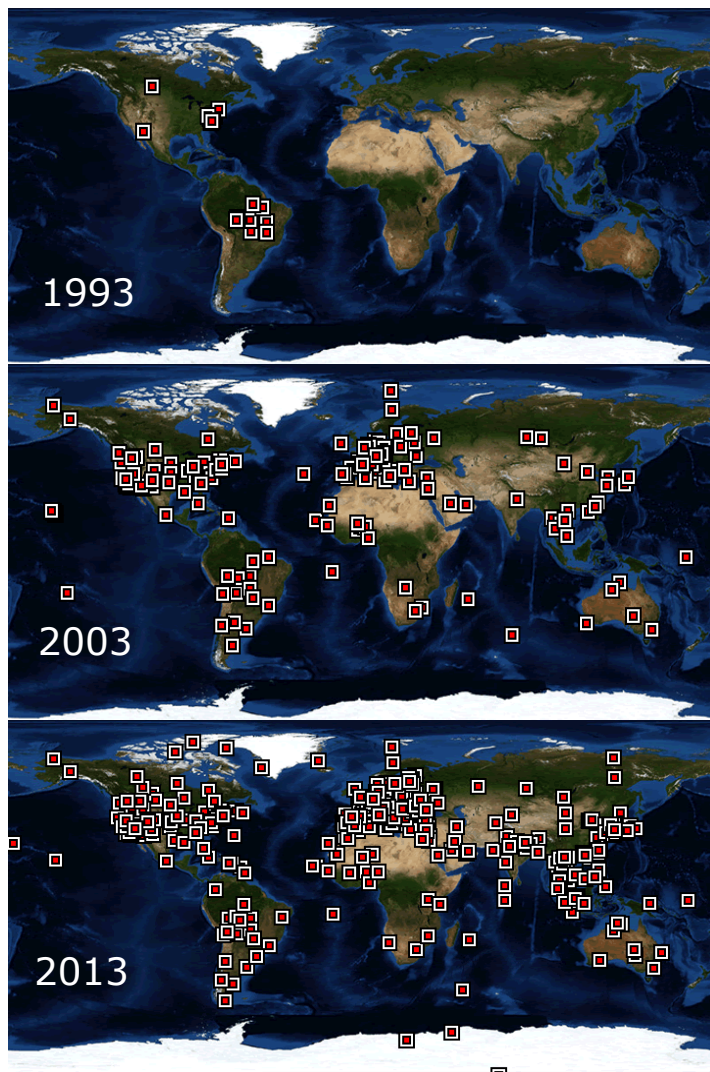
$$V_i = \int_{r_1}^{r_2} \frac{dV(r)}{d\ln r} d\ln r$$

$$\ln r_i = \frac{\int_{r_1}^{r_2} \ln r \frac{dV(r)}{d\ln r} d\ln r}{\int_{r_1}^{r_2} \frac{dV(r)}{d\ln r} d\ln r}$$

$$\sigma_i = \sqrt{\frac{\int_{r_1}^{r_2} (\ln r - \ln r_i)^2 \frac{dV(r)}{d\ln r} d\ln r}{\int_{r_1}^{r_2} \frac{dV(r)}{d\ln r} d\ln r}}$$

Source: Taylor, Kazadzis & Gerasopoulos (2014) *Proceedings of the 12th International Conference on Meteorology, Climatology & Atmospheric Physics (COMECAP)*, Heraklion, Crete, 28-31 May, Vol. 3, 191-196.

# CHALLENGE: AERONET stations have inhomogeneous spatial coverage



Source: <http://aeronet.gsfc.nasa.gov>

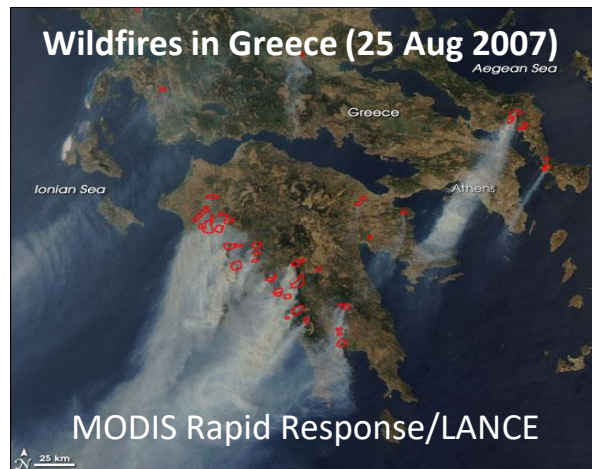
Aerosol inversion products date back to 27 May, 1993 @GSFC

Now >1000 sites...  
... occupying only 343 pixels of the global grid (1x1 degree):

$$= 343 / (360 * 180)$$

**= 0.54% membership of surface pixels**

AERONET sites in Greece providing (Level 1.5) inversions during August 2007



Source: <http://earthobservatory.nasa.gov>



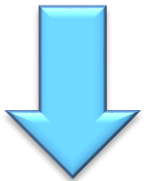
Source: <http://aeronet.gsfc.nasa.gov>



Satellite inputs  
(gridded 1x1 degree)



Function  
Approximator



"AERONET" outputs  
(gridded 1x1 degree)

MODIS H2O (to cloud)  
MODIS AOD (470nm)  
MODIS AOD (550nm)  
MODIS AOD (660nm)  
OMI AOD (380nm)  
OMI AOD (500nm)  
OMI AAOD (500nm)

From: Giovanni 3

Neural Network (NN)

- H2O=Precipitable water vapour
- AOD=Aerosol optical depth
- AAOD=Aerosol absorption AOD
- AVSD=Aerosol volume size distribution
- CRI-R=Complex refractive index (real part)
- CRI-I=Complex refractive index (imaginary part)
- SSA=Single scattering albedo
- ASYM=asymmetry factor

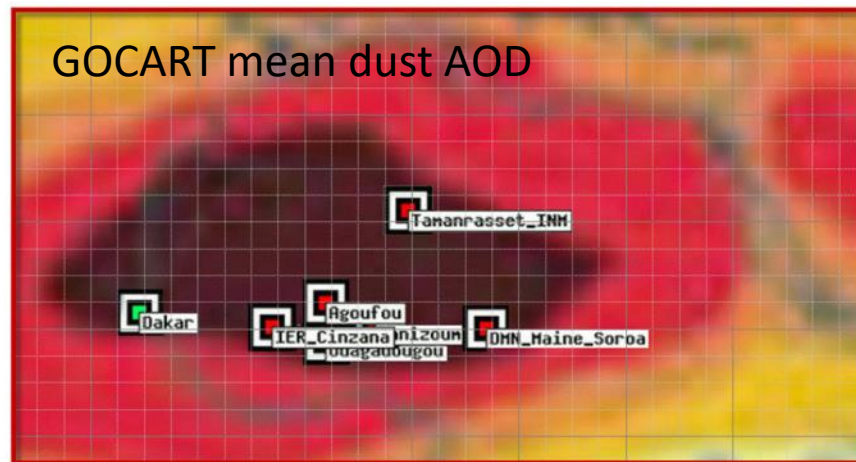
AVSD (22 radial bins)  
CRI-R (440, 675, 870, 1020nm)  
CRI-I (440, 675, 870, 1020nm)  
SSA (440, 675, 870, 1020nm)  
ASYM (440, 675, 870, 1020nm)

From: AERONET

# **PROTOTYPE:**

***A NN model for retrieval of Saharan Dust size distributions in Northern Africa***

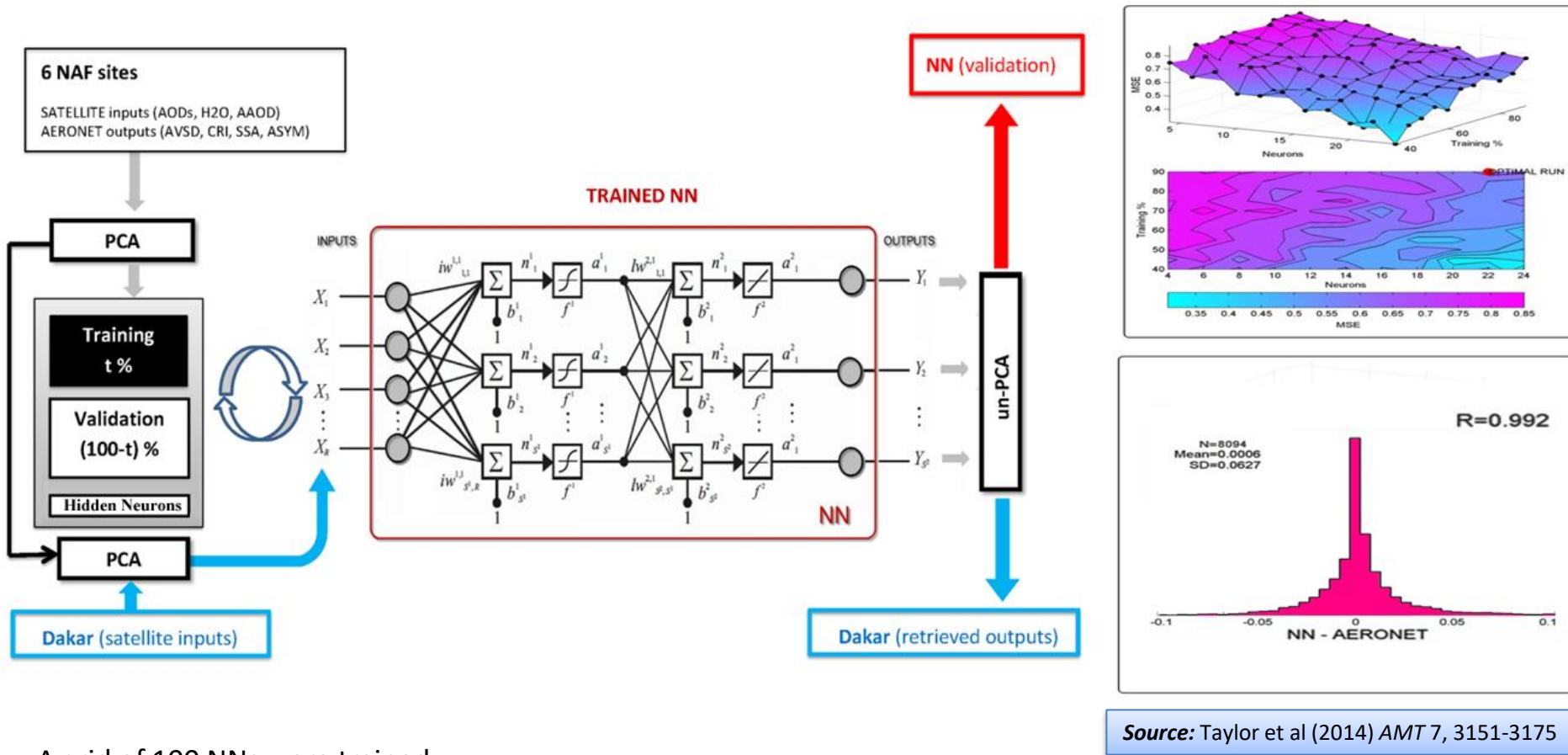
# DATA: GOCART-selected Northern African “dust” sites for the NN model



	SITE	N	GOCART Mean AOD & aerosol composition					% Dust
			< AOD >	% SO <sub>2</sub>	% OC	% BC	% Sea Salt	
TRAINING	Tamanrasset INM	407	0.793	4.54 %	1.39 %	0.63 %	0.13 %	93.44 %
	Agoufou	1028	0.973	3.70 %	2.47 %	0.82 %	0.10 %	92.91 %
	Banizoumbou	2283	0.920	4.57 %	3.48 %	1.09 %	0.11 %	90.76 %
	DMN Maine Soroba	680	0.967	5.27 %	3.52 %	1.14 %	0.10 %	90.07 %
	IER Cinzana	1469	0.823	4.86 %	4.62 %	1.22 %	0.12 %	89.19 %
	Ouagadougou	966	0.776	6.06 %	7.47 %	1.93 %	0.13 %	84.41 %
SIMULATION	Dakar	1583	0.705	7.38 %	5.53 %	1.42 %	0.71 %	84.82 %

**Source:** Taylor, M., Kazadzis, S., Tsekeri, A., Gkikas, A., Amiridis, V. (2014) *Satellite retrieval of aerosol microphysical and optical parameters using neural networks: a new methodology applied to the Sahara desert dust peak*. Atmospheric Measurement Techniques 7, 3151-3175.

# NN MODEL: Scheme for objectivizing the NN architecture



A grid of 100 NNs were trained:

- Training fraction (t%) = [40%:5%:90%]
- *Tanh* hidden neurons = [4:2:24]

Minimum mean squared error → **Optimal NN**

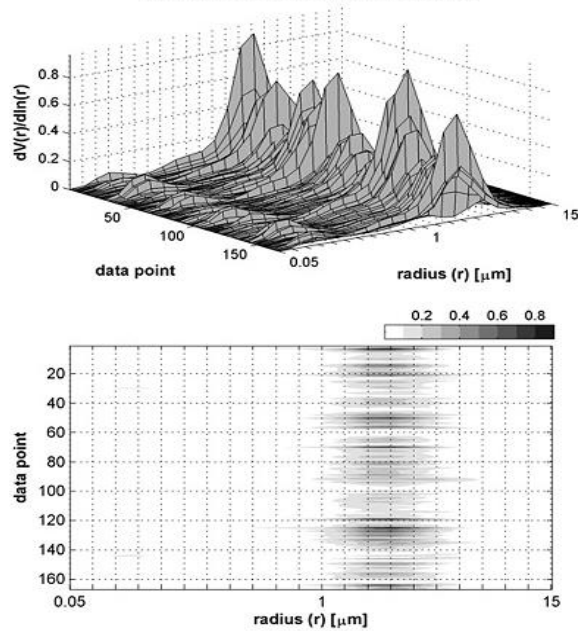
PCA = Principal Components Analysis (98% variance)

Source: Taylor et al (2014) AMT 7, 3151-3175

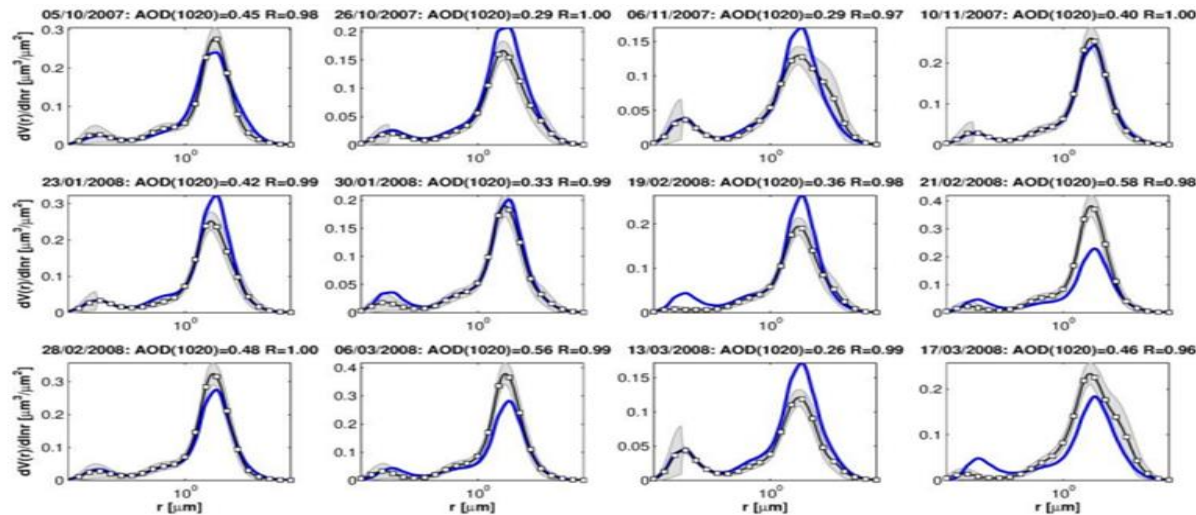
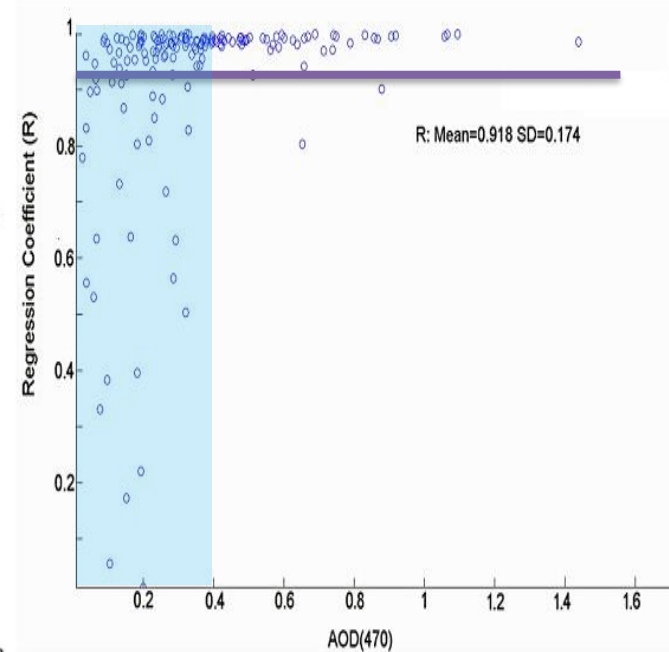
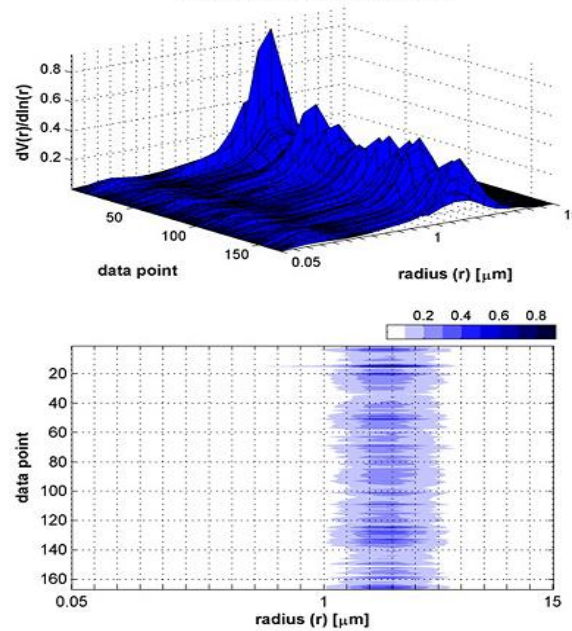


# NN SIMULATION (Dakar): AVSD (181 co-located daily averages)

AERONET (targets): AVSD daily averages



NN (outputs): AVSD daily averages



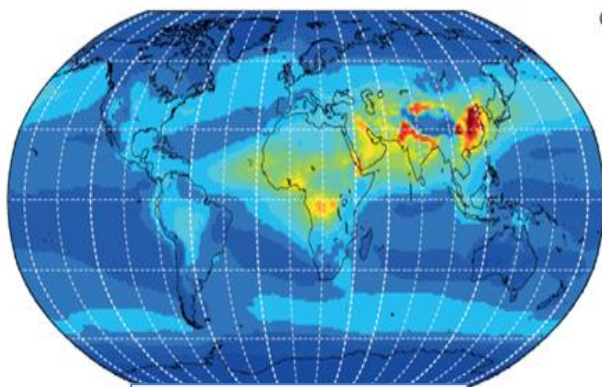
Good **daily** retrieval of the AVSD  
for **Saharan dust (only)**

Source: Taylor, M et al (2014) AMT 7, 3151-3175

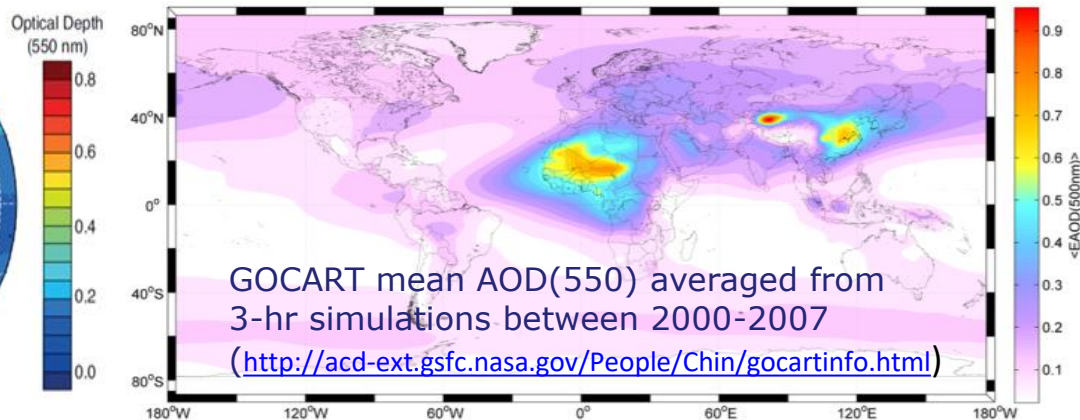


# **GLOBAL AEROSOL MODEL**

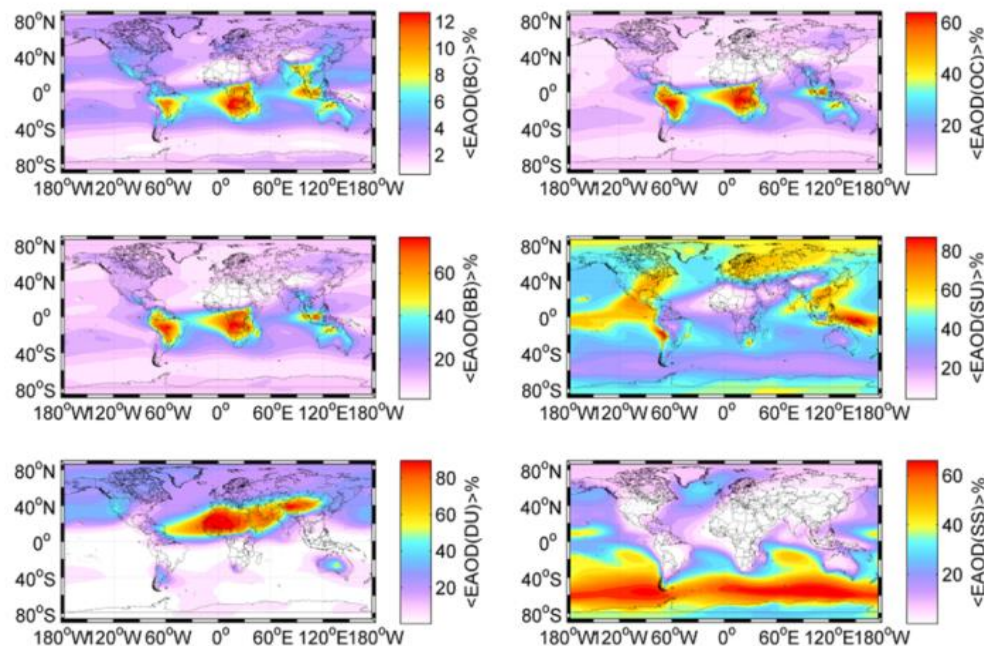
# STEP 1: Use GOCART to partition by mean aerosol type *mixture*



Source: IPCC/AR5 (2013)



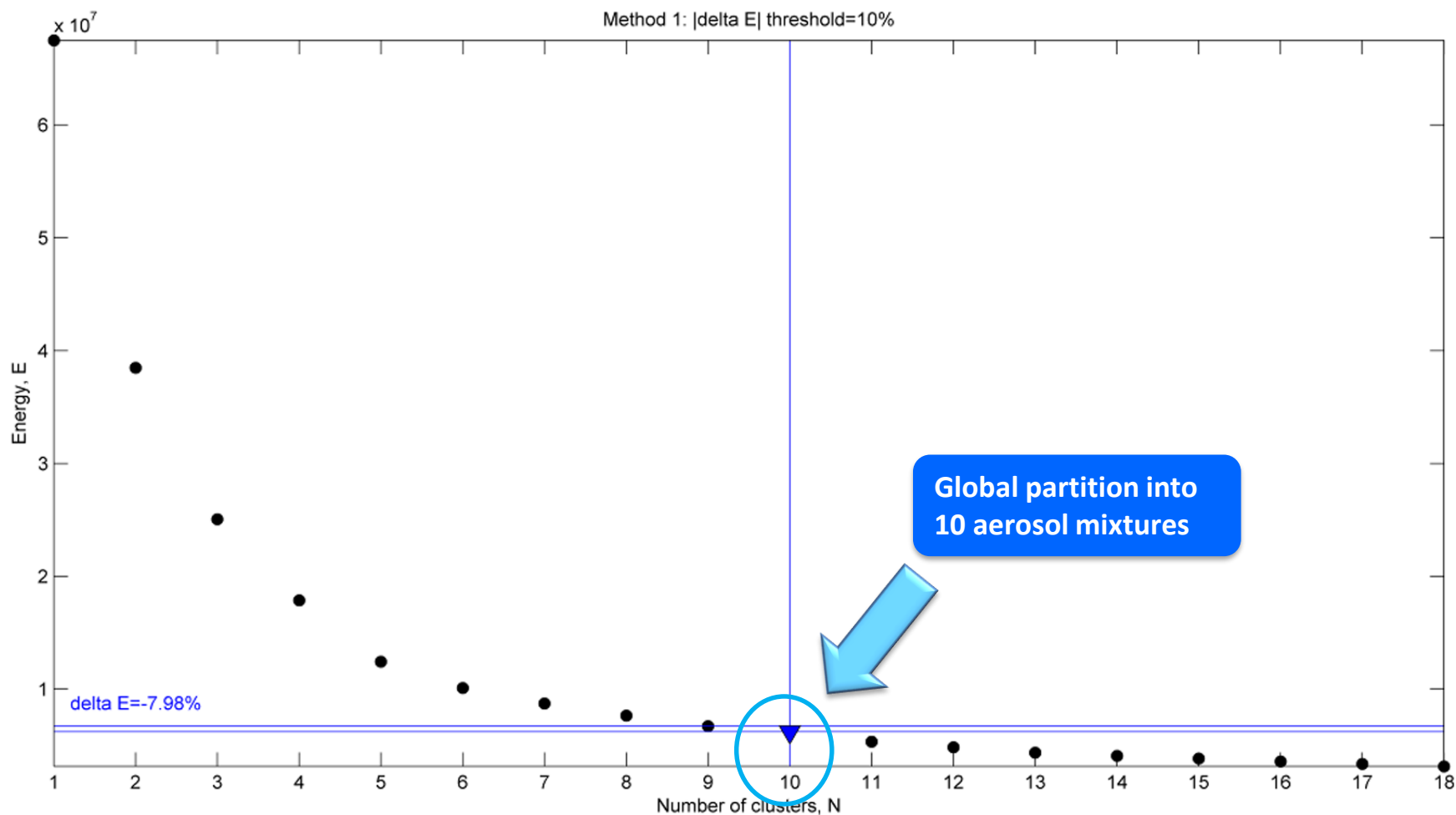
GOCART 2000-2007 global mean AOD per type :  
(BC, OC, SU, DU, SS)



BC=Black Carbon  
OC=Organic Carbon  
SU=Sulfate  
DU=Dust  
SS=Sea Salt

Source: MT

# CLUSTER ANALYSIS: of GOCART AOD ( $BB=BC+OC$ , $SU$ , $DU$ , $SS$ )

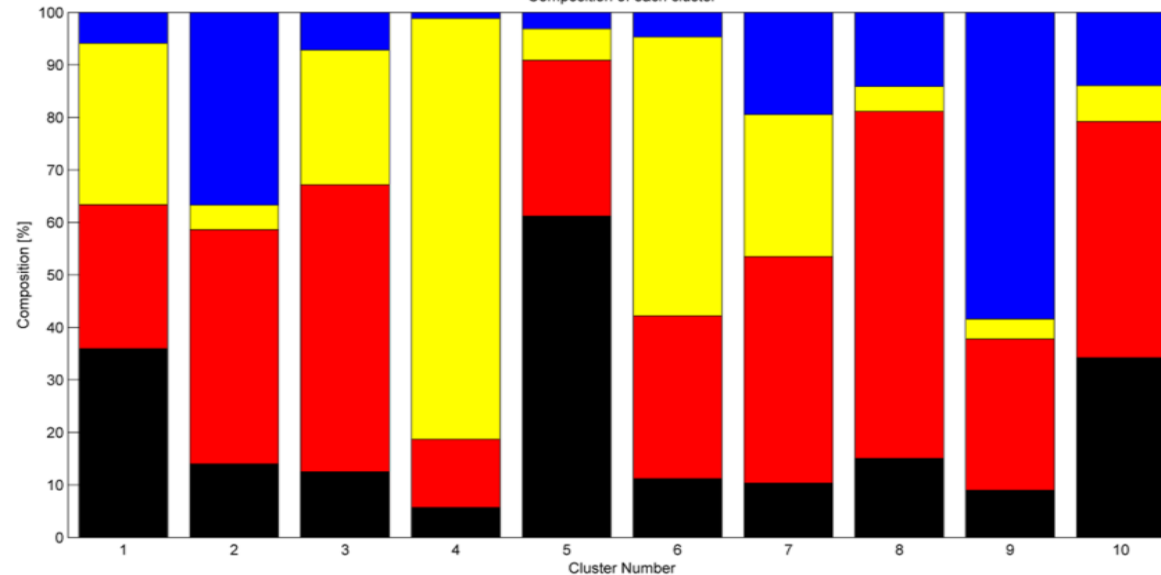


Add clusters (10 random seeds each time) until cluster centers do not change by  $> 10\%$

# CLUSTER ANALYSIS: *Composition of 10 aerosol mixtures*

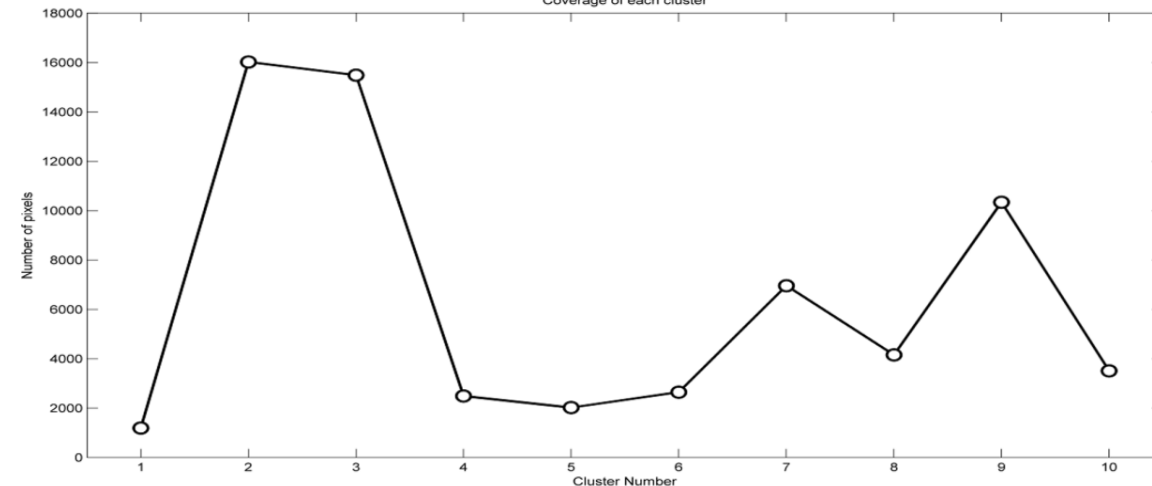
BB SU DU SS

Composition of each cluster



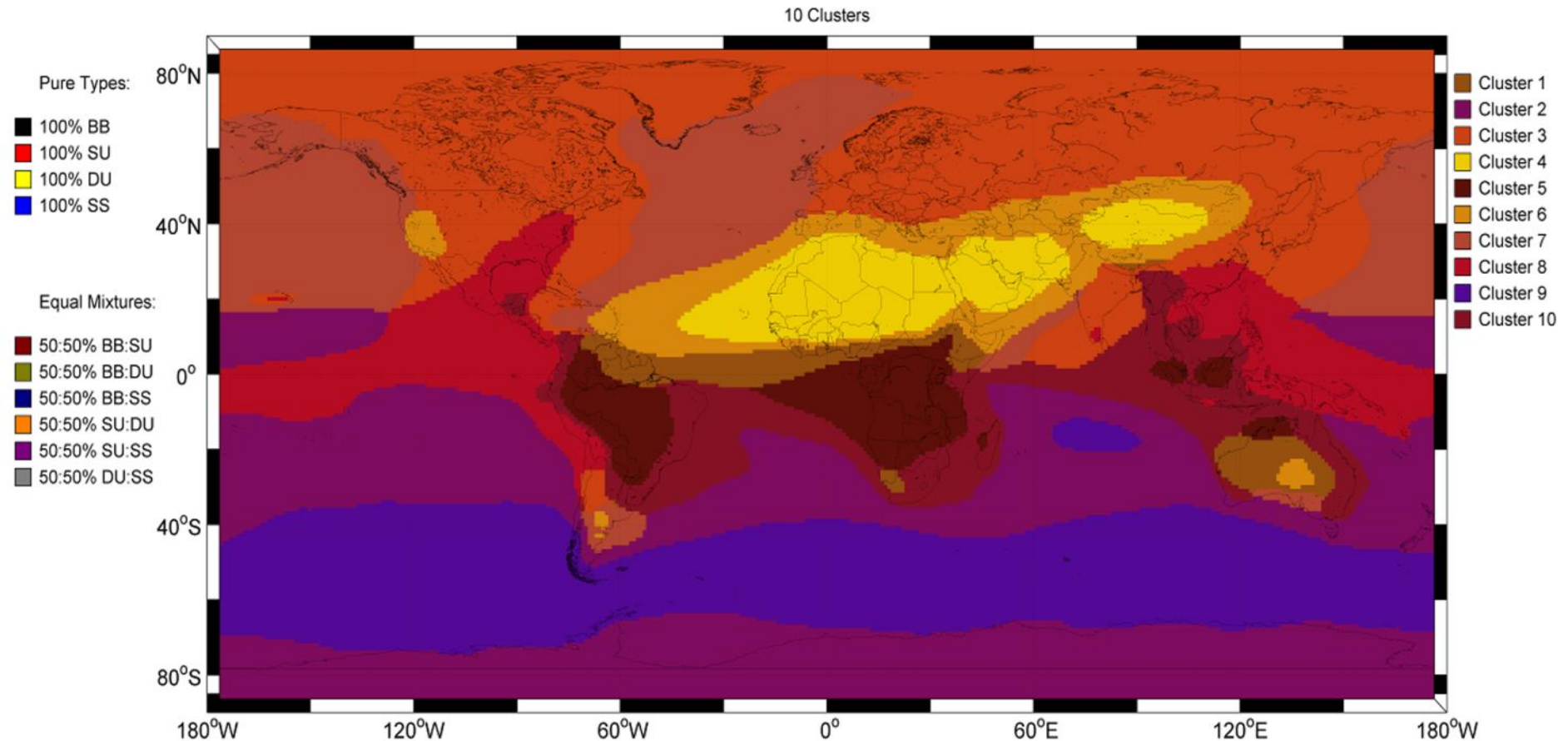
- Cluster 1 = Dusty Sulfurous **SMOKE**
- Cluster 2 = Marine **SULFATE**
- Cluster 3 = Dusty **SULFATE**
- Cluster 4 = **DUST**
- Cluster 5 = Sulfurous **SMOKE**
- Cluster 6 = Sulfurous **DUST**
- Cluster 7 = Dusty Marine **SULFATE**
- Cluster 8 = **SULFATE**
- Cluster 9 = Sulfurous **MARINE**
- Cluster 10 = Smokey **SULFATE**

Coverage of each cluster



Minimum cluster coverage  
> 1000 pixels (1x1 degree)

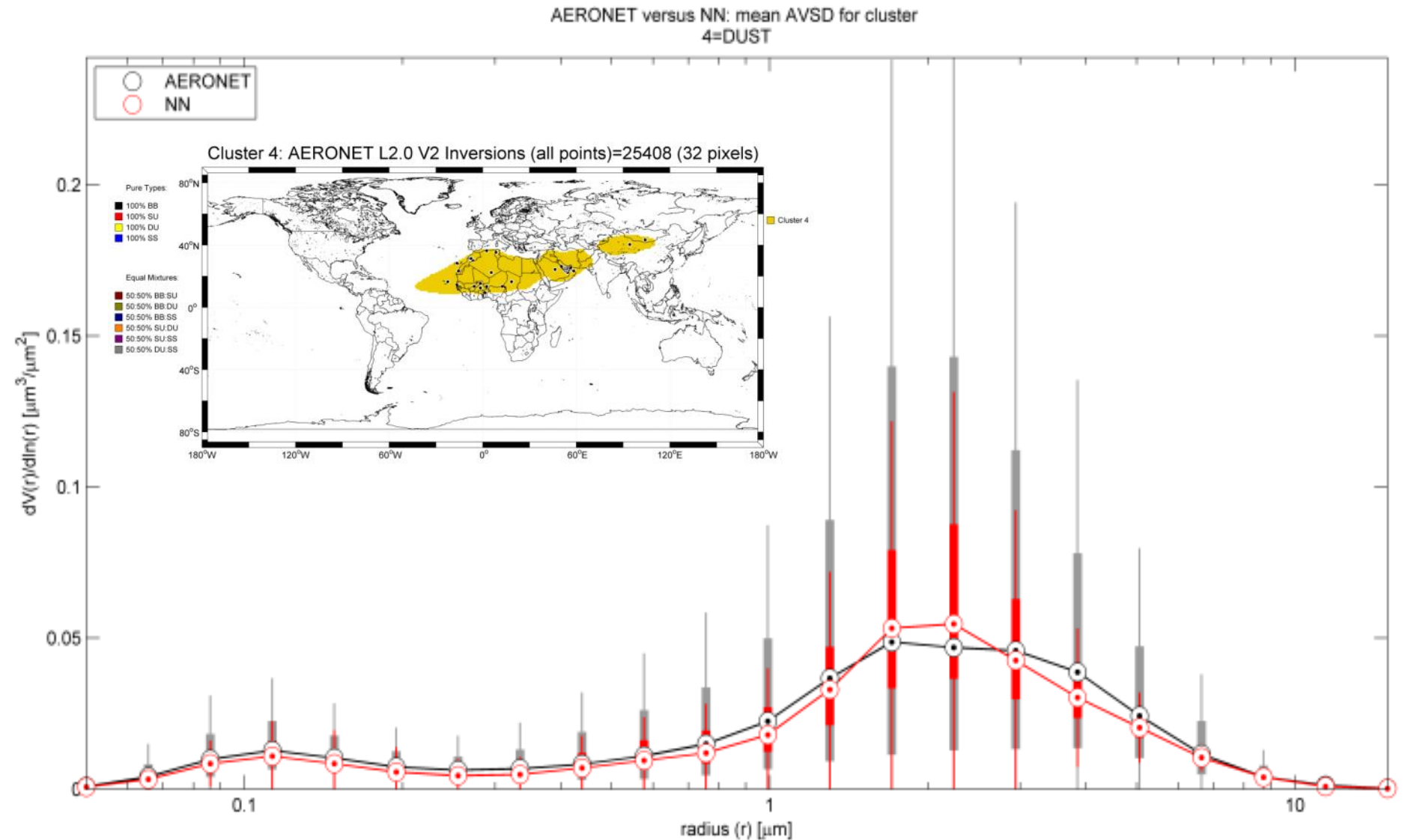
# CLUSTER ANALYSIS: *Colour-mixed global mean aerosol partitions*



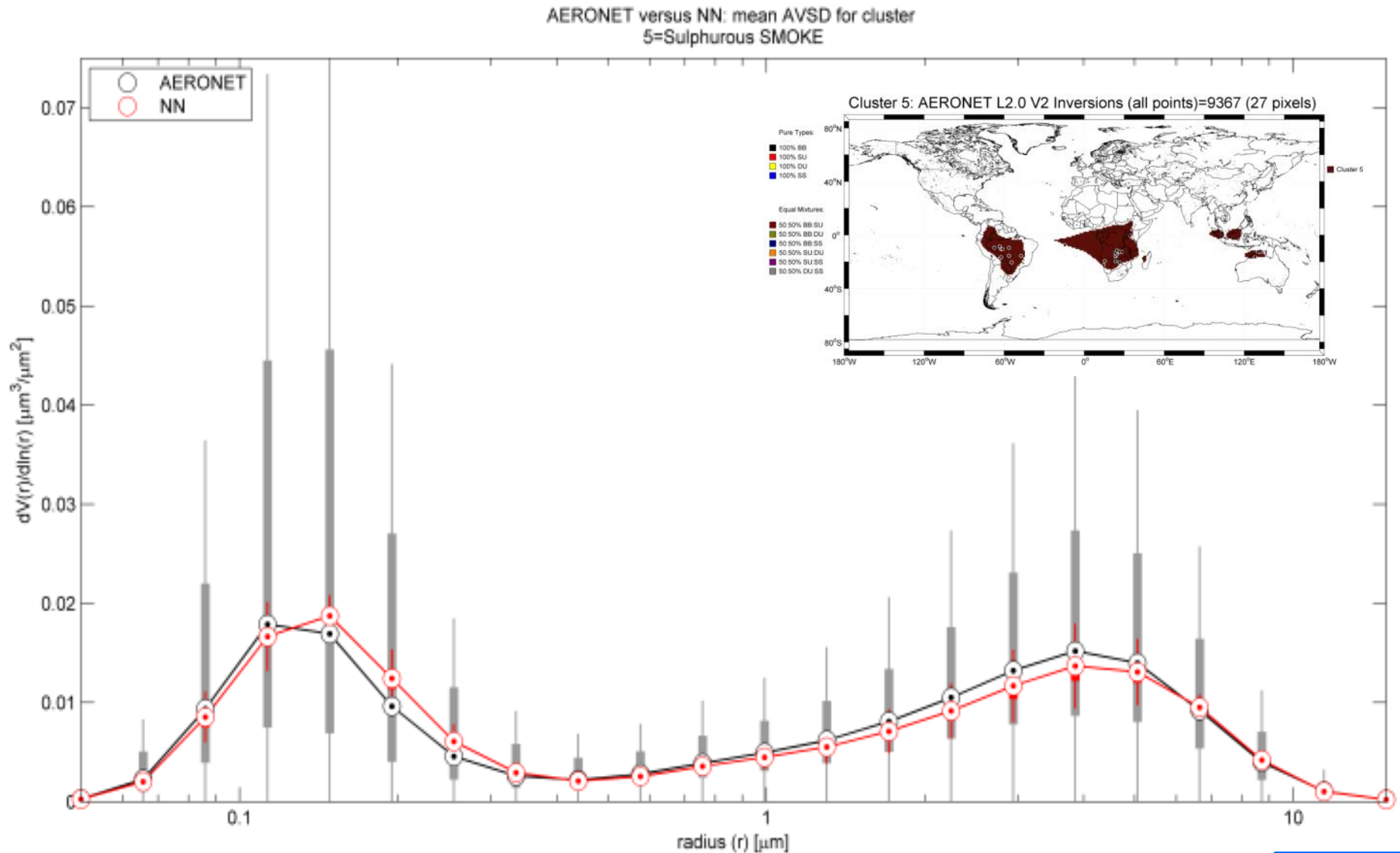
This colour scheme may help in visually interpreting aerosol mixtures



## STEP 2: Use co-located Satellite/AERONET data to train a NN for each cluster



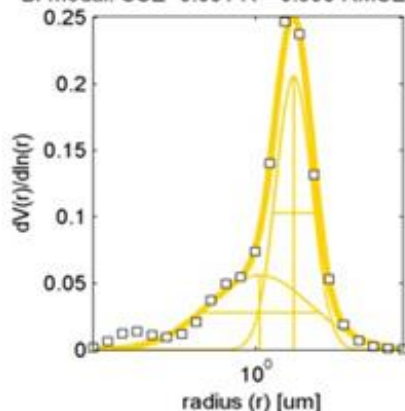
# RESULTS: The biomass burning cluster 5 ("Sulfurous SMOKE")



# STEP 3: Multimodal fitting & analysis → additional size & volume info

## Desert dust

Bi-modal: SSE=0.051  $R^2=0.995$  RMSE=0.005

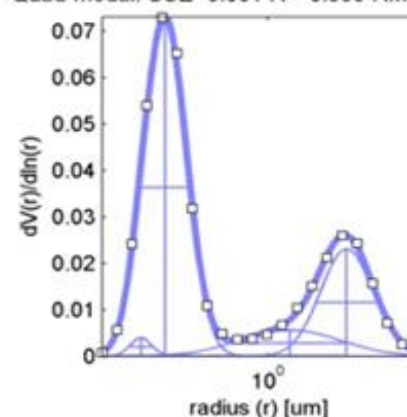


[Banizoumbou 16/03/2005]

Bi-modal fit:  $V=0.30$   
 $V(1)=0.131$   $r(1)=1.074$   $\sigma(1)=3.757$   
 $V(2)=0.170$   $r(2)=2.009$   $\sigma(2)=1.594$

## Biomass burning

Quad-modal: SSE=0.001  $R^2=0.999$  RMSE=0.001

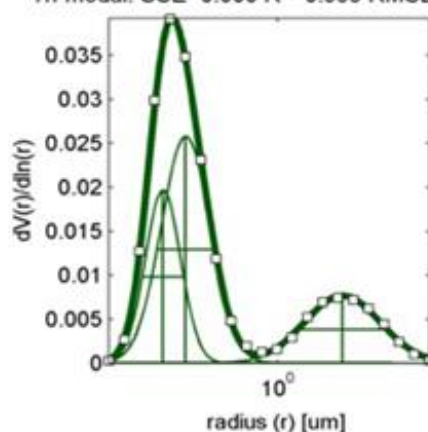


[Mongu 14/08/2003]

Quad-modal fit  $V=0.11$   
 $V(1)=0.069$   $r(1)=0.156$   $\sigma(1)=1.712$   
 $V(2)=0.013$   $r(2)=1.499$   $\sigma(2)=3.586$   
 $V(3)=0.002$   $r(3)=0.101$   $\sigma(3)=1.317$   
 $V(4)=0.027$   $r(4)=4.163$   $\sigma(4)=1.955$

## Urban

Tri-modal: SSE=0.000  $R^2=0.999$  RMSE=0.000

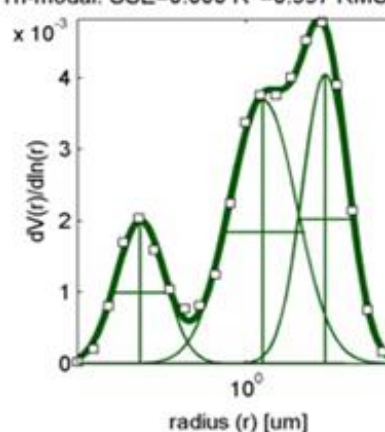


[GSFC 17/08/2005]

Tri-modal fit:  $V=0.06$   
 $V(1)=0.028$   $r(1)=0.195$   $\sigma(1)=1.851$   
 $V(2)=0.013$   $r(2)=3.168$   $\sigma(2)=2.595$   
 $V(3)=0.015$   $r(3)=0.130$   $\sigma(3)=1.561$

## Marine

Tri-modal: SSE=0.000  $R^2=0.997$  RMSE=0.000



[Lanai 21/01/2002]

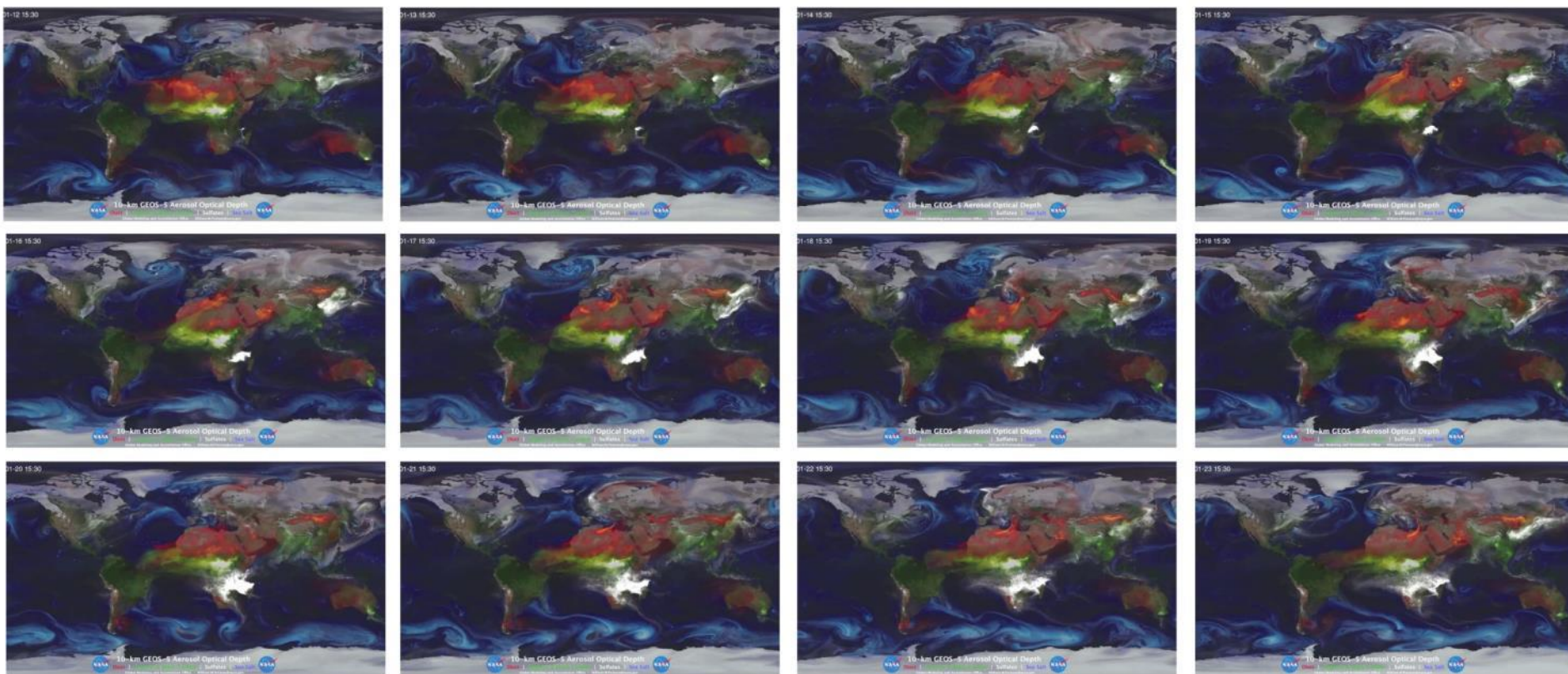
Tri-modal fit:  $V=0.01$   
 $V(1)=0.004$   $r(1)=4.104$   $\sigma(1)=1.789$   
 $V(2)=0.002$   $r(2)=0.152$   $\sigma(2)=1.846$   
 $V(3)=0.006$   $r(3)=1.351$   $\sigma(3)=2.337$

**Source:** Taylor, Kazadzis, Gerasopoulos (2014) Multi-modal analysis of aerosol robotic network size distributions for remote sensing applications: dominant aerosol type cases. *Atmospheric Measurement Techniques* 7, 839-858

## **CASE STUDY:**

***Quasi-real time monitoring of the Karthala  
Volcano Eruption  
(12-23 January, 2007)***





Karthala (Grande Comore Island)  
Shield volcano eruption (VEI=2):  
12-23 January, 2007

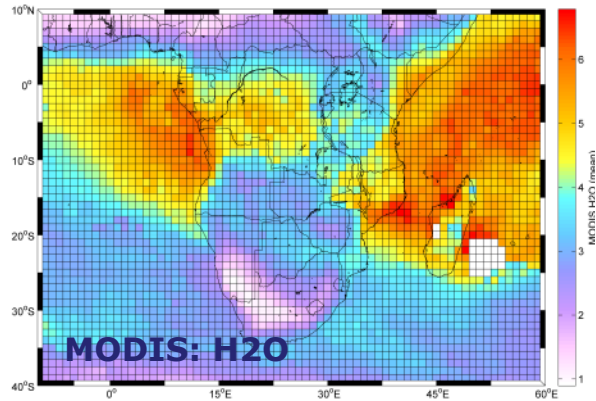
GOCART daily-averaged composite AOD  
(BB=green, SU=white, DU=orange, SS=blue)



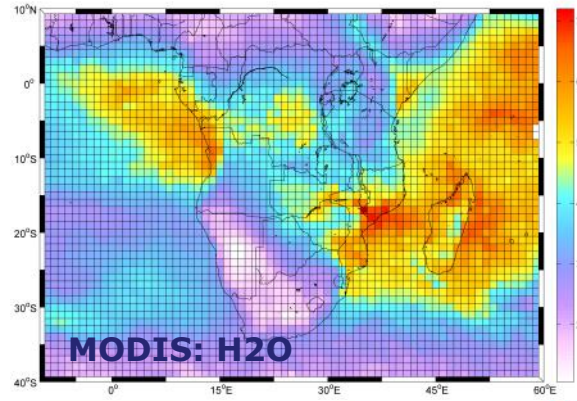


# SATELLITE INPUTS: 4-day average (to smooth out “patchiness”)

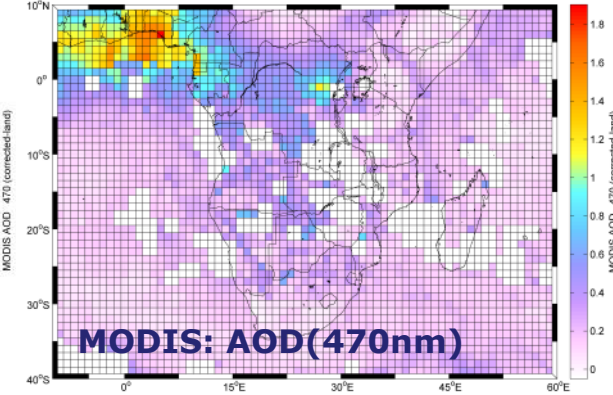
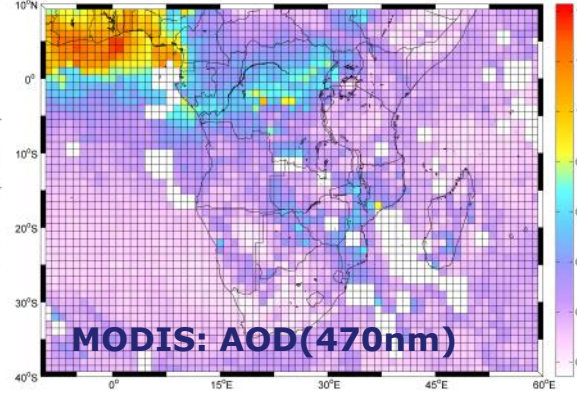
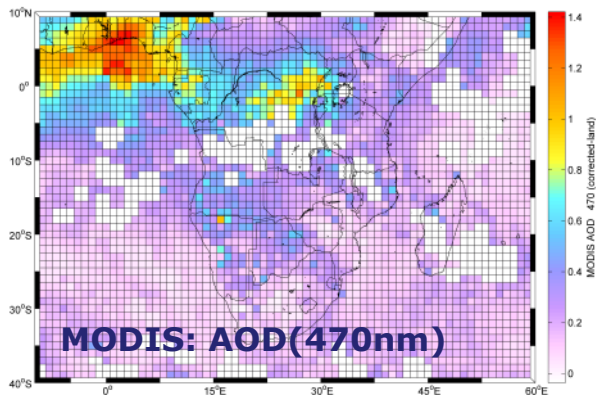
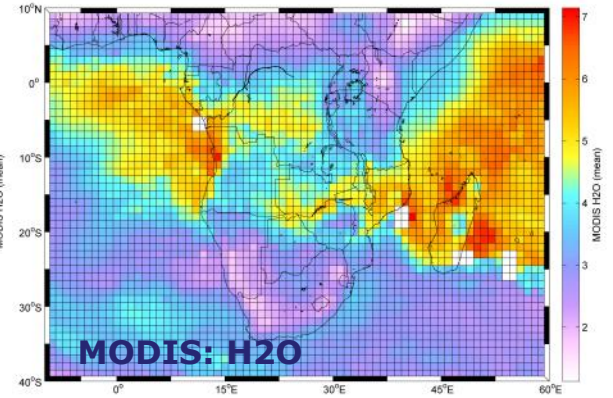
12-15 Jan 2007



16-19 Jan 2007

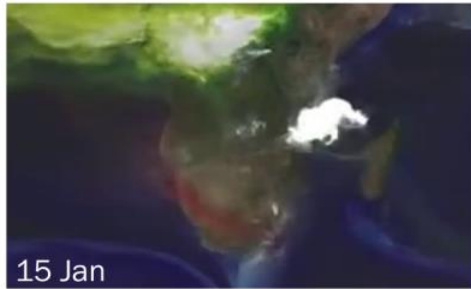


20-23 Jan 2007

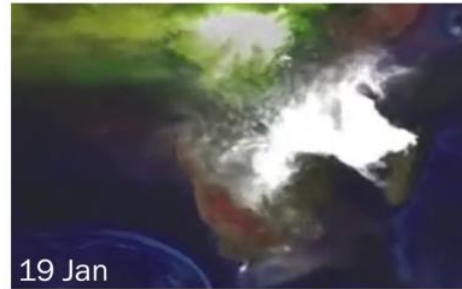


# 4-DAY AVERAGE: Quasi-realtime 1x1 degree grid of microphysics

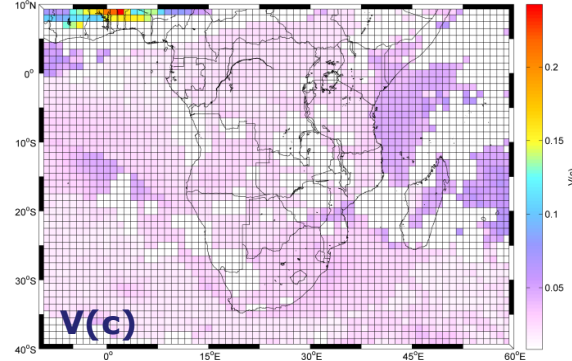
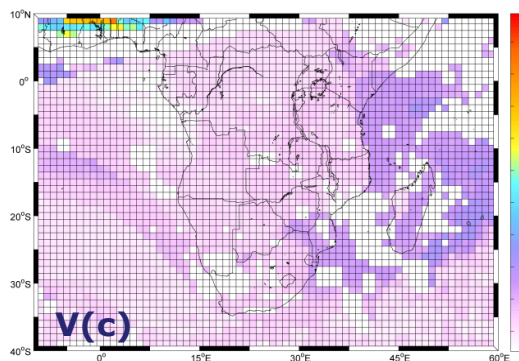
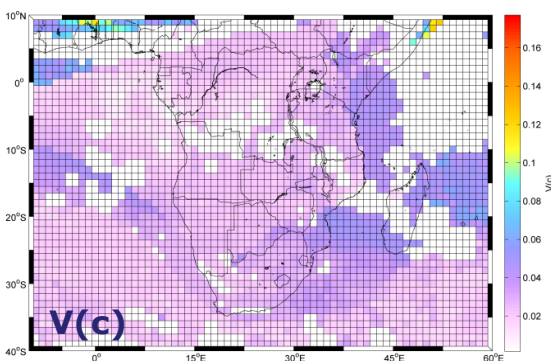
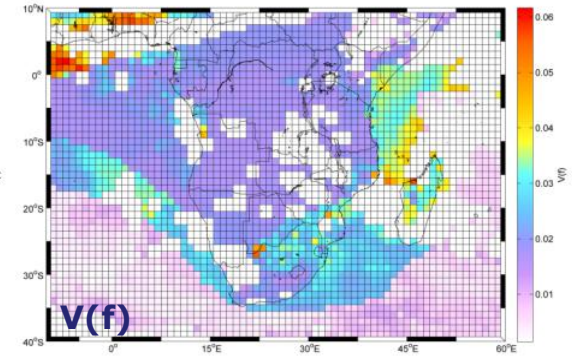
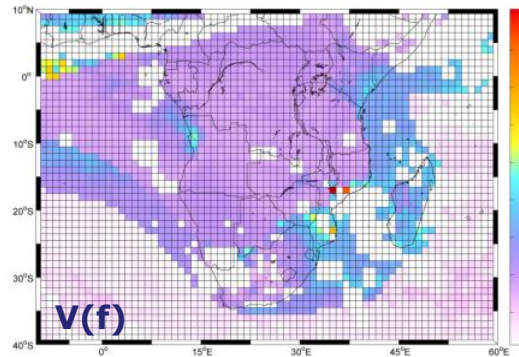
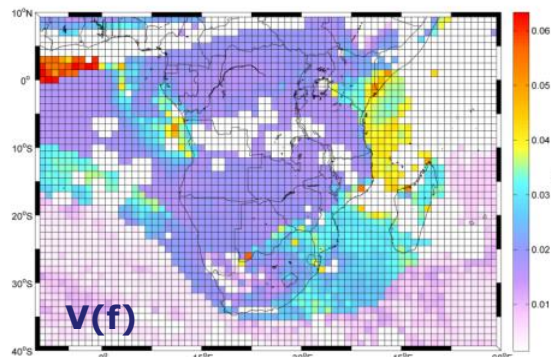
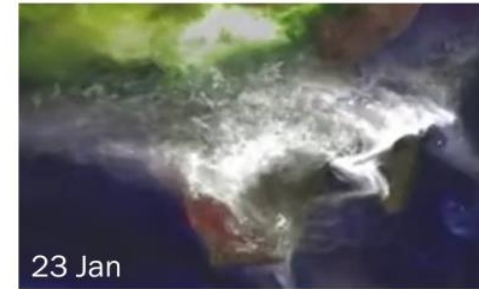
12-15 Jan 2007



16-19 Jan 2007



20-23 Jan 2007





**Prototype model** → it is possible to train NNs to invert satellite measurements to provide daily retrievals of the aerosol volume size distribution at 1x1 degree resolution

**Global aerosol model** → 1) Mean global GOCART AOD (per type) can be used to identify 10 clearly defined aerosol mixtures/partitions, 2) partitions allow extraction of co-located Satellite/AERONET data for training of aerosol mixture/region-dependent NNs, 3) Multimodal fitting & analysis of AVSDs can provide detailed size & volume information

**Case study** → quasi-realtime 1x1 degree maps of size distribution-derived microphysics can be produced at the 4-day timescale

## Many thanks to:

@NOA: Stelios Kazadzis, Vangelis Gerasopoulos, Alexandra Tsekeri, Vasilis Amiridis and

@BSC/Earth Science: Antonis Gikas (for their co-authorship of articles)

@AERONET: PIs (for maintenance & provision of HQ open data inversion products)

@NASA/GES-DISC: Giovanni 3 & 4 PIs (for maintenance & provision of HQ open data from MODIS/Aqua, OMI/Aura and GOCART 4)

@ADNET SYSTEMS INC: Jennifer Brennan & Jim Acker for kindly organizing this workshop