Overview of the IASI-derived ULB dust product and recent developments

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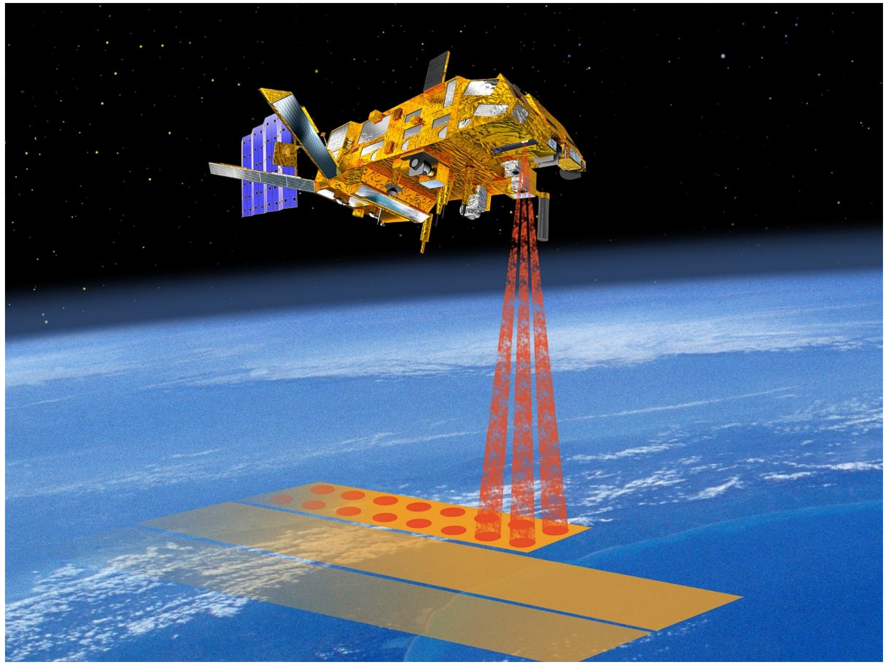
Infrared Atmospheric Sounding Interferometer (IASI)

- IASI: **Thermal IR** nadir sounder
- On board the **Metop** (-A, -B and -C) polar orbiting satellites since 2007

  >16 years of continuous and consistent measurements… + 25 years to come with IASI-NG



SAMPLING ~ 1.3 million spectra/day

- Pixel size: **12 km on ground at nadir**
- Global coverage & high sampling: **global measurements twice daily**

  ~9.30 AM & PM

INSTRUMENTAL

- Broad spectral range: **645-2760 cm^{-1} (15.5-3.62 µm), with no gaps**
- Spectral sampling : **0.25 cm^{-1}**

MISSION GOALS

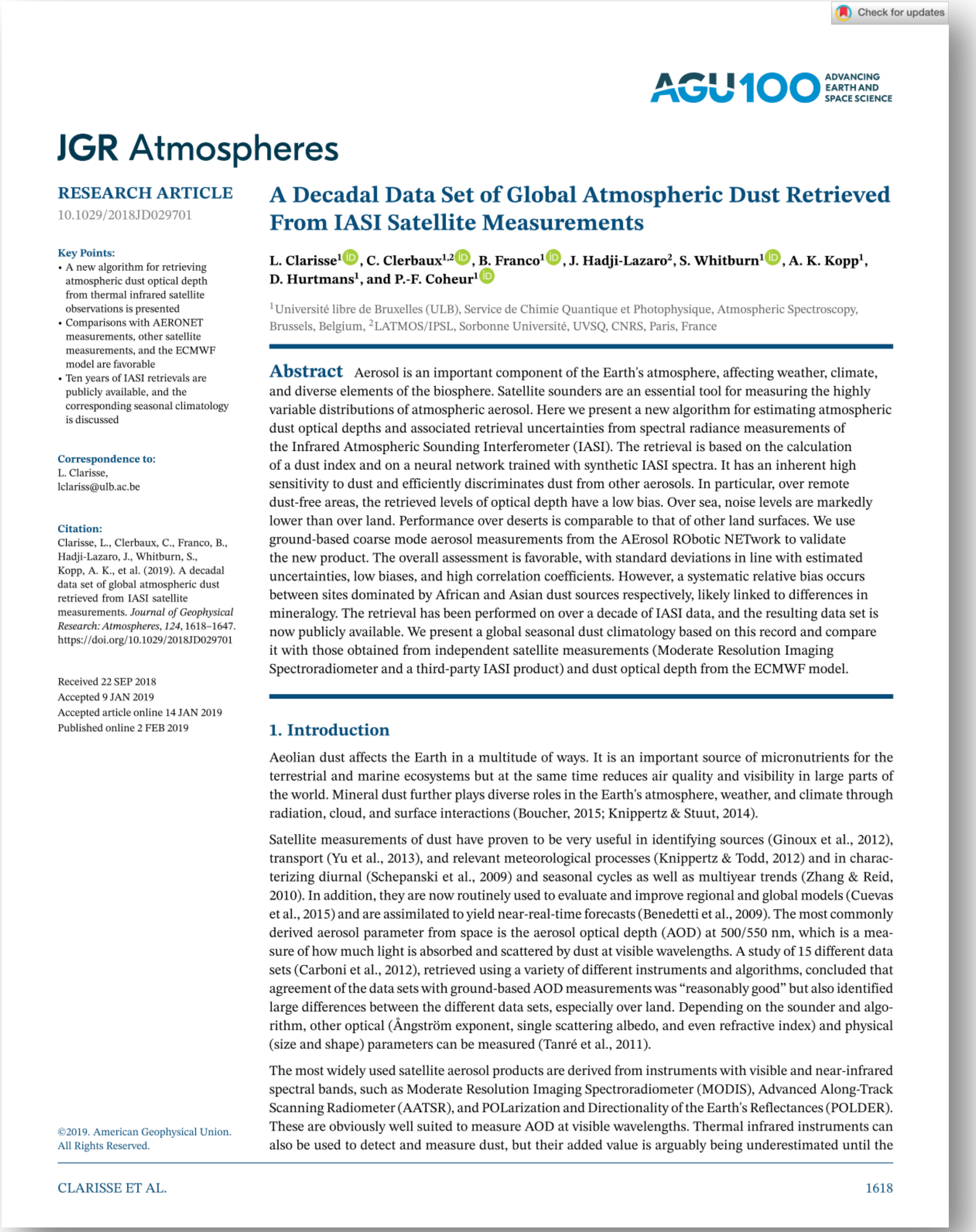
1. Meteorology (Water vapour, T profiles)
2. Atmospheric Composition and Chemistry (O3, CO, H20, …)
3. Climate (Radiation, Surface Temperature, CO2, etc..)

→ Complementarity between Visible/NIR and Thermal Infrared observations

VISIBLE/NIR	THERMAL INFRARED
Daytime only (reflected sun)	**Day or night** (Earth radiation)
Fine particles (<1 µm) (e.g. dust, smoke, PM, most aerosol)	**Coarse particles** (>1 µm) (dust, ash, sulphate, clouds, ice)
Not sensitive to **altitude** (but better on BL!)	Sensitive to **altitude** (but worse on BL!)
Challenges over **bright surfaces** (reflectivity)	Challenges over **desert/snow surfaces** (emissivity)
Limited sensitivity to **composition** dust, ash, sulphate	Sensitivity to **composition** (certain types) (dust, ash, sulphate, clouds, ice)

Outline

- **Part 1: The dust OD retrieval (cloud free)**
  - A dust index
    - Construction
    - Surface emissivity
    - v8 vs. v9: new bias corrections
    - v9: a new cloud mask
  - Neural network-based retrieval
    - Setup and training
    - Retrieval and uncertainty estimates
- **Part 2: Illustrations and comparisons**
  - Climatologies and Model comparison
  - Aeronet
  - Trends



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JGR Atmospheres

RESEARCH ARTICLE

10.1029/2018JD029701

Key Points:
- A new algorithm for retrieving atmospheric dust optical depth from thermal infrared satellite observations is presented
- Comparisons with AERONET measurements, other satellite measurements, and the ECMWF model are favorable
- Ten years of IASI retrievals are publicly available, and the corresponding seasonal climatology is discussed

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A Decadal Data Set of Global Atmospheric Dust Retrieved From IASI Satellite Measurements

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Abstract Aerosol is an important component of the Earth's atmosphere, affecting weather, climate, and diverse elements of the biosphere. Satellite sounders are an essential tool for measuring the highly variable distributions of atmospheric aerosol. Here we present a new algorithm for estimating atmospheric dust optical depths and associated retrieval uncertainties from spectral radiance measurements of the Infrared Atmospheric Sounding Interferometer (IASI). The retrieval is based on the calculation of a dust index and on a neural network trained with synthetic IASI spectra. It has an inherent high sensitivity to dust and efficiently discriminates dust from other aerosols. In particular, over remote dust-free areas, the retrieved levels of optical depth have a low bias. Over sea, noise levels are markedly lower than over land. Performance over deserts is comparable to that of other land surfaces. We use ground-based coarse mode aerosol measurements from the AErosol RObotic NETwork to validate the new product. The overall assessment is favorable, with standard deviations in line with estimated uncertainties, low biases, and high correlation coefficients. However, a systematic relative bias occurs between sites dominated by African and Asian dust sources respectively, likely linked to differences in mineralogy. The retrieval has been performed on over a decade of IASI data, and the resulting data set is now publicly available. We present a global seasonal dust climatology based on this record and compare it with those obtained from independent satellite measurements (Moderate Resolution Imaging Spectroradiometer and a third-party IASI product) and dust optical depth from the ECMWF model.

1. Introduction

Aeolian dust affects the Earth in a multitude of ways. It is an important source of micronutrients for the terrestrial and marine ecosystems but at the same time reduces air quality and visibility in large parts of the world. Mineral dust further plays diverse roles in the Earth's atmosphere, weather, and climate through radiation, cloud, and surface interactions (Boucher, 2015; Knippertz & Stuut, 2014).

Satellite measurements of dust have proven to be very useful in identifying sources (Ginoux et al., 2012), transport (Yu et al., 2013), and relevant meteorological processes (Knippertz & Todd, 2012) and in characterizing diurnal (Schepanski et al., 2009) and seasonal cycles as well as multiyear trends (Zhang & Reid, 2010). In addition, they are now routinely used to evaluate and improve regional and global models (Cuevas et al., 2015) and are assimilated to yield near-real-time forecasts (Benedetti et al., 2009). The most commonly derived aerosol parameter from space is the aerosol optical depth (AOD) at 500/550 nm, which is a measure of how much light is absorbed and scattered by dust at visible wavelengths. A study of 15 different data sets (Carboni et al., 2012), retrieved using a variety of different instruments and algorithms, concluded that agreement of the data sets with ground-based AOD measurements was "reasonably good" but also identified large differences between the different data sets, especially over land. Depending on the sounder and algorithm, other optical (Ångström exponent, single scattering albedo, and even refractive index) and physical (size and shape) parameters can be measured (Tanré et al., 2011).

The most widely used satellite aerosol products are derived from instruments with visible and near-infrared spectral bands, such as Moderate Resolution Imaging Spectroradiometer (MODIS), Advanced Along-Track Scanning Radiometer (AATSR), and POLarization and Directionality of the Earth's Reflectances (POLDER). These are obviously well suited to measure AOD at visible wavelengths. Thermal infrared instruments can also be used to detect and measure dust, but their added value is arguably being underestimated until the

CLARISSE ET AL. 1618

Part 1:

The IASI dust OD retrieval

1. A dust index

$$R_N(\boldsymbol{y}) = \frac{\boldsymbol{k}^{\mathrm{T}}\mathbf{S}^{-1}(\boldsymbol{y} - \boldsymbol{\mu}_c)}{\sqrt{\boldsymbol{k}^{\mathrm{T}}\mathbf{S}^{-1}\boldsymbol{k}}}$$

***k*: Dust Jacobian**

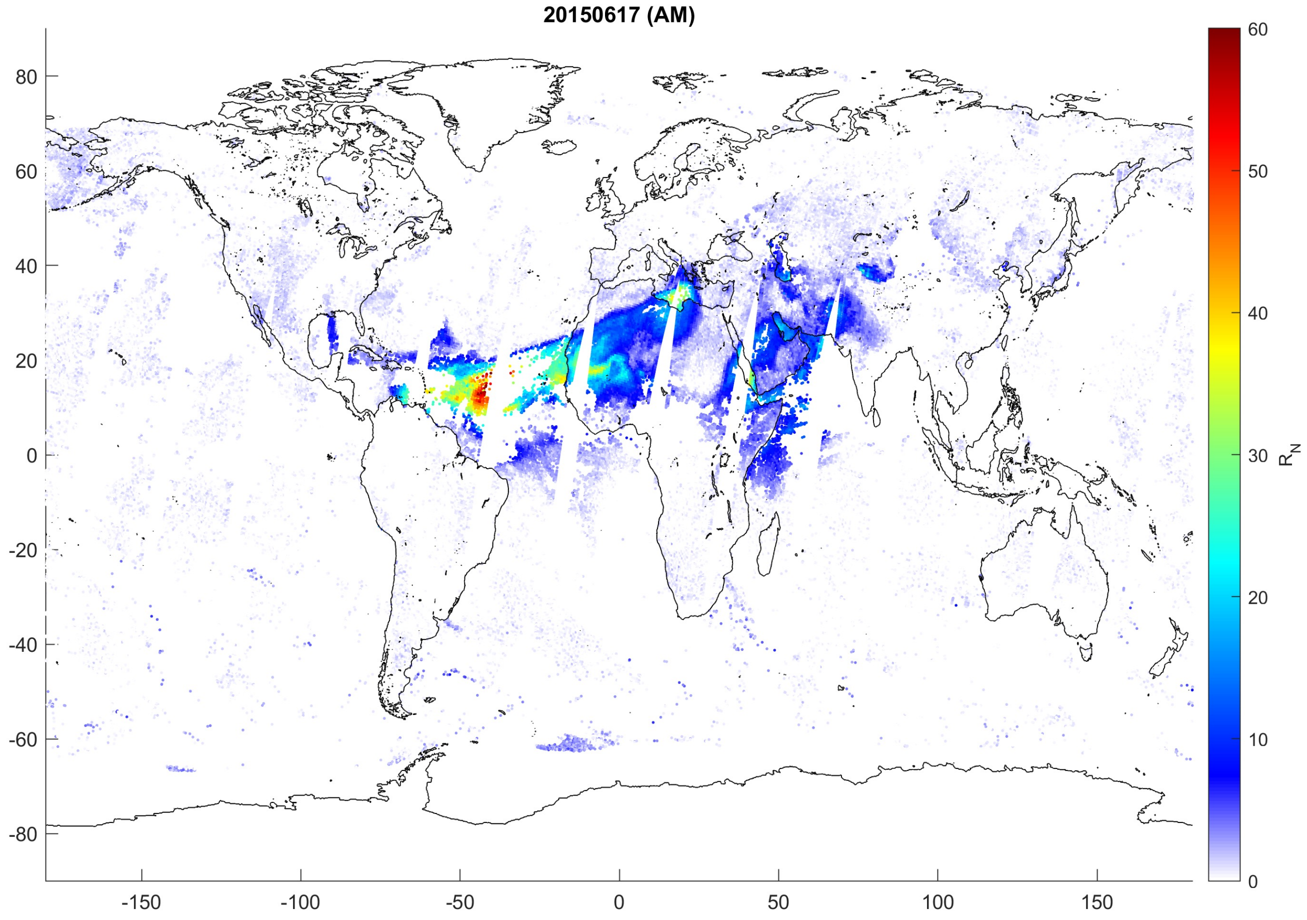
***S*: Covariance matrix of unpolluted spectra**

***μ_c*: mean unpolluted spectrum**

→ Strength of the dust signature in the IASI spectrum

Construction of k, S and μ_c directly from IASI spectra

→ Advantage: no forward model needed !

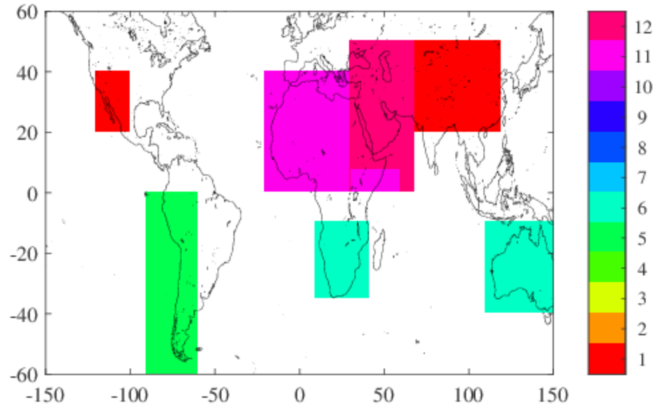


- R_N normalized → Dust-free spectra:
  - Mean 0
  - Standard deviation 1
- Value >>3: Positive detection!

Bias correction on R_N

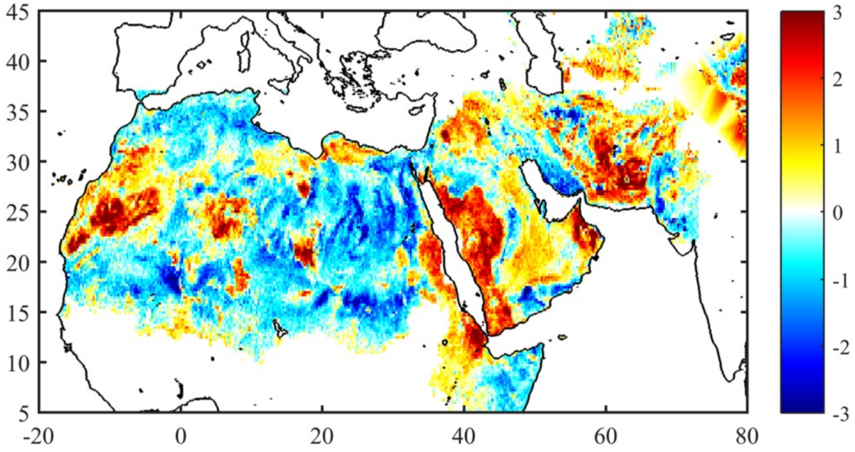
A. Surface emissivity effects

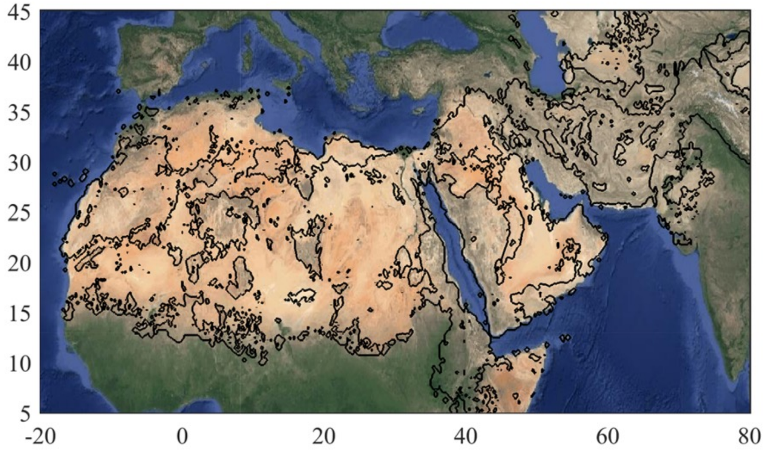
- Not completely accounted for in S
- Correction from gridded mean R-bias:



Color = month of lowest DAOD

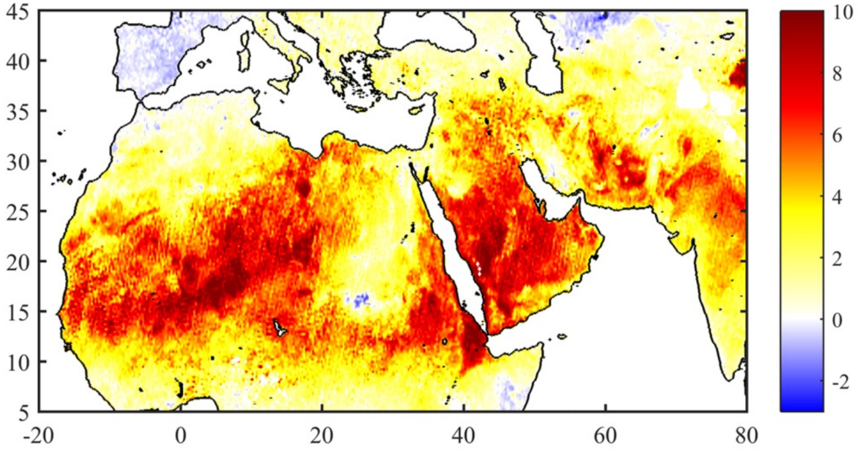
Average R-bias

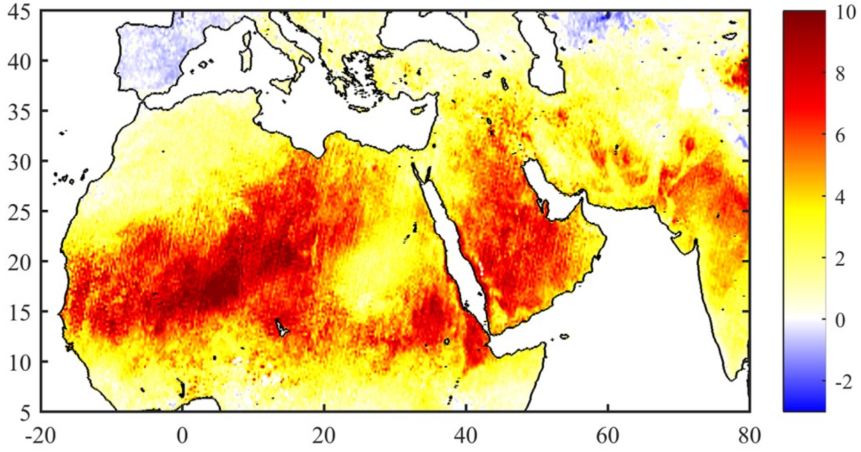




Sign change in bias

Uncorrected R (May 2013)

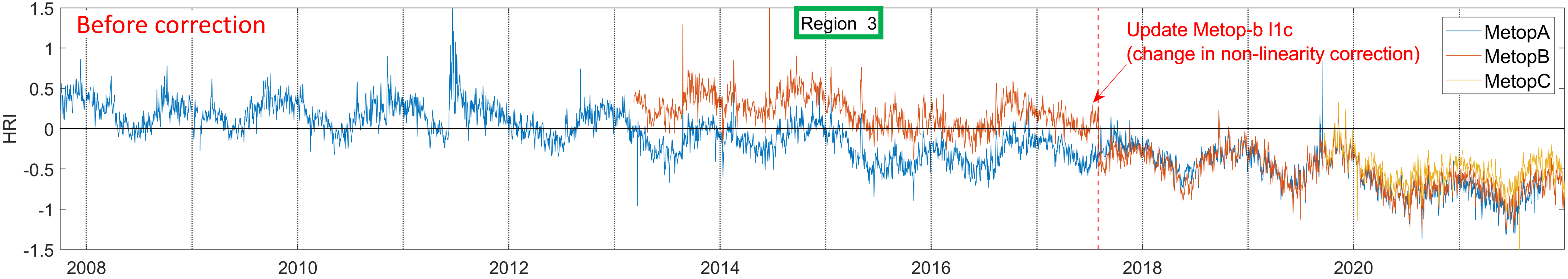




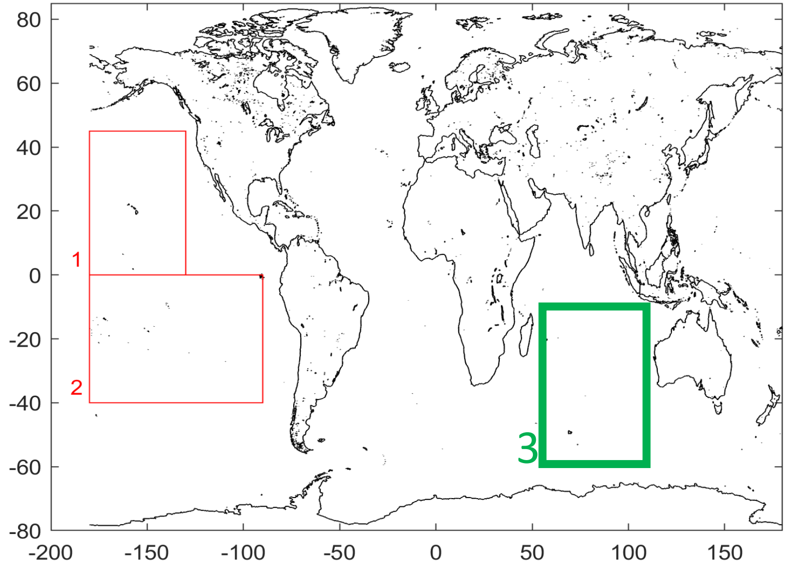
Corrected R (May 2013)

Bias correction on R_N

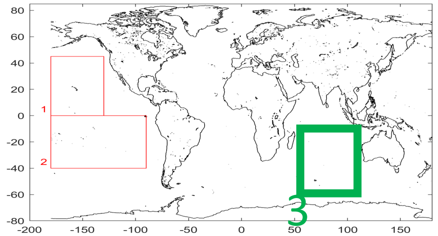
B. Offsets and trends: from v8 to v9

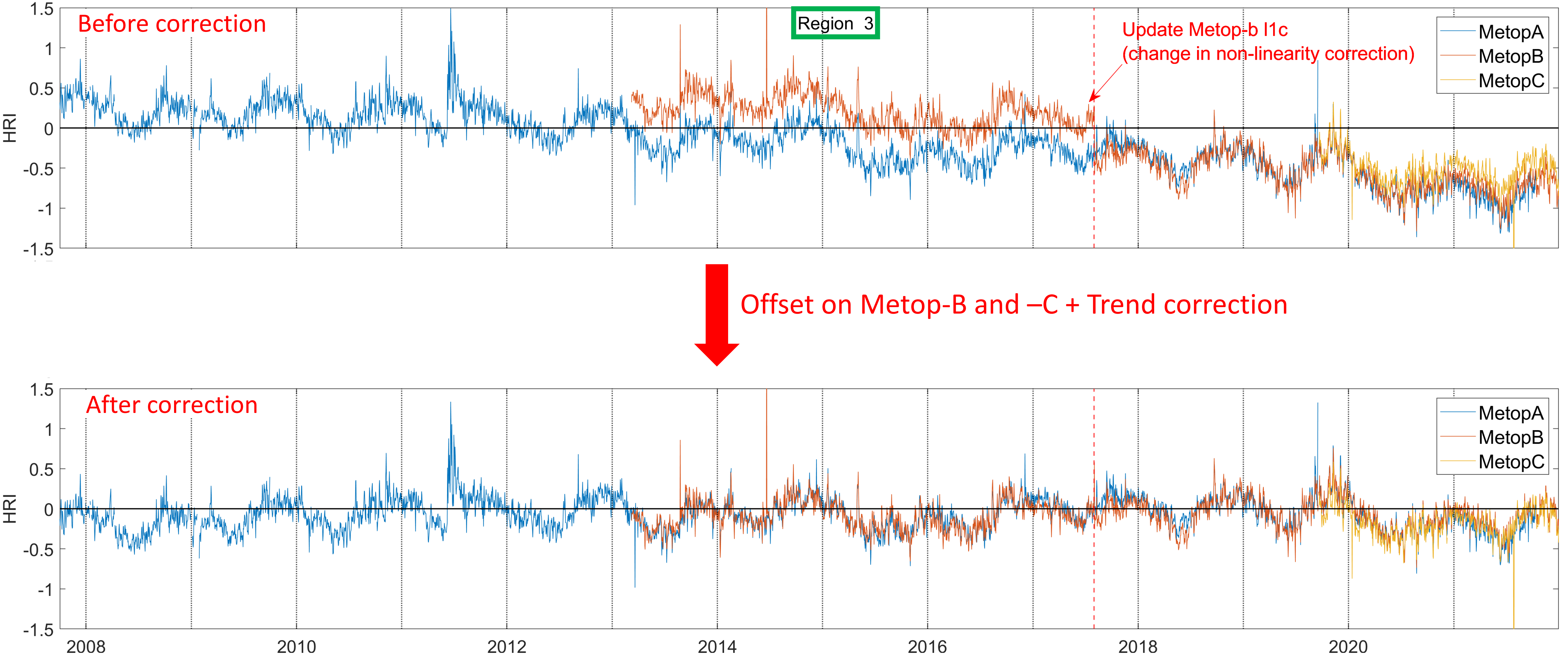


- Shift between Metop-B/-C and Metop-A (before August 2017)
- Negative trend → CO_2 concentration changes



Offsets and trends correction: from v8 to v9





Bias correction on R_N

C. v9: a new cloud mask ! Cloud-free product !

- **<u>Until v8</u>: cloud mask = IASI L2 cloud product**
- **<u>v9</u>: new IASI NN-based cloud mask:**

- Pattern recognition network (two layers)
- <u>Reference dataset</u>: latest version of the L2.
- <u>Inputs</u>: IASI radiance information only.

→ **45 IASI channels** + orography

→ Exclusion: CO_2, CH_4, N_2O, CFC-11 and CFC-12 absorption lines + ν_2 H_2O

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Atmospheric Measurement Techniques
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A CO_2-independent cloud mask from Infrared Atmospheric Sounding Interferometer (IASI) radiances for climate applications

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Abstract. With more than 15 years of continuous and consistent measurements, the Infrared Atmospheric Sounding Interferometer (IASI) radiance dataset is becoming a reference climate data record. To be exploited to its full potential, it requires a cloud filter that is accurate, unbiased over the full IASI life span and strict enough to be used in satellite data retrieval schemes. Here, we present a new cloud detection algorithm which combines (1) a high sensitivity, (2) a good consistency over the whole IASI time series and between the different copies of the instrument flying on board the suite of Metop satellites, and (3) simplicity in its parametrization. The method is based on a supervised neural network (NN) and relies, as input parameters, on the IASI radiance measurements only. The robustness of the cloud mask over time is ensured in particular by avoiding the IASI channels that are influenced by CO_2, N_2O, CH_4, CFC-11 and CFC-12 absorption lines and those corresponding to the ν_2 H_2O absorption band. As a reference dataset for the training, version 6.5 of the operational IASI Level 2 (L2) cloud product is used. We provide different illustrations of the NN cloud product, including comparisons with other existing products. We find very good agreement overall with version 6.5 of the operational IASI L2 with an identical mean annual cloud amount and a pixel-by-pixel correspondence of about 87 %. The comparison with the other cloud products shows a good correspondence in the main cloud regimes but with sometimes large differences in the mean cloud amount (up to 10 %) due to the specificities of each of the different products. We also show the good capability of the NN product to differentiate clouds from dust plumes.

1 Introduction

Clouds cover between 70 % and 80 % of the Earth's surface, at any moment (Lavanant et al., 2011; Stubenrauch et al., 2017). Because of their importance for the weather, the water cycle and the Earth radiation budget, the development of long, accurate and coherent time series of cloud properties (e.g. cloud amount, cloud top height, optical thickness, cloud type) is essential for improving our understanding of the climate and its past and future evolution. We can rely for this on satellite observations, which allow the daily cloud coverage to be studied at global scales. Their use to detect clouds and to derive climatologies began in the 1980s. One of the first global cloud climate data records is the International Satellite Cloud Climatology (ISCCP), which started in 1982 (Schiffer and Rossow, 1983; Rossow and Schiffer, 1999). With more than 40 years of record, it has become today a reference for climate analysis. Since then, the measurements from a variety of sounders on board polar and geostationary platforms have been used to detect and characterize clouds (e.g. Kaspar et al., 2009; Karlsson et al., 2013, 2017; Stengel et al., 2017; Feofilov and Stubenrauch, 2017). Despite this, they remain today one of the largest sources of uncertainties in future climate projections (Schneider et al., 2017; Zelinka et al., 2017; Satoh et al., 2018). Besides their impor-

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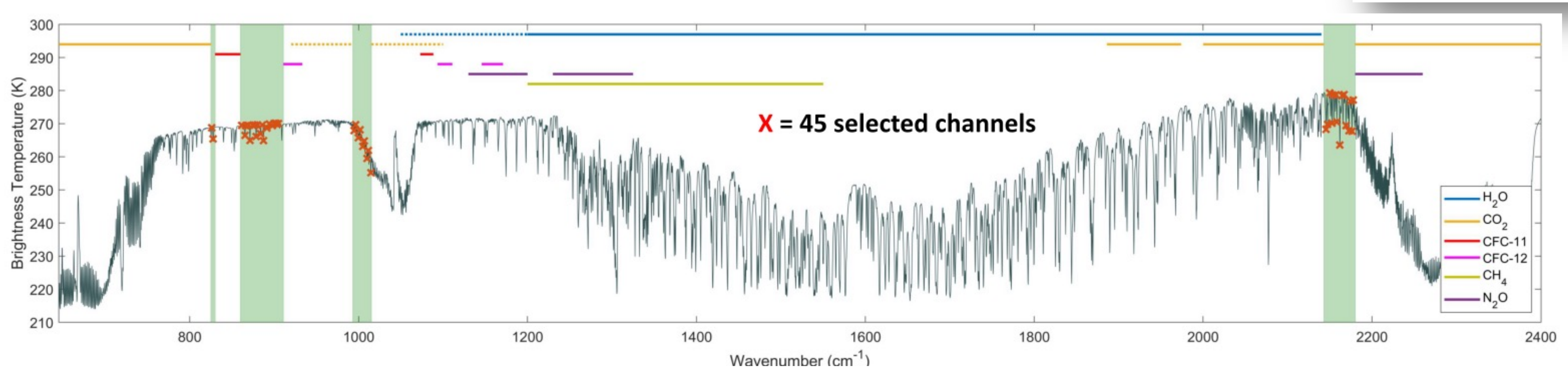
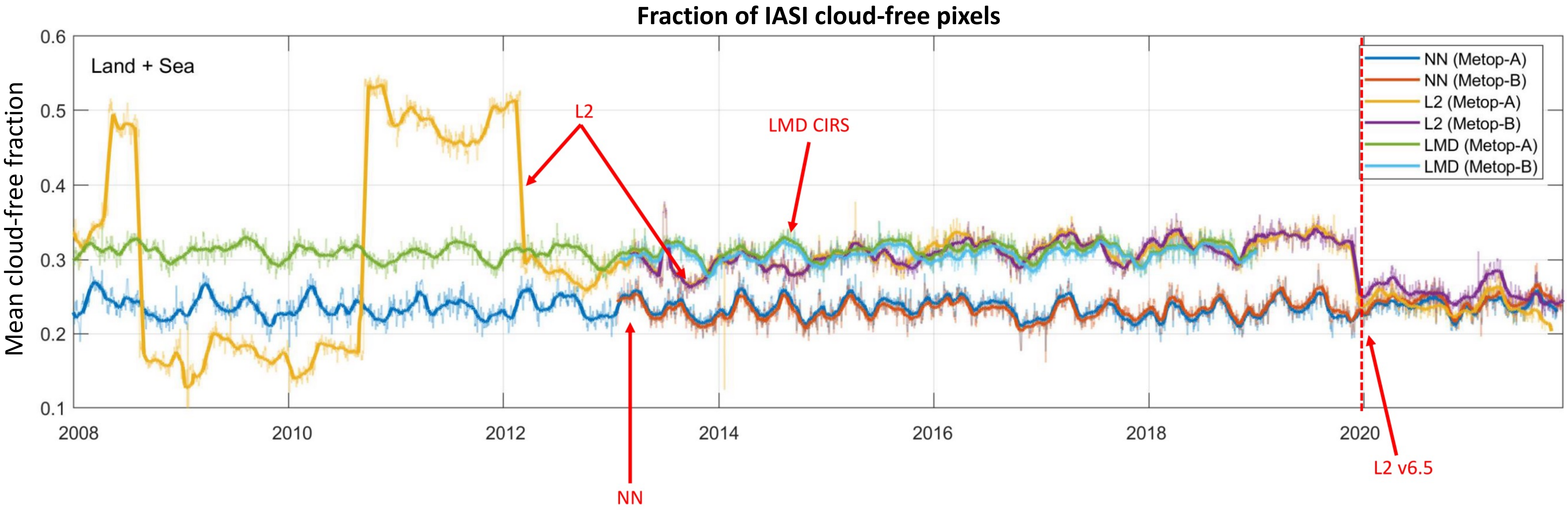


Bias correction on R_N

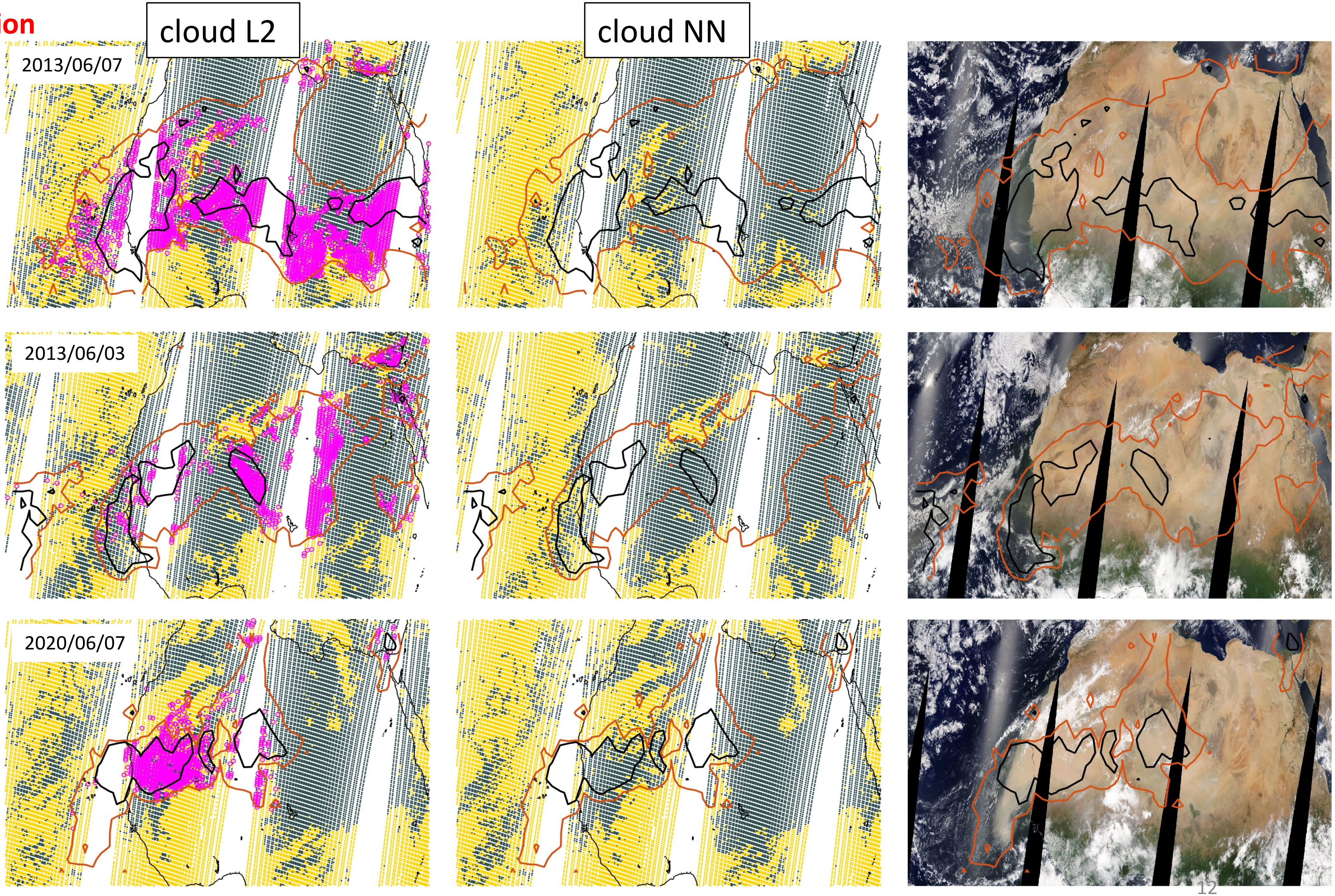
C. v9: a new cloud mask

- Accurate and strict enough to be used in retrieval frameworks,
- Consistent over time and between the 3 IASI/Metop,
- Able to differenciate clouds from dust plumes

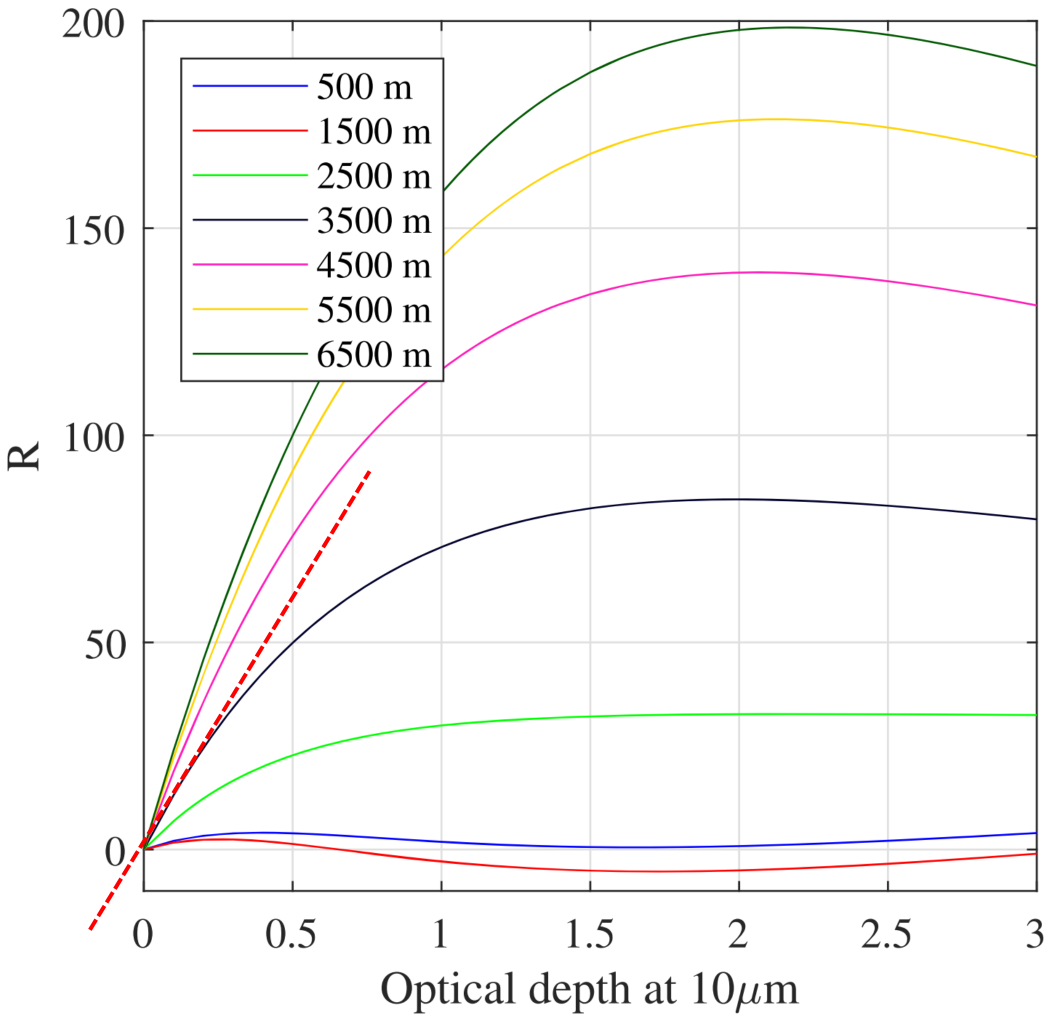


Cloud/dust differenciation

- Cloud scenes
- Cloud-free scenes
- Cloud in L2 only
- $R_N > 10$
- $R_N > 20$



How does the R_N index vary with optical depth?



Sensitivity to:

- the dust amount
- the dust layer altitude
- the atmospheric state

For a given atmosphere:

- R_N increases monotonically with increasing OD
- ODs>2-3: Saturation level
- Small ODs: linear relationship between OD and R_N
  - ➢ Slope determined by the thermal contrast (Tskin – Tdust)

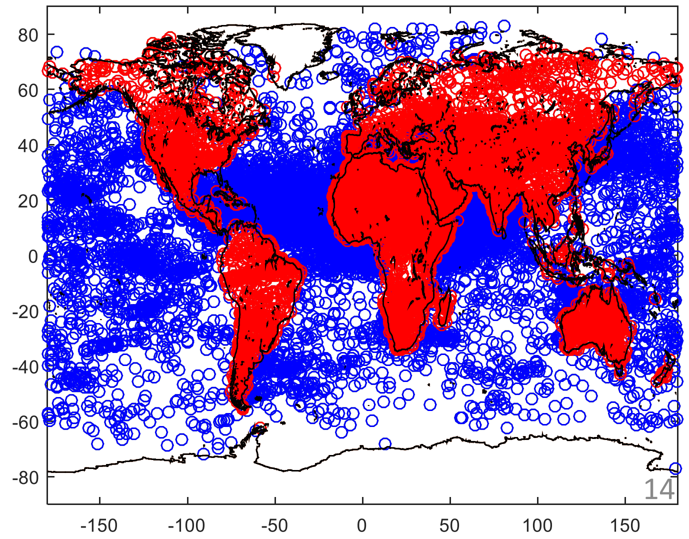
2. Conversion of the R_N to dust AOD

… using a neural network

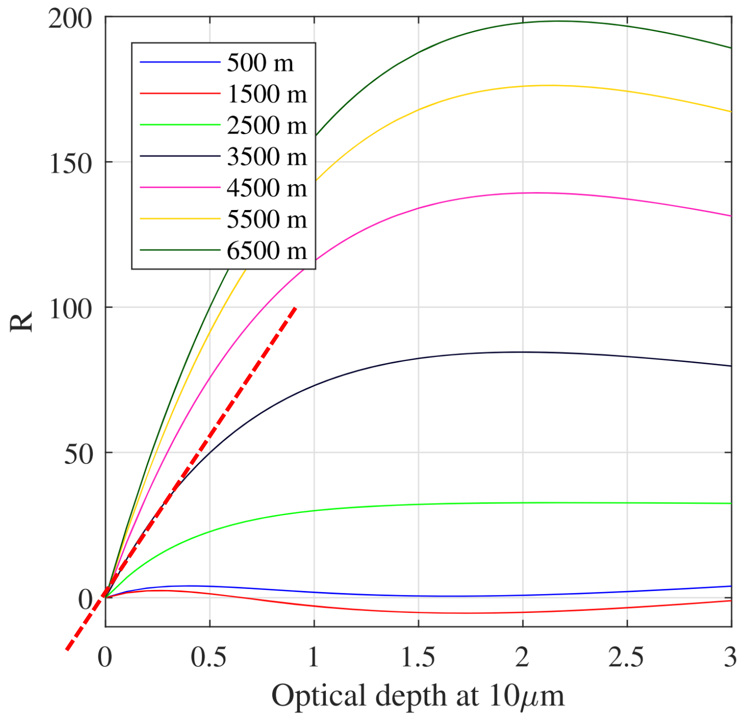
INPUT DATA	**Auxiliary data**	Dust height
		Viewing angle
		Temperature of the dust layer
		Surface pressure
		Humidity profile
		Surface Emissivity
	Radiance data	Dust index + couple of channels (“baseline temperature”)
OUTPUT DATA	**Optical depth**	**At 10 µm**

A. Training the NN:

- Building of the training set
  - Atmospheric state of random IASI observations (>200,000 in total)
  - random DOD (0-3) and altitude layer (0-7 km)
- Simulation of IASI spectra
- Calculation of corresponding R_N



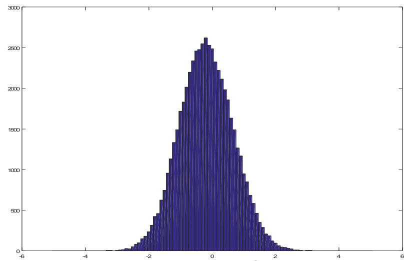
Subtlety: training of ratio CR=OD/R.

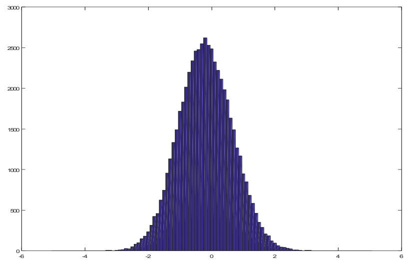


➔ OD = CR x R

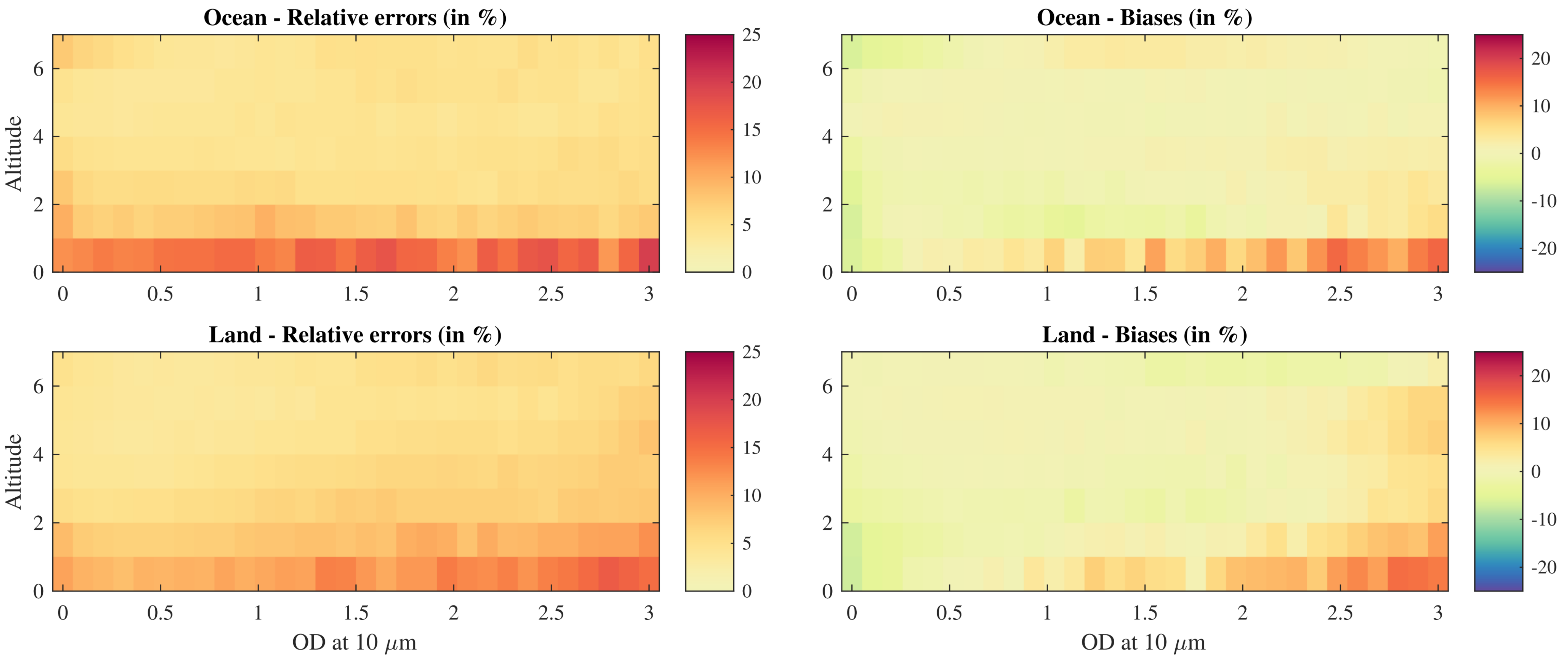
Advantages:

- Much smaller dynamic range! → better training
- Noiseless neural network (unbiased data set):
  low sensitivity: OD ≈ R_{noise} x CR (normal distribution)
- Noise is preserved outside of the network


Dust index


OD retrieval

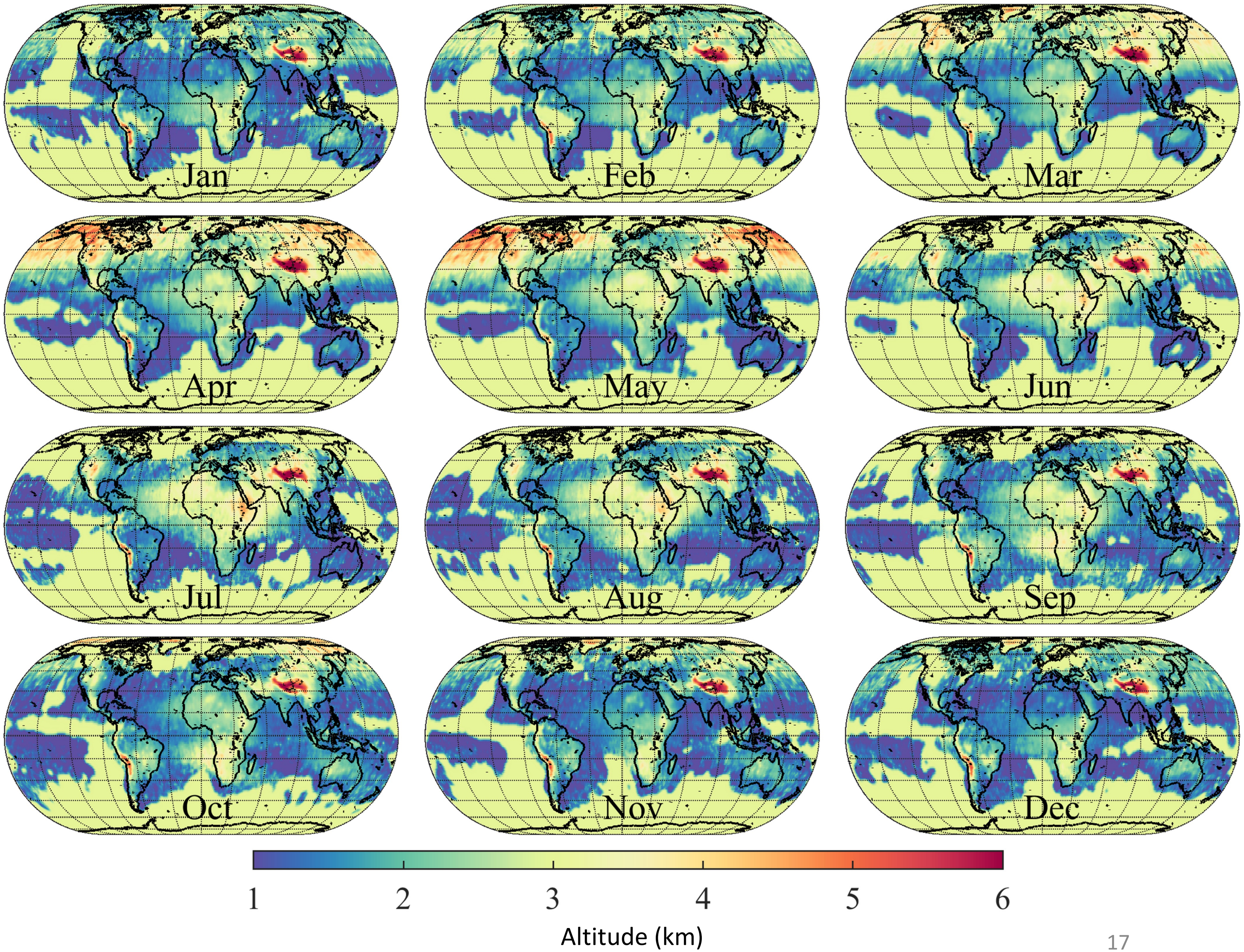
Training performances



<u>Relative error:</u> ~10%, except for low altitudes (up to 25%)
<u>Biases:</u> close to 0, except for low altitudes

B. Running the NN:

- **<u>Inputs</u>: IASI L1c or L2 data** (water vapor, P_{surf}, BT, Ta, sat. angle, ε_s)
- **<u>Exception</u>: Dust altitude →** climatology from CALIOP



Uncertainty estimates

$$\sigma_{OD} = \sqrt{\left(\frac{\partial OD}{\partial A}\sigma_{ALT}\right)^2 + \left(\frac{\partial OD}{\partial R}\sigma_{R}\right)^2 + \left(\frac{\partial OD}{\partial B}\sigma_{BL}\right)^2 + \left(\frac{\partial OD}{\partial T}\sigma_{T}\right)^2 + \left(\frac{\partial OD}{\partial H}\sigma_{HUM}\right)^2 + (\sigma_{NN})^2}$$

"Random errors"

Typical uncertainties when dust : 15-30%

1. Aerosol altitude.
2. **IASI instrumental noise on R.**
3. IASI instrumental noise on the input baseline channels.
4. Temperature profile.
5. Humidity profile.

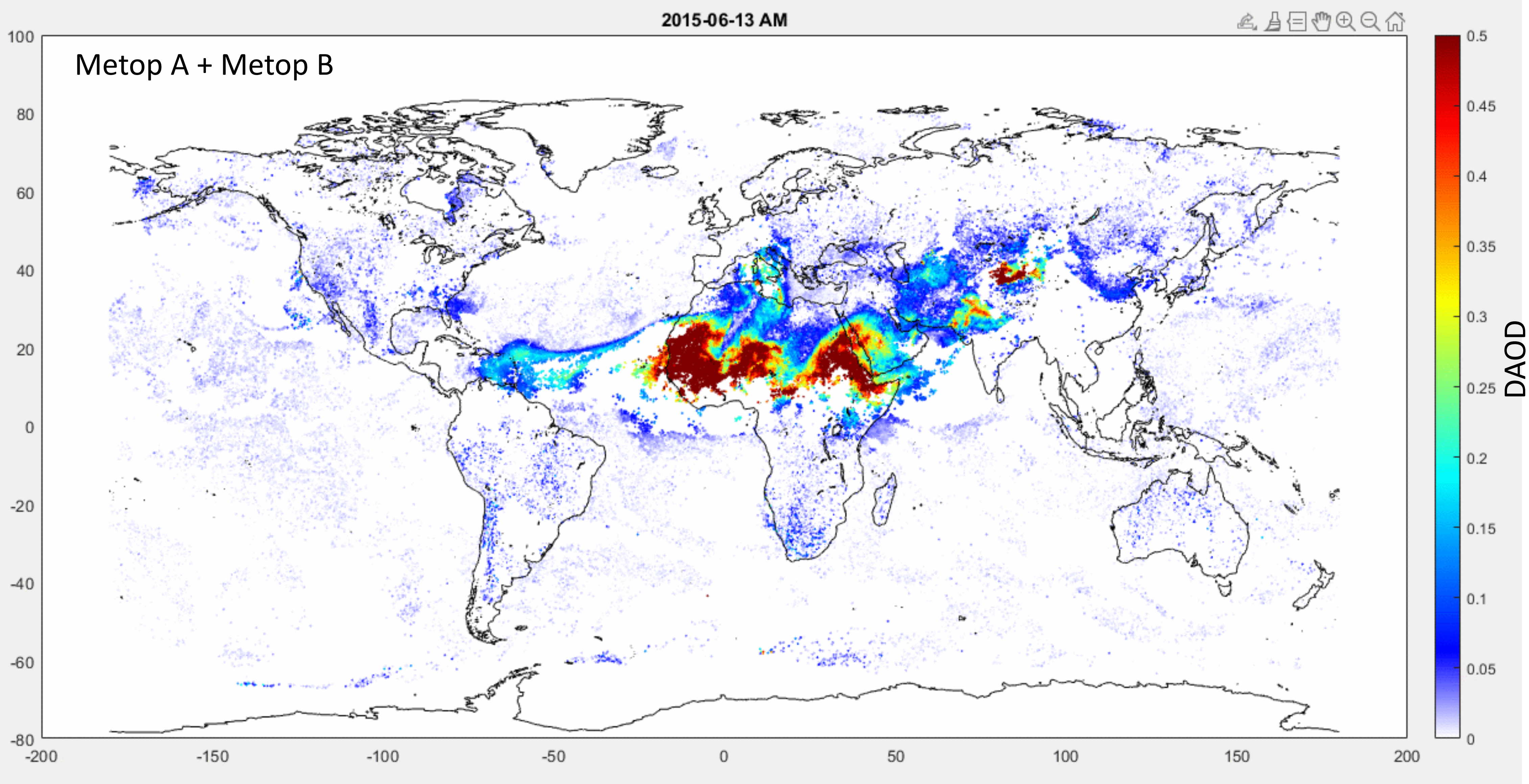
"Systematic errors"

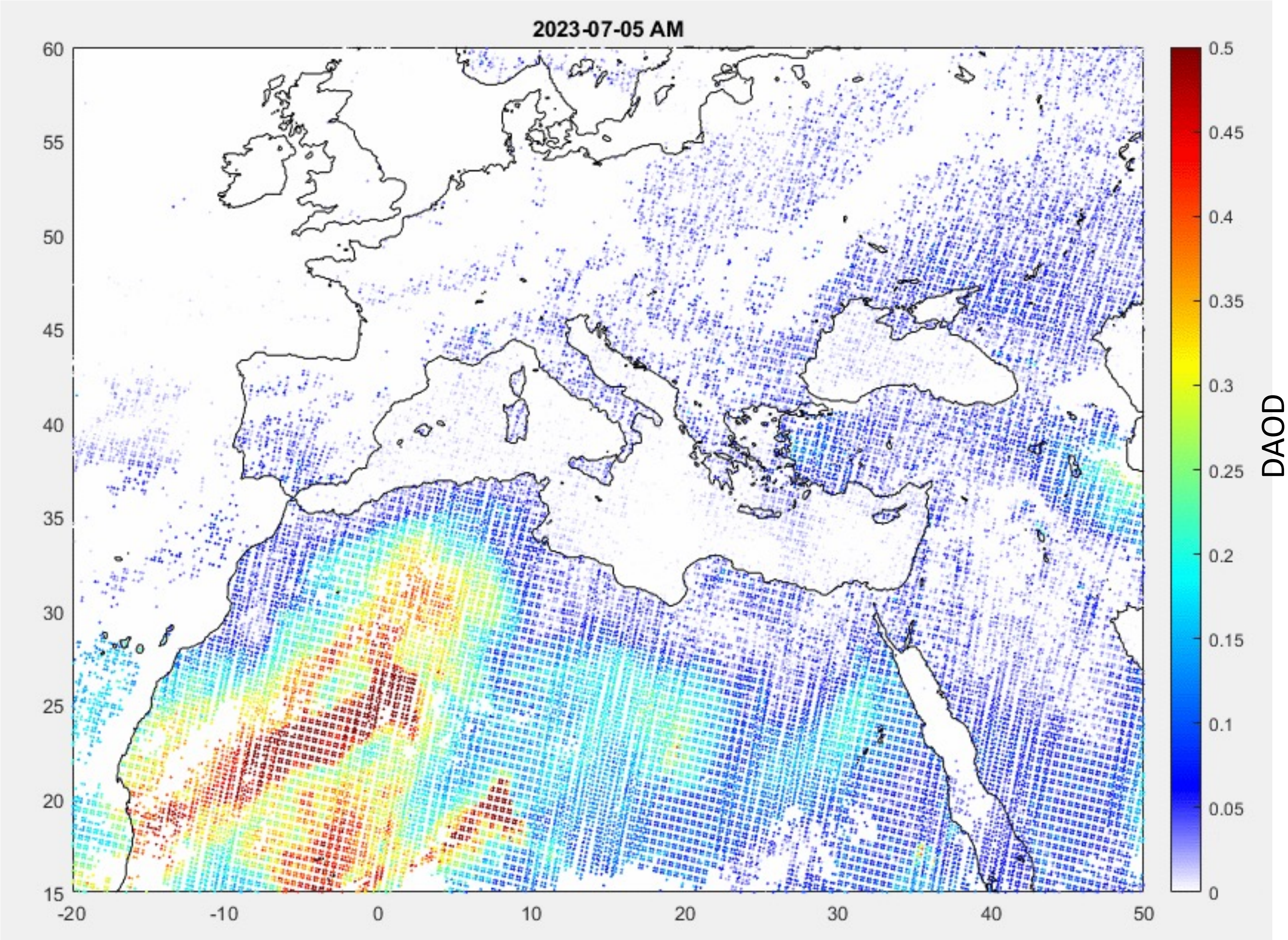
1. Neural network errors (10%)
   a. Training
   b. Auxiliary data (emissivities, refractive indices)

Part 2:

Illustrations and comparisons

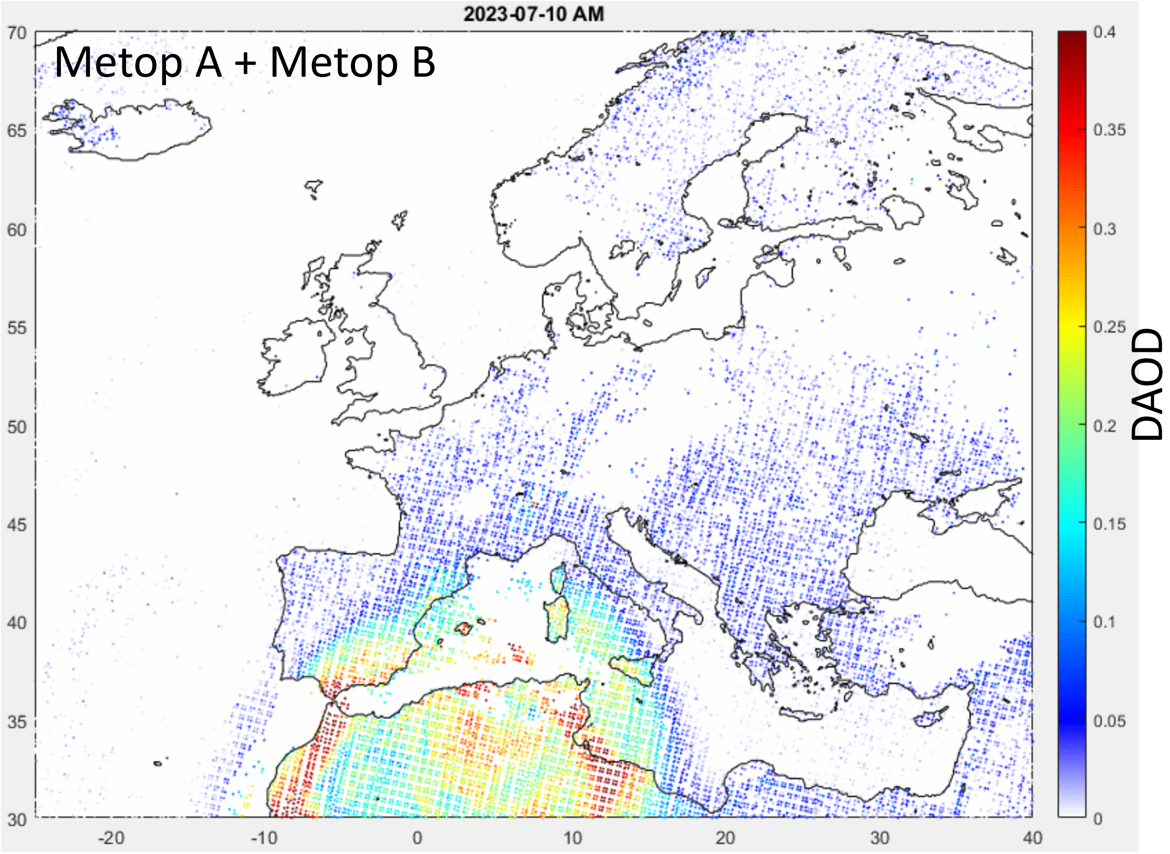
Transported dust over the Atlantic Ocean

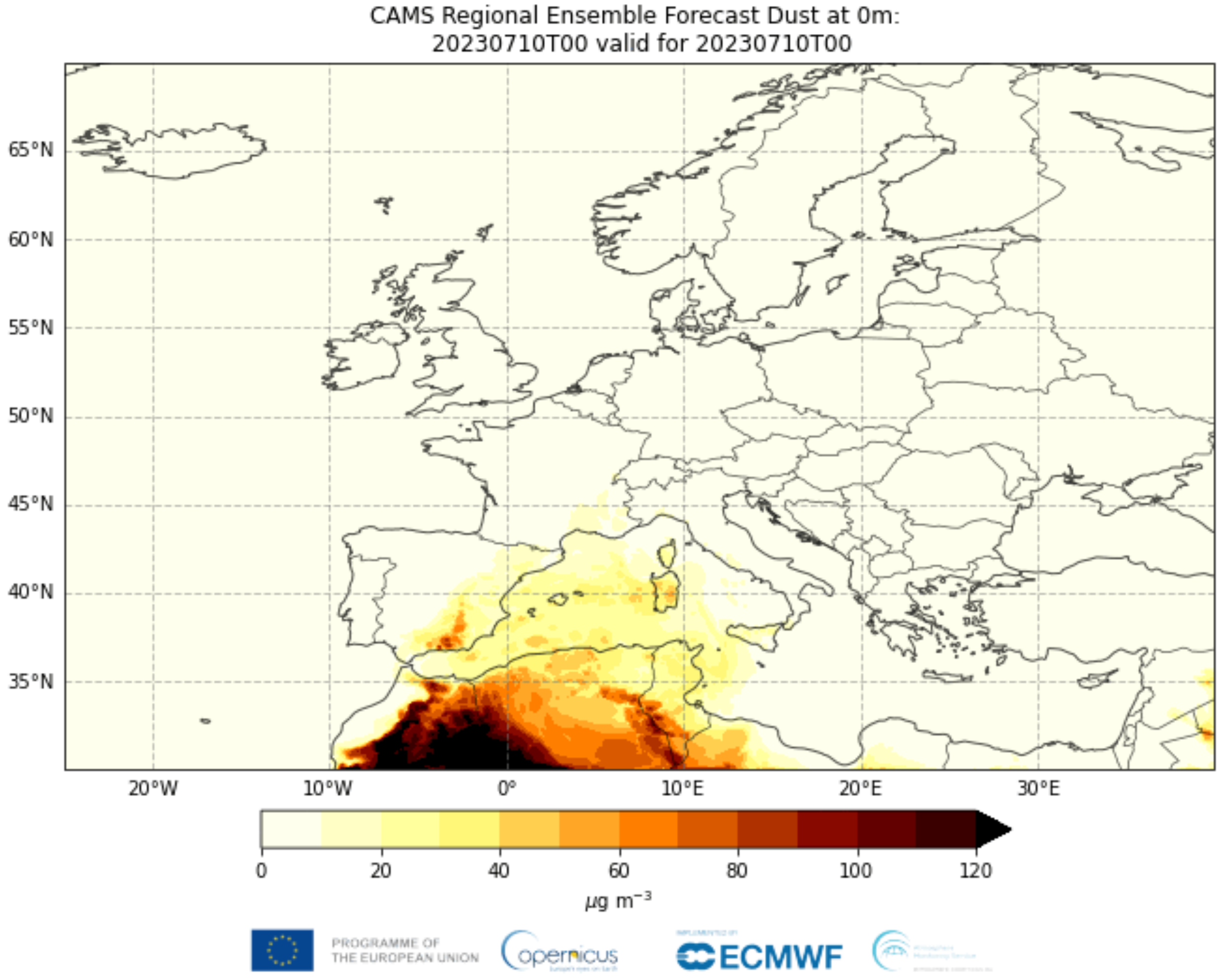




Metop A + Metop B

Transported dust over Europe and the Mediterranean Sea





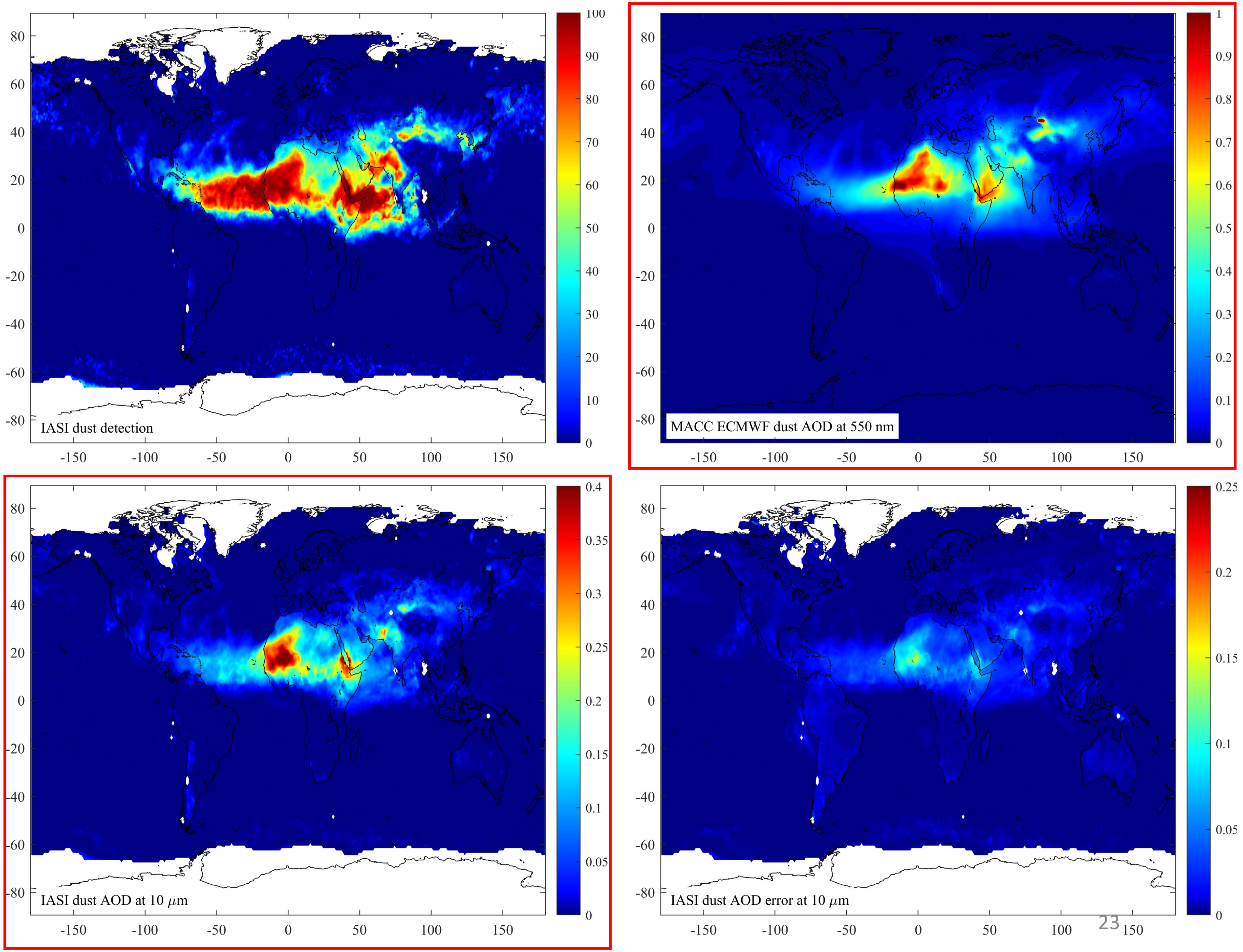
Transported dust over Europe and the Mediterranean Sea: **<u>Comparison with CAMS Forecast Dust at surface</u>**

1. MACC ECMWF comparison

June 2013

IASI OD 10µm vs ECMWF 550 nm:

<u>Qualitative</u> agreement
- Sources areas
- Transport patterns
- Remote areas

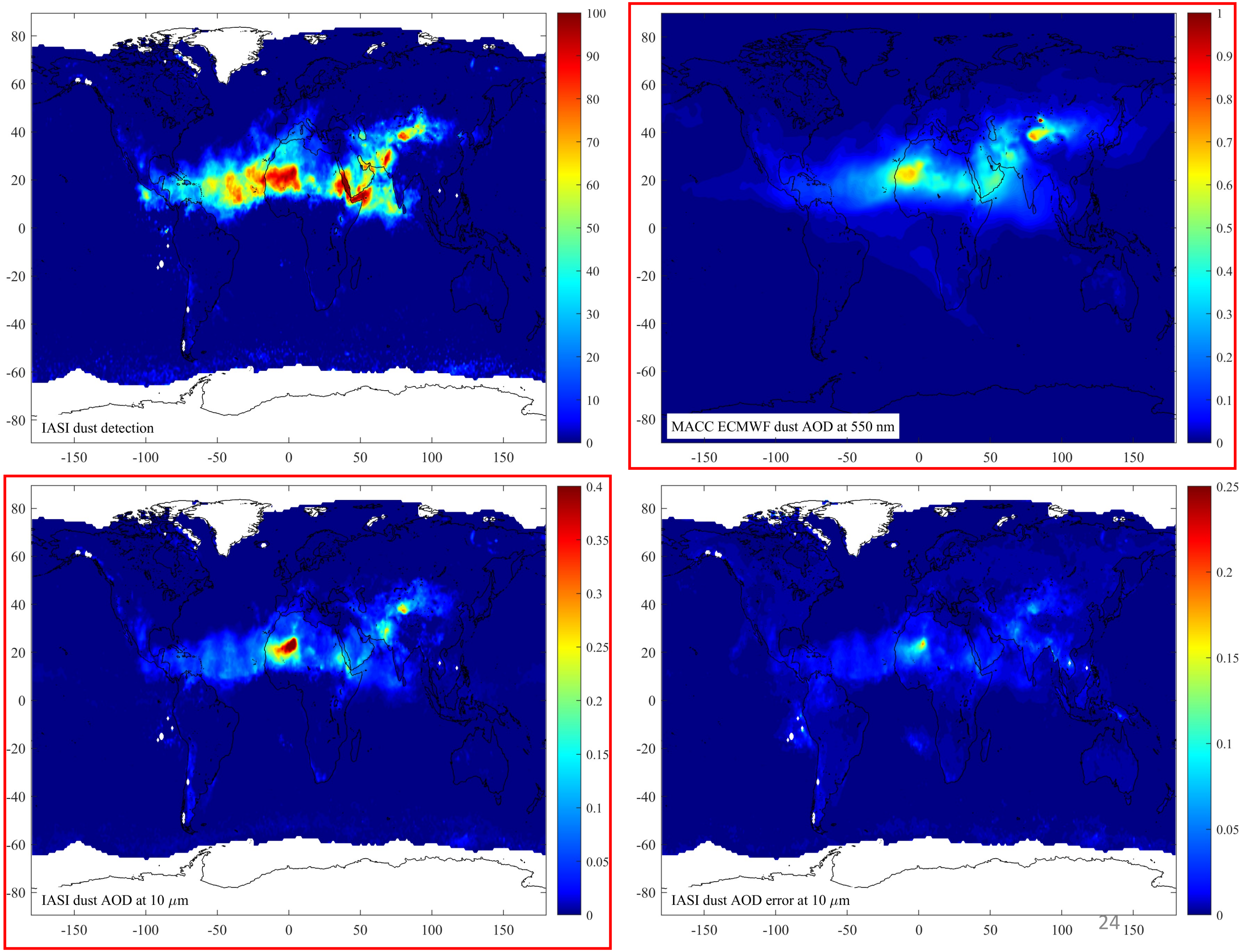


1. MACC ECMWF comparison

August 2013

IASI OD 10µm vs ECMWF 550 nm:

Qualitative agreement
- Sources areas
- Transport patterns
- Remote areas



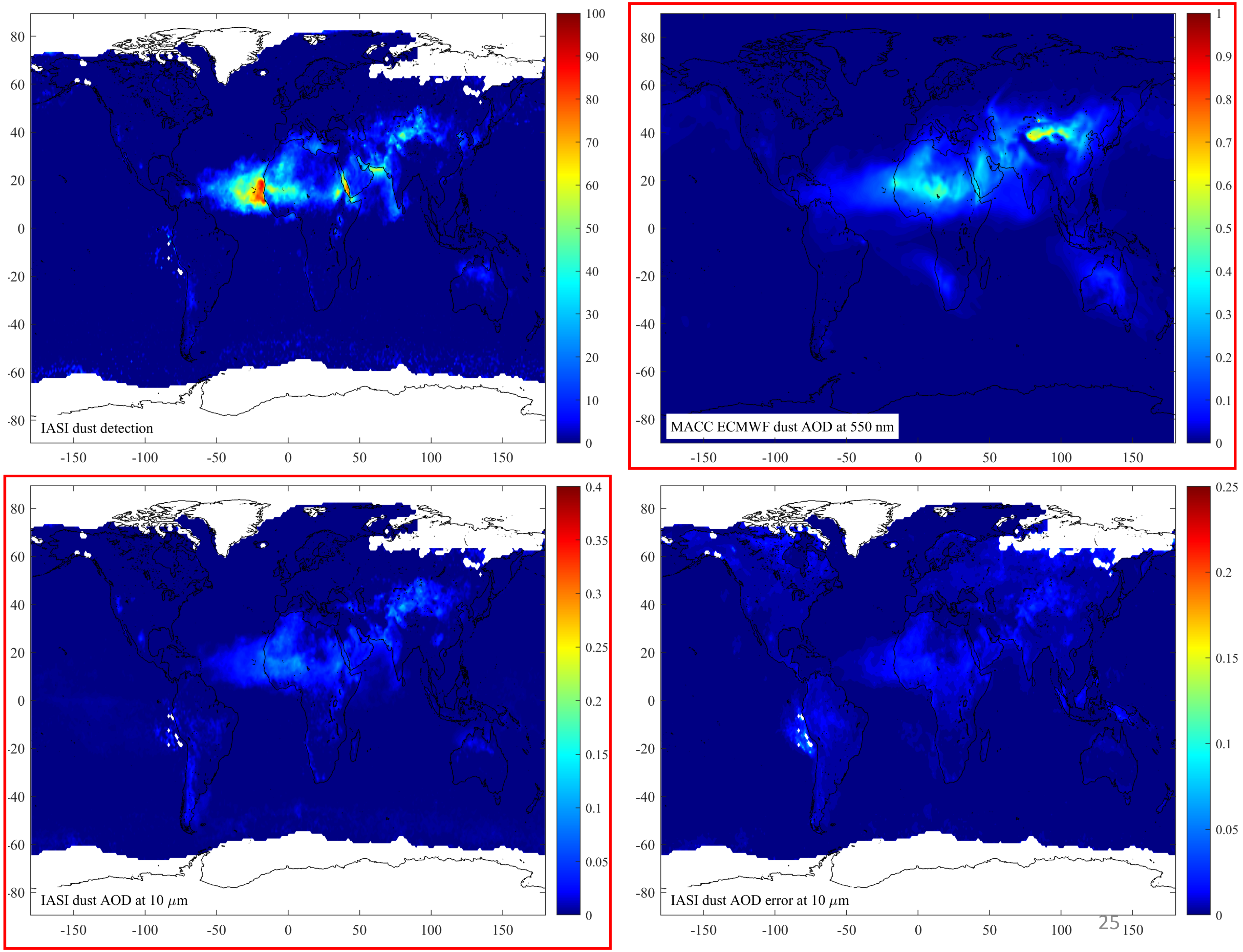
1. MACC ECMWF comparison

October 2013

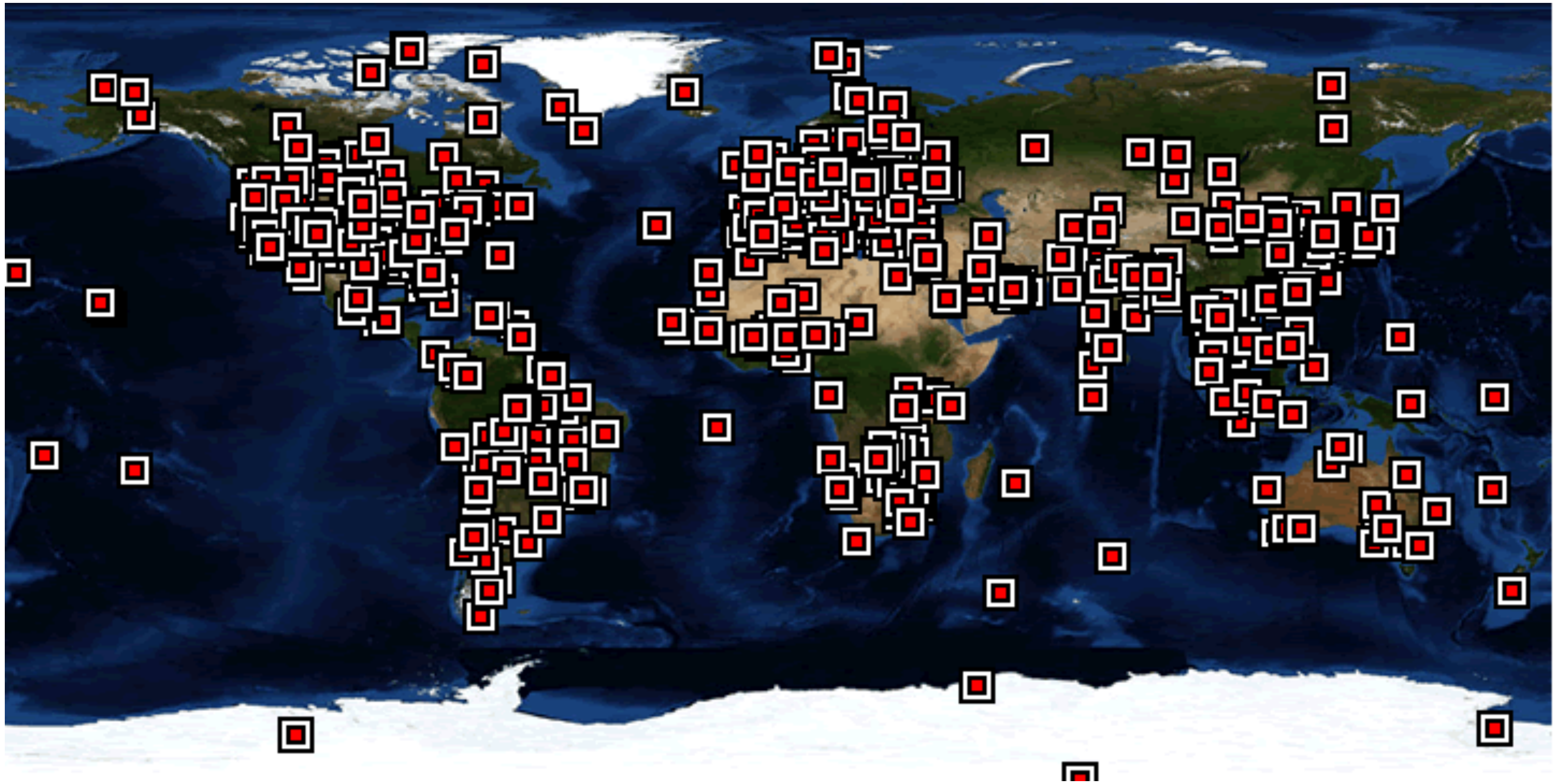
IASI OD 10µm vs ECMWF 550 nm:

<u>Qualitative</u> agreement

- Sources areas
- Transport patterns
- Remote areas

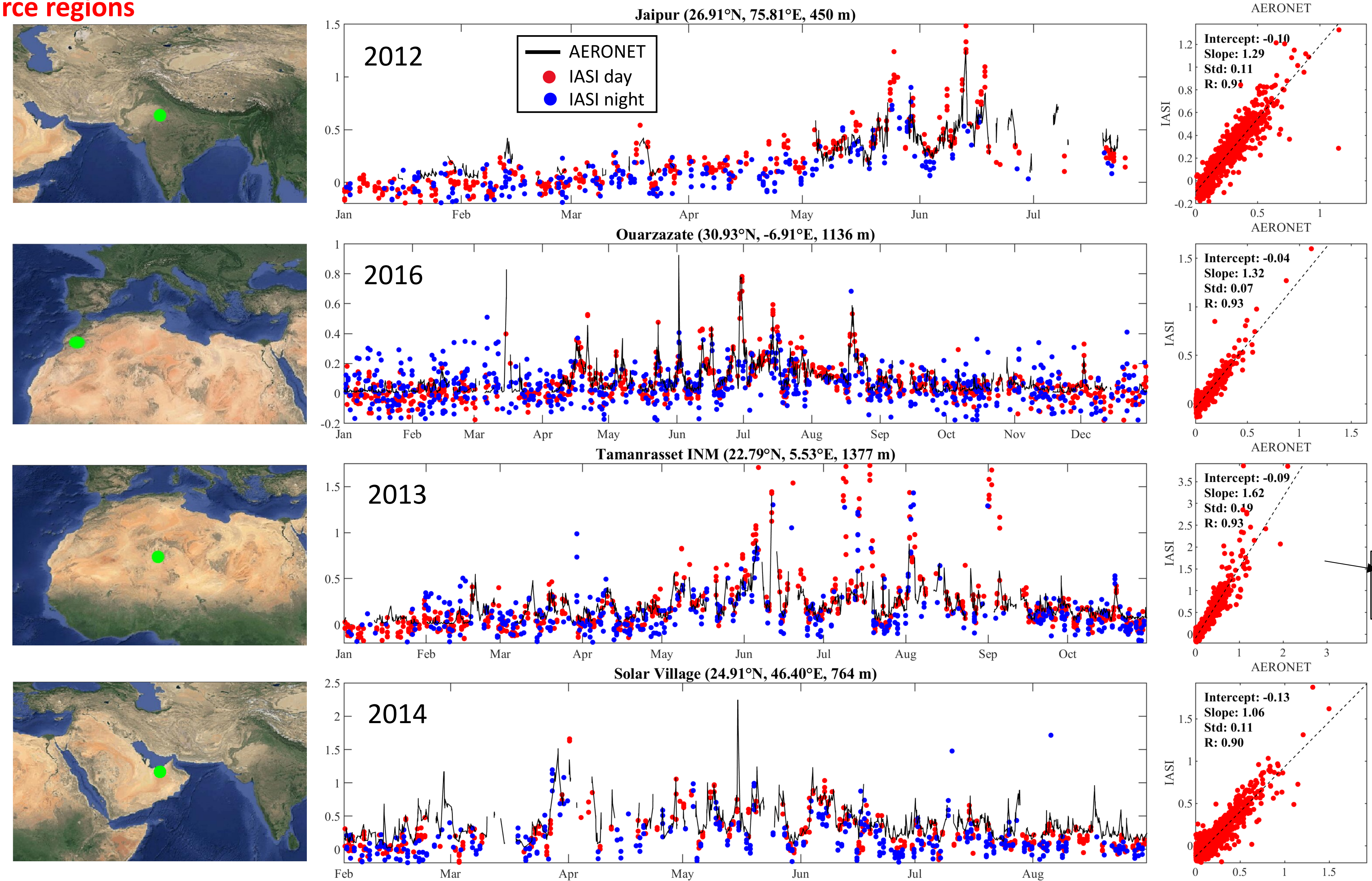


2. Aeronet comparison



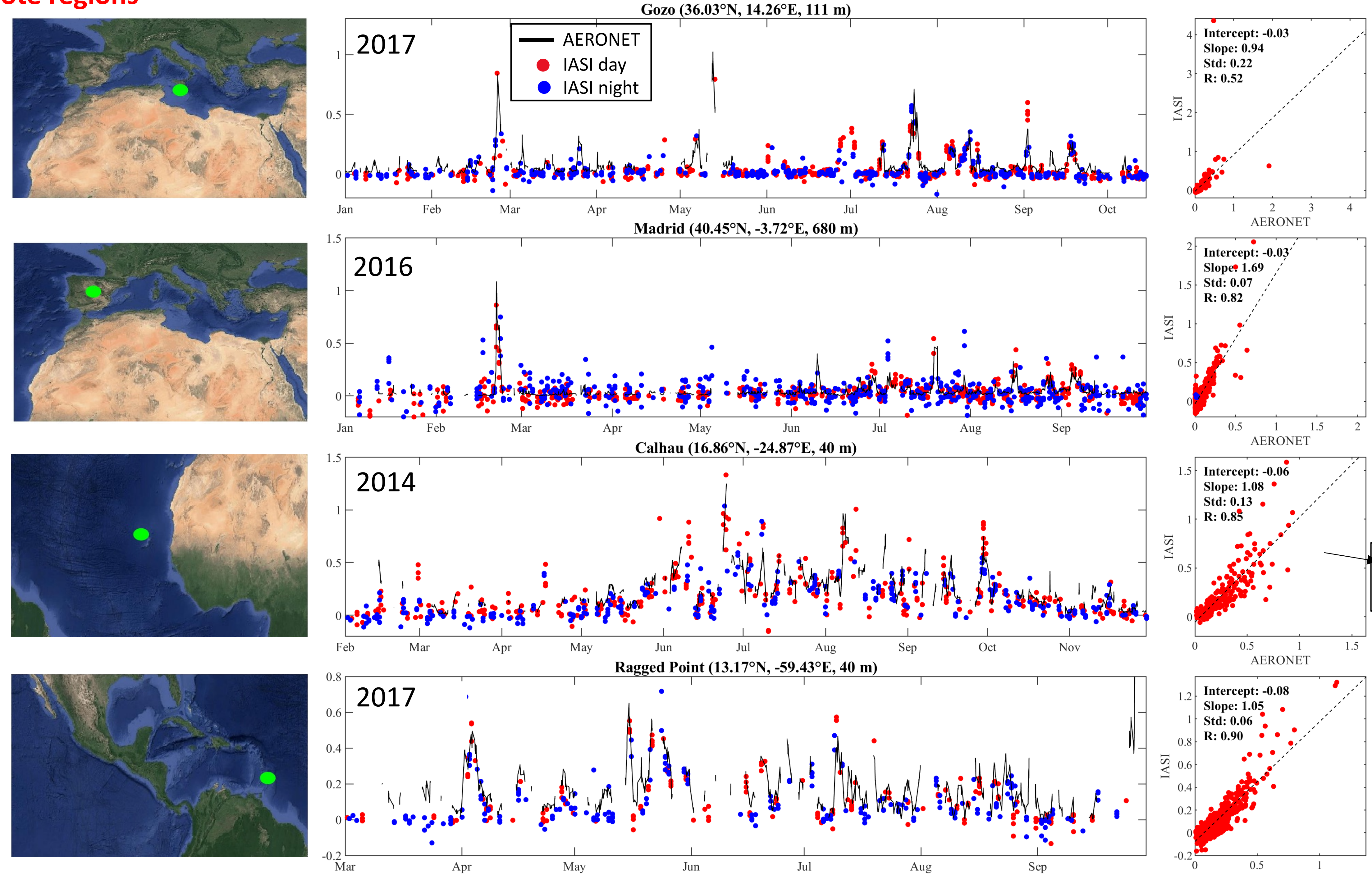
- For comparison with IASI/IASI-NG, the coarse mode products OD (e.g. SDA 2.0) are most representative
- Conversion from 10µm to 0.55 often problematic (i.e. assumptions on the PSD are needed). Here, constant factor of 2.
- Comparison: (1) AERONET averaged in +/- 30 min. of IASI overpass;
  (2) IASI averaged within +/- 30 km of AERONET site.

Source regions



All data pairs in 2008-2017

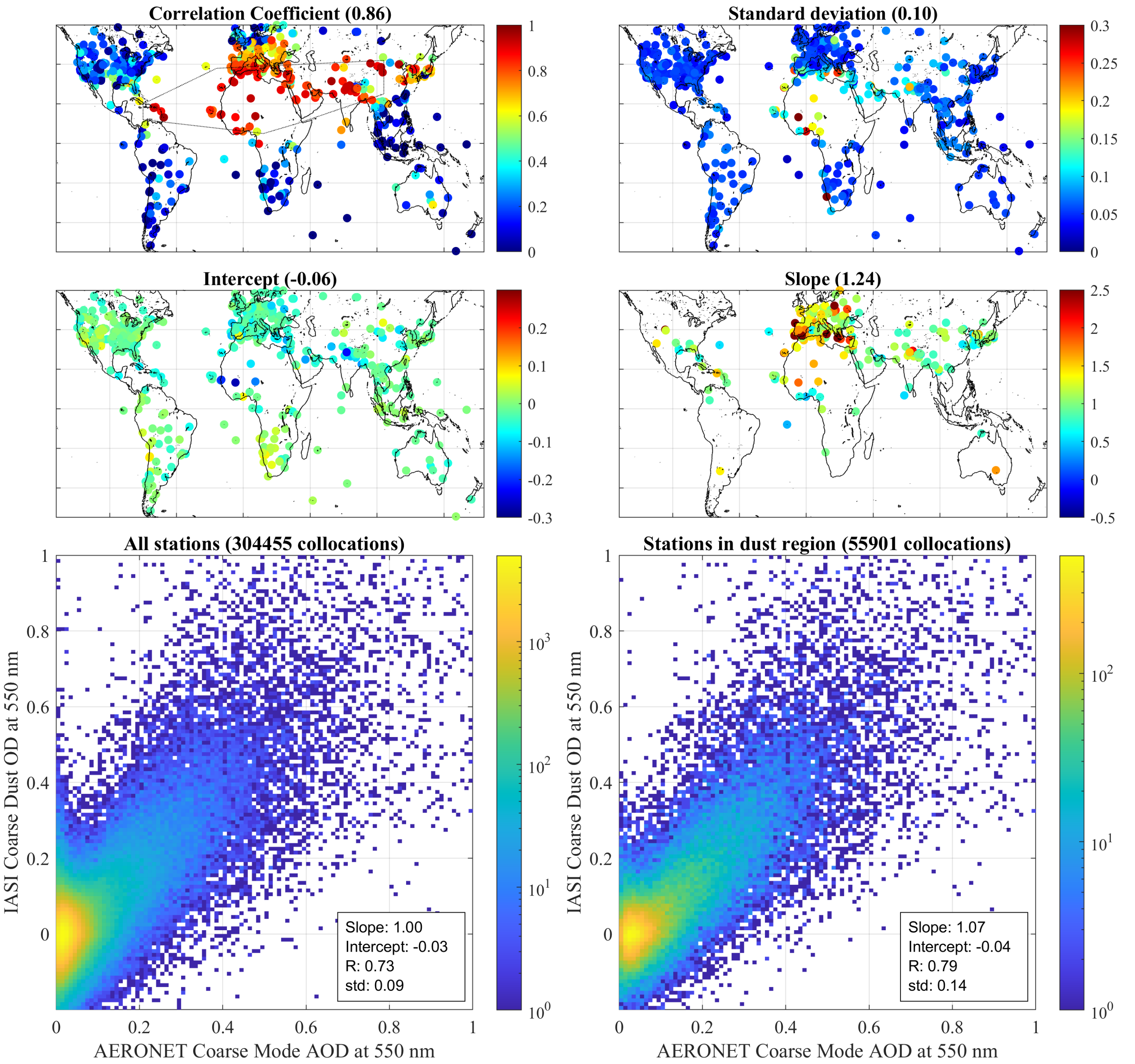
Remote regions

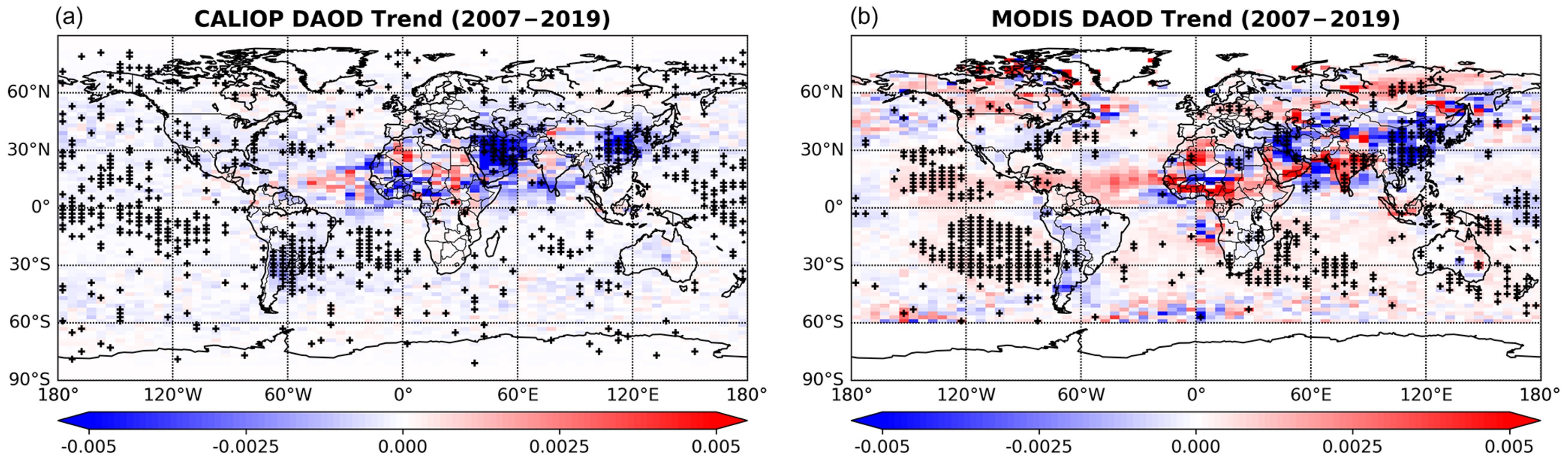


All data pairs in 2008-2017

All stations:

Summary AERONET vs IASI



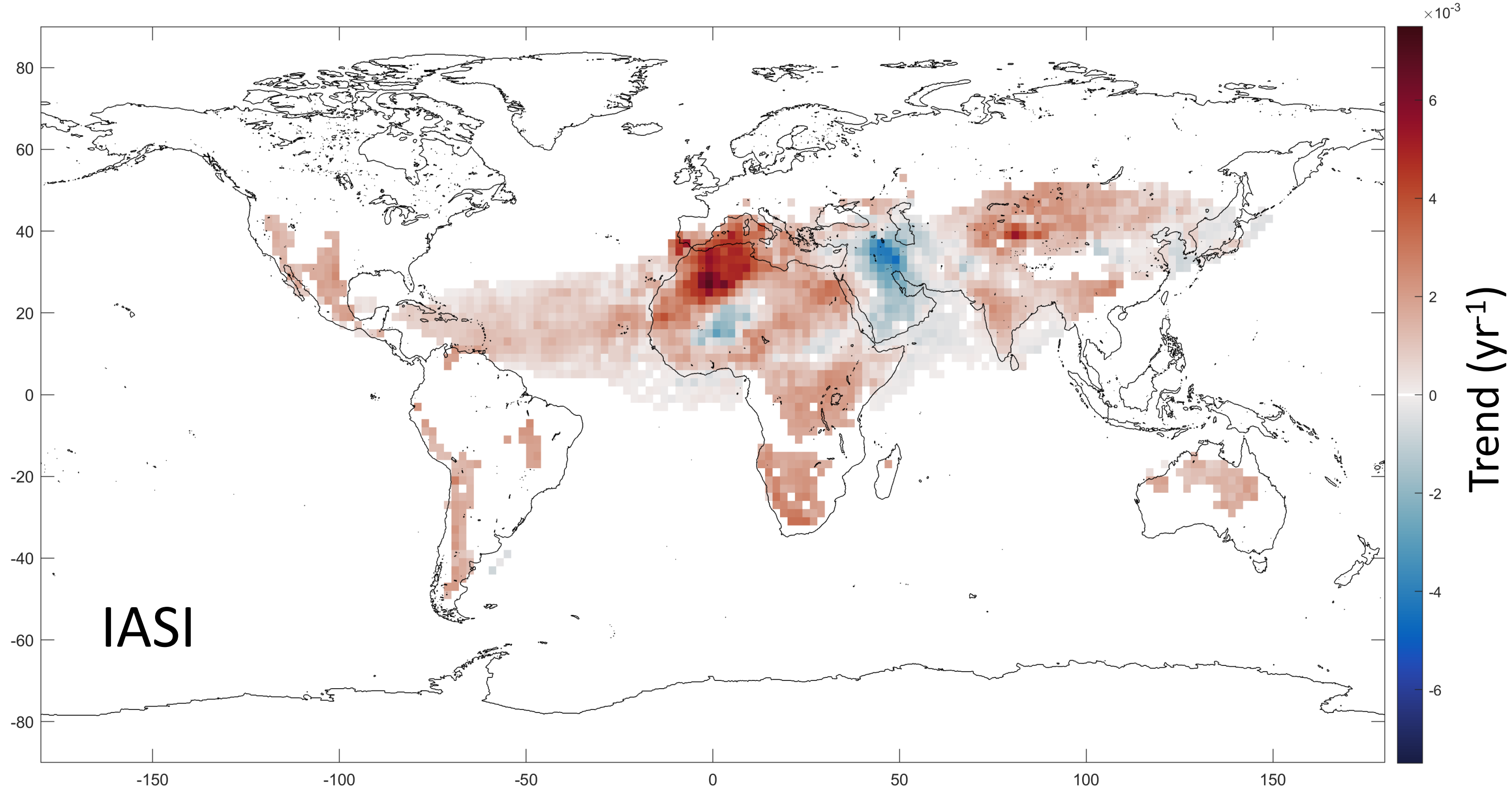


From Song et al. 2021 (acp)

DAOD trends

(2008-2022)

Preliminary results !



Summary

Theoretical advantages

- Fast
- Full spectral range (highly sensitive)
- Low dependency on the forward model (RI, emissivity, etc, ….)
- Full atmospheric state
- Full uncertainty analysis (propagation of input parameters)

Current limitations

- No retrieval of altitude
- Cloud free conditions

Evaluations

- Correlations with AERONET > ~0.8
- Comparison with model ‘satisfactory’ (qualitatively)
- Continuity: Land/Ocean – AM/PM

Data availability (L2 and gridded L3 data)

ICARE Data and Service Center: https://www.icare.univ-lille.fr/