Data Assimilation: Integrating satellite data into the CAMS global system

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Fourth Joint School on Atmospheric Composition
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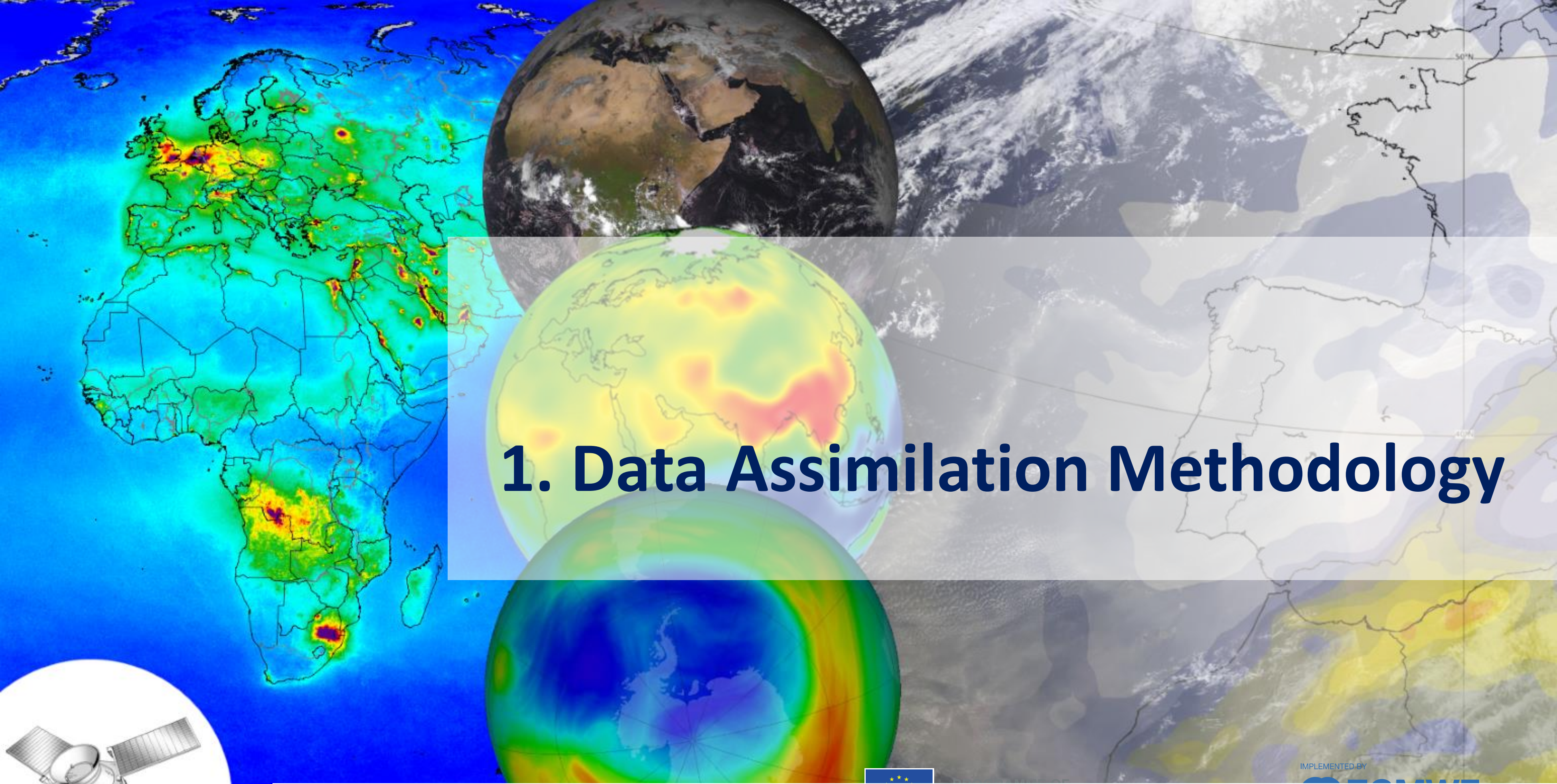
Atmosphere Monitoring

Outline

1. Data assimilation methodology for atmospheric composition
2. Emission inversion
3. Potential issues when assimilating satellite data
4. Reanalysis
5. Summary

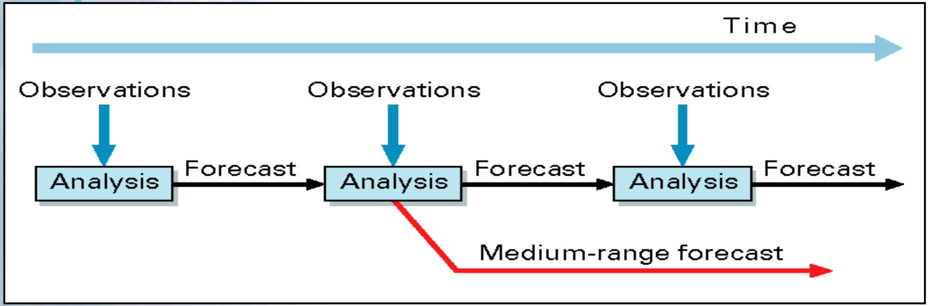
With thanks to the ECMWF CAMS team, particularly Melanie Ades and Nicolas Bousserez.

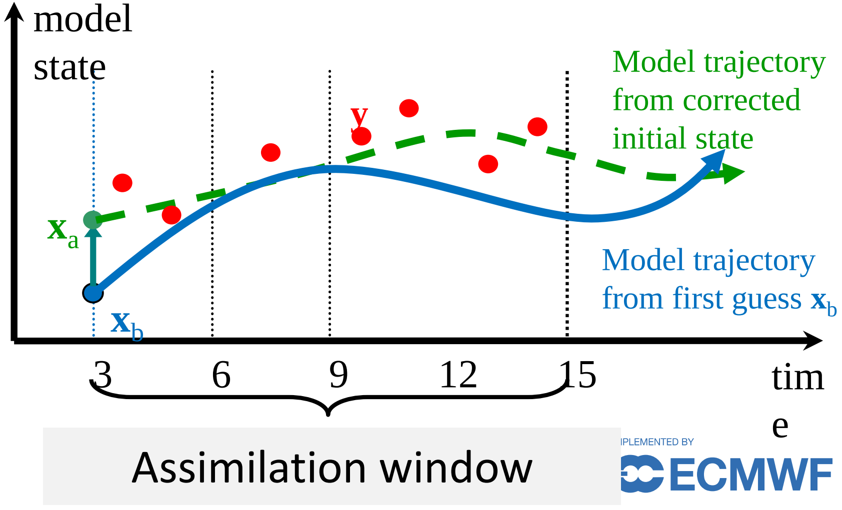


1. Data Assimilation Methodology

Variational Data assimilation

- 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
- CAMS uses ECMWF's 4-dimensional variational data assimilation system or 4D-Var
- For AQ other parameters than IC might be of interest





Cost function

Data assimilation for atmospheric composition is in principle no different from NWP data assimilation

Analysis: x that minimizes cost function

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

Cost function

J_b
Background term

J_o
Observation term

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

- **Strong constraint 4D-Var** assumes perfect model over assimilation period
- Weak constrained 4D-Var includes a model error term

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Data assimilation methodology

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Control variables

NWP

vorticity
divergence
temperature
surface pressure (logarithm)
specific humidity

Atmospheric Composition

ozone
carbon monoxide
nitrogen dioxide
formaldehyde
sulphur dioxide

carbon dioxide
methane

aerosol mixing ratio

IFS

Data assimilation methodology

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Chemical module

GHG module

Aerosol module

Chemical Module

IFS

TM5 (CB05)
57 species, 131 reactions
Photolysis, dry and wet deposition

Data assimilation methodology

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IFS

Chemical module

GHG module

Aerosol module

Greenhouse Gas Module

CHTESSEL
Photosynthesis & ecosystem respiration model
Diagnoses the gross primary production of CO_2 by plants and release of CO_2 by soil

CH_4 comes from prescribed emissions and climatological loss

Data assimilation methodology

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IFS

Chemical module

GHG module

Aerosol module

Aerosol bin scheme

14 aerosol-related prognostic variables:
3 bins sea-salt, 3 bins dust, Black carbon, Organic matter, Sulphate,
2 bins Nitrate, Ammonium

Emissions, dry and wet deposition, sedimentation

Incremental 4D-Var

Min J $\Longleftrightarrow$ $\nabla_{\boldsymbol{\delta x_0}} J = \mathbf{B}^{-1}\,\delta x_0 + \sum_{i=0}^{n} \boldsymbol{M}'^{T}\,\boldsymbol{H}_i^{T}\boldsymbol{R}_i^{-1}(\boldsymbol{H}_i\boldsymbol{M}'_i[\delta x_0] - d_i) = 0$

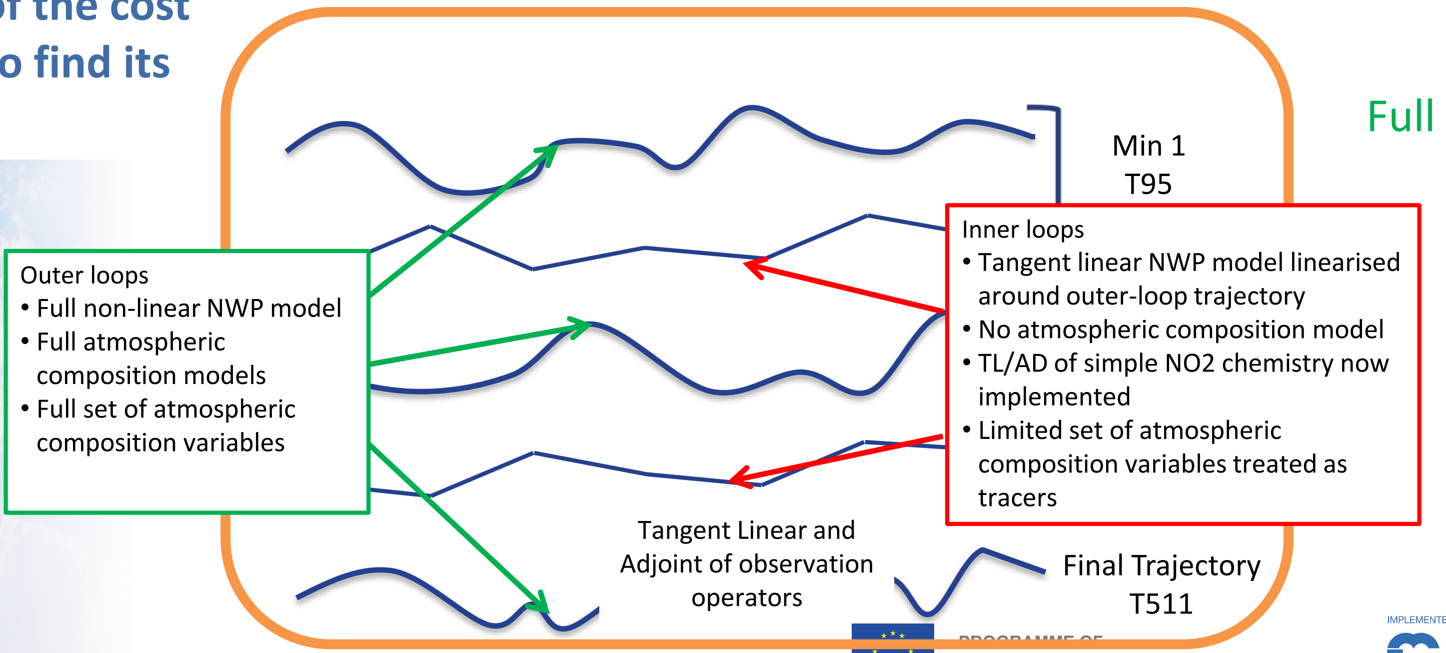
Adjoint

Tangent linear

$d_i = y_i - H_i x_b(t_i)$

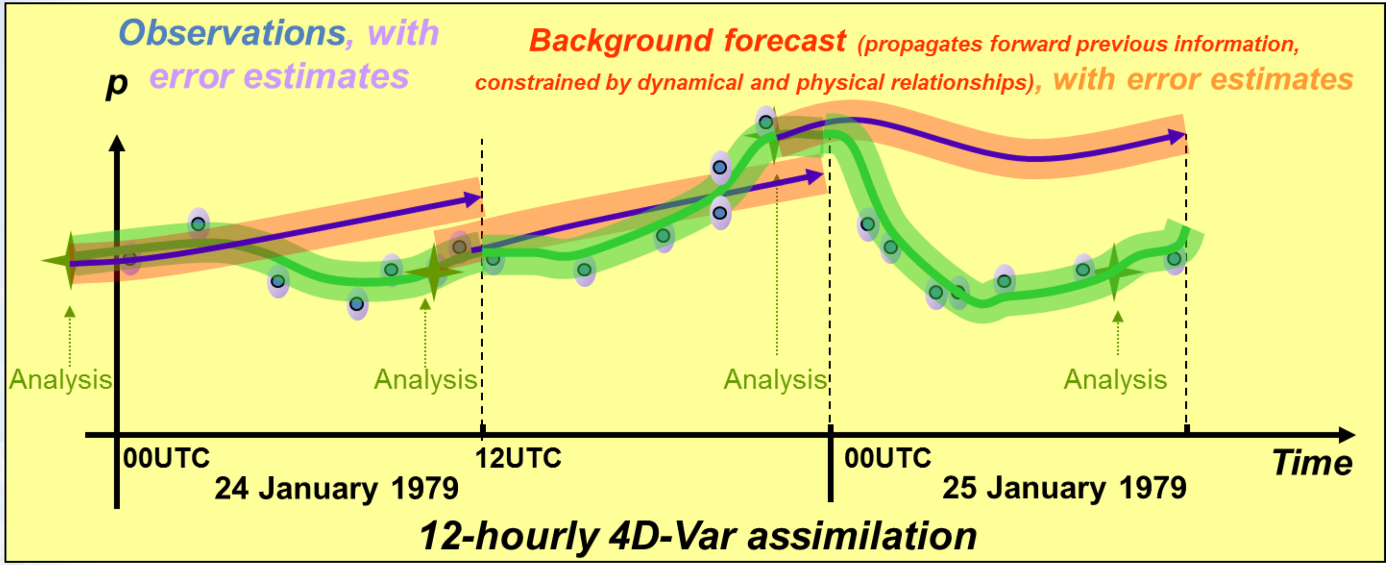
Full model

We calculate the gradient of the cost function to find its minimum



2. Emission Inversion

Initial condition vs boundary problem



- NWP 4D-Var is mostly defined as an initial value problem. Only initial conditions are changed and model error is relatively small.
- AC modelling depends on initial state and surface fluxes
- Large part of chemical system not sensitive to initial conditions because of chemical equilibrium, but dependent on other parameters (e.g. emissions, deposition, reaction rates, …) which all might have errors

Short-lived memory of NO2 assimilation

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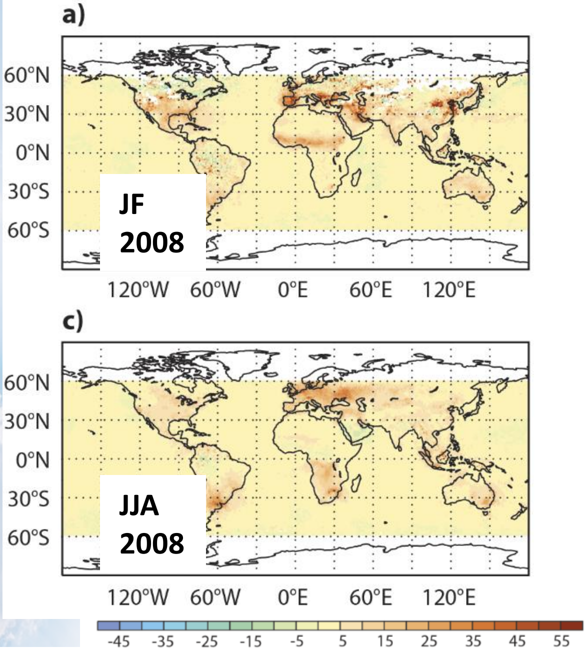
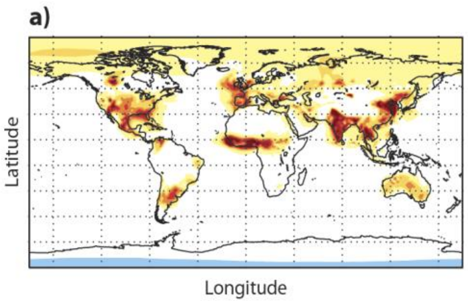
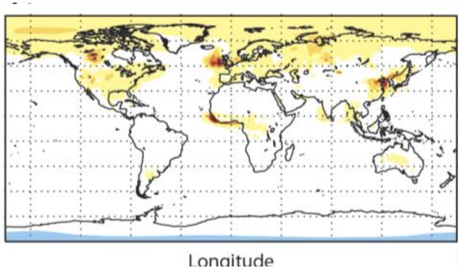
OMI NO2 analysis increment [%]





Differences between Assim and CTRL (JF 2008)



Difference between 12h forecasts from ASSIM and CTRL (JF 2008)

- Large positive increments from OMI NO2 assim
- Large differences between analyses of ASSIM and CTRL
- Impact is lost during subsequent 12h forecast
- Constraining emissions (in addition of IC) would give a better initial state and persistence of forecast improvements throughout the DA window

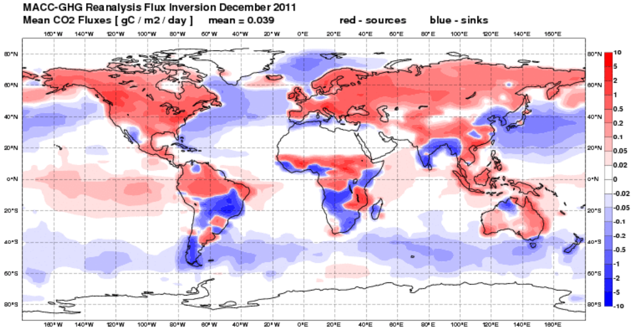
Inness et al. (2015, ACP)

Examples of emissions

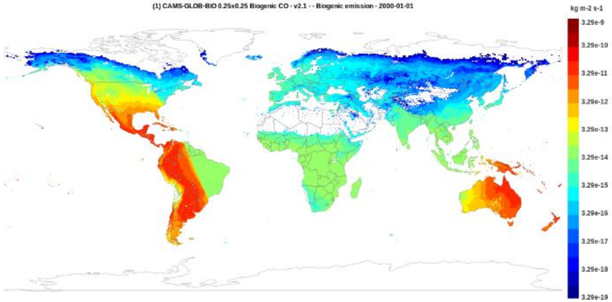
TNO European anthropogenic NOx emissions

Monitoring

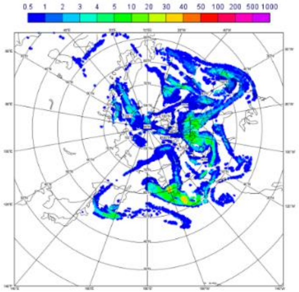
CO2 fluxes



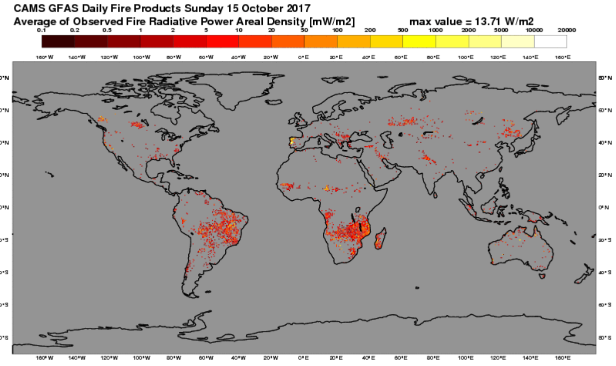
CAMS_GLOB biogenic CO emissions



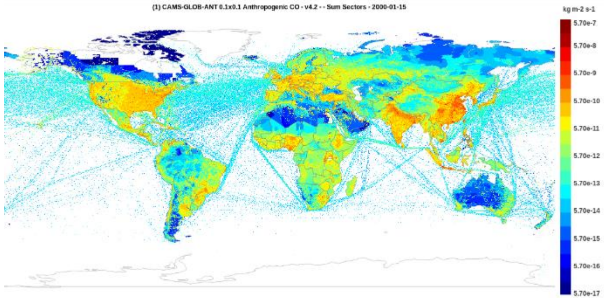
Volcanic SO2



Biomass burning, 15 October 2017



CAMS_GLOB anthropogenic emissions



AMME OF THE EUROPEAN UNION

Europe's eyes on Earth

IMPLEMENTED BY ECMWF

Emissions

- Emissions are one of the major uncertainties in composition modeling (can not be measured directly)
- The compilation of emissions inventories is a labour-intensive task based on a wide variety of socio-economic and land use data
- Some emissions can be “modeled” based on wind (dust and sea salt aerosol) or temperature (biogenic emissions)
- Some emissions can be observed indirectly from satellites instruments (Fire radiative power, burnt area, volcanic plumes)
- Trends are applied to inventories from previous years to produce future emission datasets
- “Inverse” methods can be used to correct prior emission estimates using observations of concentrations and models

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Joint state/emissions 4D-var inversion system

$$J(x,p) = \underbrace{(x - x_b)^T B^{-1} (x - x_b)}_{J_b\text{: background constraint for } x} + \underbrace{(p - p_b)^T B_p^{-1} (p - p_b)}_{J_p\text{: constraint for emission scaling factors}}$$

State control vector

Parameter (e.g. scaling factors)

$$+ \underbrace{\sum_{i=0}^{n} (y_i - H_i[x_i, p])^T R_i^{-1} (y_i - H_i[x_i, p])}_{J_o\text{: observation constraint}}$$

- Joint optimisation of emissions and initial conditions
- Optimized emissions e.g. CO2, CH4, CO & NO2
- TL/AD of simplified chemistry: link between NO emissions and NO2 observations
- 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)
    - NO/CO2 emission error correlation in B_p -> NO2 obs can contrain CO2 emissions

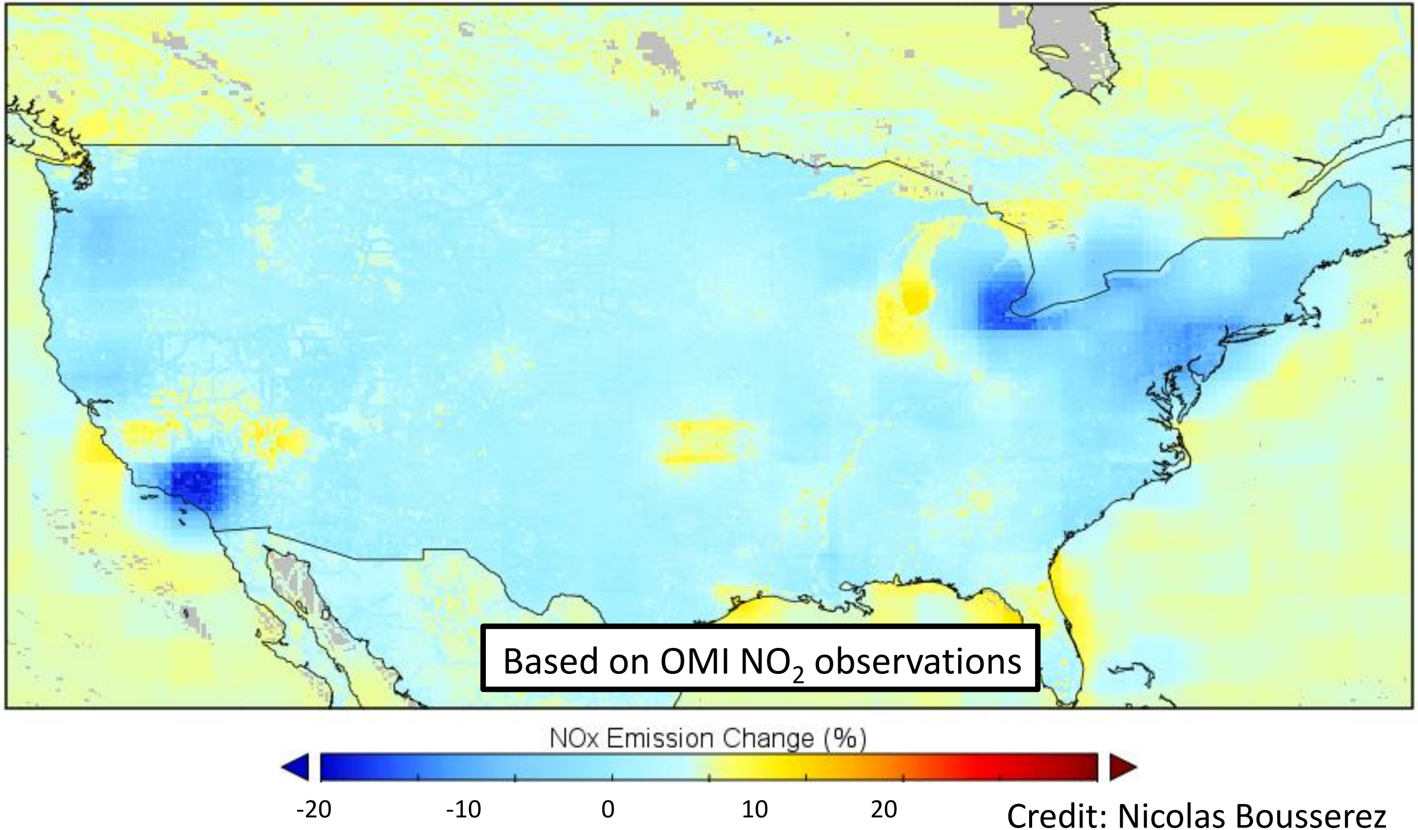
ED BY ECMWF

Credit: Nicolas Bousserez

Impact of Covid lockdown on US anthropogenic emissions

- Differences between posterior emissions May 2020 – May 2019 show impact of covid lockdown
- Based on CAMS operational emissions in the prior and a fixed prior uncertainty of 40%.
- **10-20%** reduction consistent with previous studies (e.g., *Keller et al. (2020); Liu et al. (2020)*)
- Provided uncertainties in NO/CO_2 emission ratios are accounted for, top-down NO_2 estimates could help quantify CO_2 emissions variability

NO_x emission changes (%) between May 2020 and May 2019



Credit: Nicolas Bousserez

3. Potential issues when assimilating satellite data

Biases and Bias correction

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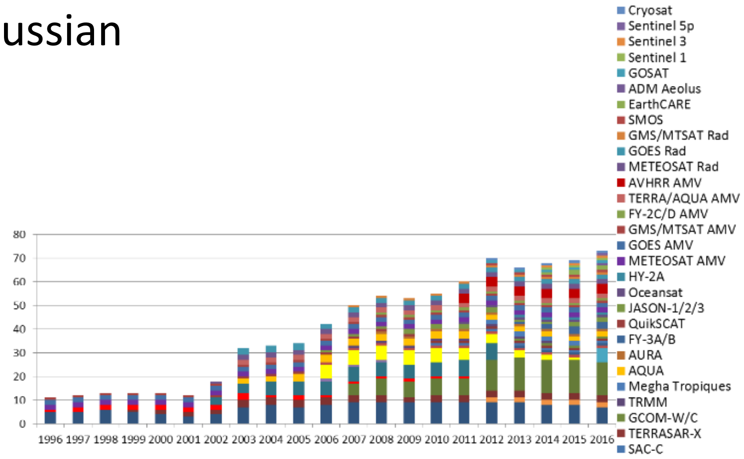
$$J(x) = \underbrace{(x - x_b)^T B^{-1} (x - x_b)}_{\text{Background constraint}} + \underbrace{\sum_{i=0}^{n} (y_i - H_i[x_i])^T R_i^{-1} (y_i - H_i[x_i])}_{\text{Observation constraint}}$$

- 4D-Var assumes that errors are unbiased and gaussian
- Biases in the input [y – h(x)] can arise from:
  - errors in the actual observations
  - errors in the model background
  - errors in the observation operator
- Often no true reference in the real world
- Need an adequate bias model to correct for this
  - Correct observation biases before use
  - Adaptive bias correction system (better for complex and changing observation system)



Variational bias correction scheme

The original problem:

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

The modified problem:

$$\mathbf{J}(\mathbf{x}, \boldsymbol{\beta}) = \overbrace{(\mathbf{x} - \mathbf{x}_b)^T \mathbf{B}_x^{-1} (\mathbf{x} - \mathbf{x}_b)}^{J_b\text{: background constraint for x}} + \overbrace{(\boldsymbol{\beta}_b - \boldsymbol{\beta})^T \mathbf{B}_{\beta}^{-1} (\boldsymbol{\beta}_b - \boldsymbol{\beta})}^{J_\beta\text{: background constraint for bias } \beta}$$
$$+ \underbrace{[\mathbf{y} - \mathbf{b}_o(\mathbf{x}, \boldsymbol{\beta}) - \mathbf{h}(\mathbf{x})]^T \mathbf{R}^{-1} [\mathbf{y} - \mathbf{b}_o(\mathbf{x}, \boldsymbol{\beta}) - \mathbf{h}(\mathbf{x})]}_{J_o\text{: bias-corrected observation constraint}}$$

Examples of variational bias correction

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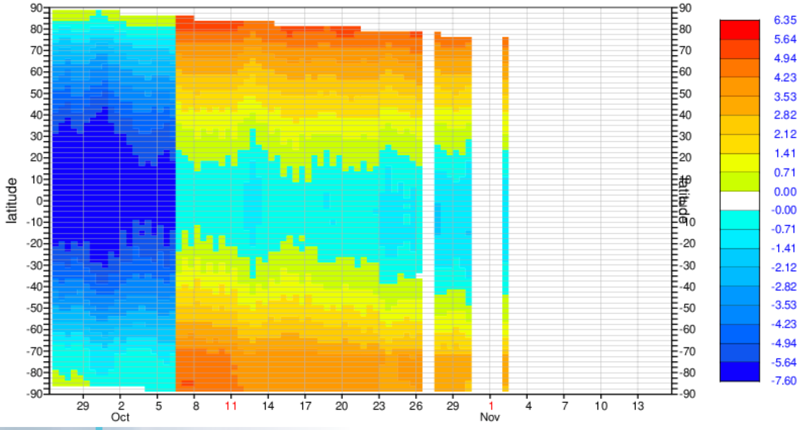
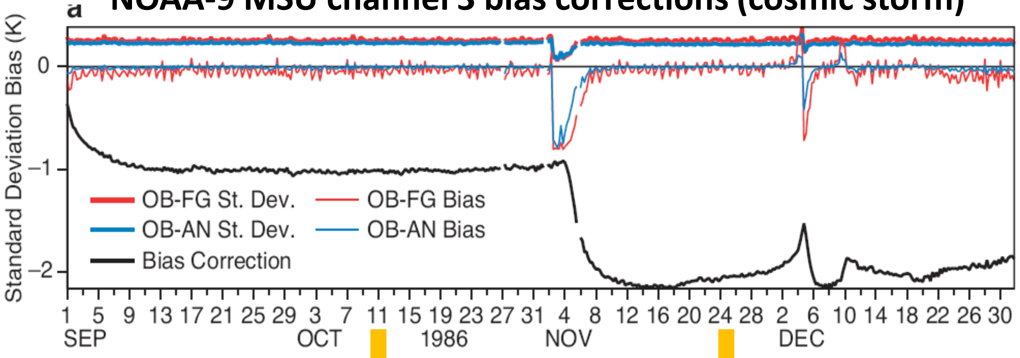
Variational bias correction:

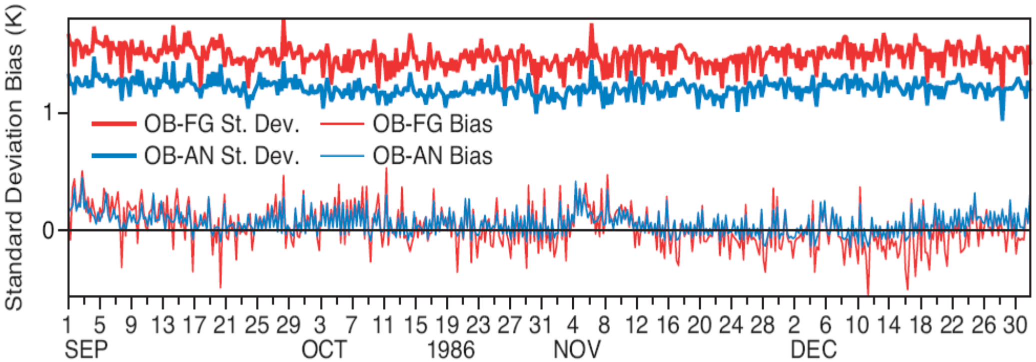
- Spins up
- Adjusts to changes in model or data
- Removes biases



NOAA-9 MSU channel 3 bias corrections (cosmic storm)



200 hPa temperature departures from radiosonde observations



Observation operators: Mapping model and obs

$$\sum_{i=0}^{n}(y_i - H_i[M_i(x_0)])^T R_i^{-1}(y_i - H_i[M_i(x_0)])$$

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 hopes to explore this in the future

Assimilation of retrievals:

Good characterization of retrieval is crucial:

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

Assimilating retrievals: Column retrieval

We can make use of the averaging kernel **A** in the observation operator

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

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

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

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

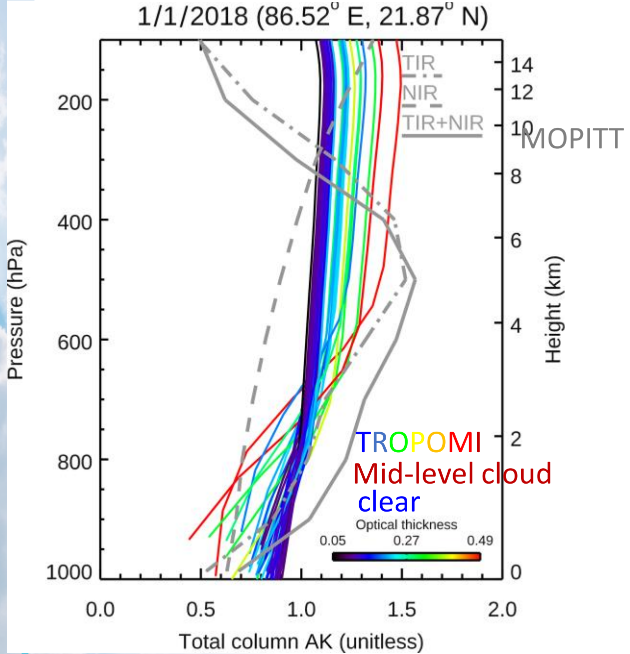
$$d = \hat{y} - \widehat{H}(\mathbf{x}_m) = \mathbf{y}_a + \mathbf{A}(\mathbf{y} - \mathbf{y}_a) + \varepsilon - (\mathbf{y}_a + \mathbf{A}(H(\mathbf{x}_m) - \mathbf{y}_a))$$
$$= \mathbf{A}(\mathbf{y} - H(\mathbf{x}_m)) + \varepsilon$$

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 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

Examples of total column CO averaging kernels

TROPOMI & MOPITT AKs

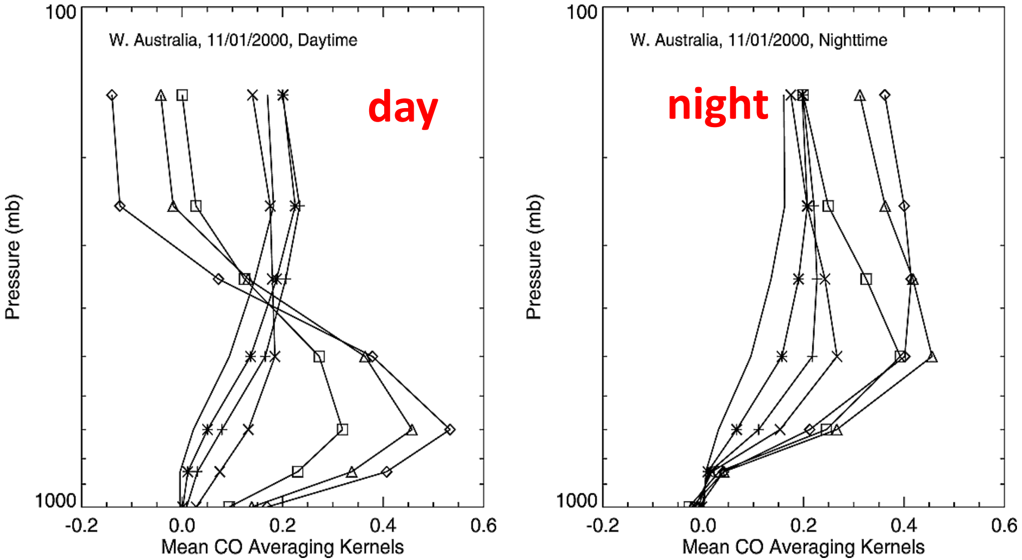


Martínez-Alonso et al. (2020, AMT)

- TROPOMI has sensitivity to the CO column
- Clear TROPOMI data have some sensitivity to lower troposphere and PBL

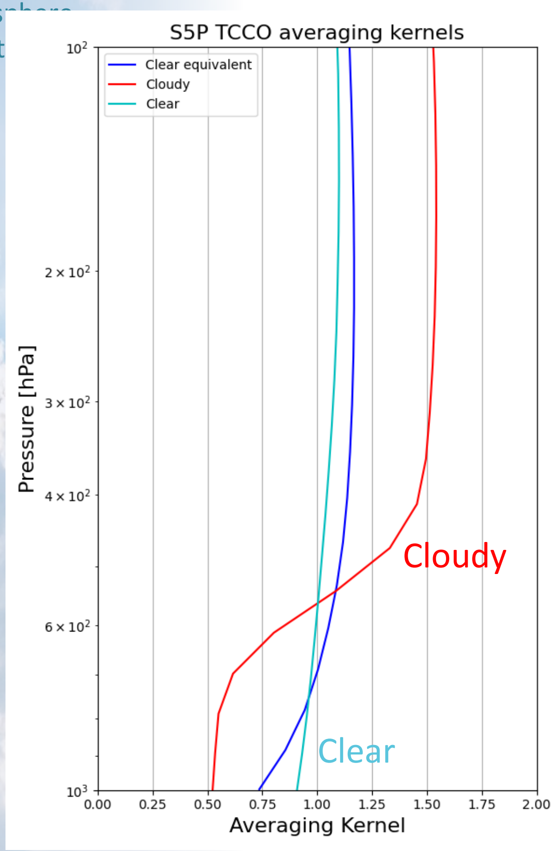
MOPITT AKs

Deeter et al. (2003, JGR)

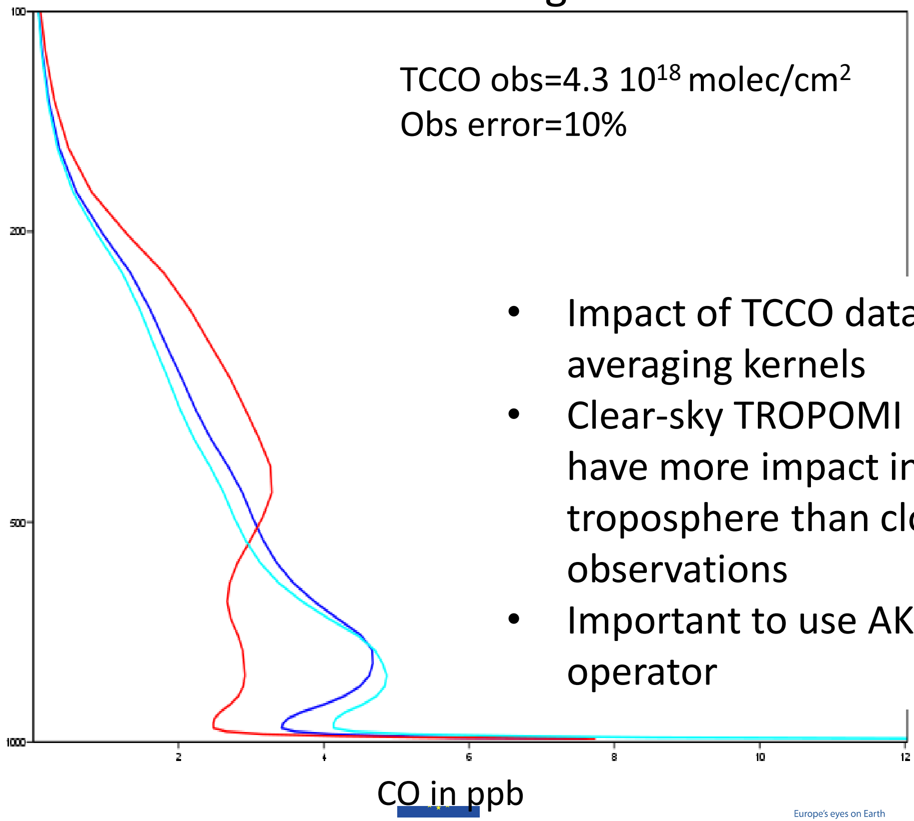


- TIR retrievals give information about mid troposphere
- Diurnal variations of Tsurf affect TIR retrieval over land
- CO near surface more detectable during day, AKs shift downwards
- Diurnal variability of AKs largest over e.g. deserts, smallest over sea

Impact of TROPOMI CO retrievals in DA



Increment from single obs



- Impact of TCCO data depends on averaging kernels
- Clear-sky TROPOMI observations have more impact in lower troposphere than cloudy observations
- Important to use AKs in observation operator

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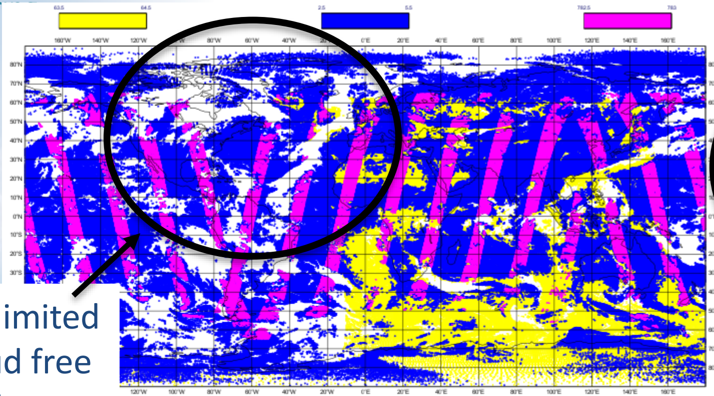
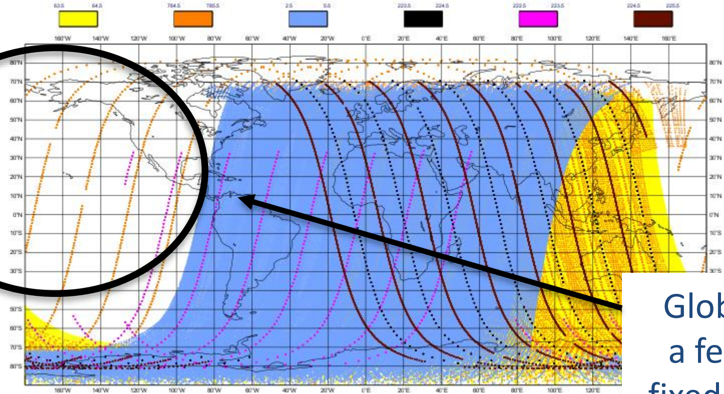
Example of satellite observation coverage

CO: TROPOMI, MOPITT, IASI



O3: TROPOMI, GOME-2,OMI,SBUV,OMPS,MLS

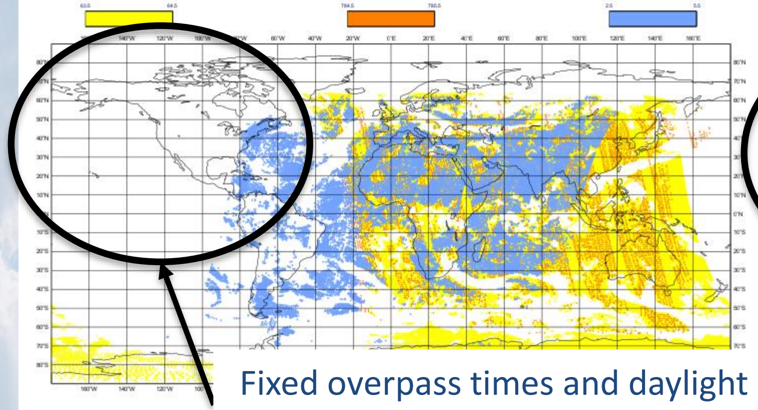


12-hour analysis cycle

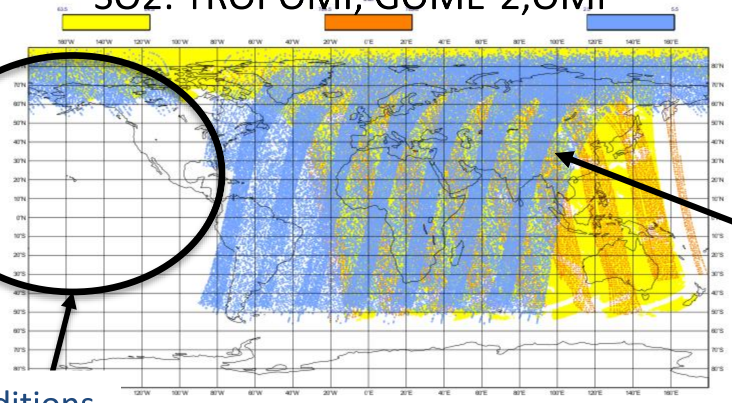
Often limited to cloud free conditions

Global coverage in a few days (LEO) – fixed overpass time

NO2: TROPOMI, GOME-2,OMI



SO2: TROPOMI, GOME-2,OMI



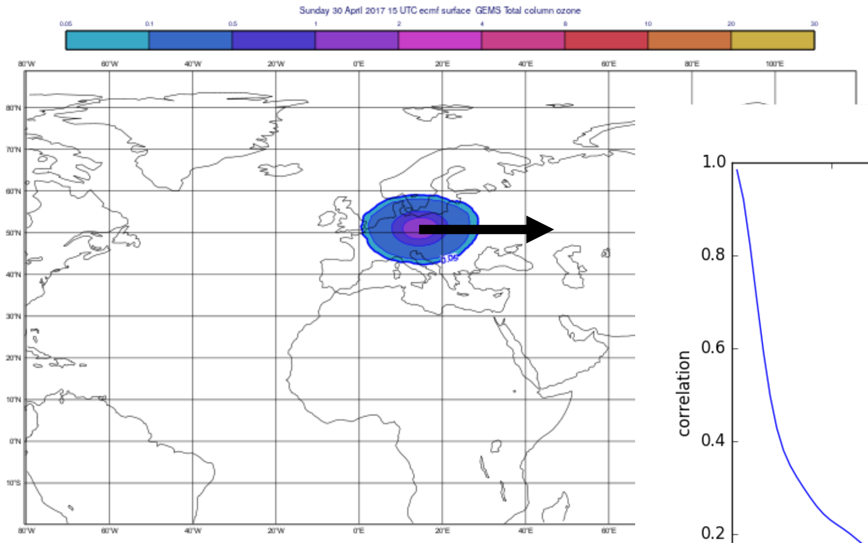
Total or tropospheric columns

Fixed overpass times and daylight conditions only (UV-VIS) -> no daily maximum/cycle

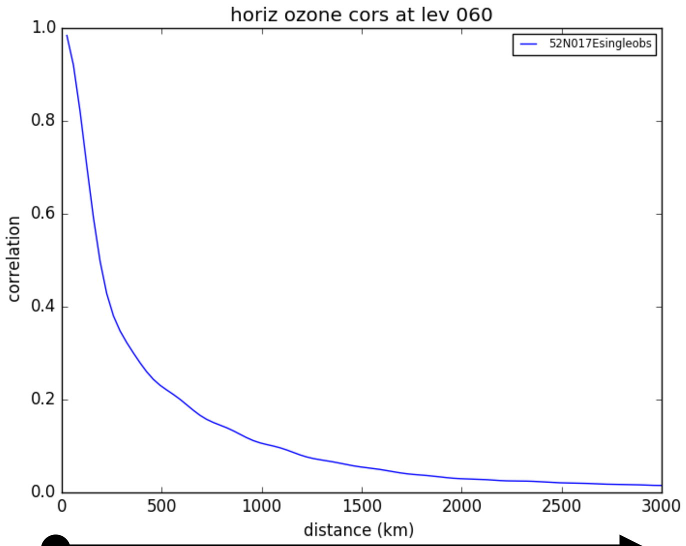
MWF

Limited information content: Total column

Increment from one TC ozone retrieval

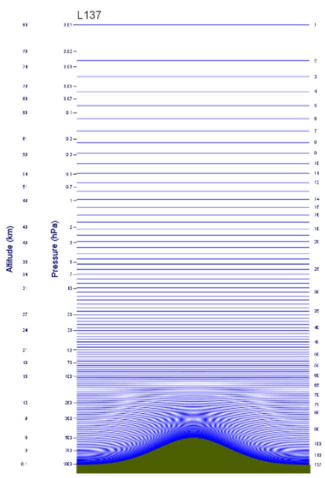


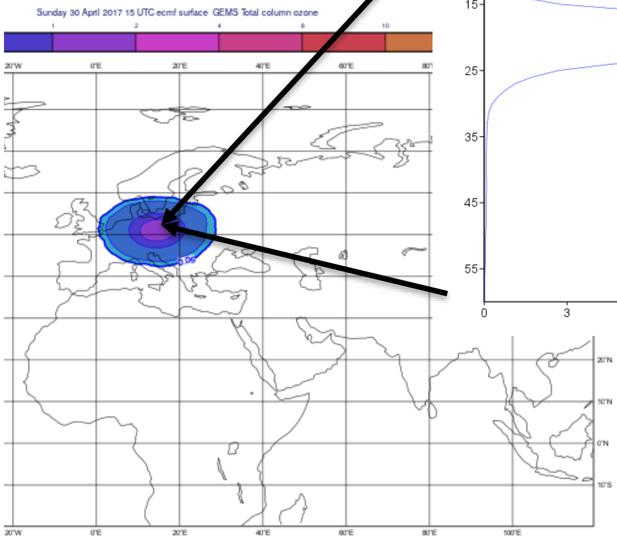
Increment created by a single ozone observation of 375 DU, 10 DU higher than background

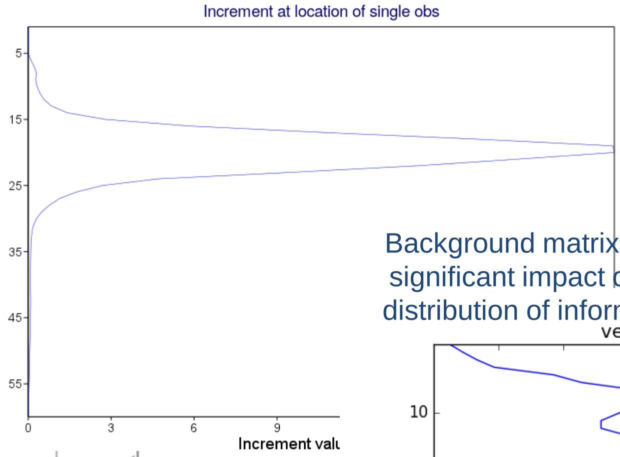


Horizontal correlation from the B-matrix that spreads the information from the single observation in the horizontal

Increment from one TC ozone retrieval

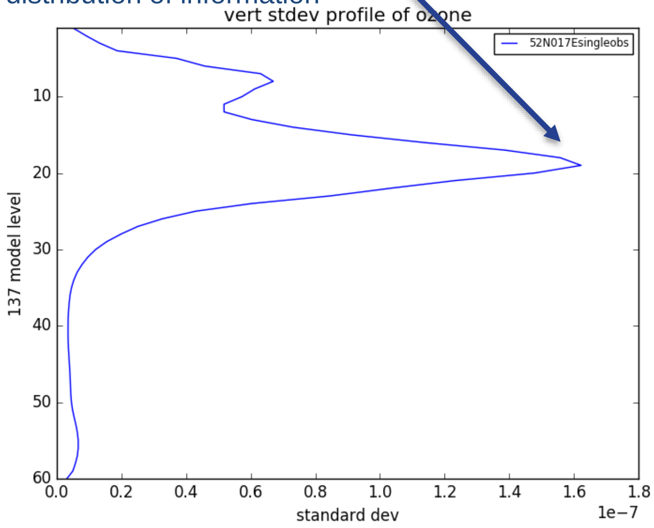






Vertical profile of the increment at the observation location

Background matrix has a significant impact on the distribution of information

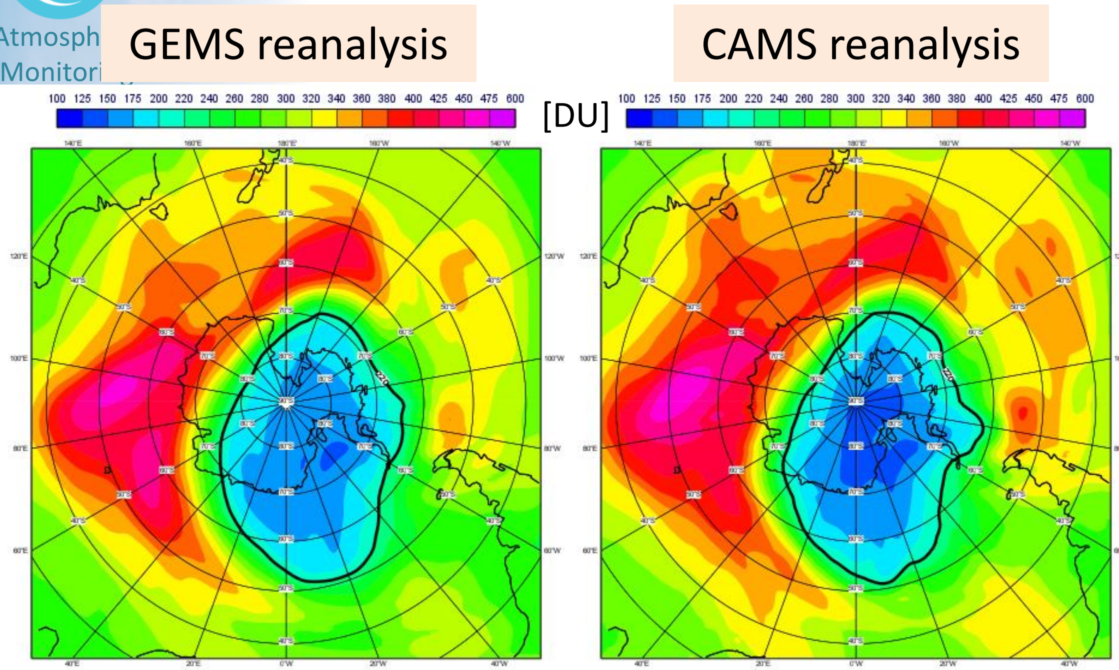


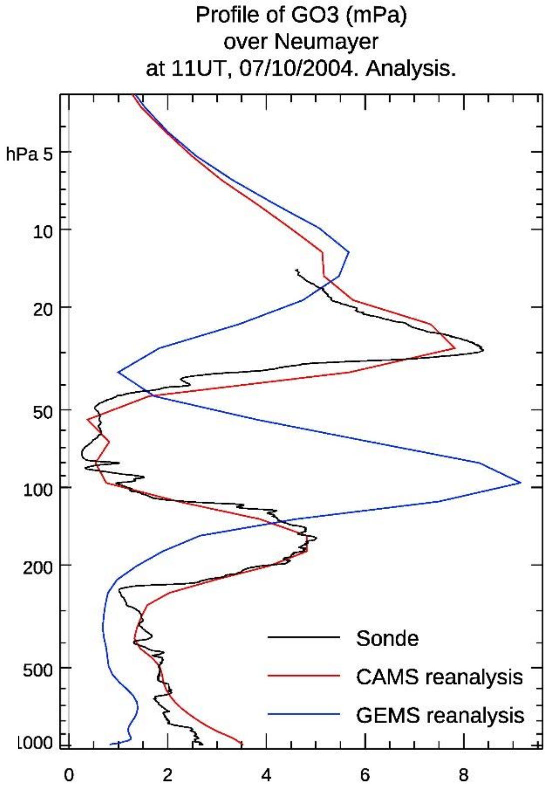
Increment created by a single ozone observation of 375 DU, 10 DU higher than background

Standard deviation from the background matrix at the observation location

Formulation of the B-matrix is very important for AC

An extreme example: Ozone 7 October 2004





Sonde launched by AWI

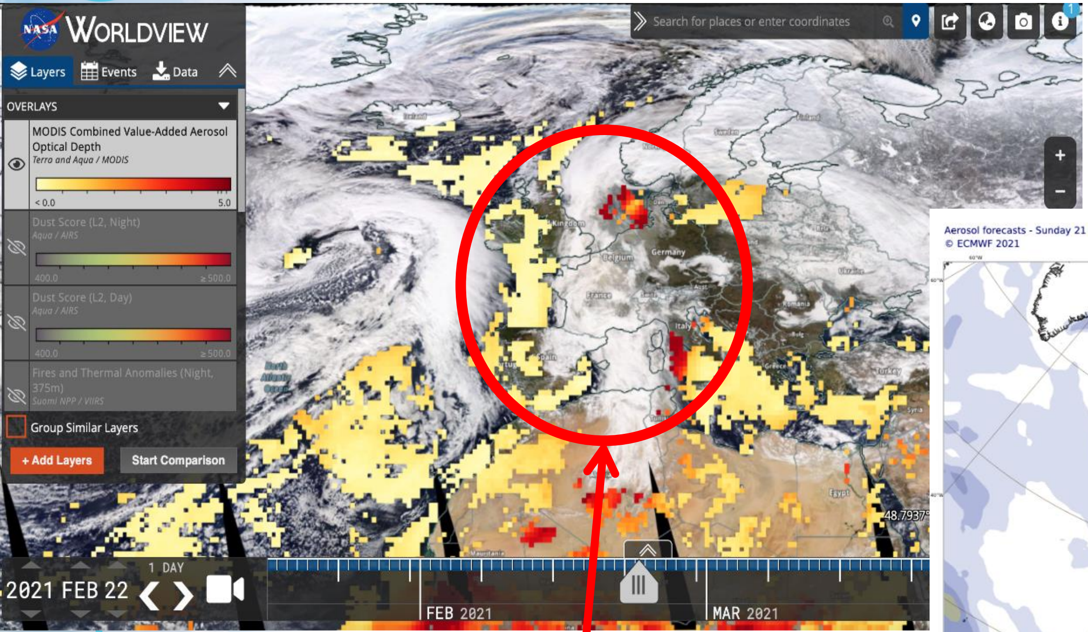
- Similar TCO3 analysis from (old) GEMS reanalysis and CAMS reanalysis
- Huge differences between corresponding O3 profiles
- No profile data (MIPAS, MLS) were assimilated in GEMSRA in Oct 2004 and model had a large O3 bias leading to very bad vertical O3 analysis profiles
- Shows importance of using limb sounding data for O3 analysis

Aerosol analysis

- CAMS aerosol model has 14 aerosol bins:
  - 3 size bins each for sea-salt and desert dust
  - 2 bins (hydrophilic and hydrophobic) each for organic matter and black carbon
  - 1 bin for sulphate
  - 2 bins (fine and coarse) for nitrate
  - 1 bin for ammonium
- Assimilated observations are AOD at 550 nm from MODIS (Aqua and Terra) over land and ocean & PMAp (Metop-BC) over ocean
- Assimilation tests with VIIRS and SLSTR AOD
- Control variable is formulated in terms of the total aerosol mixing ratio.
- Analysis increments are repartitioned into the species according to their fractional contribution to the total aerosol mixing ratio.
- The repartitioning of the total aerosol mixing ratio increment into the different bins is difficult

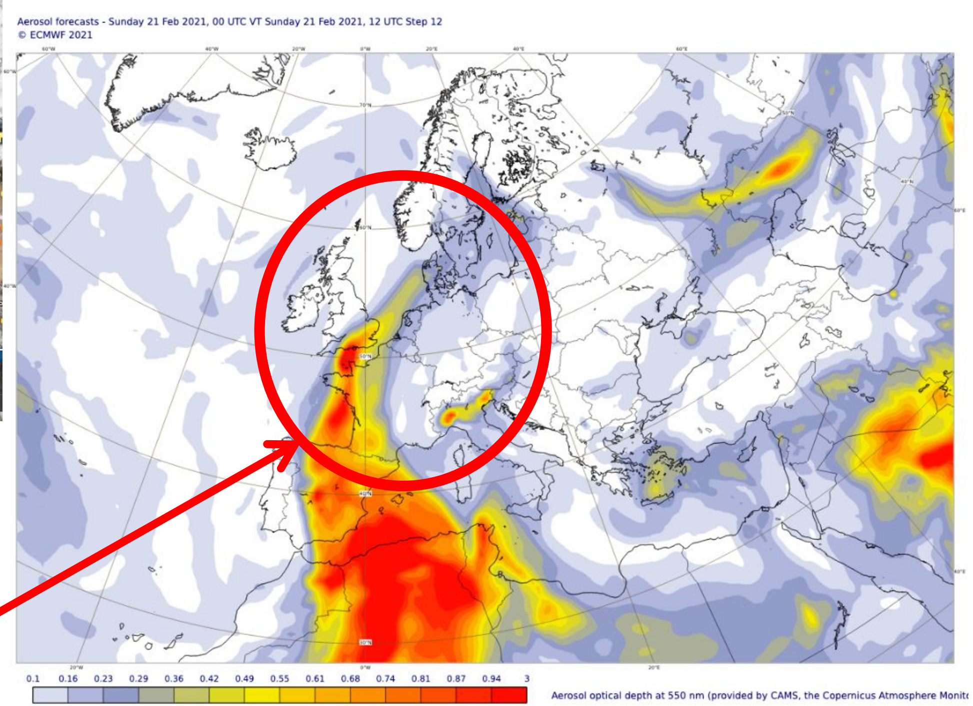
Dust storm February 2021

Credit: Melanie Ades



NASA Worldview – MODIS Aqua and Terra AOD 550nm observations for 20210222

CAMS Total AOD at 550nm 12hr forecast valid at 20210222 12hr

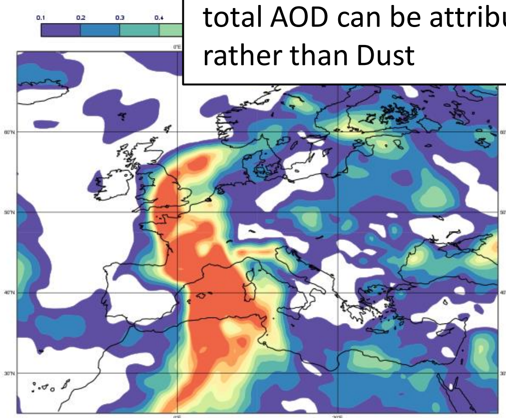


The CAMS forecast does a good job of forecasting the AOD plume from Africa over Northern Europe

Dust test case February 2021

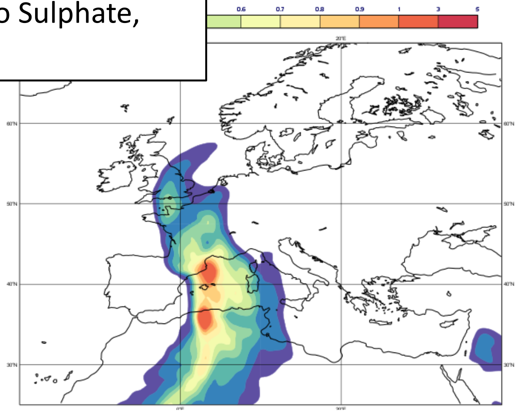
Credit: Melanie Ades

Closer examination shows that some of this total AOD can be attributed to Sulphate, rather than Dust

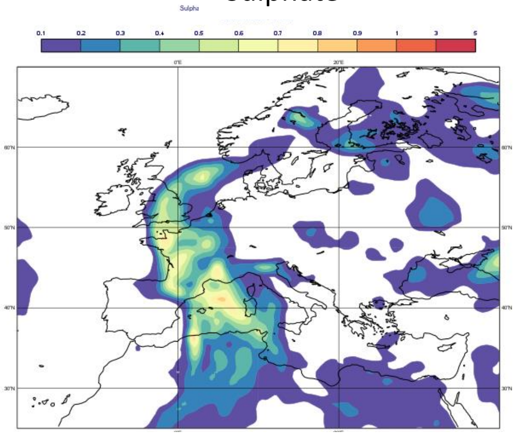


Total AOD at 550nm: 20210222 03hr

Dust

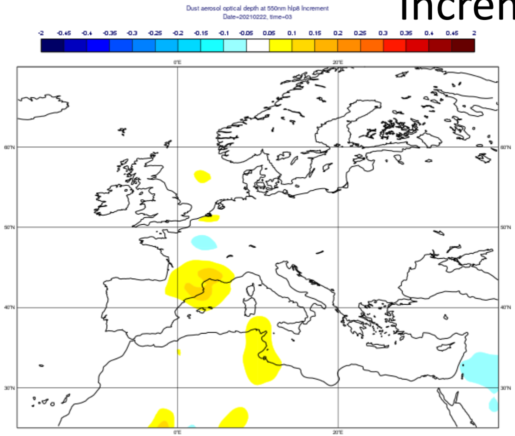


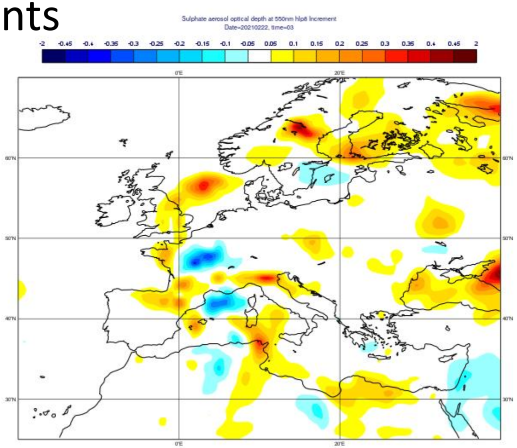
Sulphate



AOD at 550nm

Increments





AOD incr at 550nm

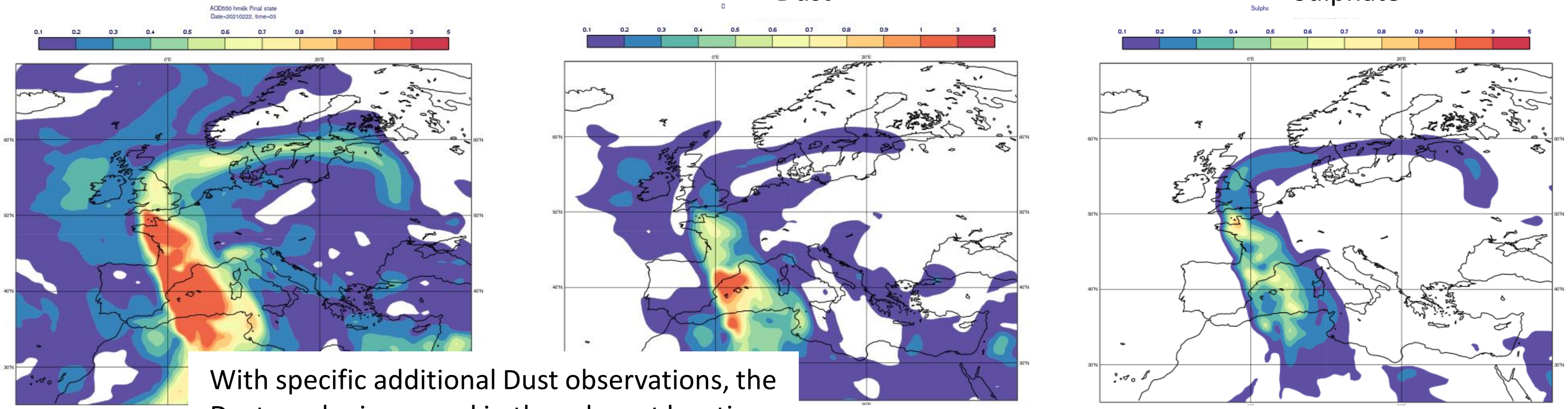
- AOD increments are attributed to the different species according to their proportion in the nonlinear forecast.
- If there is no dust in the forecast in a specific location then the increment will be given to whatever species are there – in this case Sulphate

Dust test case February 2021

Credit: Melanie Ades

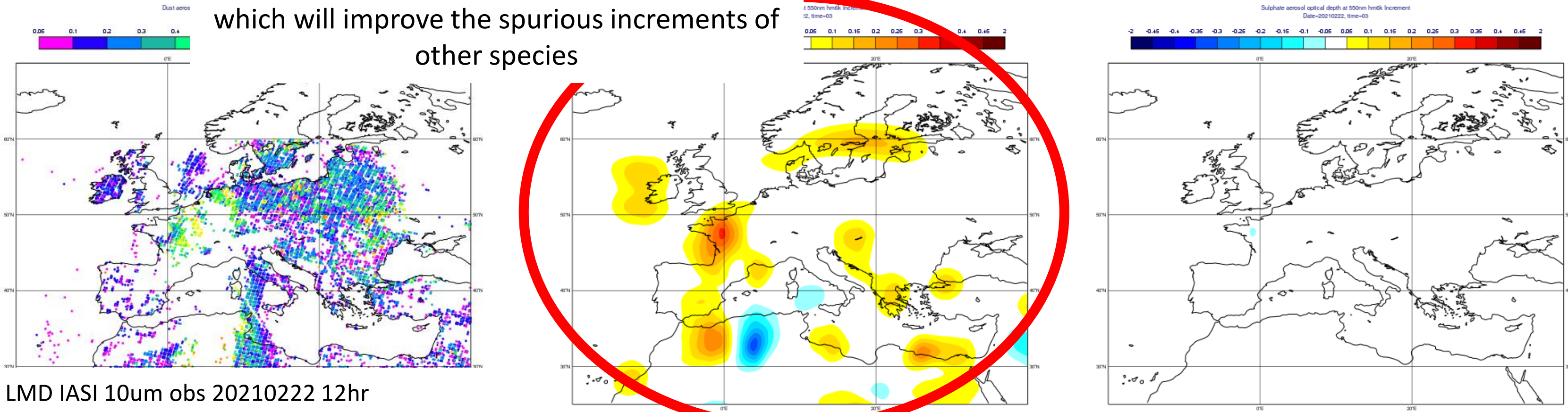
Dust

Sulphate



AOD at 550nm

With specific additional Dust observations, the Dust can be increased in the relevant locations which will improve the spurious increments of other species



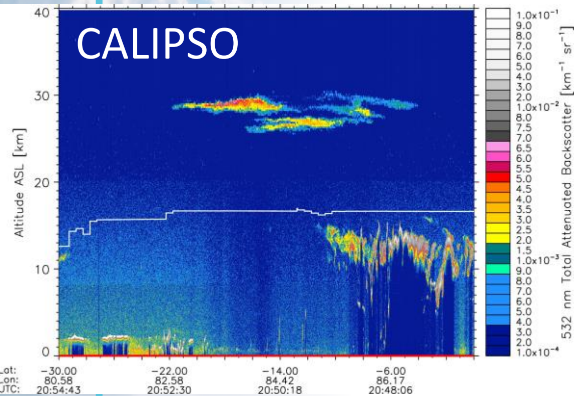
AOD incr at 550nm

LMD IASI 10um obs 20210222 12hr

MWF

SO2 assimilation

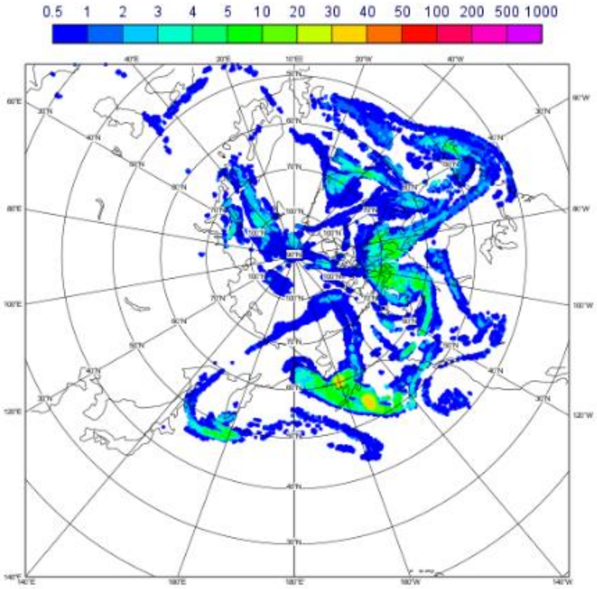
- Volcanic eruptions put ash and SO2 into the atmosphere
- Altitudes of volcanic plumes and emission strengths vary
- CAMS uses SO2 outgassing emissions but has no emission data set providing information about volcanic eruptions in NRT
- How can CAMS provide SO2 forecasts?



Credit: NASA

Current use of SO2 data in CAMS NRT system

- CAMS assimilates **GOME-2BC** and **TROPOMI** **total column SO2** TCSO2 retrievals making use of the volcanic flags provided by data providers (AC-SAF, ESA; algorithm from DLR)



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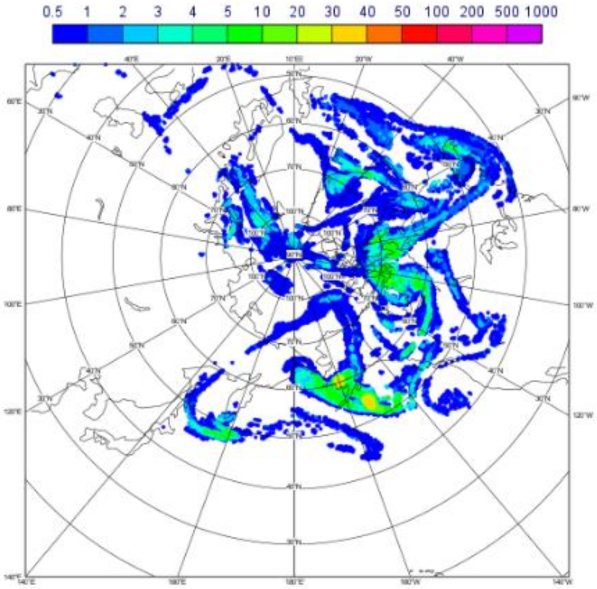
- We need to make assumptions about the plume height if this is not known in NRT
- Default: SO2 is placed in mid-troposphere at model level 98 (~ 550 hPa, 5 km) by using a prescribed bg-error stdv profile
- This can be modified if injection height is known
- Currently: Globally constant injection height
- 'Baseline configuration: BLexp'



Current use of SO2 data in CAMS NRT system

Atmosphere Monitoring

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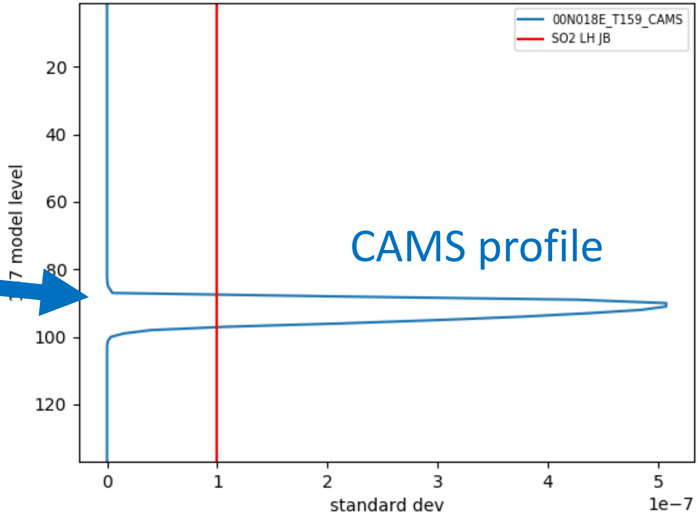
SO2 background error standard deviation



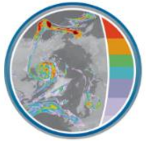
Atmosphere Monitoring

Use of SO2 Layer Height data by CAMS

- DLR have developed algorithm to provide information about the plume height in NRT from TROPOMI (Hedelt et al., 2019, doi.org/10.5194/amt-12-5503-2019)
- Full-Physics Inverse Learning Machine (FP_ILM) algorithm
- SO2 LH project - one of ESA's S5P Innovation projects
- Data useful for **SO2 > 20 DU**
- CAMS is testing the use of these data: 'LHexp'
- Inness et al. (2022): https://doi.org/10.5194/gmd-15-971-2022

TROPOMI

sentinel-5p

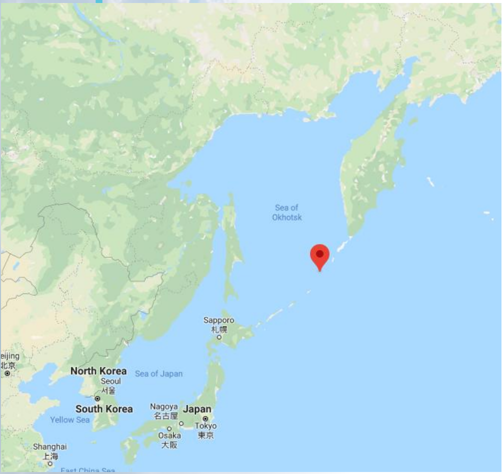


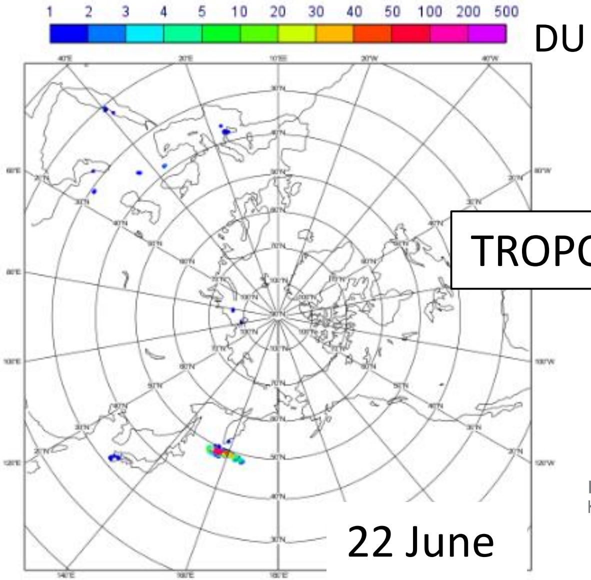
SO2 Layer height project

Case Study: Raikoke eruption June 2019

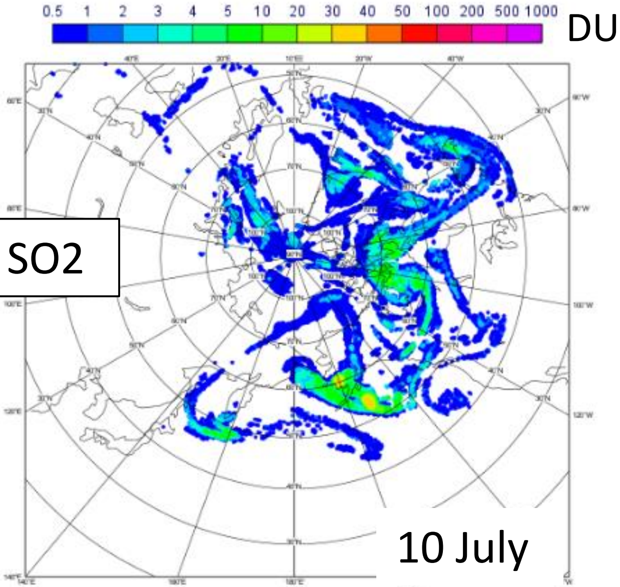
Atmosphere Monitoring

- Raikoke volcano erupted on 22 June 2019
- SO2 and ash injected up to 13-17 km -> into stratosphere
- SO2 plumes could be observed from space for a long time in NH
- Compare BLexp and LHexp

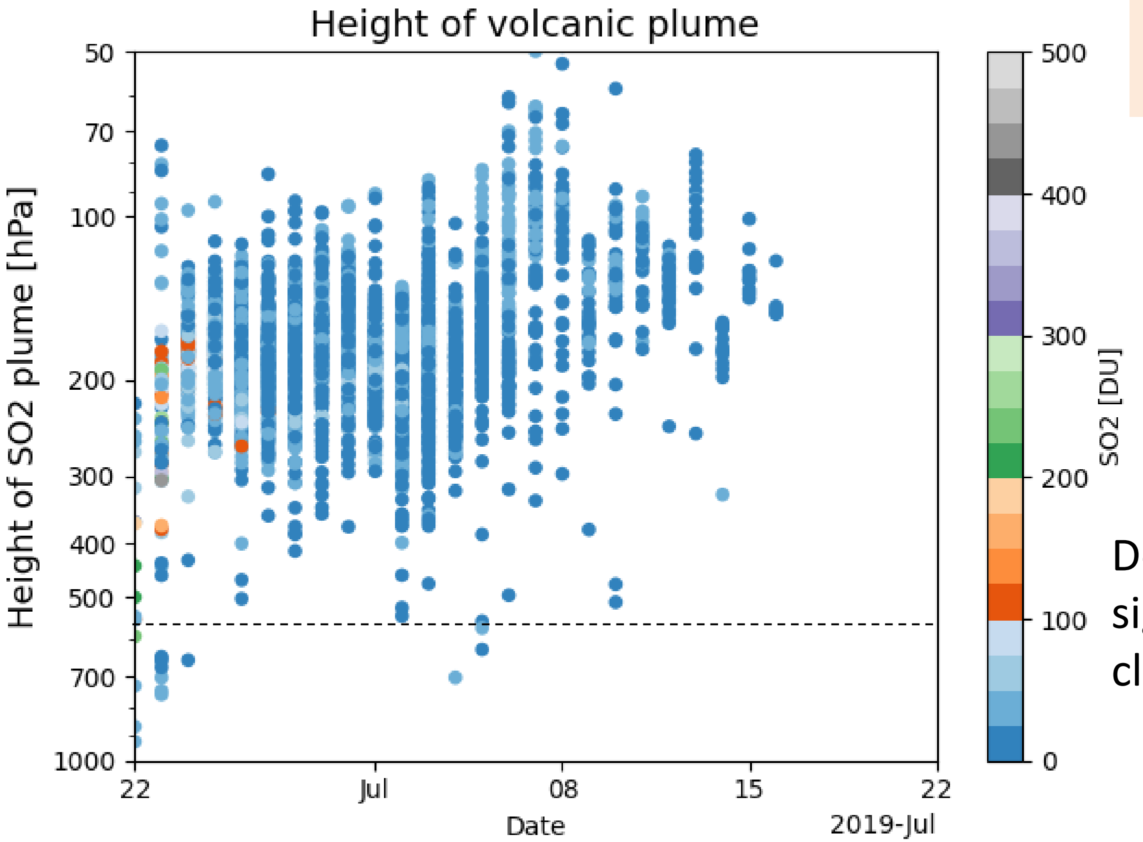




TROPOMI SO2



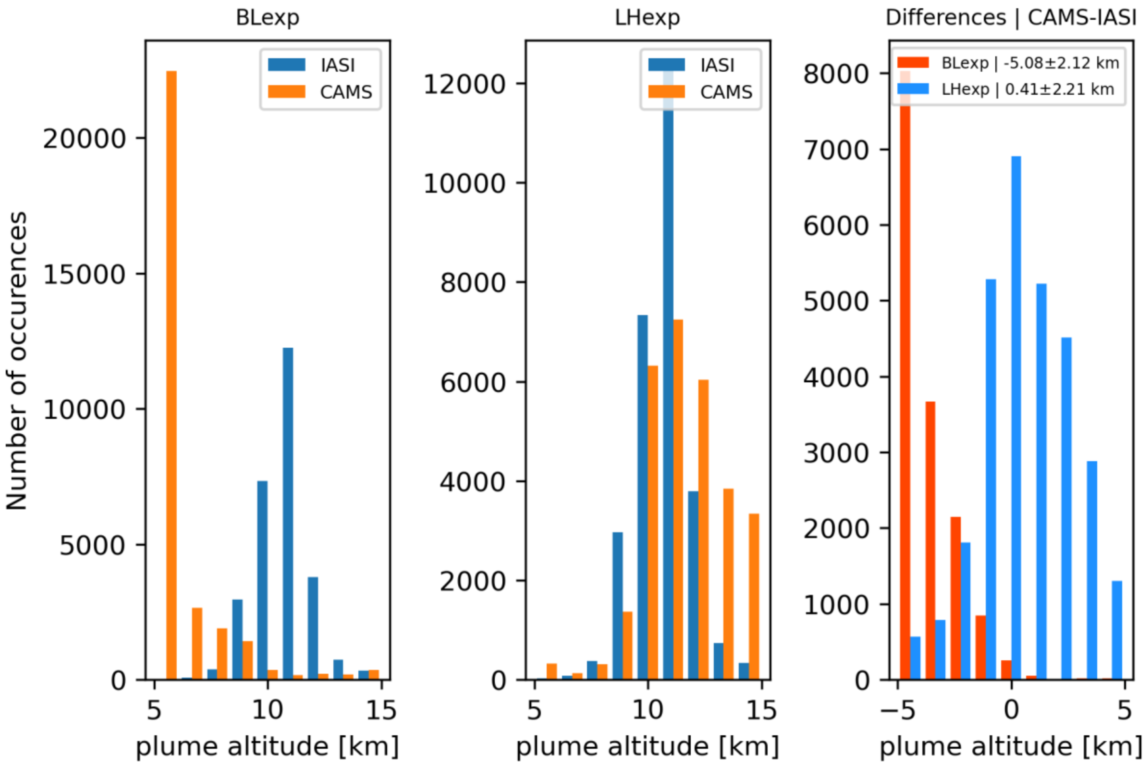
Height of SO2 plume from S5P LH data



Raikoke eruption
22 June -21 July 2019

Default of placing the SO2 signal around 550 hPa is clearly wrong in this case

Comparison of CAMS plume height with IASI



Period:
22 -29 June 2019

CAMS SO2 analysis shows improved agreement with IASI LATMOS/ULB SO2 altitude data if TROPOMI SO2 LH data are used

Biases against IASI:

BL exp: -5.1 ± 2.1 km

LH exp: 0.4 ± 2.2 km

Using the LH data leads to improved SO2 analyses and SO2 forecasts

Plot provided by MariLiza Koukouli

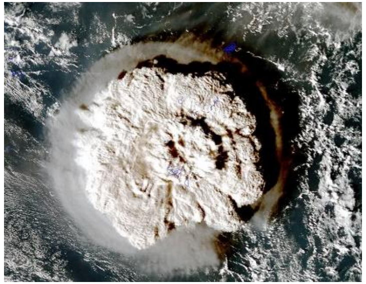
IASI SO2 altitude retrieval from LATMOS/ULB

Inness et al. (2022): doi.org/10.5194/gmd-15-971-2022

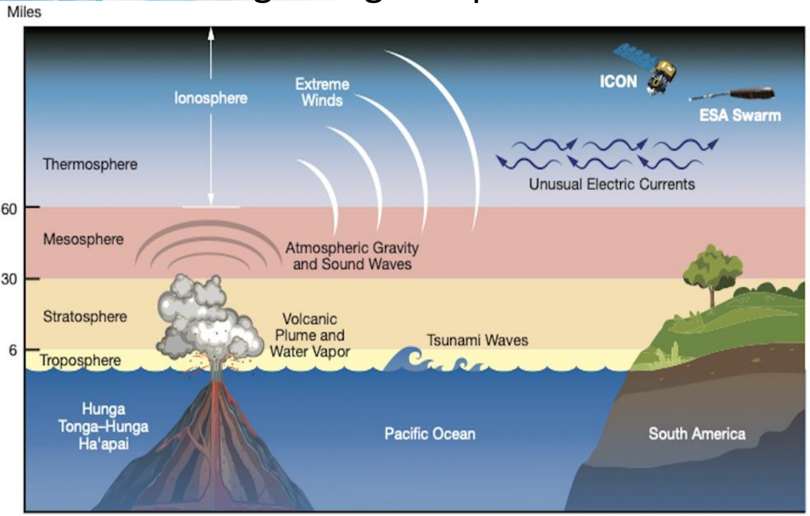
Atmosphere Monitoring

Hunga Tonga eruption January 2022

- Eruption of Hunga Tonga-Hunga Ha‘apai volcano in January 2022 caused atmospheric shock waves, sonic booms, and tsunami waves
- It injected SO2, ash and water vapour into the stratosphere

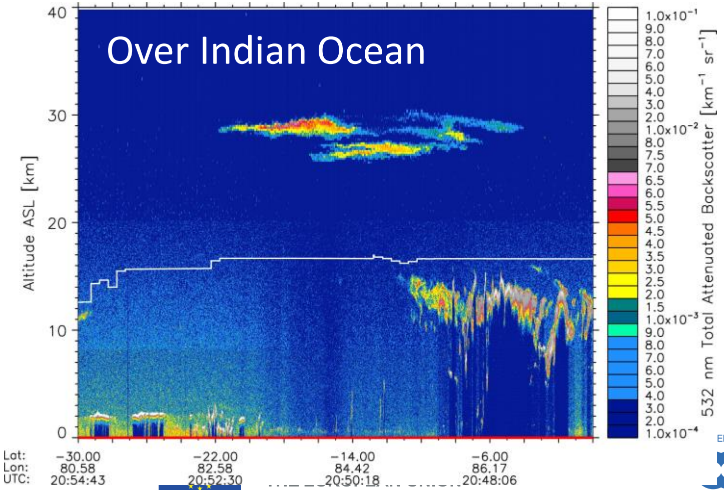


Hunga Tonga eruption



Credits: NASA’s Goddard Space Flight Center/Mary Pat Hrybyk-Keith

CALIPSO 19 January 2022

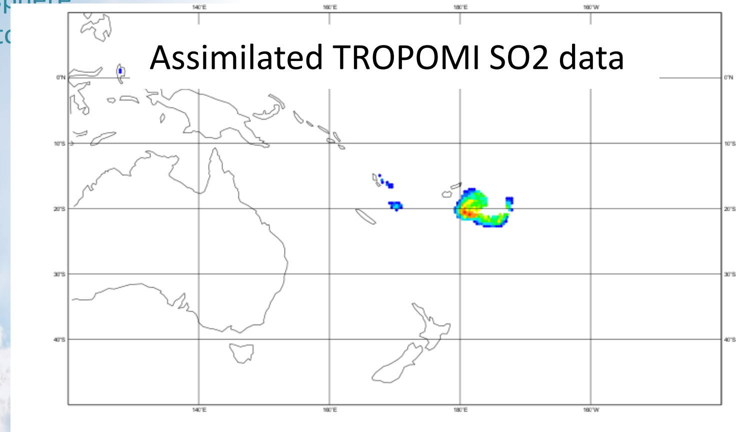


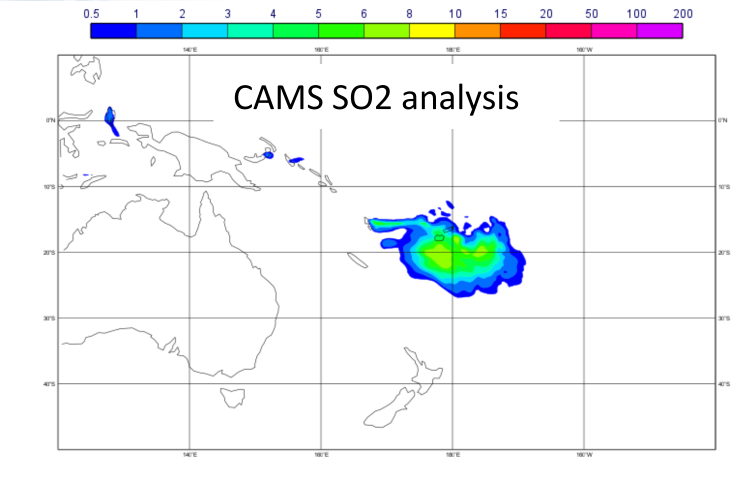
source Simon Carn on twitter: https://twitter.com/simoncarn/status/1484527916960595973?s=20)

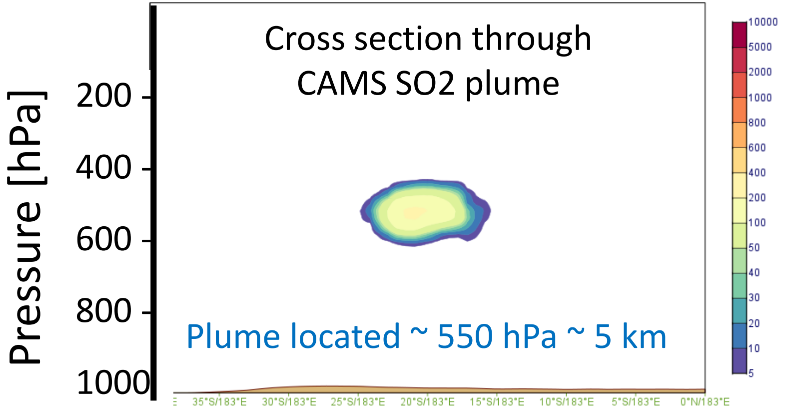
Europe's eyes on Earth

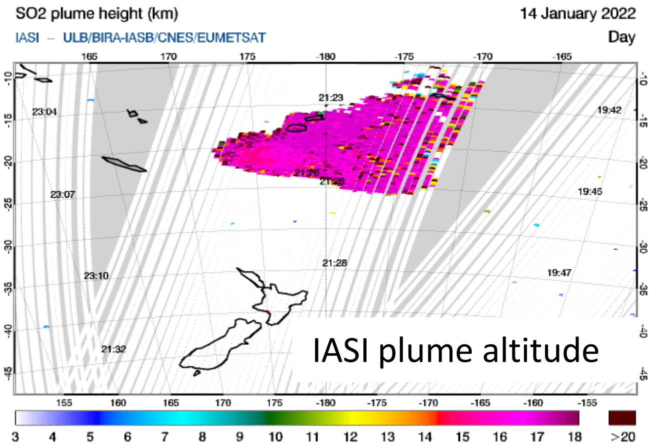
EMENTED BY ECMWF

Beginning of eruption 14 January 2022, 0z





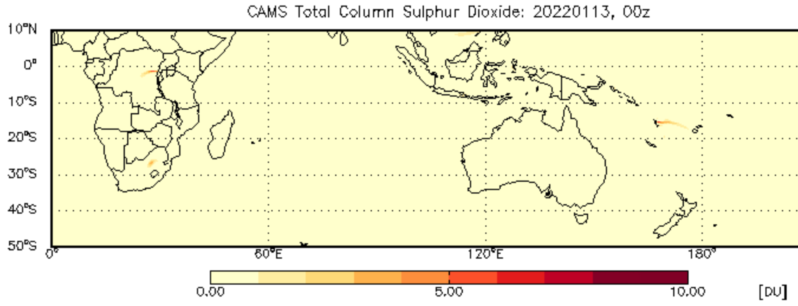




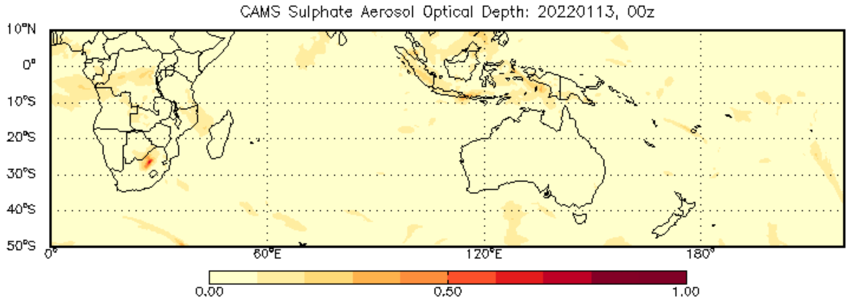
Animation of CAMS SO2 analysis

Atmosphere

CAMS TCSO2



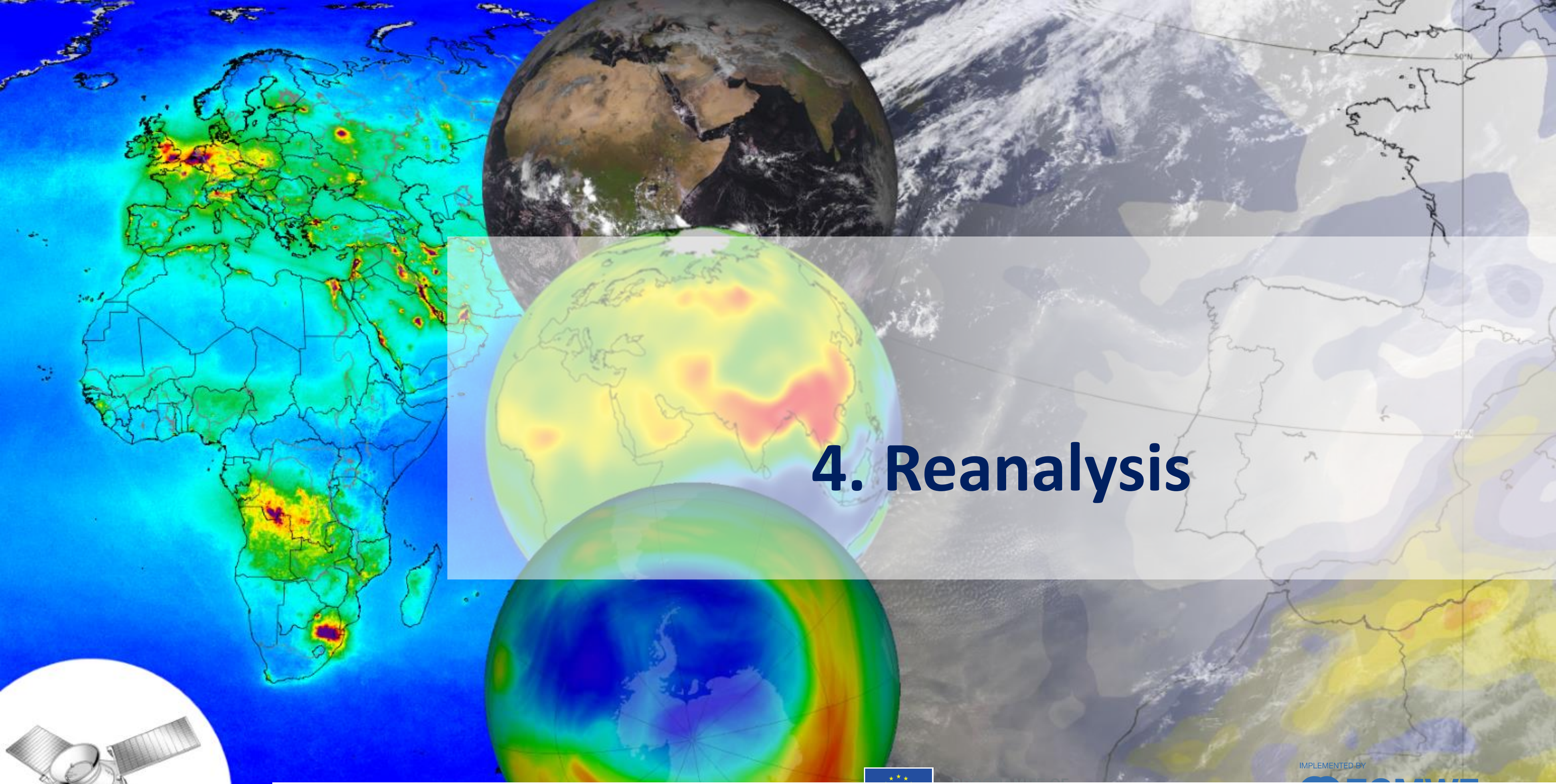
CAMS sulphate aerosol



Credit: Mark Parrington

- Assimilation brings the volcanic SO2 signal into the analysis
- SO2 is converted to sulphate aerosols
- Initial plume is advected south-eastwards because SO2 is placed too low, i.e. in the mid-troposphere
- On subsequent days the plume is moved further westwards by adjusting initial conditions (while still at the wrong altitude)

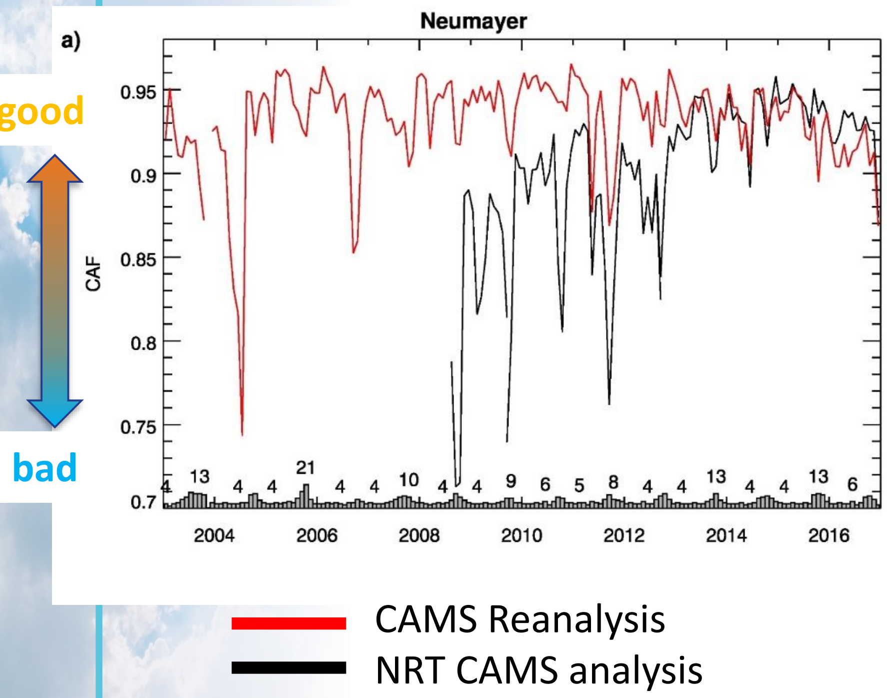
4. Reanalysis



Near-real time model versus reanalysis

Atmosphere Monitoring

Ozone score



NRT global CAMS system (daily analyses and 5-day forecasts):

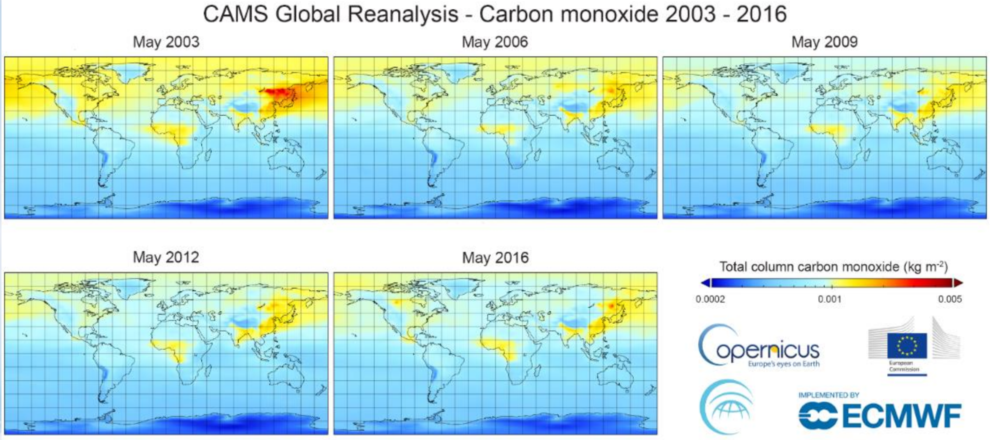
- Evolves with time: Usually 1-2 model updates per year
- Horizontal and vertical resolution can change
- Observation usage changes
- Emission data sets might change

Reanalysis (retrospective):

- Consistent long term dataset produced with one model version (from 2003 onwards)
- Consistent emissions
- Consistent, reprocessed observations
- Can be used for trend analysis

CAMS global reanalysis 2003 – 2021 (updated every 6 months)

Atmosphere Monitoring



Reanalysis
Using a combination of observations and computer models to recreate historical climate conditions.

DATA DESCRIPTION	
Data type	Gridded
Horizontal coverage	Global
Horizontal resolution	0.75°x0.75°
Vertical coverage	Surface, total column, model levels and pressure levels.
Vertical resolution	60 model levels. Pressure levels: 1000, 950, 925, 900, 850,
Temporal coverage	2003 to 2020
Temporal resolution	3-hourly
File format	GRIB (optional conversion to netCDF)
Versions	Only one version
Update frequency	Twice a year with 4-6 month delay

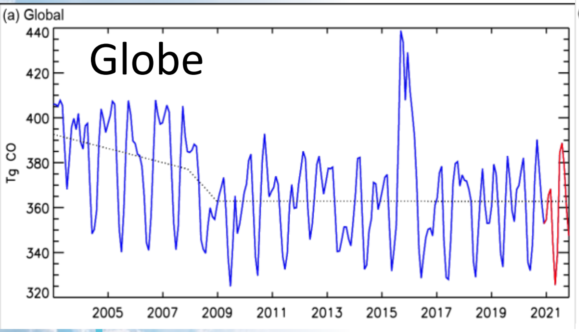
CAMS global reanalysis (CAMSRA, eac4)

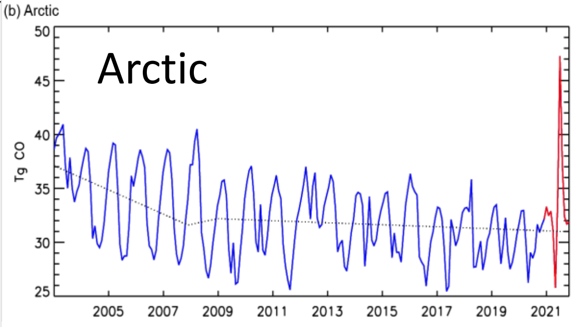
- 2003 –2021, with new years being added
- Aerosols, chemical pollutants, CO_2 & CH_4
- 80 km spatial resolution
- Inness et al. (2019): https://doi.org/10.5194/acp-19-3515-2019
- Wagner et al. (2021): https://doi.org/10.1525/elementa.2020.00171
- atmosphere.copernicus.eu/eqa-reports-global-services
- Available from ADS https://atmosphere.copernicus.eu/data

- CB05 tropospheric chemistry
- Cariolle-Déqué scheme for stratospheric ozone
- Interactive prognostic O3 and AER

Use EAC4 to study CO trends

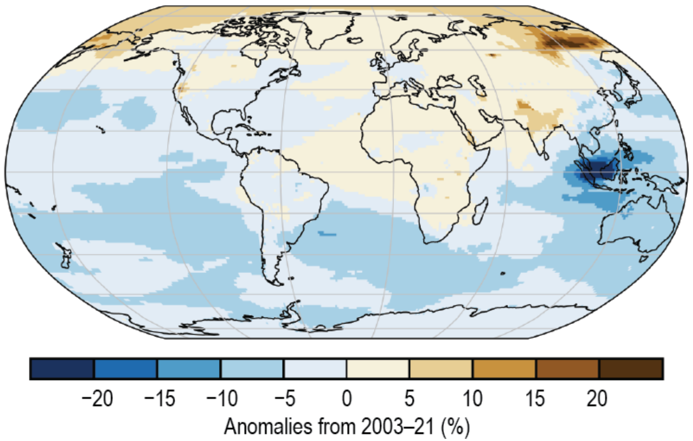
CO burdens





(ab) Carbon Monoxide

TCCO Anomaly 2021



Flemming and Inness (2022), BAMS State of Climate 2021

Comparison of xCO with TCCON at Parkfalls

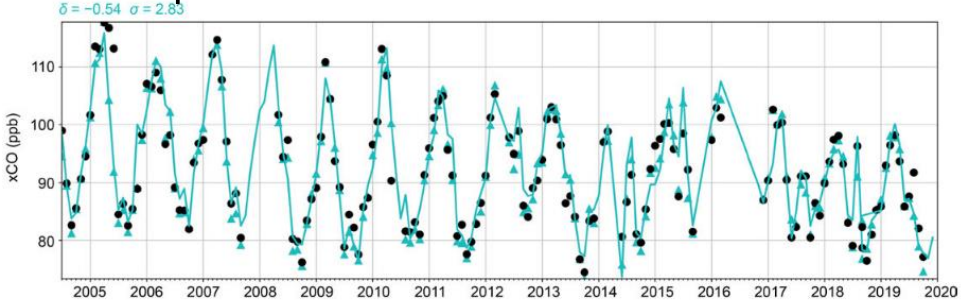


Fig. 2.62. Column-averaged CO (xCO, in ppb) at the Park Falls TCCON station. Monthly mean observations are shown by the black dots, and corresponding monthly mean xCO columns calculated using the TCCON-averaging kernels are shown by the blue triangles. The continuous blue line is the monthly xCO from the CAMS reanalysis.

Flemming et al. (2020), BAMS State of Climate 2019

TCCON data from: https://tccondata.org/

TCCON total carbon column observing network

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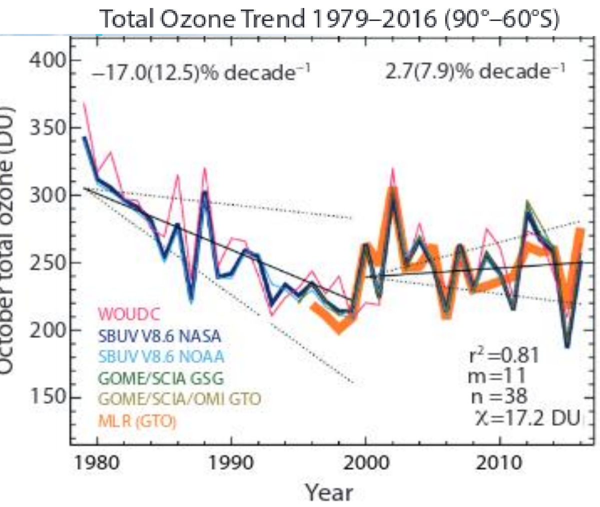
Europe's eyes on Earth

IMPLEMENTED BY ECMWF

Atmosphere

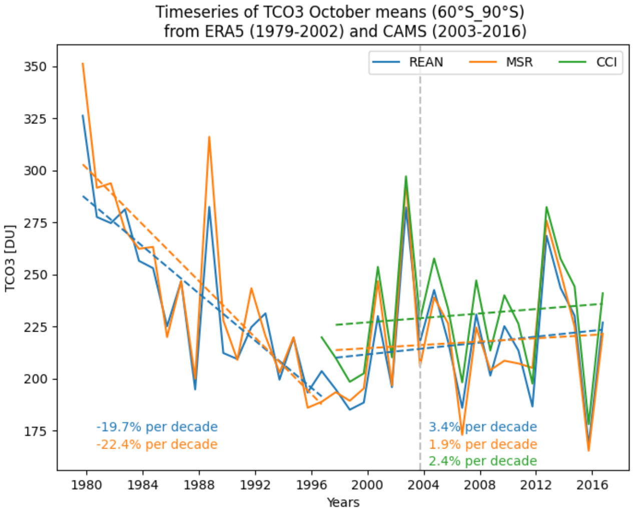
Antarctic October TCO3 trends

1979-2016

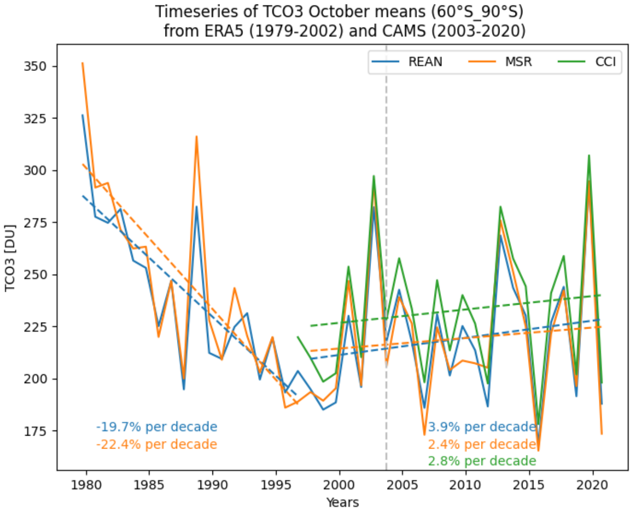


WMO (2018)

1979-2016



1979-2020



ERA5 (1979-2002) & CAMSRA (2003 ->)

Linear trends calculated for periods 1979-1996, 1997-2020

- Good agreement
- Trend depends on turnaround year and length of dataset

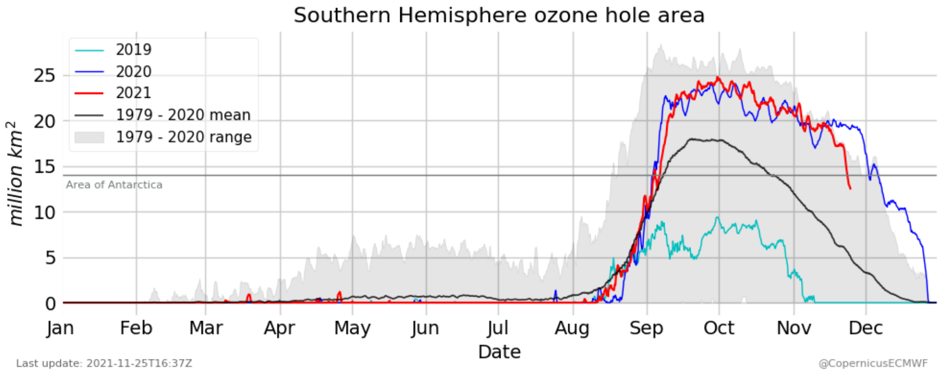
CCI merged data set and Multi Sensor Reanalysis from: cds.climate.copernicus.eu

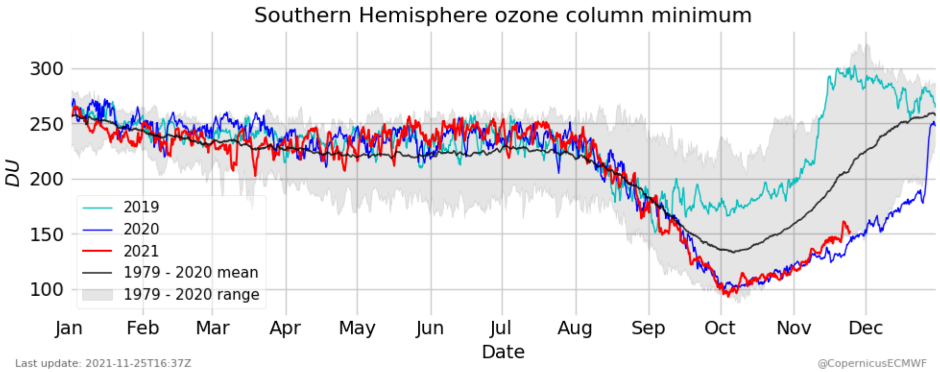
Europe's eyes on Earth

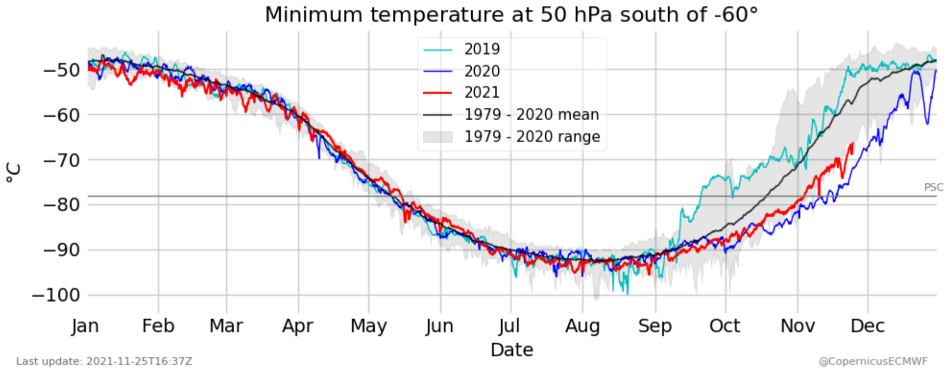
Antarctic ozone hole 2019, 2020 & 2021

Atmosphere

In addition to long-term O3 recovery there is a lot of interannual variability







- 2019 and 2020 both had exceptional Antarctic ozone holes
- 2019 small and short-lived because of unusual stratospheric warming
- 2020 deep, big & long-lived due to very cold stratosphere and stable polar vortex
- 2021 very similar to 2020

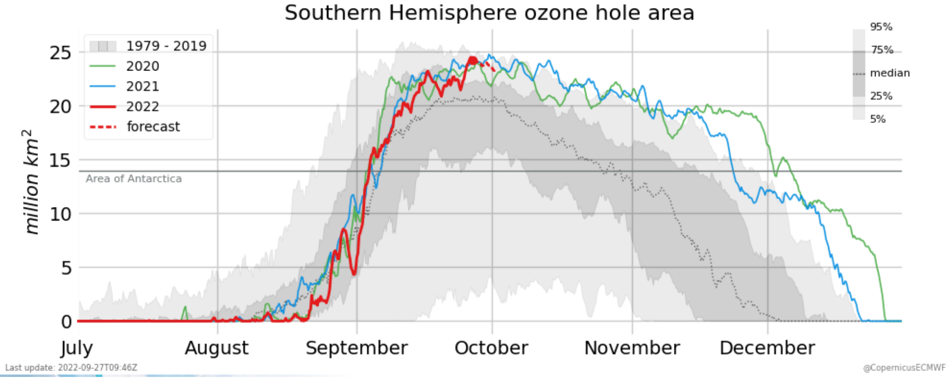
PROGRAMME OF

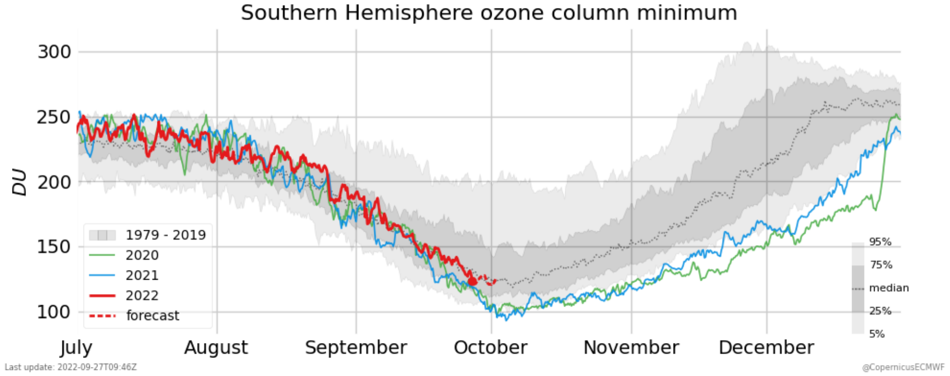
yes on Earth

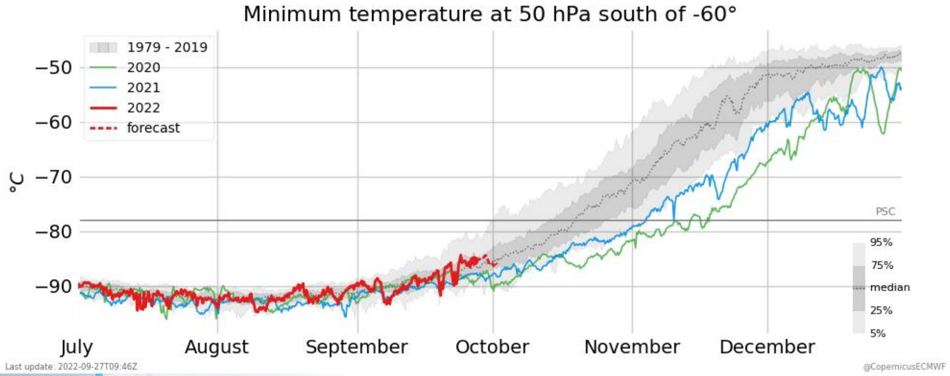
ECMWF

(1979-2002 from ERA5; 2003-2020 from CAMSRA; 2021 CAMS NRT)

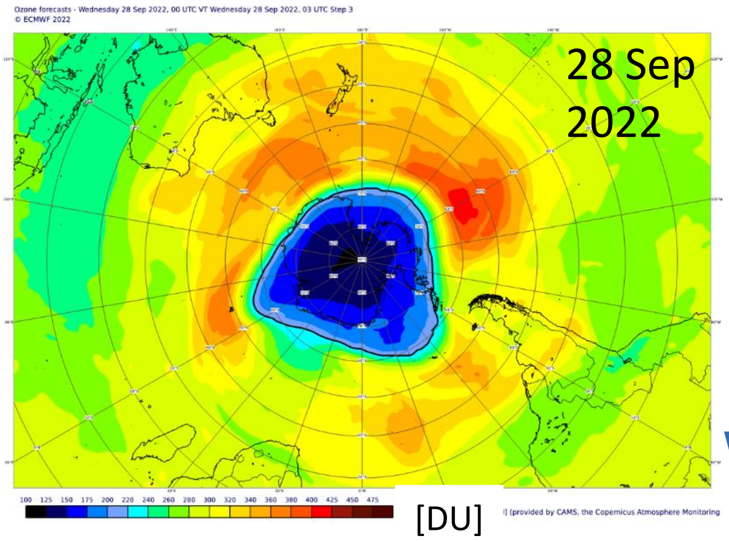
O3 hole 2022







- 2022 is another big and deep ozone hole
- It will be interesting to see how it evolves



WF

Atmosphere Monitoring

Summary

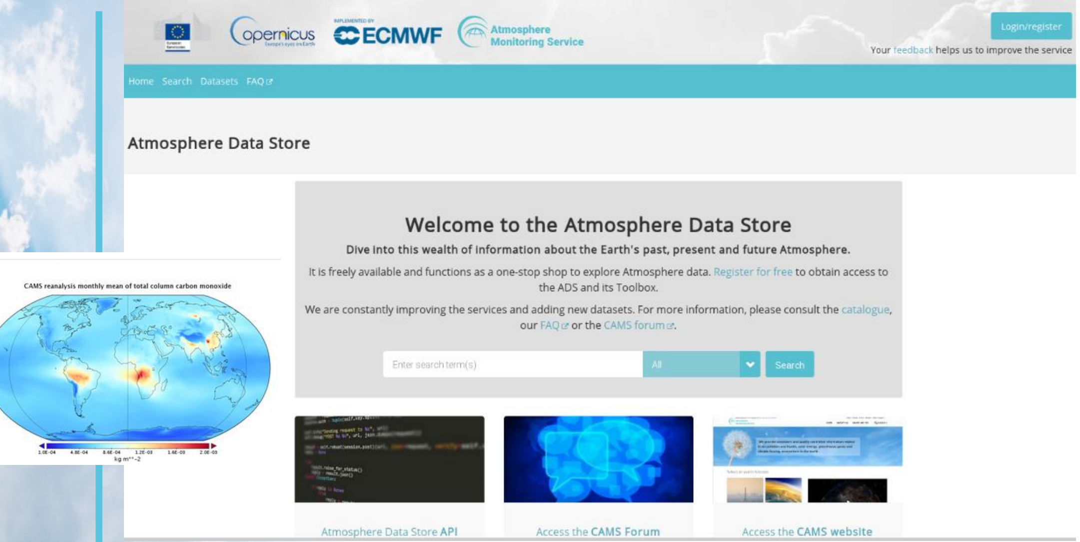
- 4D-Var data assimilation methodology, including the importance of emission inversion
- Examples of challenges or limitations when assimilating atmospheric composition observations
  - Bias correction
  - Observation operators and application of averaging kernels
  - Issues when assimilating total column observations
  - Aerosol assimilation
  - SO2 assimilation
- Reanalysis and examples of data usage, e.g. trends, Antarctic Ozone hole

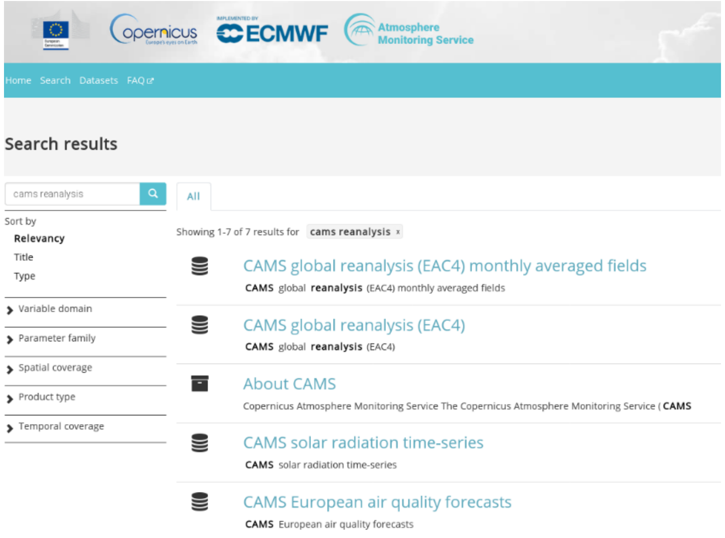
- CAMS provides atmospheric composition data at global and European regional scale
- CAMS data freely available from ADS https://atmosphere.copernicus.eu/data

The Atmosphere Data Store (ADS)

Atmosphere Monitoring

All CAMS data are freely available https://atmosphere.copernicus.eu/data





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