PROGRAMME OF THE EUROPEAN UNION

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Atmosphere Monitoring Service
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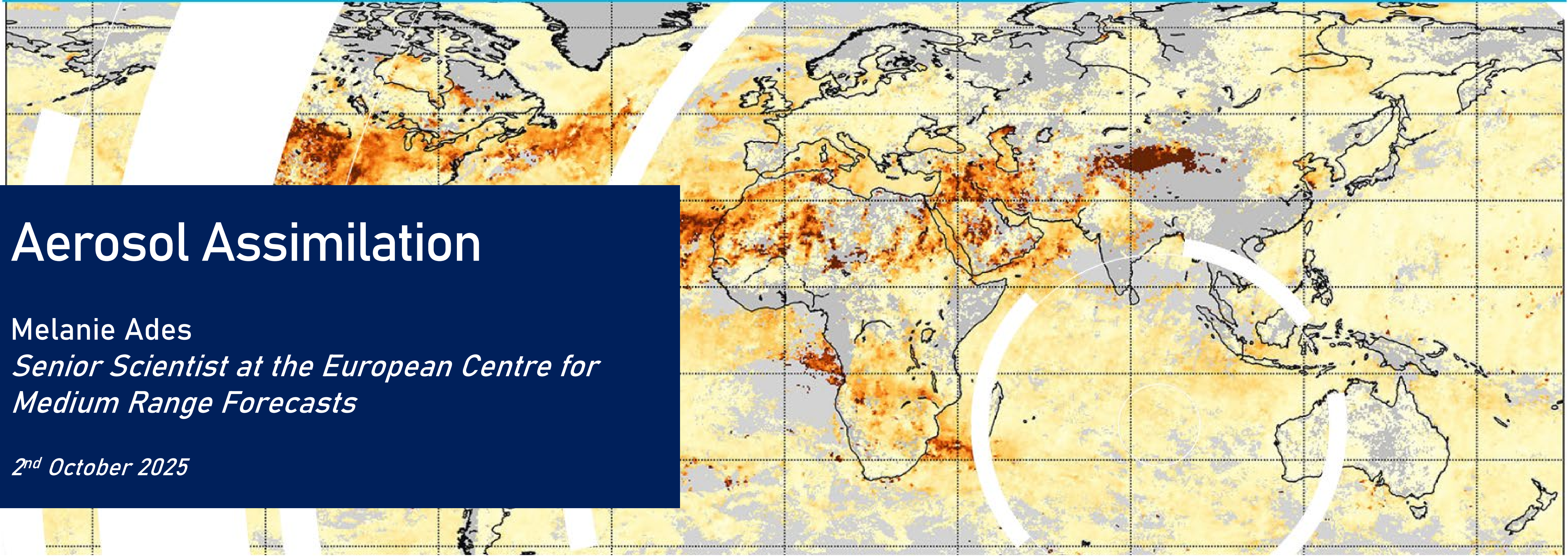
JOINT TRAINING IN ATMOSPHERIC COMPOSITION

13 -17 OCTOBER 2025, BRUSSELS



Aerosol Assimilation

Melanie Ades
Senior Scientist at the European Centre for Medium Range Forecasts

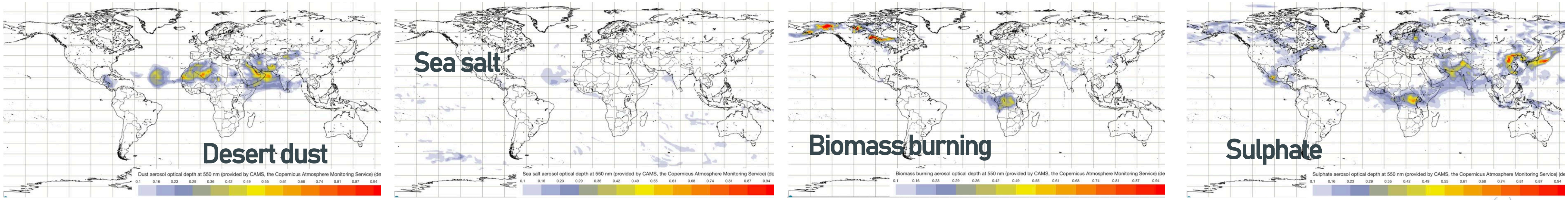
2nd October 2025

CAMS Aerosol model

Sea salt (0.03-0.5um)	Sea salt (0.5-5um)	Sea salt (5-20um)	Black carbon hydrophobic
Desert dust (0.03-0.55um)	Desert dust (0.55-9um)	Desert dust (9-20um)	Black carbon hydrophilic
Ammonium	SOA biogenic	Nitrate from gas/particle partition	Organic matter hydrophobic
Sulphate	SOA anthropogenic	Nitrate from het. reactions	Organic matter hydrophilic

See Samuel Remy lecture

- CAMS uses a bin/bulk aerosol scheme to model the transport, emission and deposition of small particles/aerosols
- 16 different tracers are used to represent 8 different aerosol species
- Each type of aerosol has bespoke processes modelling how that aerosol behaves in the model: emission, deposition, sedimentation, chemical reactions
- Coupled to chemistry via sulphate, nitrate and ammonium and via aerosol input to the CB05 chemical scheme



Aerosol optical depth at 550nm valid for Tuesday 8th July 2025, 3 UTC

Agenda

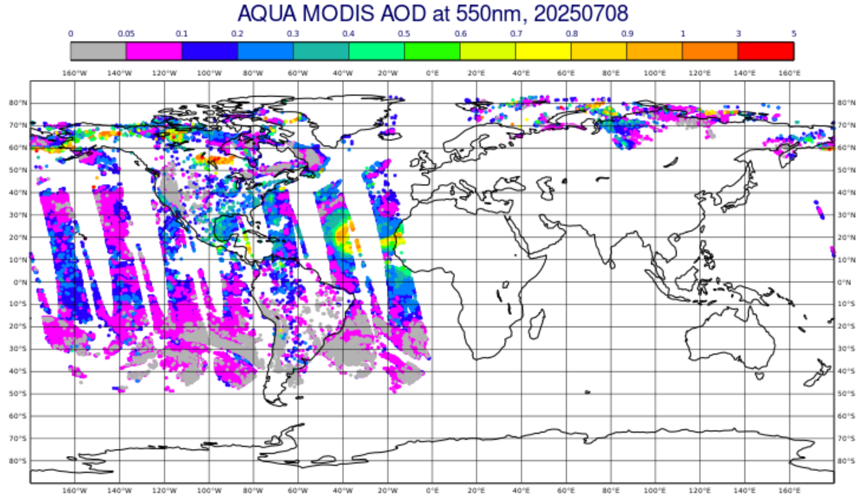
Data Assimilation
What is it and how does it work for aerosols?

Challenges of DA for aerosols
Correcting different species height profiles of aerosols

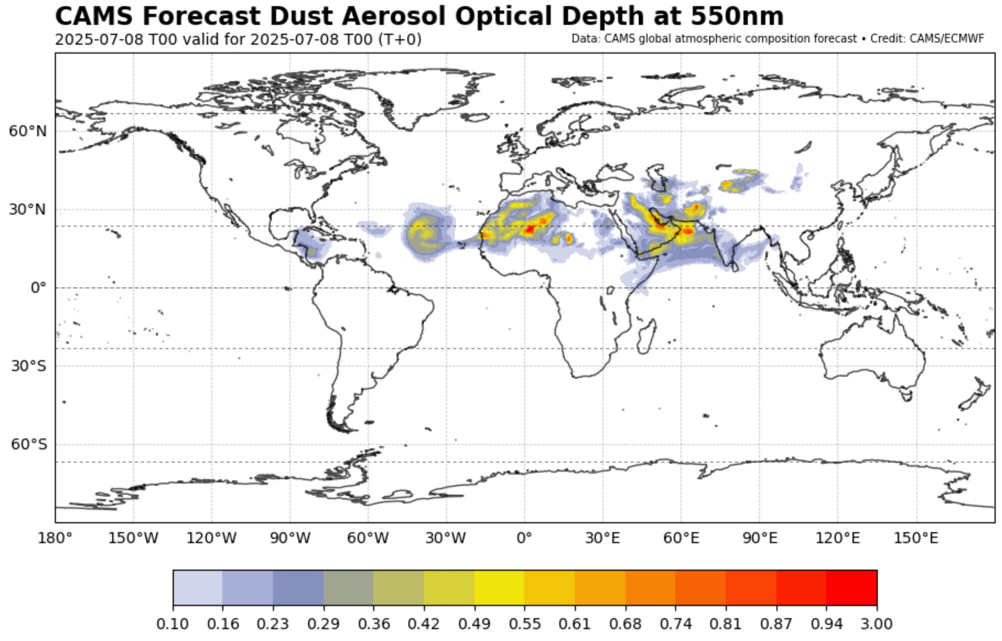
Emission inversions for aerosols
Can we use satellite aerosol observations to correct emissions?

CAMS aerosol applications
How are the aerosol forecasts used?

Data Assimilation: what is it?



Satellite observations



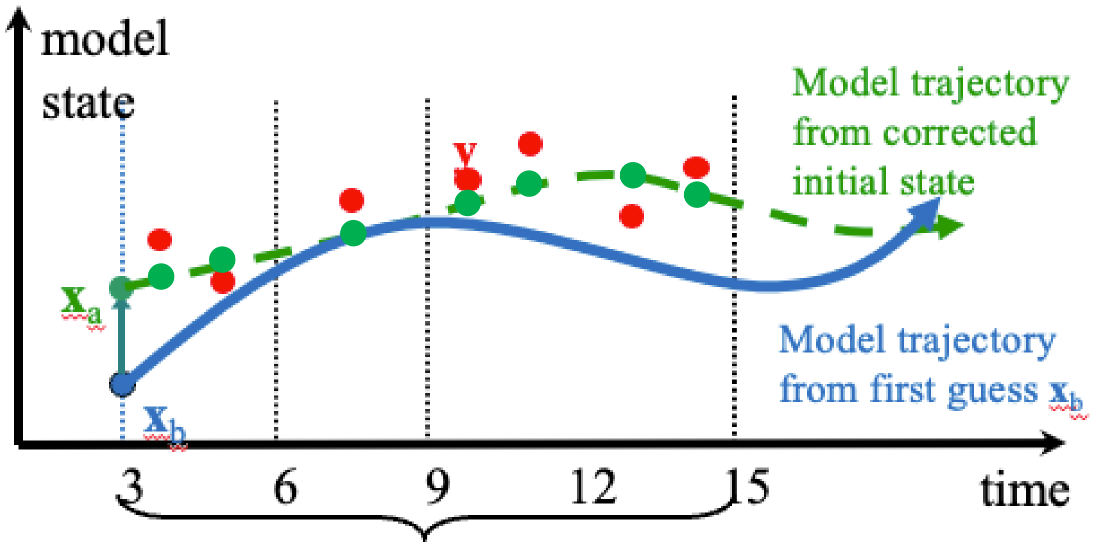
Medium-range forecast

Forecast → **Analysis** → **Forecast** → **Analysis** →

Yesterday's forecast is adjusted by today's observations to produce the outlook for tomorrow. Every day.

Data Assimilation: what is it?

- NWP definition: Combining data and model in an 'optimal' way to produce the best possible initial conditions for a numerical forecast
- Optimal in a statistical sense: minimize error and/or maximize probability of the analysis being correct
- Many different methods exist for solving this problem; ENKF, En-4D-Var, EnVar, 3D-Var, 4D-Var
- CAMS uses ECMWF's 4-dimensional variational data assimilation system or 4D-Var with a 12-h window



$$J(x) = (x - x_b)^T B^{-1} (x - x_b) + \sum_{i=0}^{n} (y_i - H_i[x_i])^T R_i^{-1} (y_i - H_i[x_i])$$

Data Assimilation: what is it?

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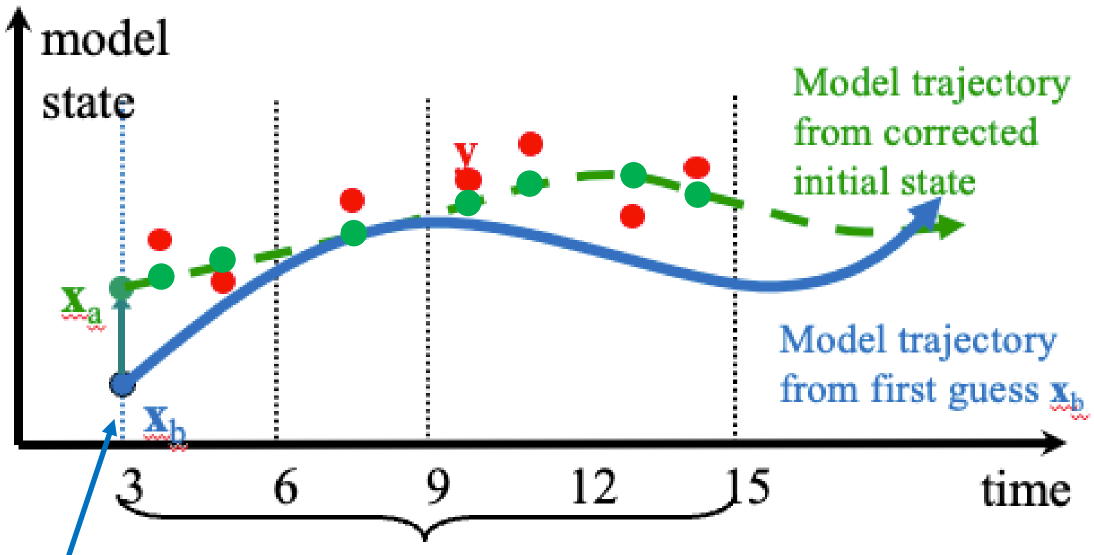
The background model state comes from the previous forecast and is the initial best guess of the state of the aerosols in the atmosphere



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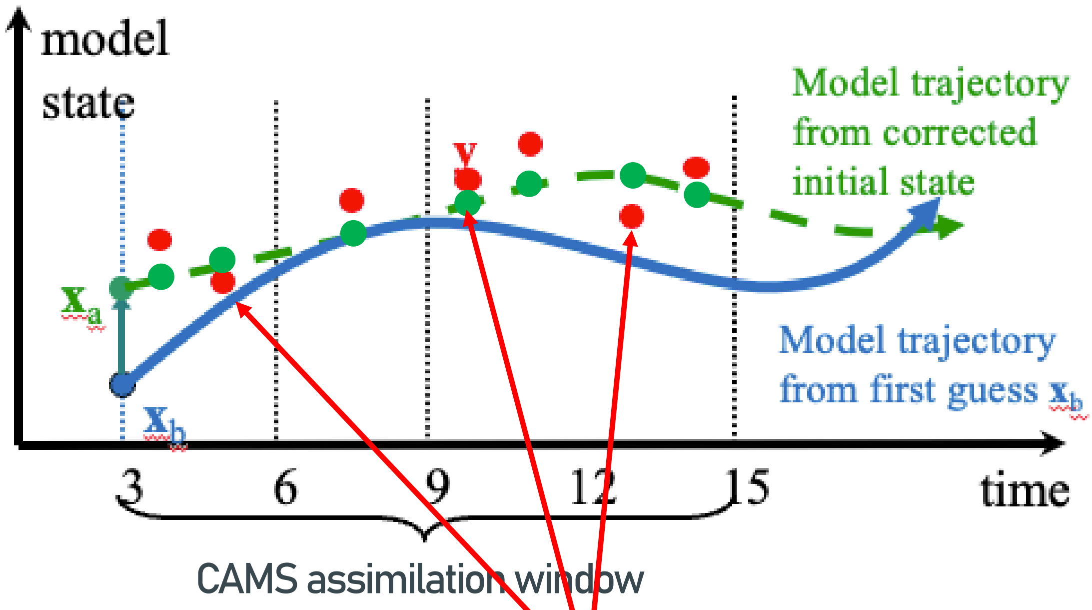

The observations for aerosols come from satellites in the CAMS system and are of Aerosol Optical Depth

$$J(x) = (x - x_b)^T B^{-1} (x - x_b) + \sum_{i=0}^{n} (y_i - H_i[x_i])^T R_i^{-1} (y_i - H_i[x_i])$$

Data Assimilation: what is it?

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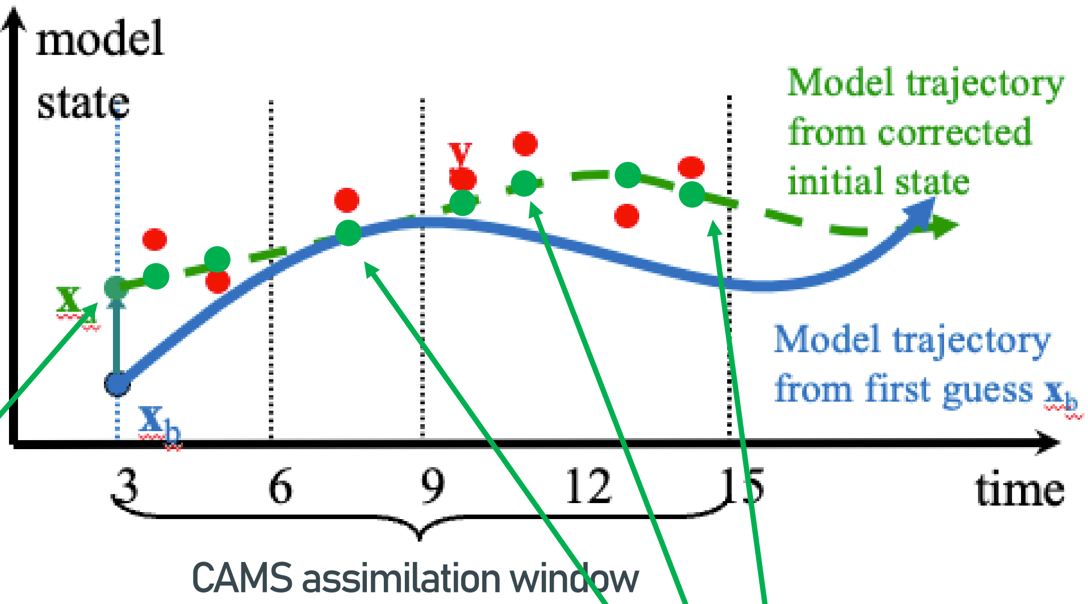

The observation equivalent model values are calculated from a trajectory started from a new initial condition and the difference to the actual observations calculated

$$J(x) = (x - x_b)^T B^{-1} (x - x_b) + \sum_{i=0}^{n} (y_i - H_i[x_i])^T R_i^{-1} (y_i - H_i[x_i])$$

Control variables

$$J(x) = (x - x_b)^T B^{-1} (x - x_b) + \sum_{i=0}^{n} (y_i - H_i[x_i])^T R_i^{-1} (y_i - H_i[x_i])$$

- x: control vector
- x_b: model background (short forecast)
- B: background error covariance matrix
- y: observations
- H[x]: Model equivalent of observations
- R: Observation error covariance matrix

NWP

vorticity
divergence
temperature
surface pressure (logarithm)
specific humidity

Atmospheric Composition

aerosol mixing ratio
ozone
carbon monoxide
nitrogen dioxide
formaldehyde
sulphur dioxide
carbon dioxide
methane

AC control variables mainly treated as passive tracers when minimising the cost function. No emission, deposition or chemical reactions are modelled.

Aerosol observations used

$$J(x) = (x - x_b)^T B^{-1}(x - x_b) + \sum_{i=0}^{n} (y_i - H_i[x_i])^T R_i^{-1}(y_i - H_i[x_i])$$

Observation operator H maps model state at beginning of the assimilation window (t=0) to the observation time and location

Direct assimilation of radiance observations:
The observation operator must incorporate an additional step to compute radiances from the model state variables (radiative transfer model, e.g. RTTOV)

CAMS is starting to explore this in the HE CAMEO project

Assimilation of retrievals:
Good characterization of retrieval is crucial:

- Averaging kernels
- A priori
- Error estimates
- Quality flags

CAMS currently assimilates retrievals of Aerosol Optical Depth

Aerosol observations used

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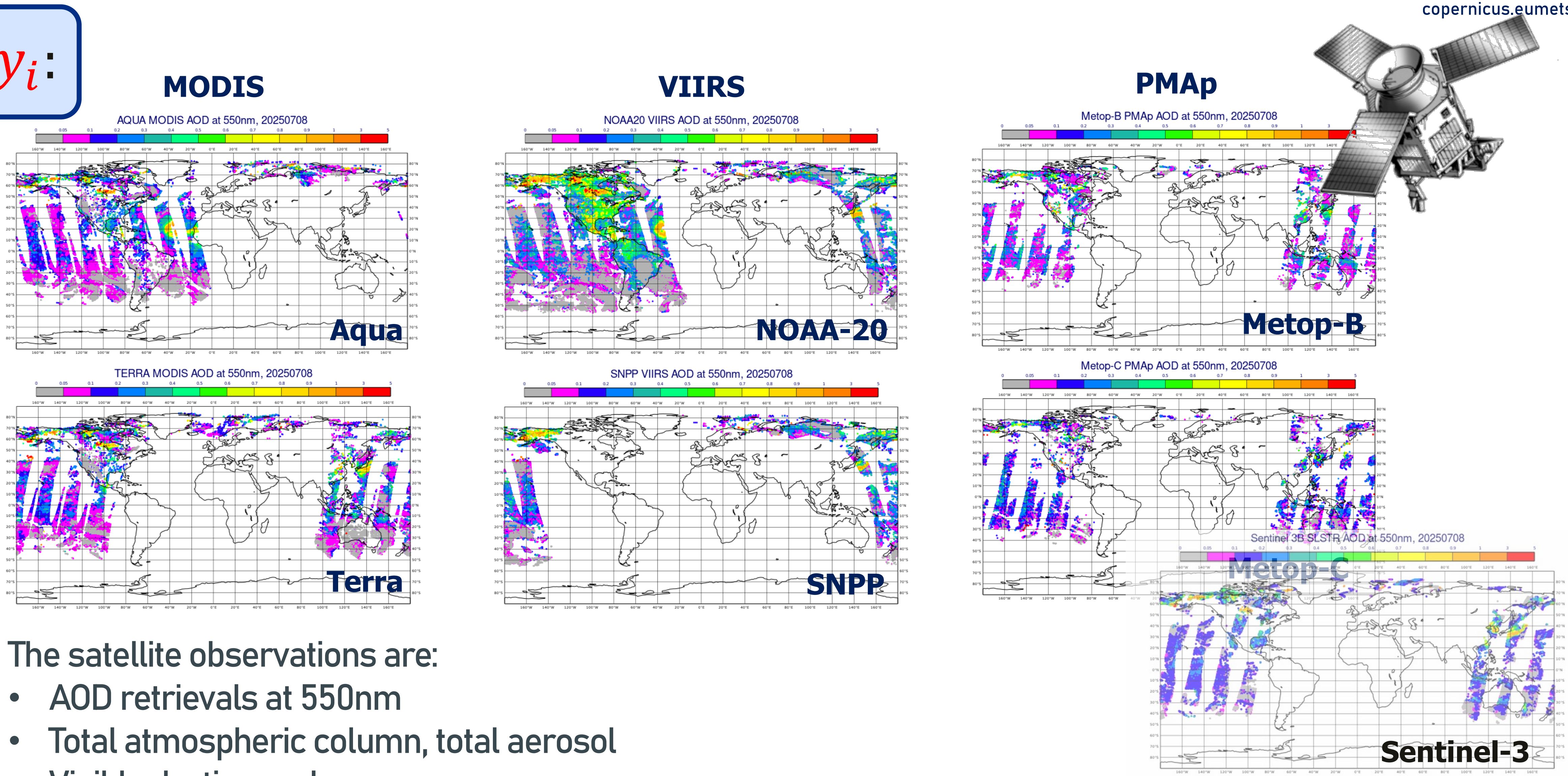
y_i:



The satellite observations are:

- AOD retrievals at 550nm
- Total atmospheric column, total aerosol
- Visible daytime only

Aerosol observation operator

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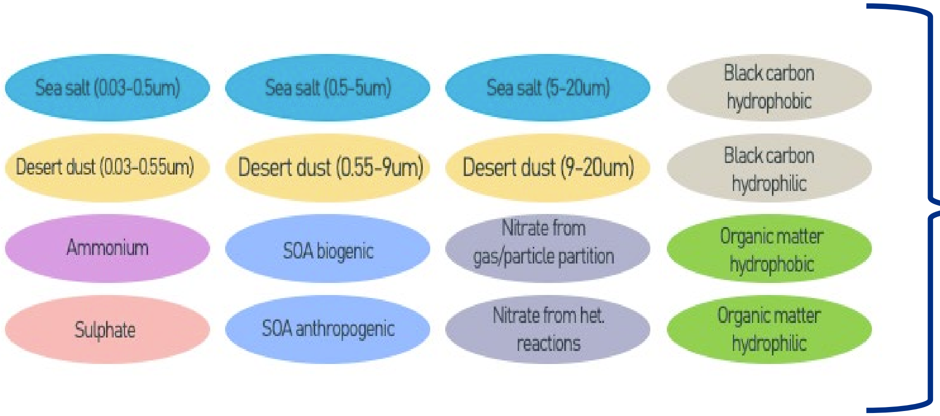
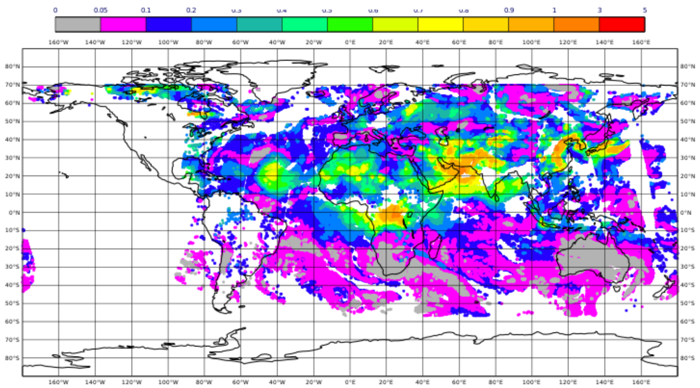
$H_i[x_i]$:

AOD Observation operator (model equivalent to observations):

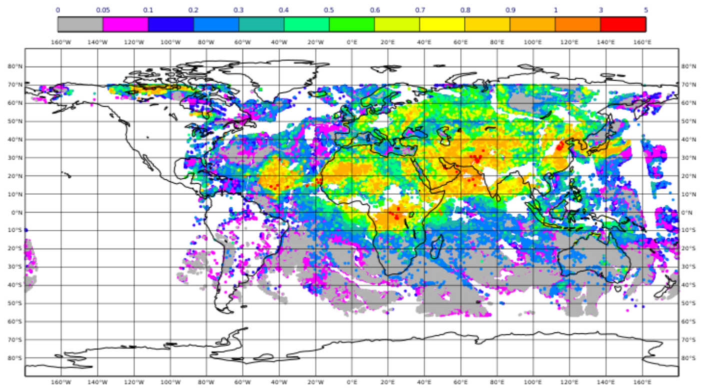
1. Interpolate aerosol mass mixing ratios from the individual aerosol tracers to obs location & time
2. Calculate model RH: it has an impact on hygroscopic aerosol
3. Get mass extinction coef at wavelength (e.g. 550nm) from a look-up table
4. Mutiply (3) * (1) to get single-species AODs
5. Total AOD is sum of single-species AOD



Model AOD



AOD Obs

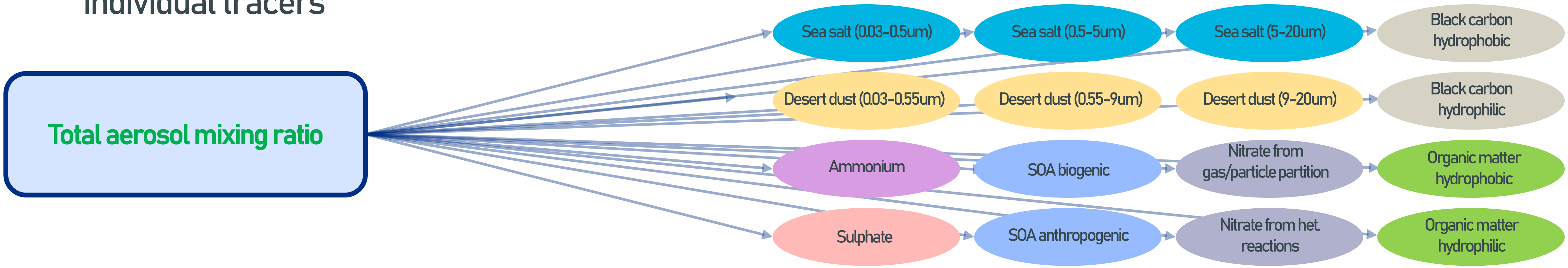


Although we calculate AOD using all the aerosol tracers, there is not enough information it constrain them all and so we use "total aerosol" as the control variable

For aerosols we are trying to minimise the difference between the modelled AOD and the AOD observations, whilst not moving too far from our background or first guess model state

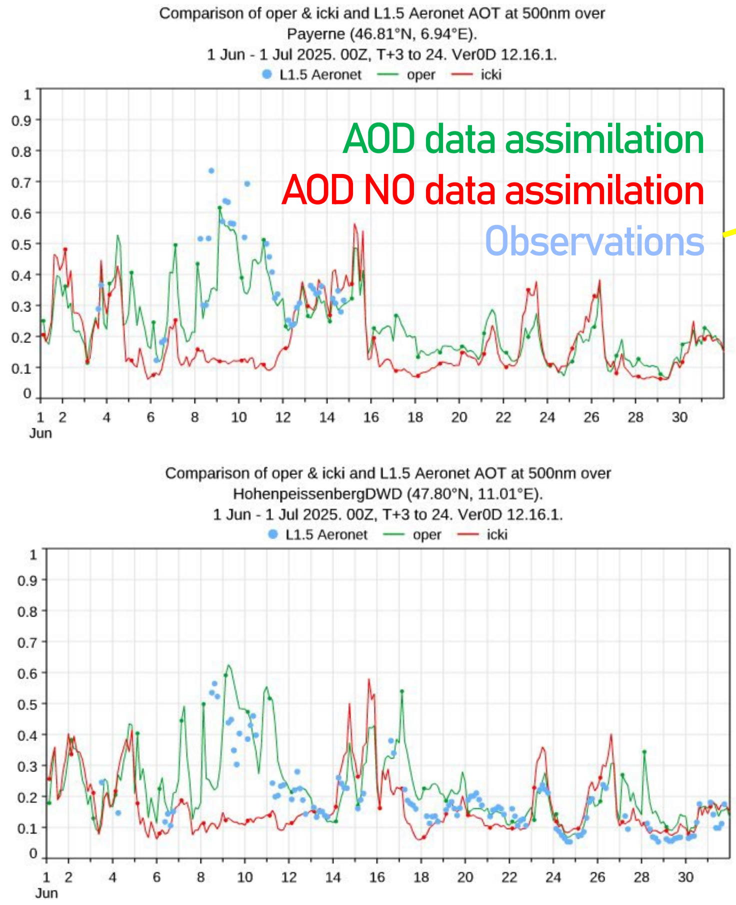
Division of aerosol increment into tracers

Model information from the background forecast (x_b) is used to divide the total aerosol increment from the minimisation of the cost function back into the individual tracers



- Largest contribution from dominant aerosol species
- Can not 'create' a tracer if not present in the background forecast
- The repartitioning of the total aerosol mixing ratio increment into the different bins can lead to problems with the aerosol speciation

Why do data assimilation?



Aeronet verification: Comparison of the CAMS model, with and without data assimilation, against independent in-situ aeronet stations

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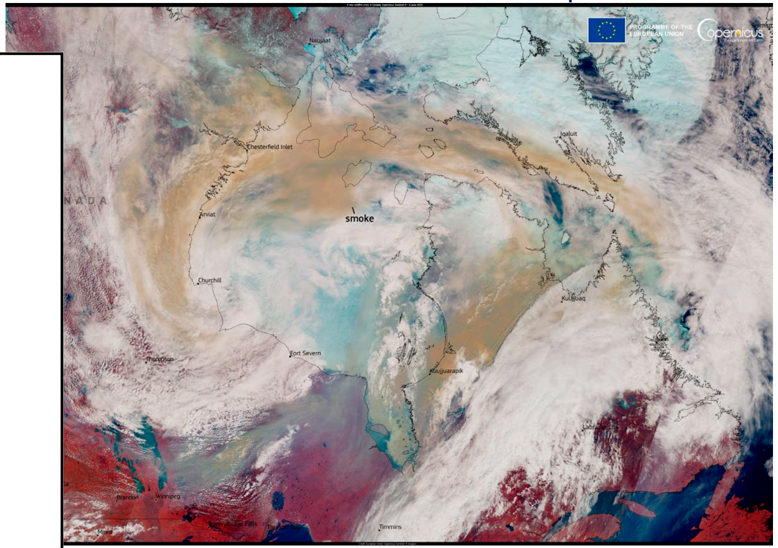

Sentinel-3 satellited on 4 June (source: https://www.copernicus.eu/en/media/image-day-gallery/new-wildfire-crisis-canada).

Updating the forecast using real-time observations improves the forecast, particularly when there are significant aerosol events that the model does not capture.

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Data Assimilation

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Challenges of DA for aerosols

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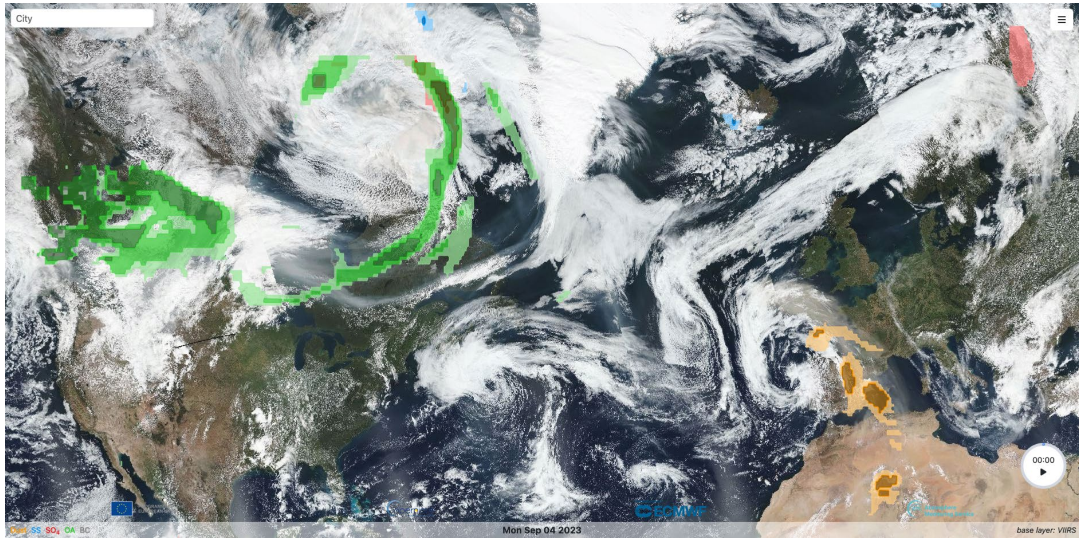
CAMS aerosol applications

How are the aerosol forecasts used?

Challenges: Speciation

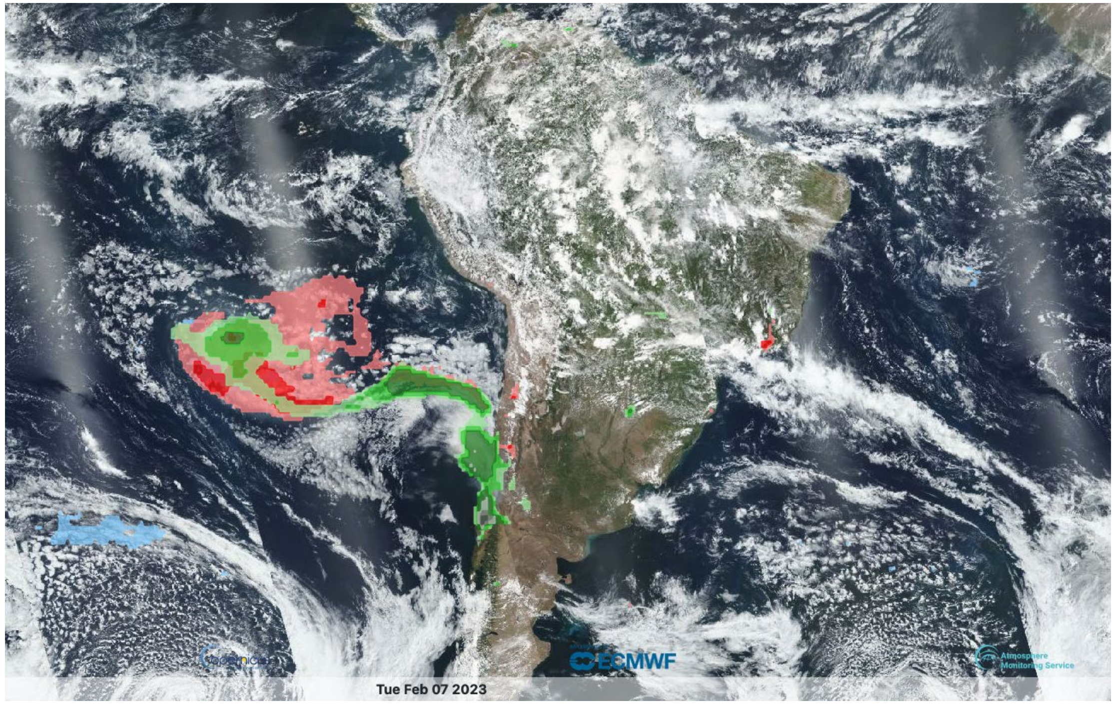
Dividing the total aerosol mixing ratio back into the individual aerosol tracers using forecast information can lead to issues with the speciation:

Good example



Organic matter, desert dust, sea salt, sulphate

Bad example

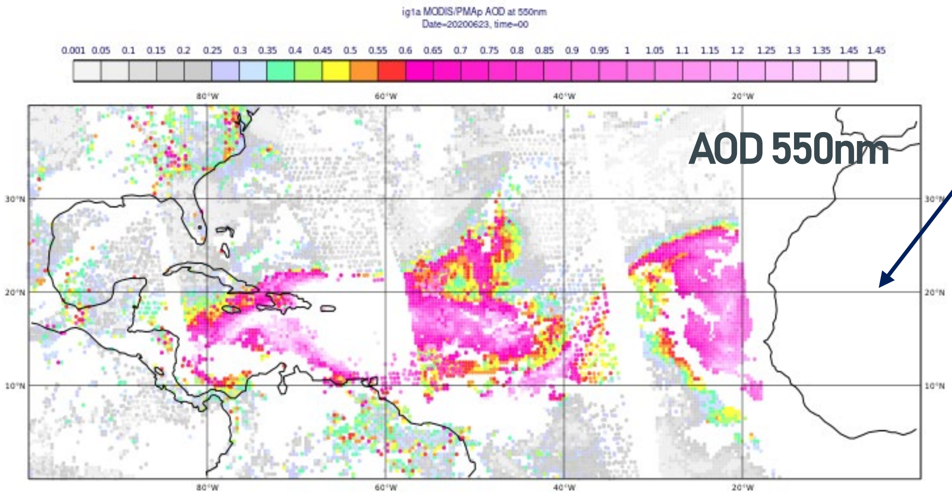


Part of fire plume is attributed to sulphate which is the dominant species in the background forecast

CAMS aerosol alerts:
https://aerosol-alerts.atmosphere.Copernicus.eu/

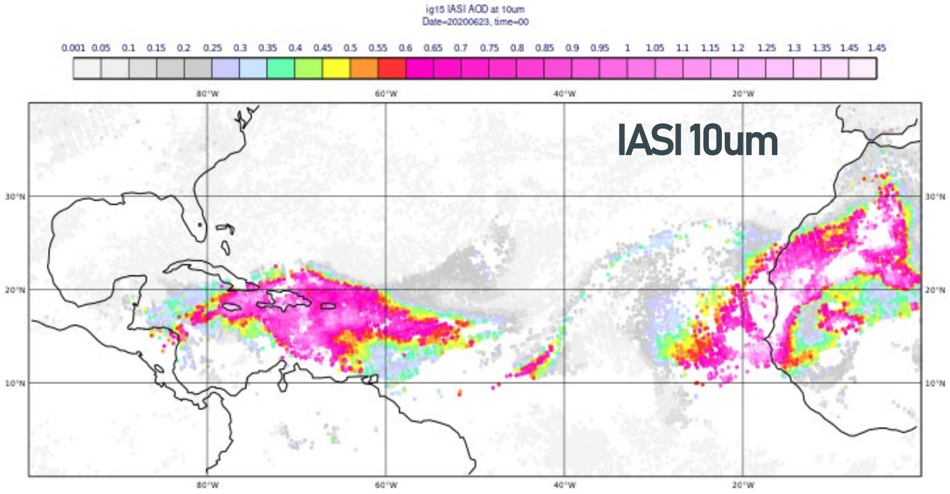
Can using IASI retrievals improve dust forecasts?

- Godzilla event in June 2020 – large incursion of Saharan dust across the Atlantic to the Caribbean



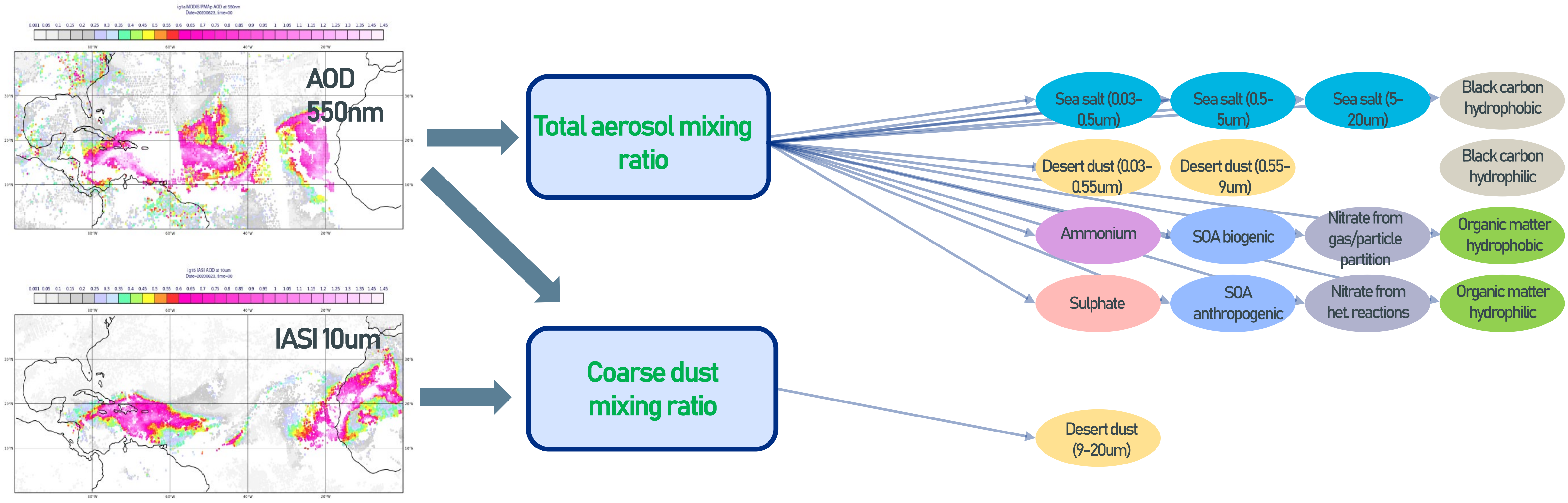
No night-time observations

- CAMS uses AOD 550nm obs from PMAp, MODIS and VIIRS with overpass times at 0930, 1030 and 1330
- AOD at 550nm is in the visible spectrum and so is only measured in daylight hours
- Total aerosol, total column measurement



- IASI 10um measures in the infrared spectrum and so is available in both day- and night-time
- Onboard the Metop-B/C satellites with overpass times at 0930 (desc) and 2130 (asc)
- Only measures coarse particles

Coarse dust control variable



Can using IASI retrievals improve dust forecasts?

Saharan dust plume over Europe in Feb 2023

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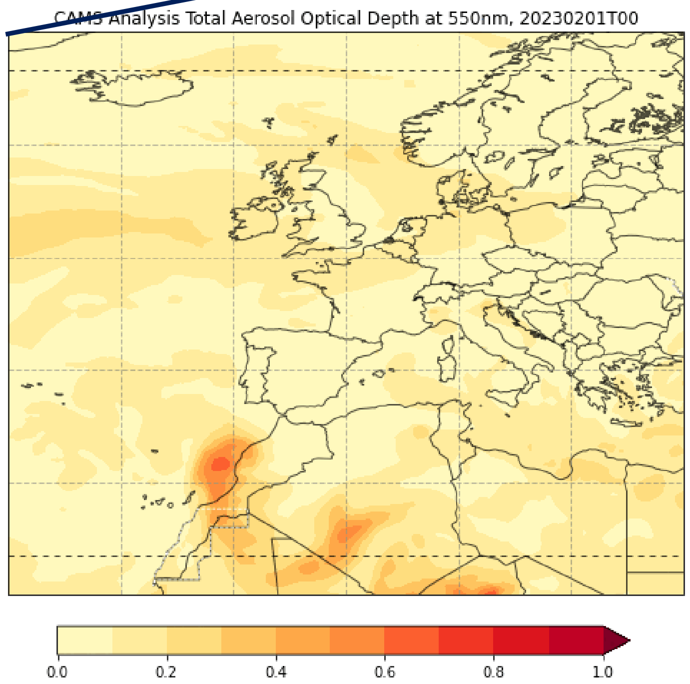
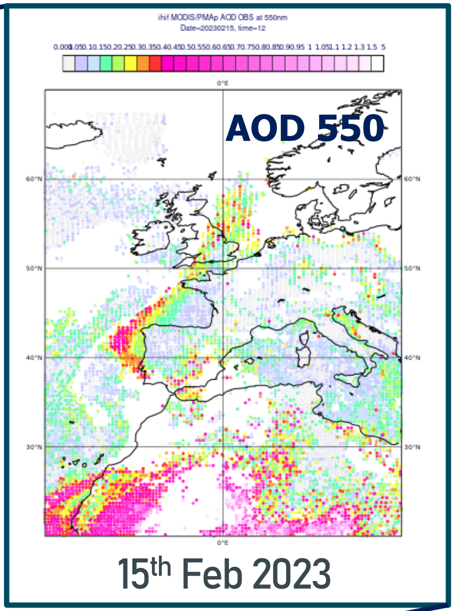
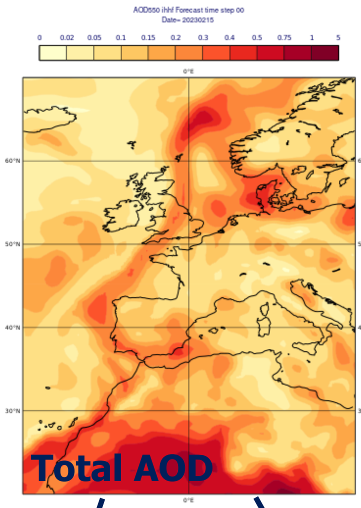
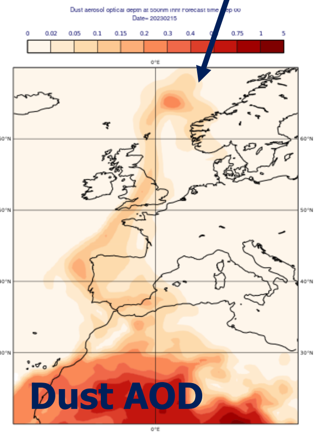
The model has an AOD plume that is very similar to the satellite observations



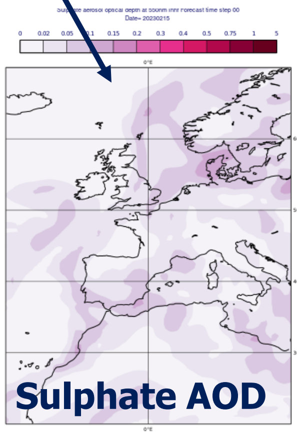




The total aerosol AOD increment calculated by the minimisation



The dust AOD increment based on the proportion of dust in the background forecast



The sulphate AOD increment based on the proportion of dust in the background forecast

Again, the division of the total increment into the individual tracers means the sulphate is increased, despite the fact that we know it is a plume of desert dust

Can using IASI retrievals improve the dust forecast?

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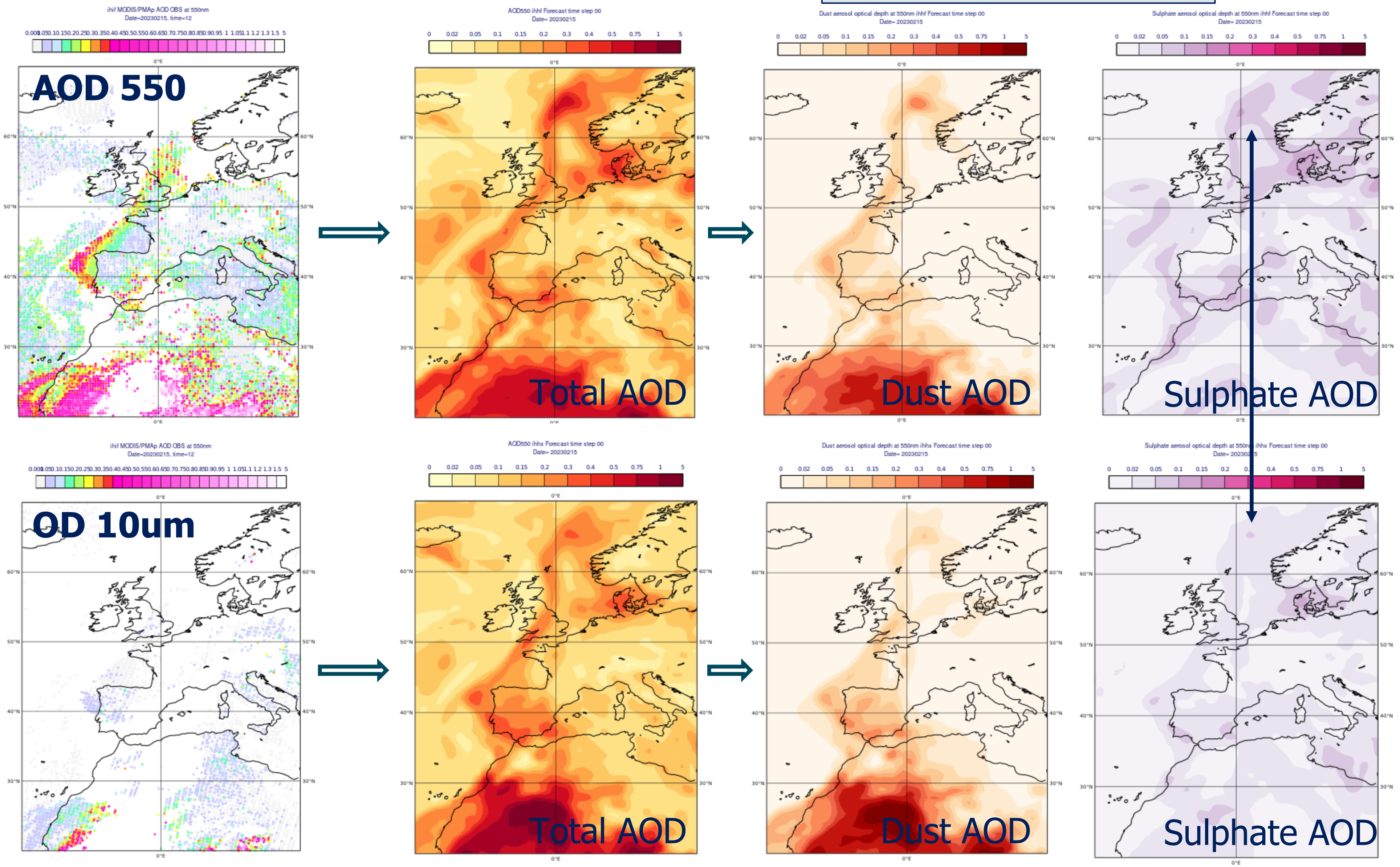
15th Feb 2023: 0300-1500

Reduction in sulphate plume

- Using IASI OD 10um observations reduces the sulphate plume
- Dust plume still present



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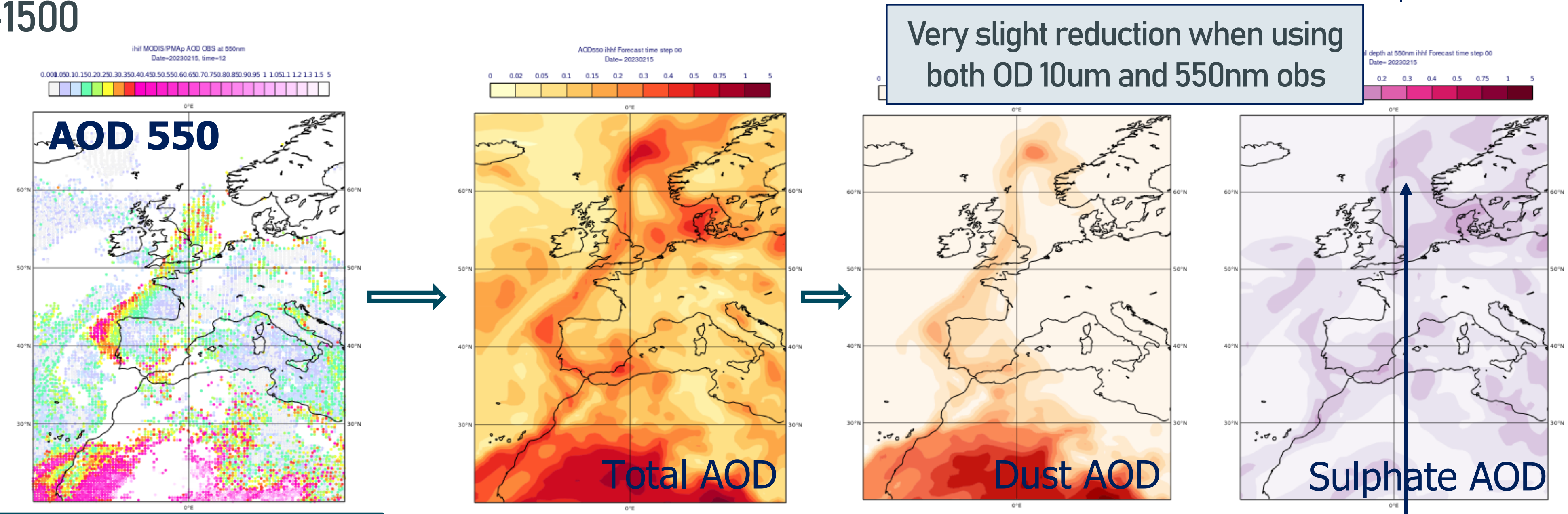

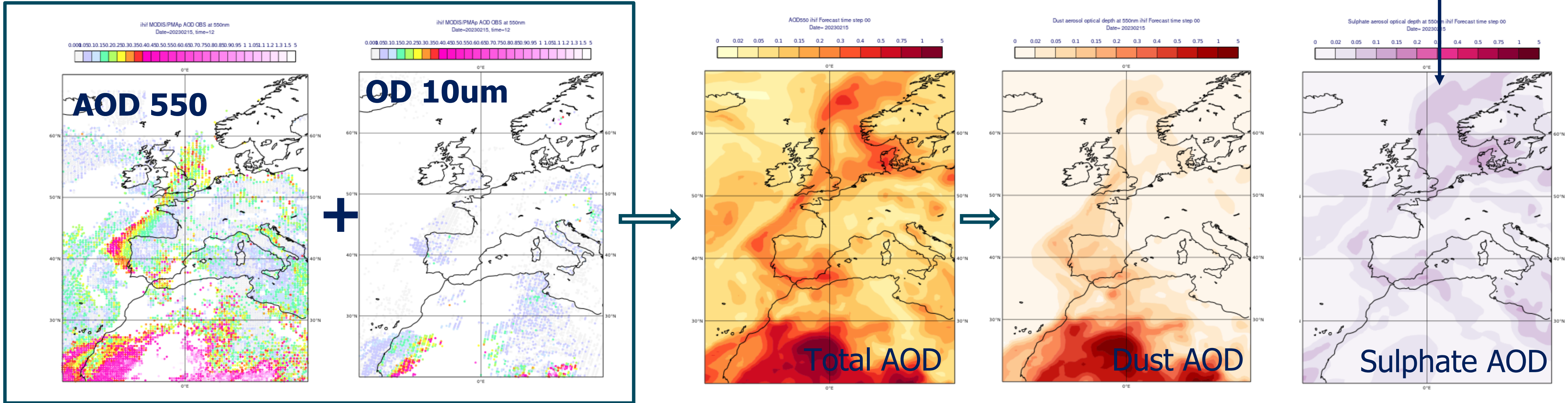

Can using IASI retrievals improve dust forecasts?

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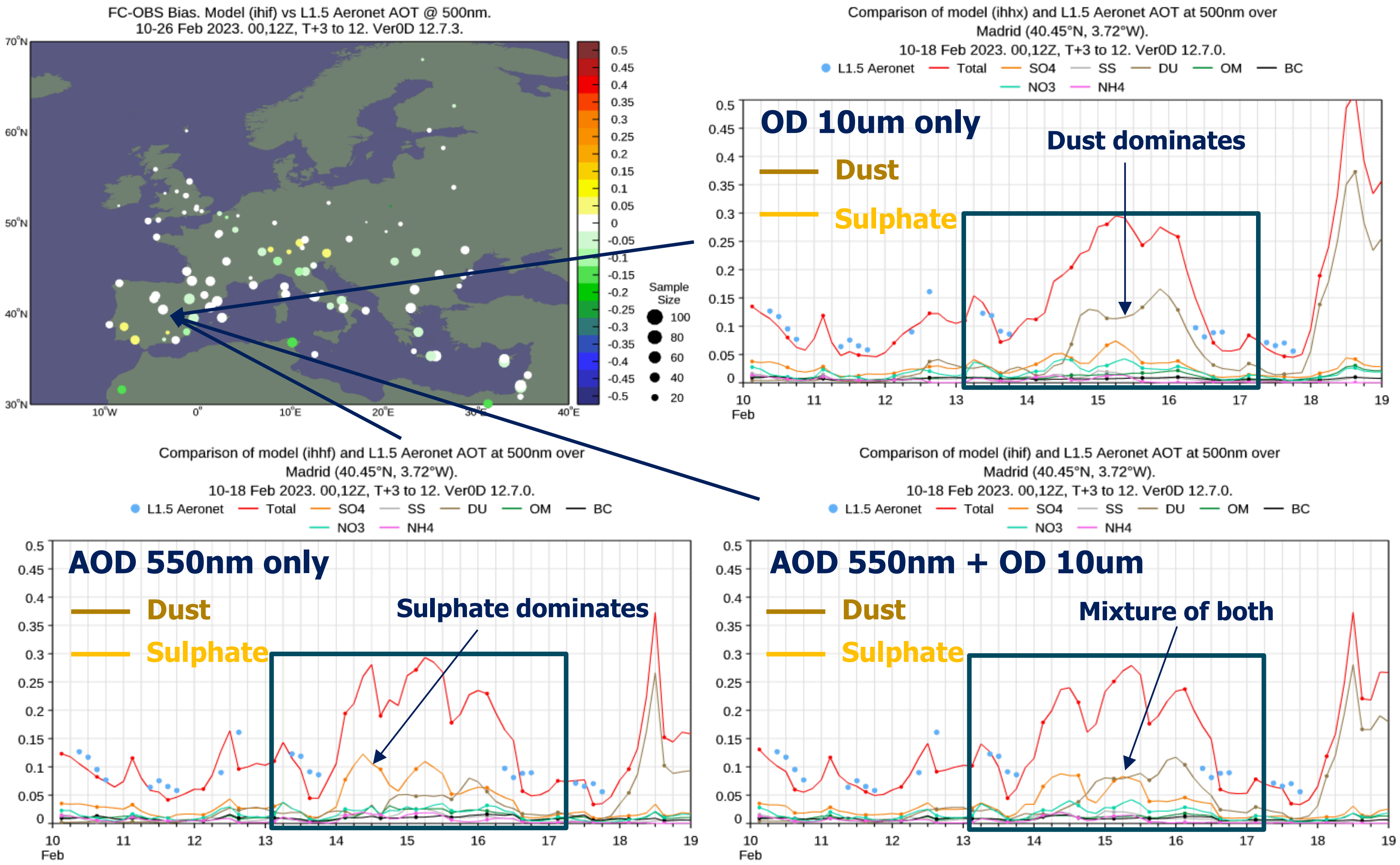
Saharan dust plume over Europe in Feb 2023



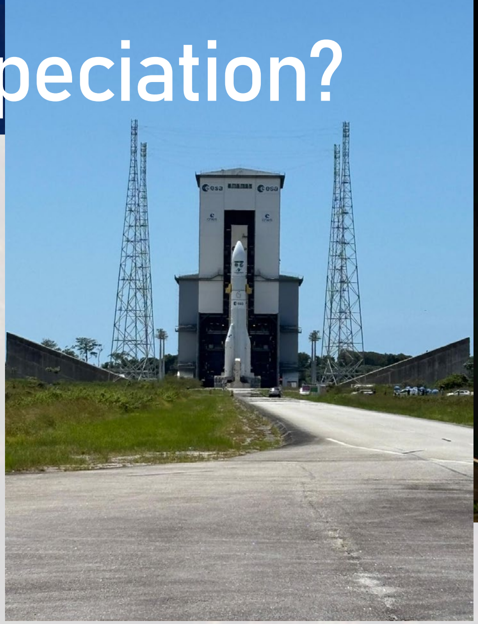
Only using IASI 10um obs leads to dust being the dominant species

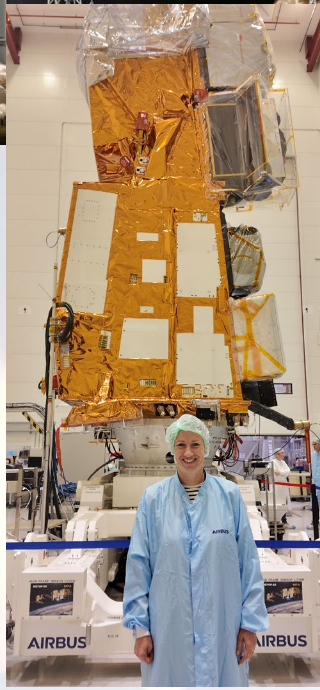
Only using AOD 550nm obs leads to sulphate being the dominant species

Using both types of observations means sulphate is still present, but dust gets more weight

Aeronet verification at the Madrid station: different colours represent the different aerosol species

Can using 3MI retrievals improve speciation?





- Launched onboard MetOp-SG-A1 on the 13th August 2025
- 3MI – Multi-viewing Multi-channel Multi-polarisation Imager
  - The multiple viewing angles, wavelengths, polarisation channels enable additional information to be extracted about aerosols

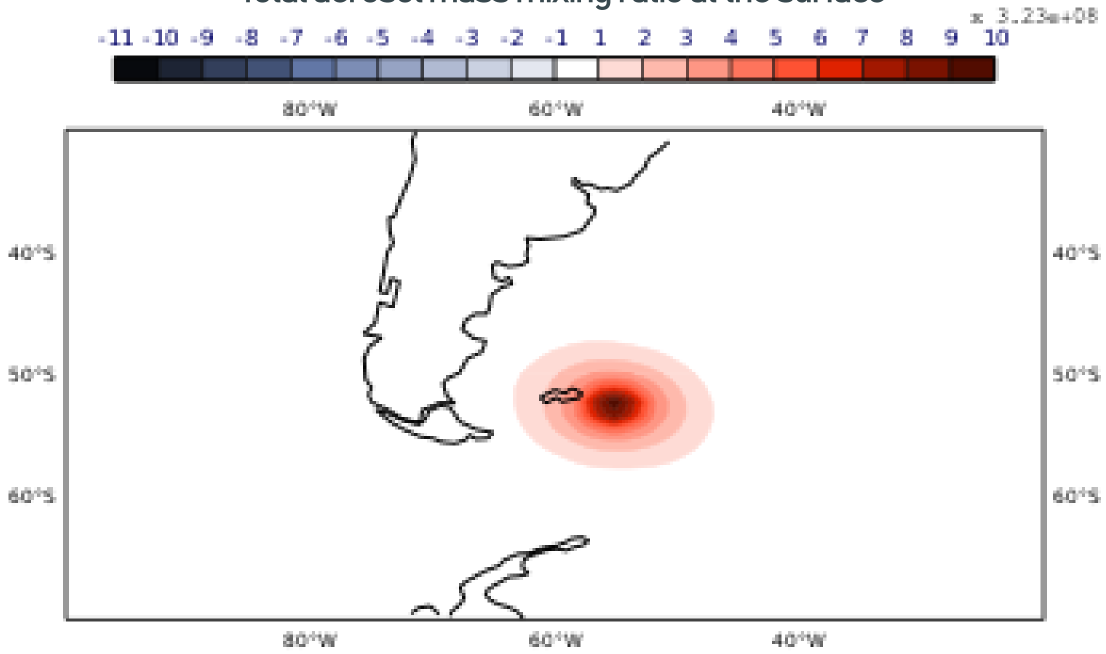
AOD:	Aerosol Optical Depth	Standard total aerosol, total column observation
Fine and Coarse AOD:	Separates the AOD caused by fine and coarse particles	Enables aerosol species such as sulphate/fine dust to be constrained separately to coarse dust/sea-salt
AAOD:	Absorbing AOD	Applies to absorbing aerosol species, such as black carbon, dust and part of organic matter
SSA:	Single Scattering Albedo	Identifies aerosols that are more scattering, such as sulphate, nitrate and sea-salt
AE:	Angstrom Exponent	Distinguishes different sizes of aerosols

- How to use these new observations most effectively within the CAMS data assimilation set-up is an interesting current research question

See Rasmus Lindstrot lecture

Challenges: Lack of profile observations

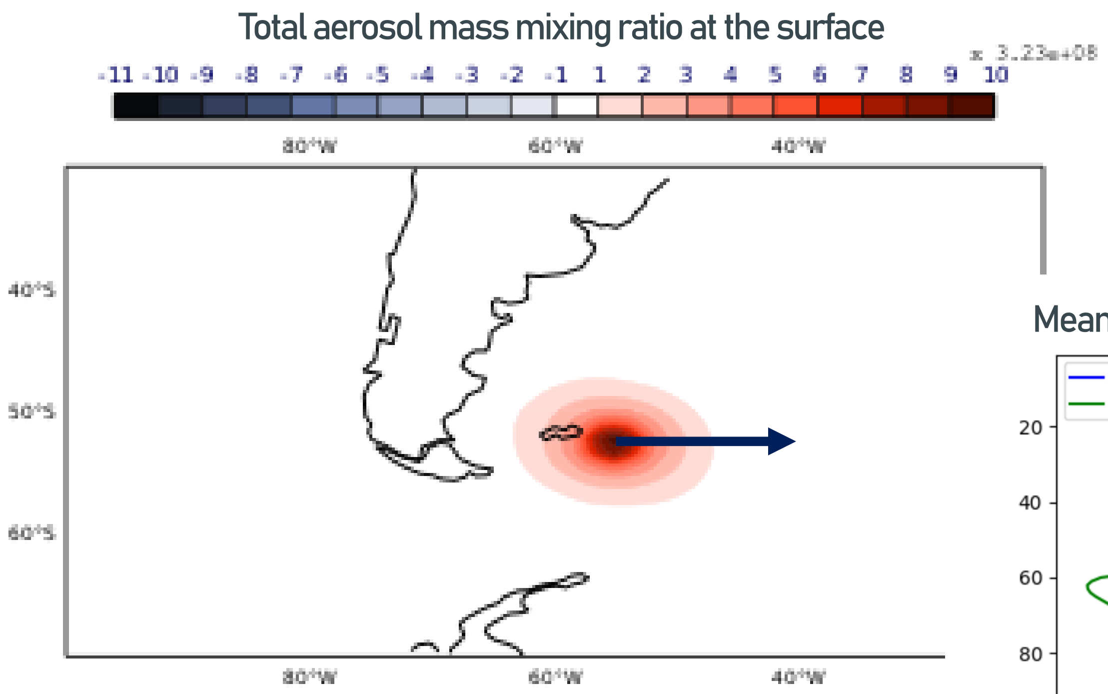
Total aerosol mass mixing ratio at the surface



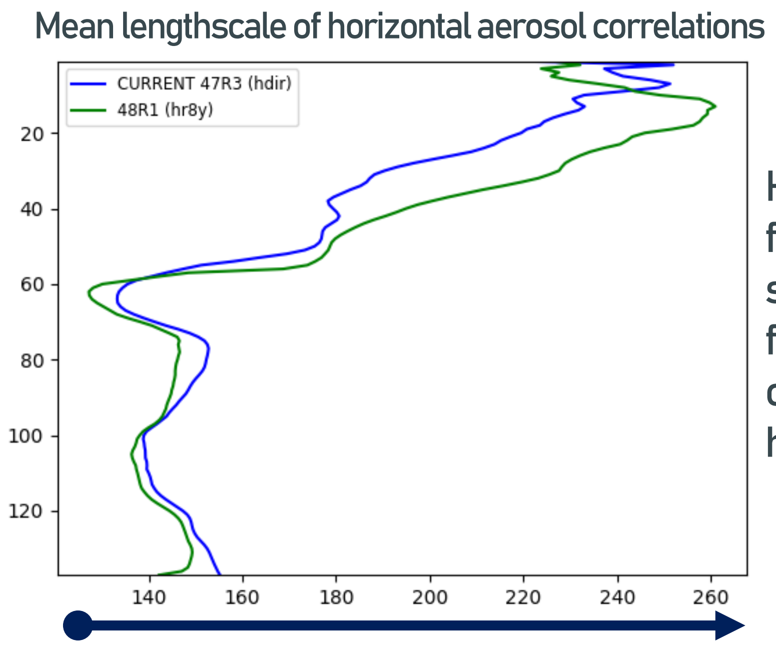
Increment created by a single AOD observation

Challenges: Lack of profile observations

- We calculate the background or model errors using the statistics from forecasts.
- The aim is to capture the uncertainty we have in our model
- We need to update this when we change our model

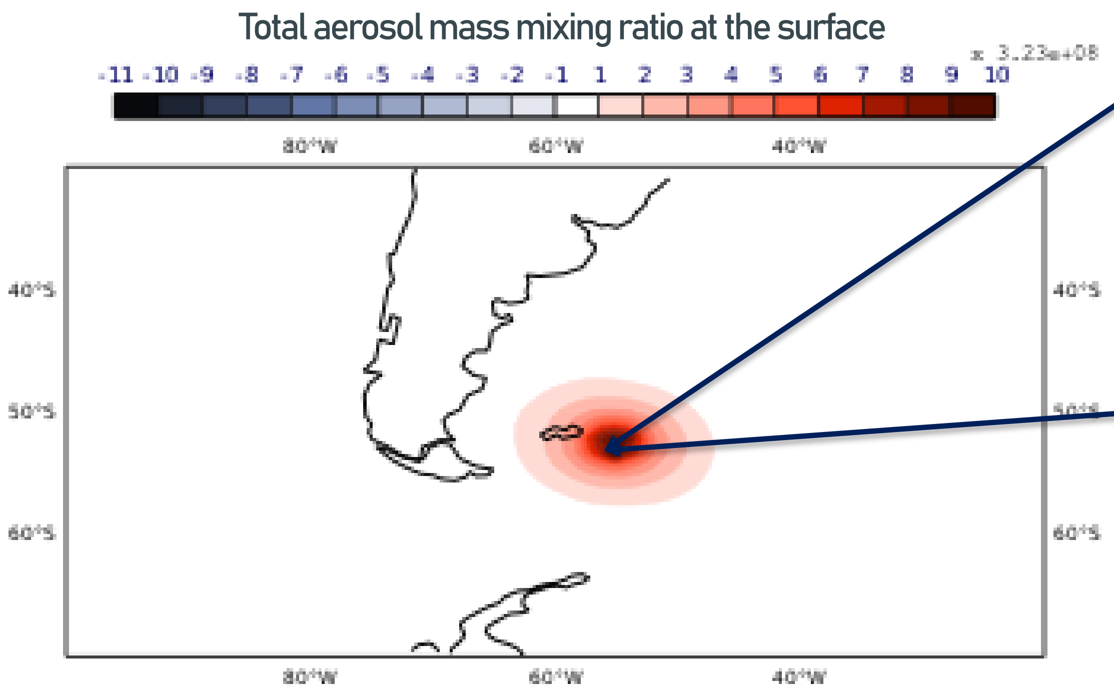


Increment created by a single AOD observatio



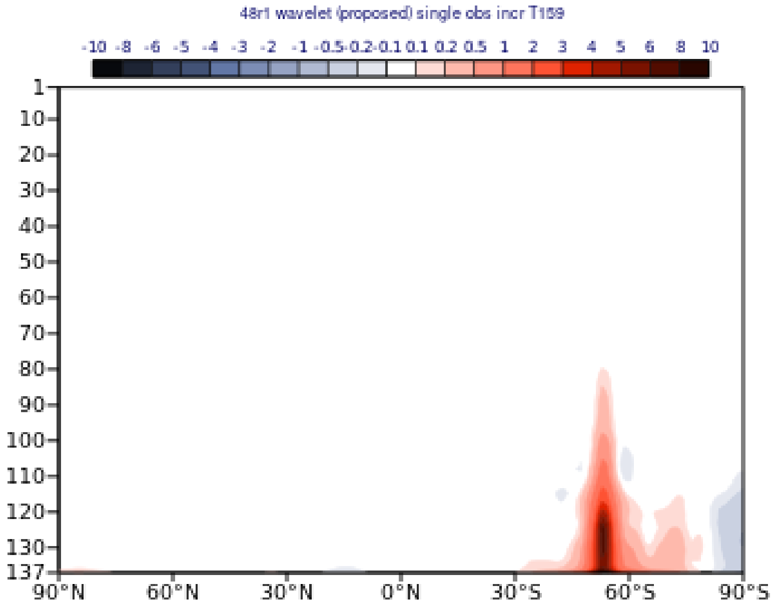
Horizontal correlation from the B-matrix that spreads the information from the single observation in the horizontal

Challenges: Lack of profile observations

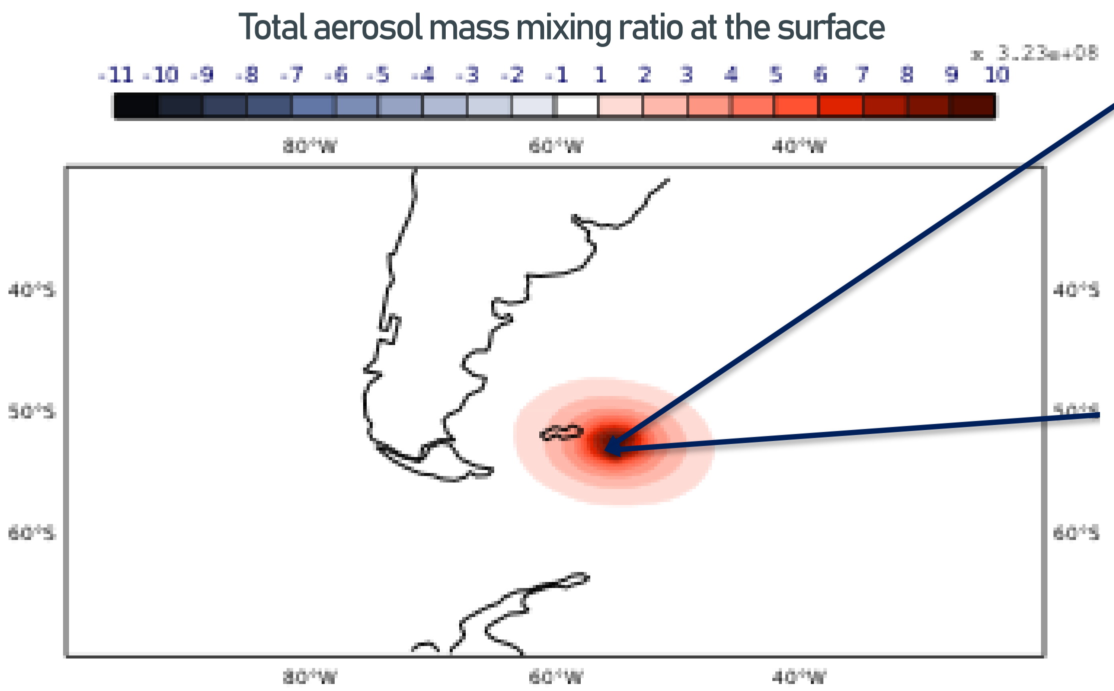


Increment created by a single AOD observation

Vertical increment as a zonal average

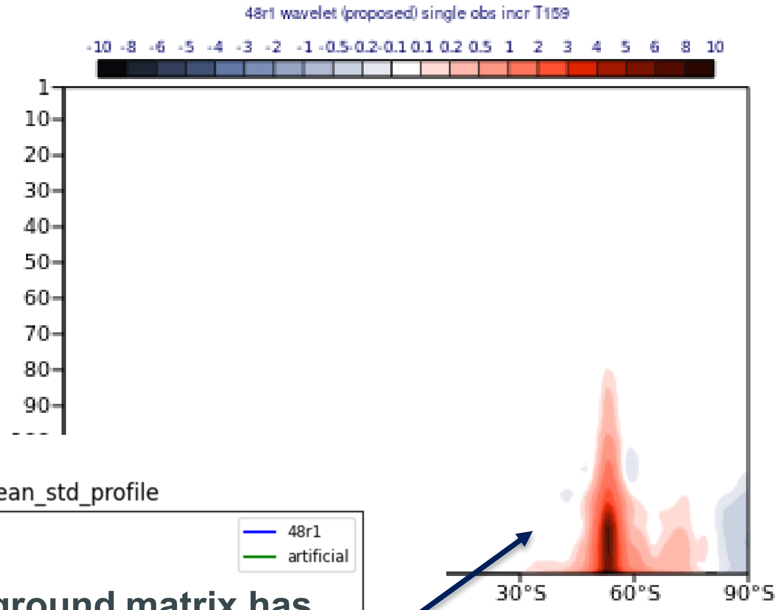


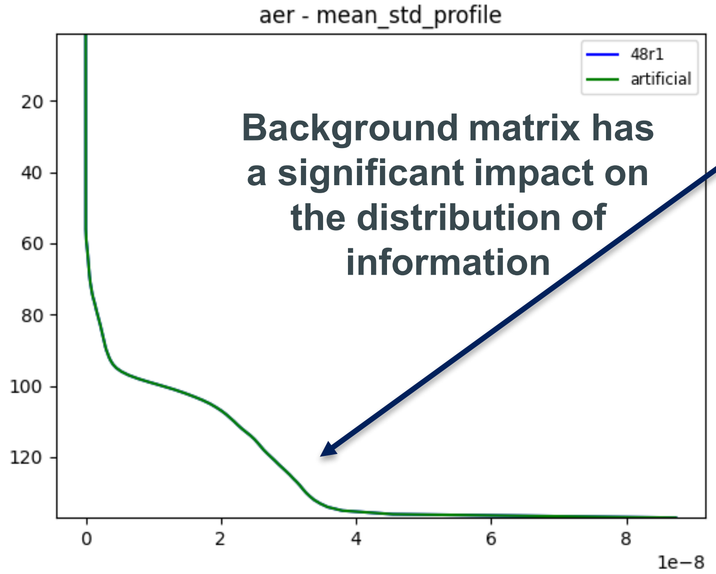
Challenges: Lack of profile observations



Increment created by a single AOD observation

Vertical increment as a zonal average





Background matrix has a significant impact on the distribution of information

Standard deviation from the background matrix at the observation location

With no profile observations, formulation of the B-matrix is very important for how the AOD information is distributed in the vertical

Available operational profile observations

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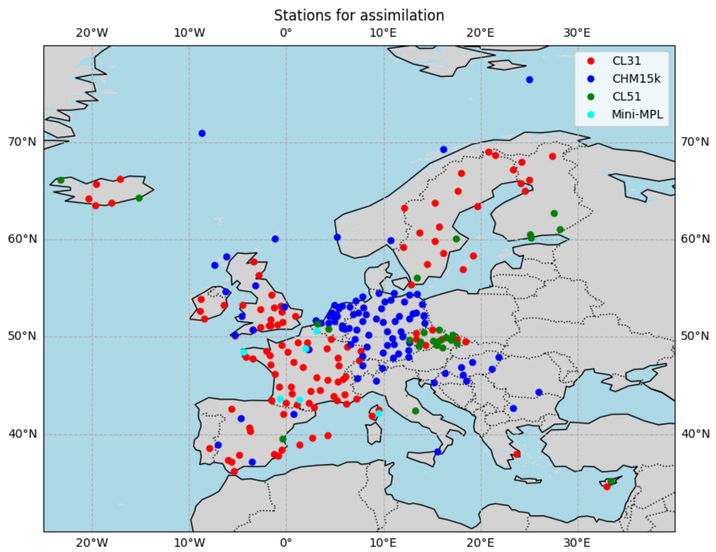


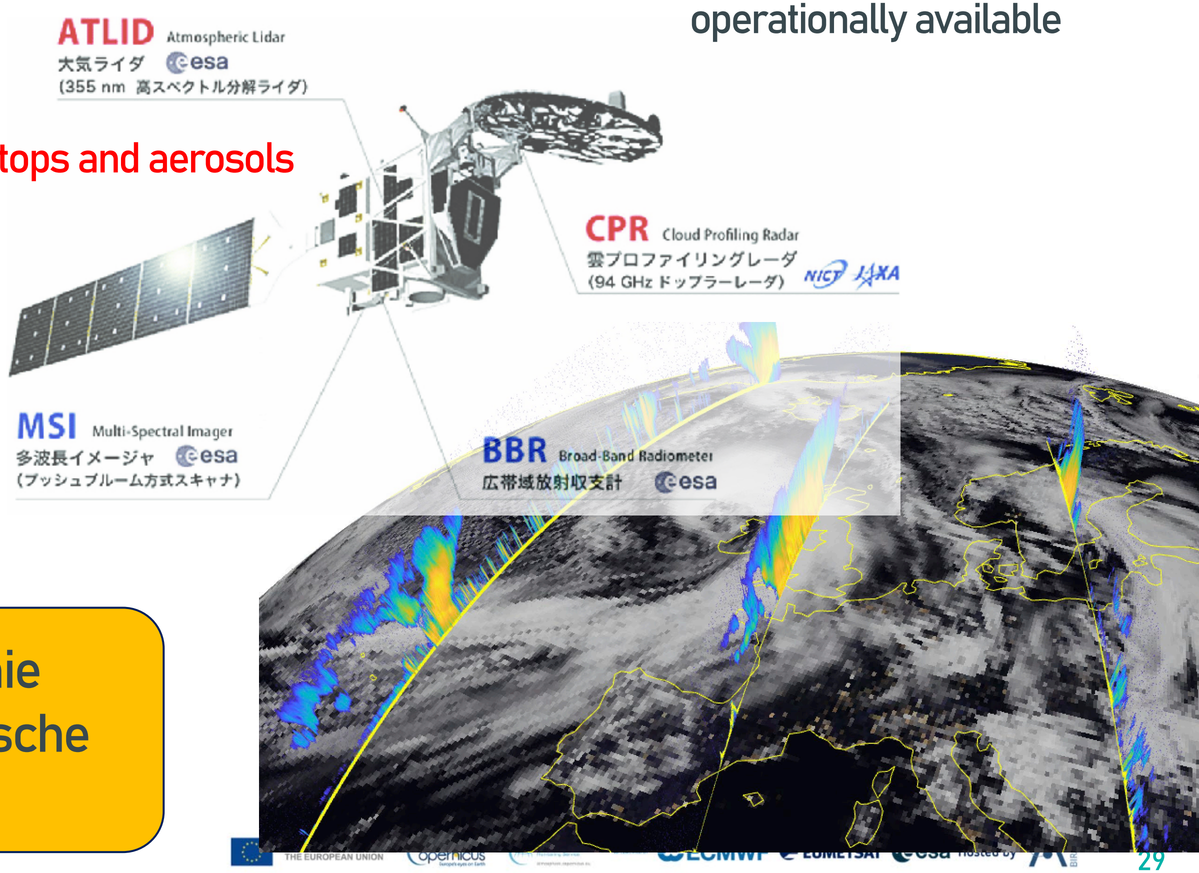
E-PROFILE network

- Network of lidar and ceilometer instruments based across Europe
- Profile observations of aerosol attenuated backscatter
- Regional and in-situ observations
- Operationally disseminated

EarthCARE

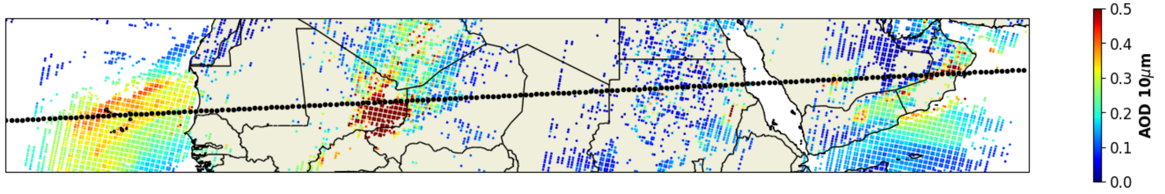
- Satellite observations that provide a profile of aerosol
- Global coverage
- In the process of becoming operationally available

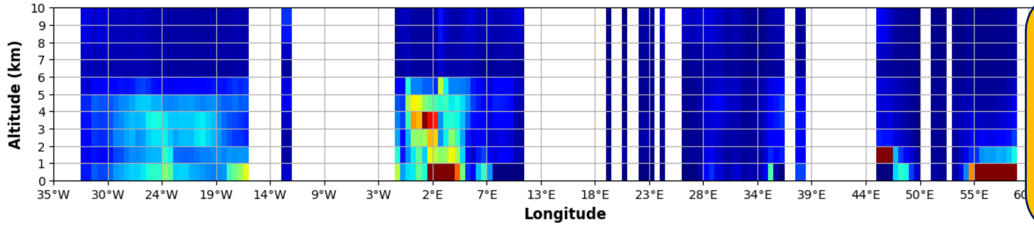
Cloud tops and aerosols



MAPIR IASI 10um dust profiles

- Covered by Sophie's lecture yesterday
- In the process of becoming operationally available
- Coarse profiles but of a specific aerosol species





See Sophie Vandenbussche lecture

Assimilating E-Profile data

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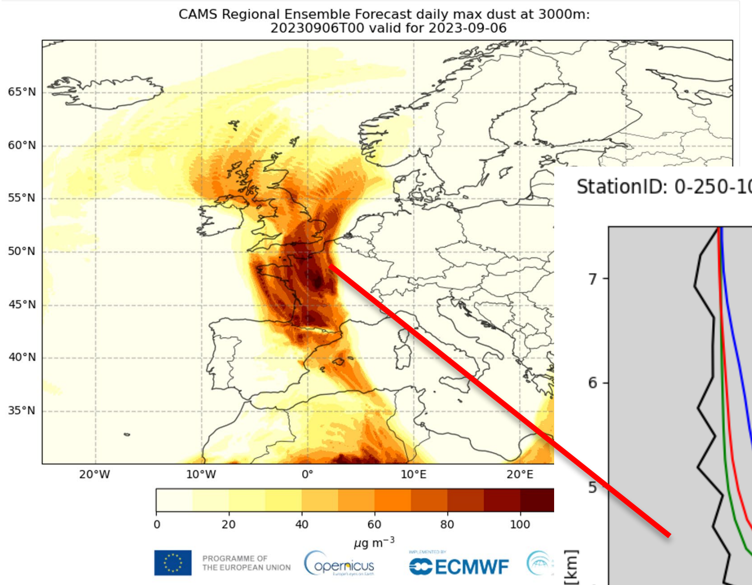
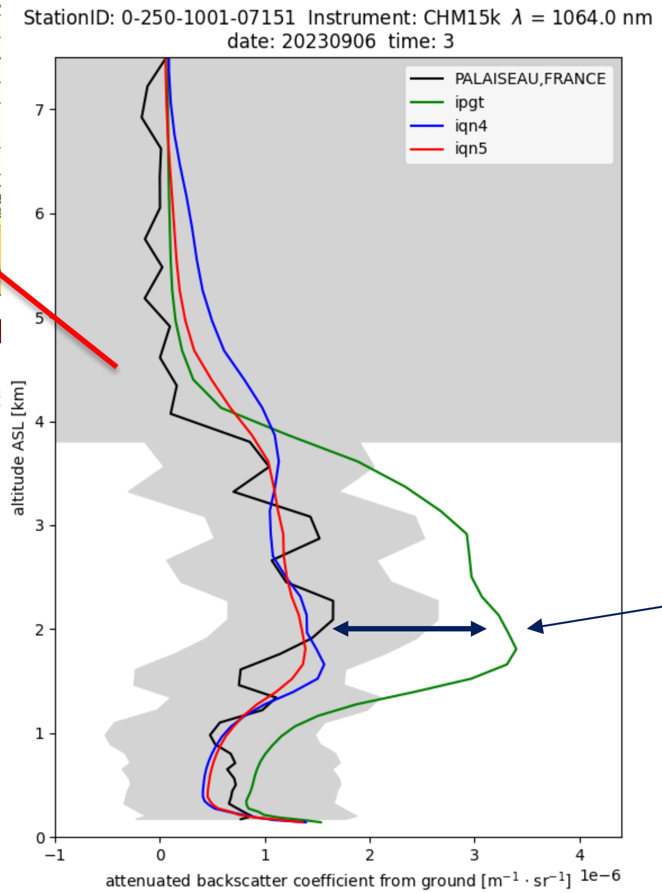
Saharan dust storm Sept 2023

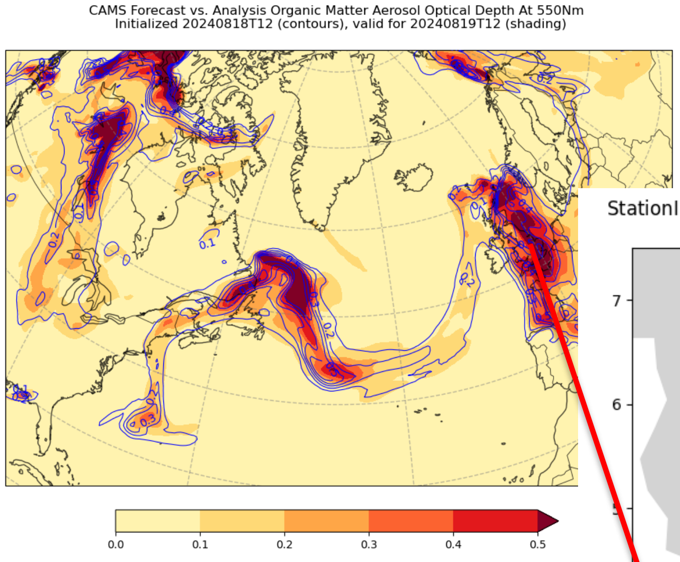


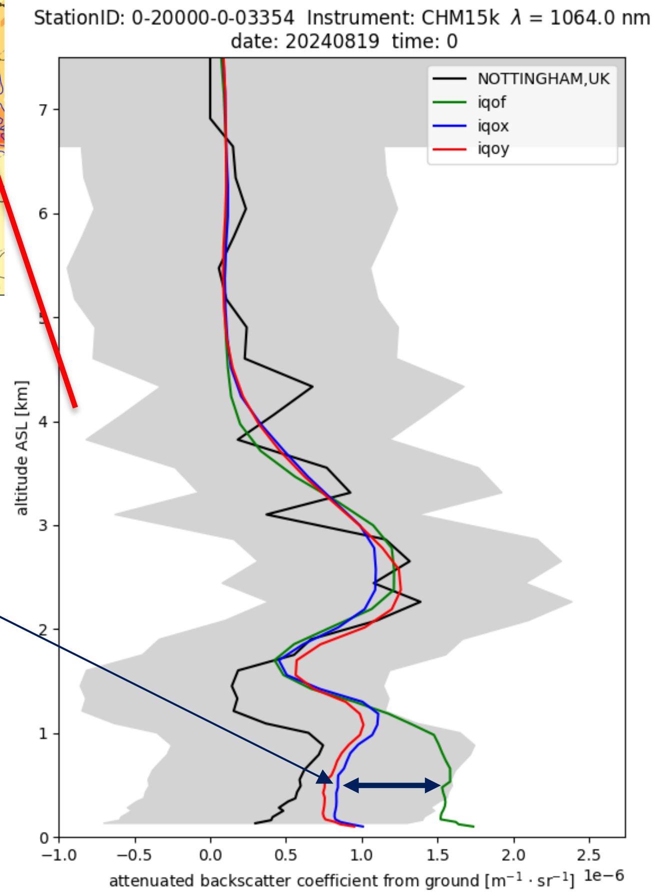


Non-assimilated E-PROFILE station

Obs
Ctrl (AOD assimilation only)
E-PROFILE (spheres)
E-PROFILE (spheroids)

Canadian wildfires August 2024





Non-assimilated E-PROFILE station

Assimilating profile observations on top of AOD improves the profile of total aerosol from the model

Assimilating MAPIR IASI profile data

IASI MAPIR profile retrievals use the same methodology as data assimilation – minimize a cost function that contains the observations and some a-priori constraint

See Sophie Vandenbussche lecture

$$\hat{y} = y_a + \mathbf{A}(y - y_a) + \varepsilon$$

Retrieved value: true state y smoothed by the averaging kernel **A**;
y_a: a-priori, ε: retrieval error

See Antje Inness's talk from last year's training for further details

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$$d = \hat{y} - H(\mathbf{x}_m) = \mathbf{y}_a + \mathbf{A}(\mathbf{y} - \mathbf{y}_a) + \varepsilon - H(\mathbf{x}_m)$$

Without averaging kernels in observation operator (e.g. simple vertical integral)

Option 1:

- Transform the model to match the observation units
- Interpolate to the time and location/height of the profile

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Without averaging kernels in observation operator (e.g. simple vertical integral)

Prior information has an impact on the difference between the retrieval and the model

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$$= \mathbf{A}(\mathbf{y} - H(\mathbf{x}_m)) + \varepsilon$$

With averaging kernels in observation operator

Option 2:

- Transform the model to match the observation units
- Interpolate to the time and location/height of the profile
- Remove the prior profile
- Apply the averaging kernel
- Add the prior profile

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With averaging kernels in observation operator

No longer any impact of the prior and the comparison now becomes between the model value and the “truth”

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With averaging kernels in observation operator

- We remove the influence of the a-priori profile if we use the averaging kernel to sample the model profile according to the assumptions made in the retrieval
- The model data is smoothed by the averaging kernel to produce a profile or column that is directly comparable to the product derived from the instrument radiances
- We still need to know y_a and **A** in the observation operator calculations

See Antje Inness's talk from last year's training for further details

Agenda

Data Assimilation

What is it and how does it work for aerosols?

Challenges of DA for aerosols

Correcting different species height profiles of aerosols

Emission inversions for aerosols

Can we use satellite aerosol observations to correct emissions?

CAMS aerosol applications

How are the aerosol forecasts used?

Emission inversion

- Samuel Remy has already talked comprehensively about the importance of emissions as an input parameter to aerosol models
- Some of the relevant aerosol emissions come from emission inventories, such as SO2
- Other emissions are calculated online based on wind (dust or sea salt aerosol) or temperature (biogenic emissions)
- Some emissions can be observed indirectly from satellite instruments (Fire radiative power, burnt area, volcanic plumes)
- “Inverse” methods can be used to correct prior emission estimates using observations of concentrations and models

See Samuel Remy lecture

Including emissions in the control vector

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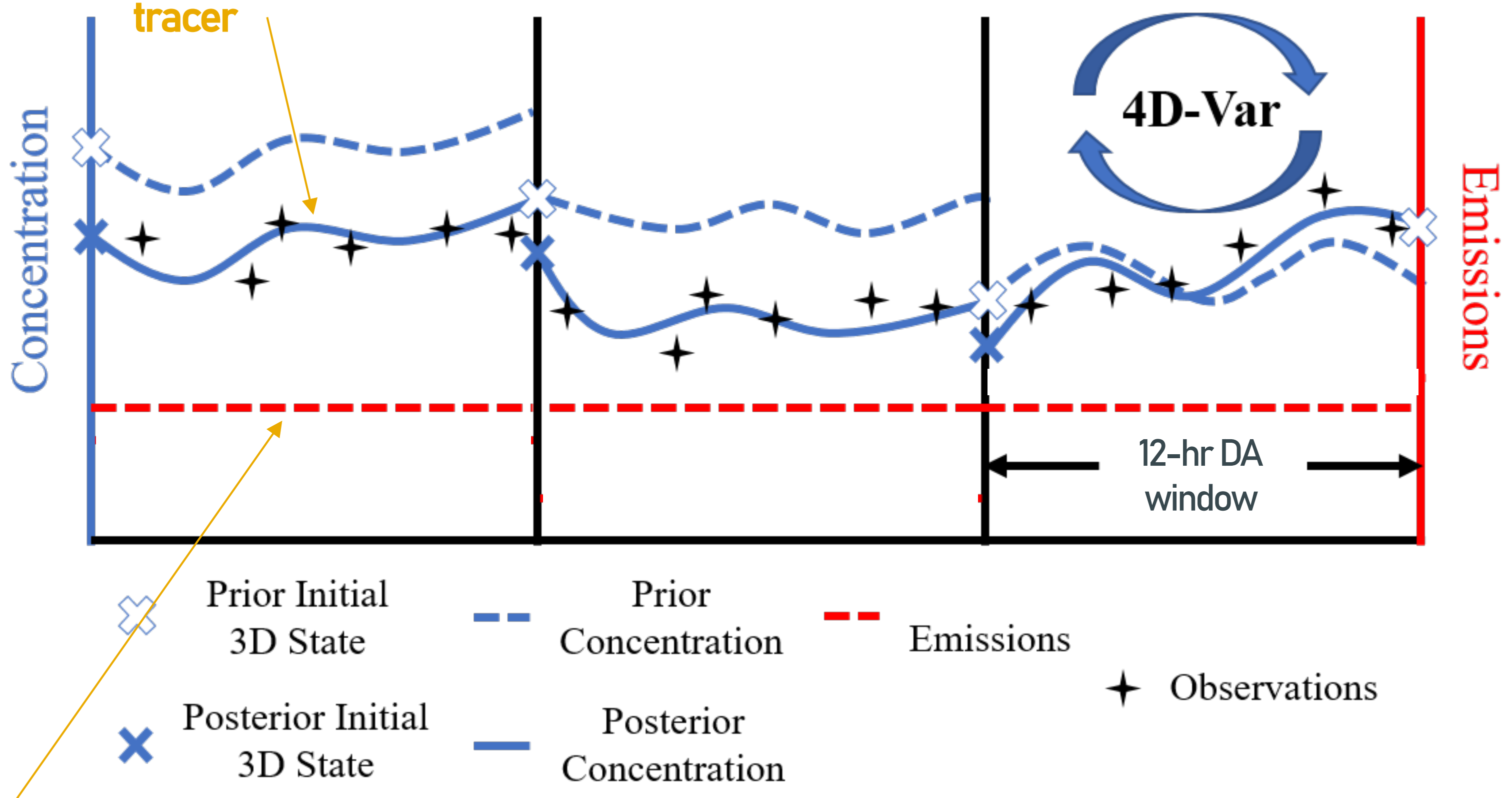
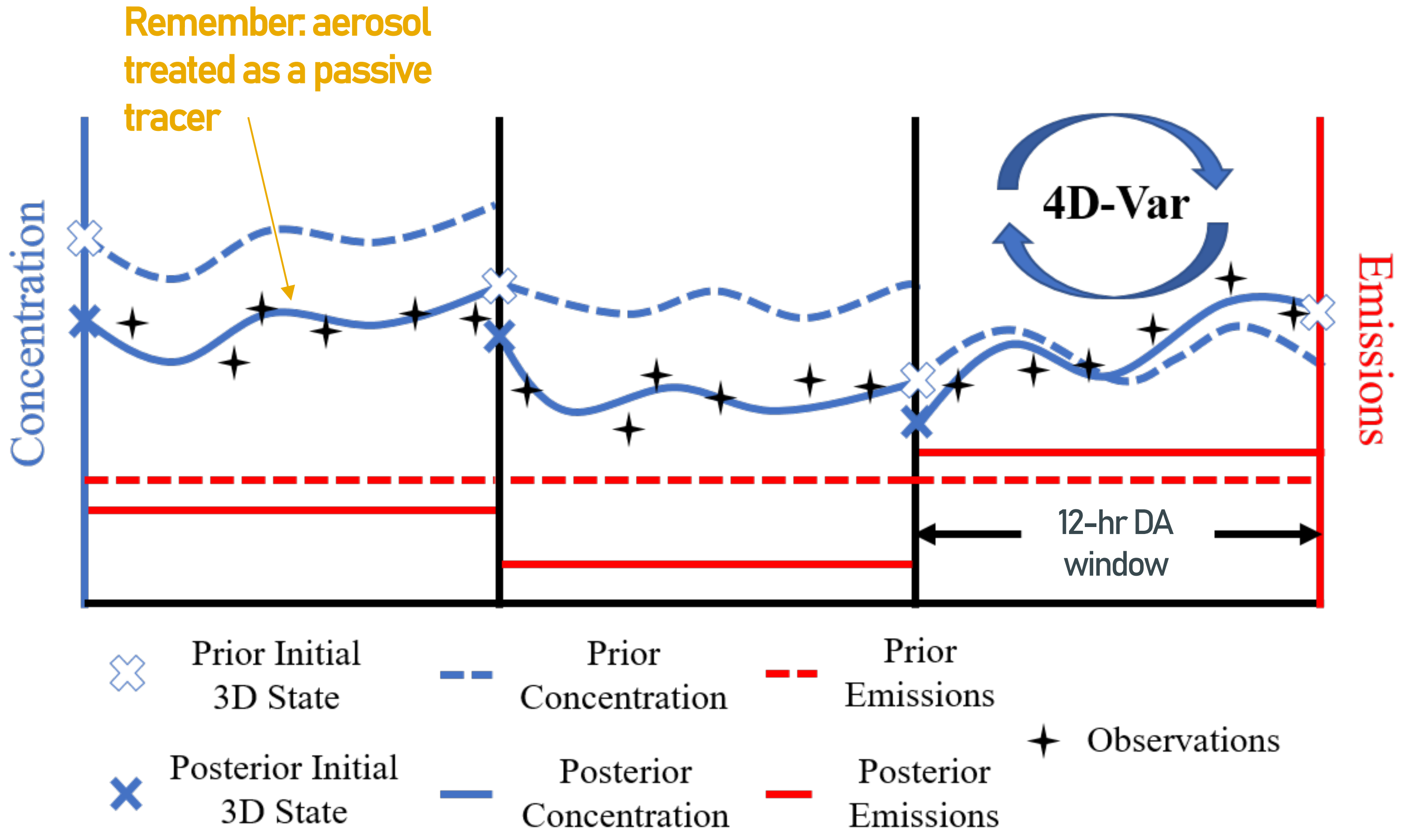
Remember: aerosol treated as a passive tracer



Emissions assumed constant over the 12hr window

NWP 4D-Var is mostly defined as an initial value problem. Only initial conditions are changed, and model error is relatively small

Including emissions in the control vector



NWP 4D-Var is mostly defined as an initial value problem. Only initial conditions are changed, and model error is relatively small

How to improve?

Use the data assimilation system to adjust surface fluxes at the same time as the initial conditions

Joint state/emissions 4D-var inversion system

J_b: background constraint for x

J_p: constraint for emission scaling factors

$$J(x,p) = (x - x_b)^T B^{-1}(x - x_b) + (p - p_b)^T B_p^{-1}(p - p_b)$$

State control vector

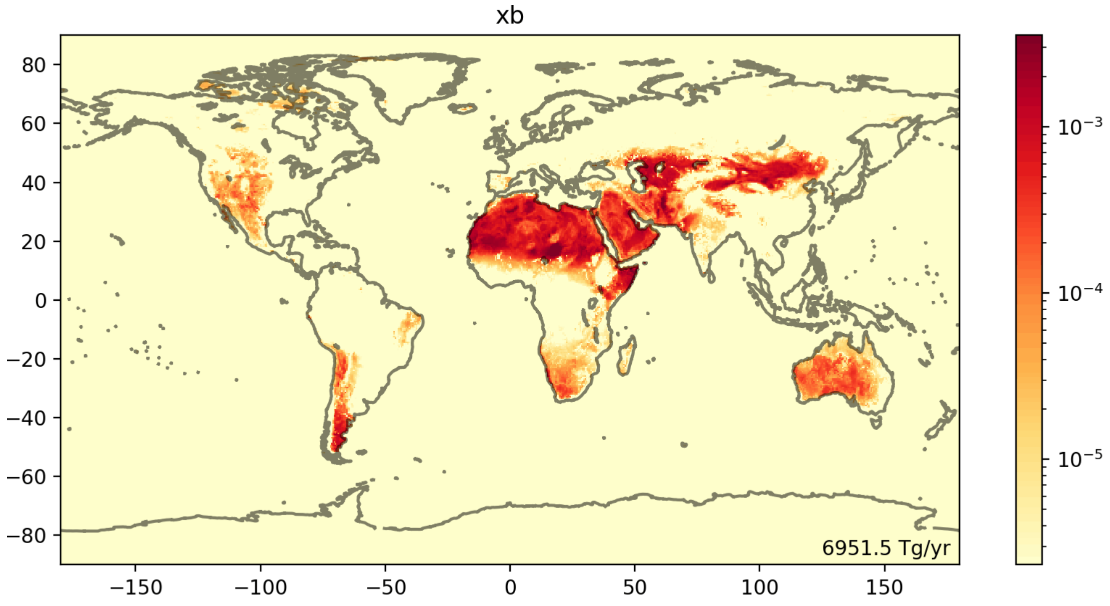
Parameter (e.g. scaling factors)

$$+ \quad \sum_{i=0}^{n}(y_i - H_i[x_i,p])^T R_i^{-1}(y_i - H_i[x_i,p])$$

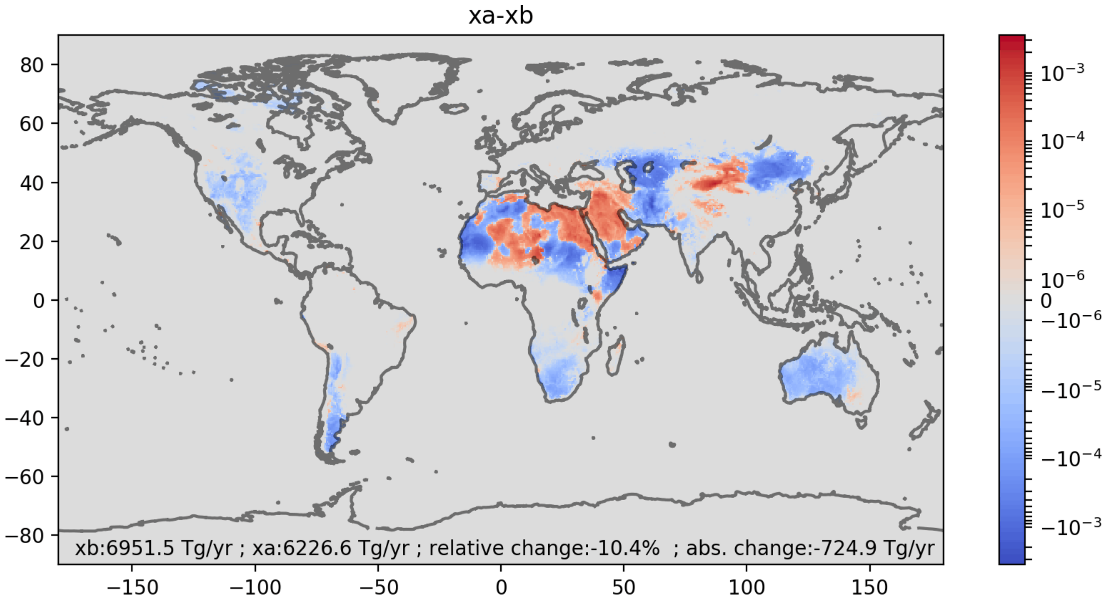
J_o: observation constraint

- Joint optimisation of emissions and initial conditions
- Optimised emissions for dust
- TL/AD of simplified dust emissions; currently no dust emissions are included within the minimisation process
- 2D scaling factors p applied to emission fields
- Prior error definition:
  - Global constant or 2D map of standard error
  - Spatial correlation length scale (via B_p)

Scaled emissions



Yearly averaged dust emissions for 2017



Yearly averaged emission increments for 2017 due to scaling factors

- Untangling the signal from total AOD into the emissions for a specific tracer would be very complicated, if not impossible
- More feasible is using specific aerosol species observations to constrain the emissions of that species
- VIIRS dust flagged AOD observations used to produce scaling factors for IFS dust emissions as part of the CAMAERA HE project
- IASI 10um AOD would also be another option, since it targets coarse dust.

HE CAMAERA project results

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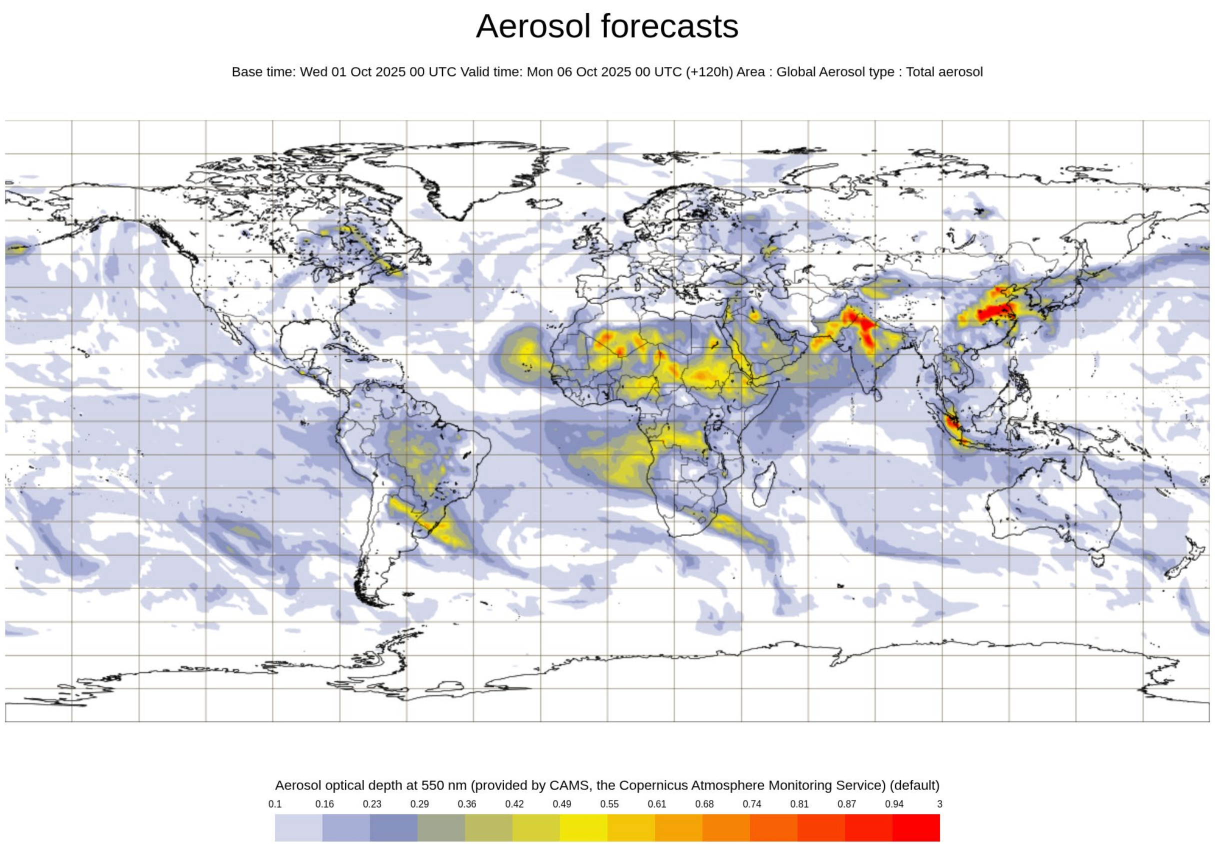
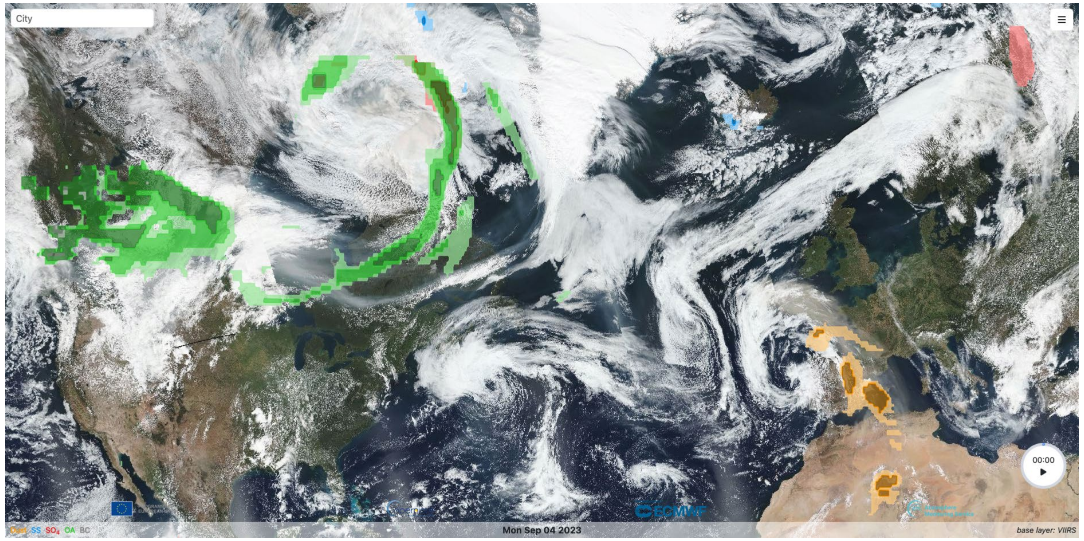
Forecasts (aerosol alert service)

- CAMS produces two five-day forecasts every day
- These start from initial conditions at 0300 and 1500 calculated through data assimilation
- They are freely available from the CAMS website



https://atmosphere.copernicus.eu/charts/packages/cams/

CAMS aerosol alerts:
https://aerosol-alerts.atmosphere.Copernicus.eu/



Organic matter, desert dust, sea salt, sulphate

- The CAMS aerosol alert service provides daily warnings for significant events like forest fires, dust storms, and intense anthropogenic pollution episodes
- Register to the service and get specific warnings tailored to your requirements

Surface air quality (policy support)

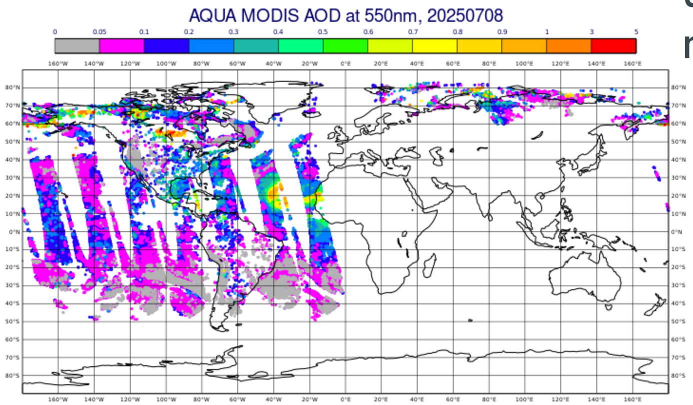
- CAMS provides policy tools to help identify the source, sector and quantity of PM
  - Chemical species of aerosol
  - Country impact/contribution
  - Sector apportionment
  - Policy scenarios

https://atmosphere.copernicus.eu/policy-tools

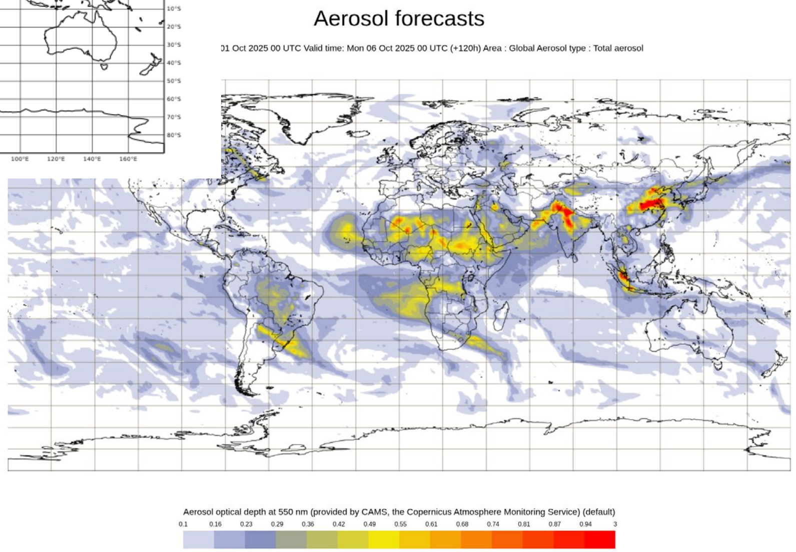
- Air quality is a very important aspect of the work of CAMS
- Surface quantity, which is impacted by short- and long-range aerosols
- PM10 – Particulate Matter smaller than 10um

Summary and conclusions

Using observations to update forecasts keeps models close to reality



Correctly estimating and understanding the uncertainty in both the model and the observations is very important



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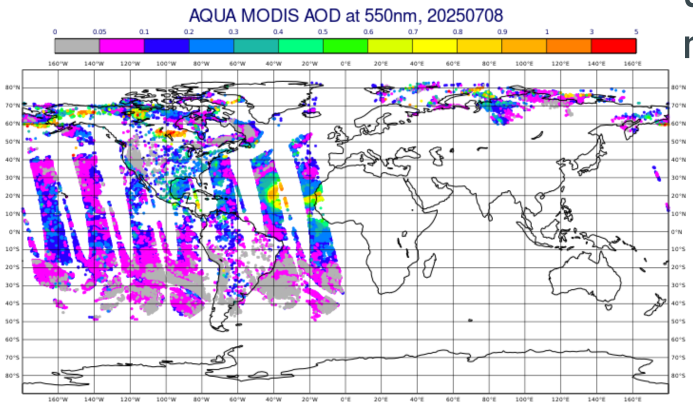

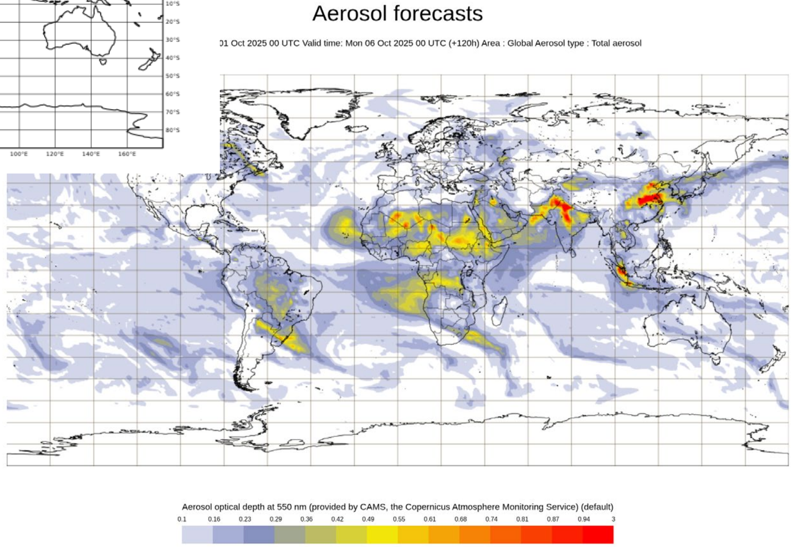

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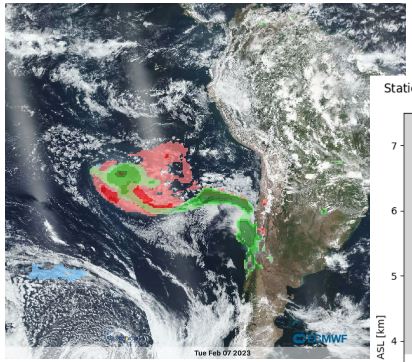

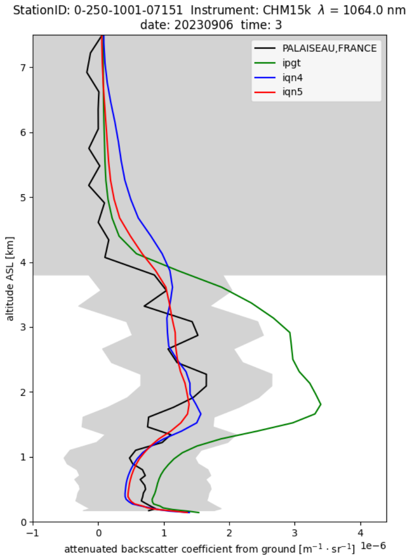

Challenges still remain to adjust the individual aerosol species and the profiles of aerosols

Summary and conclusions

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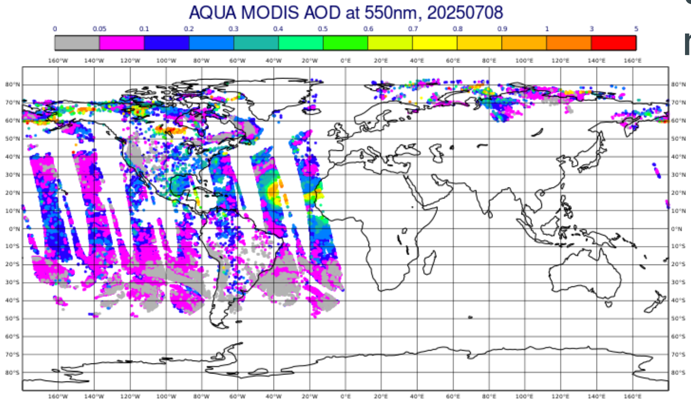

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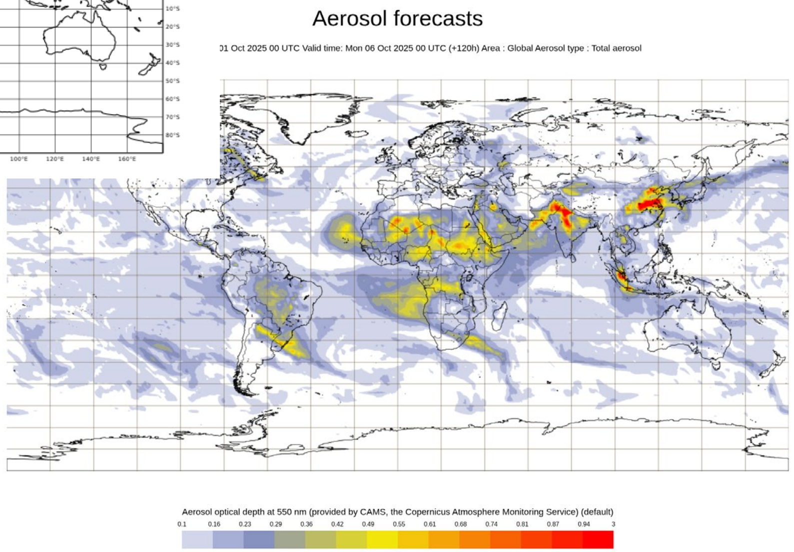

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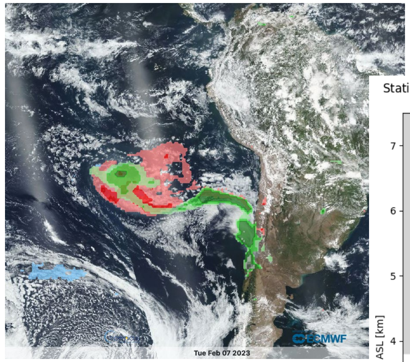

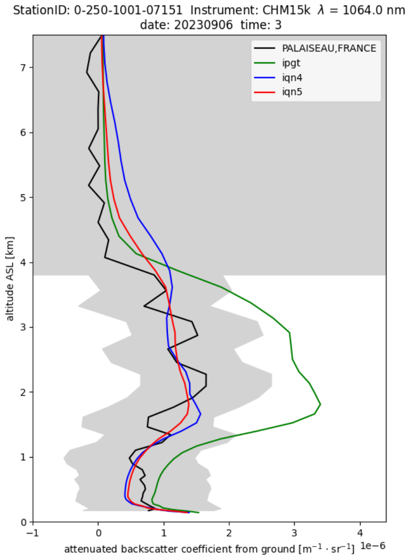

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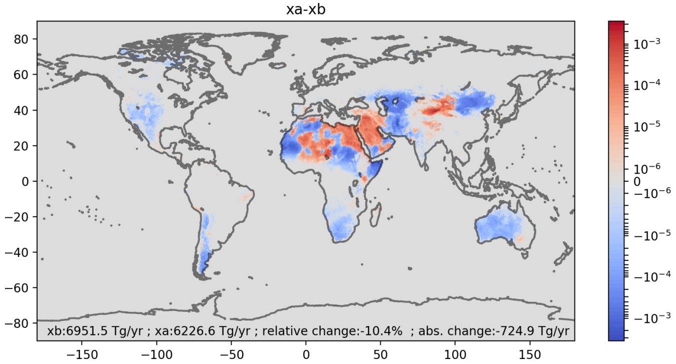

There is the potential to improve emissions as well as initial conditions through observations

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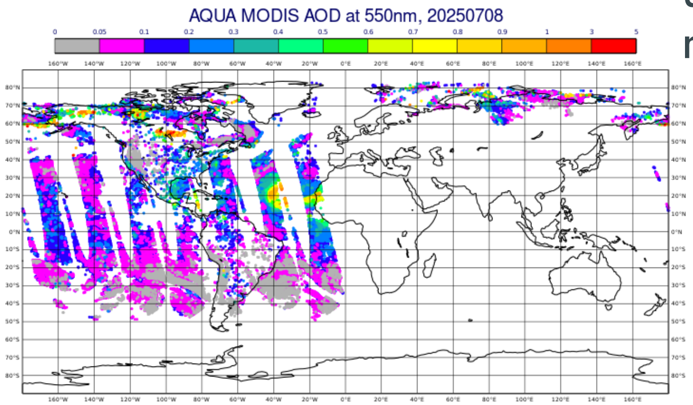
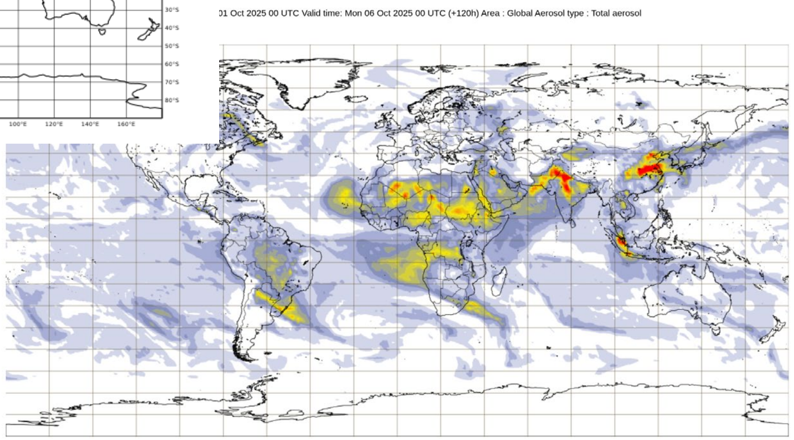
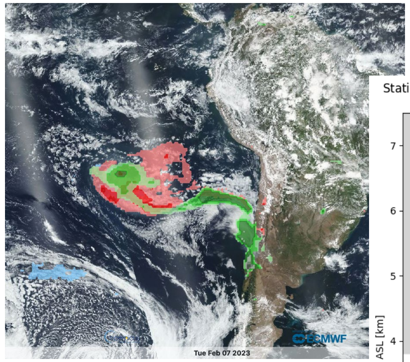
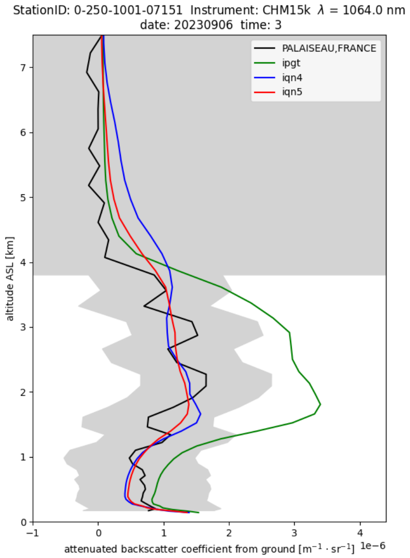


Aerosol forecasts







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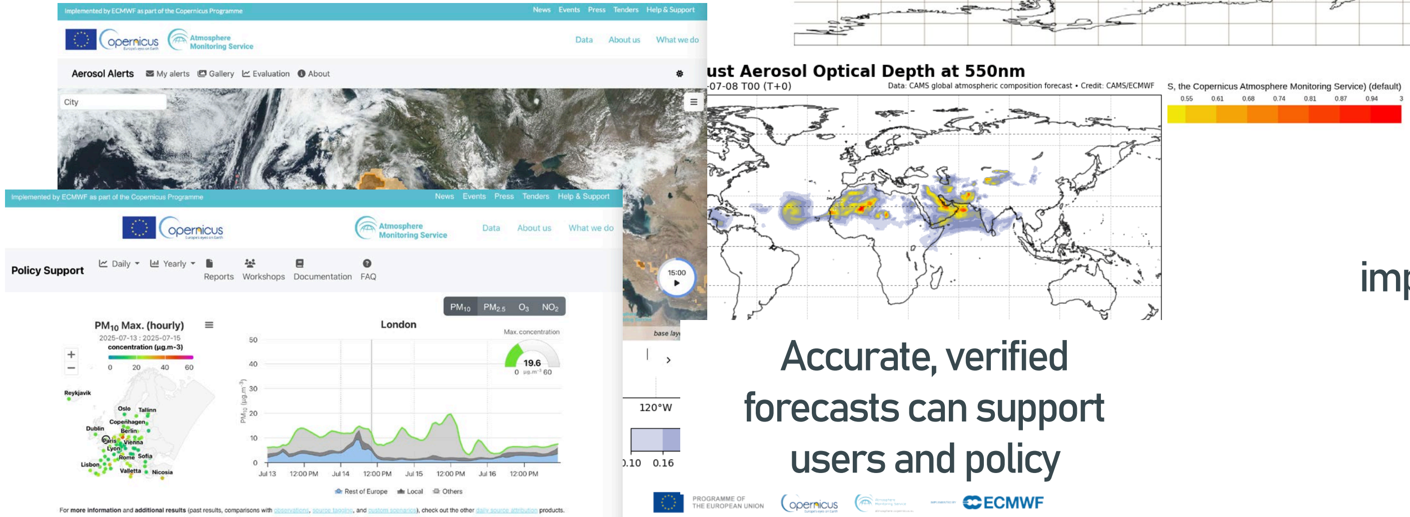
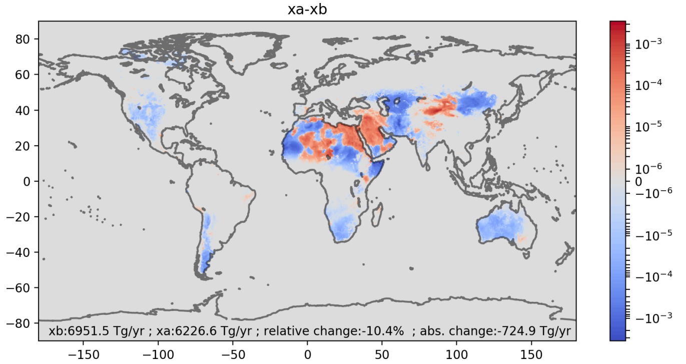


Accurate, verified forecasts can support users and policy

There is the potential to improve emissions as well as initial conditions through observations



Thank you!

Questions are welcome.