Preliminary study of long-term trends of N2O as a proxy of the Brewer-Dobson Circulation

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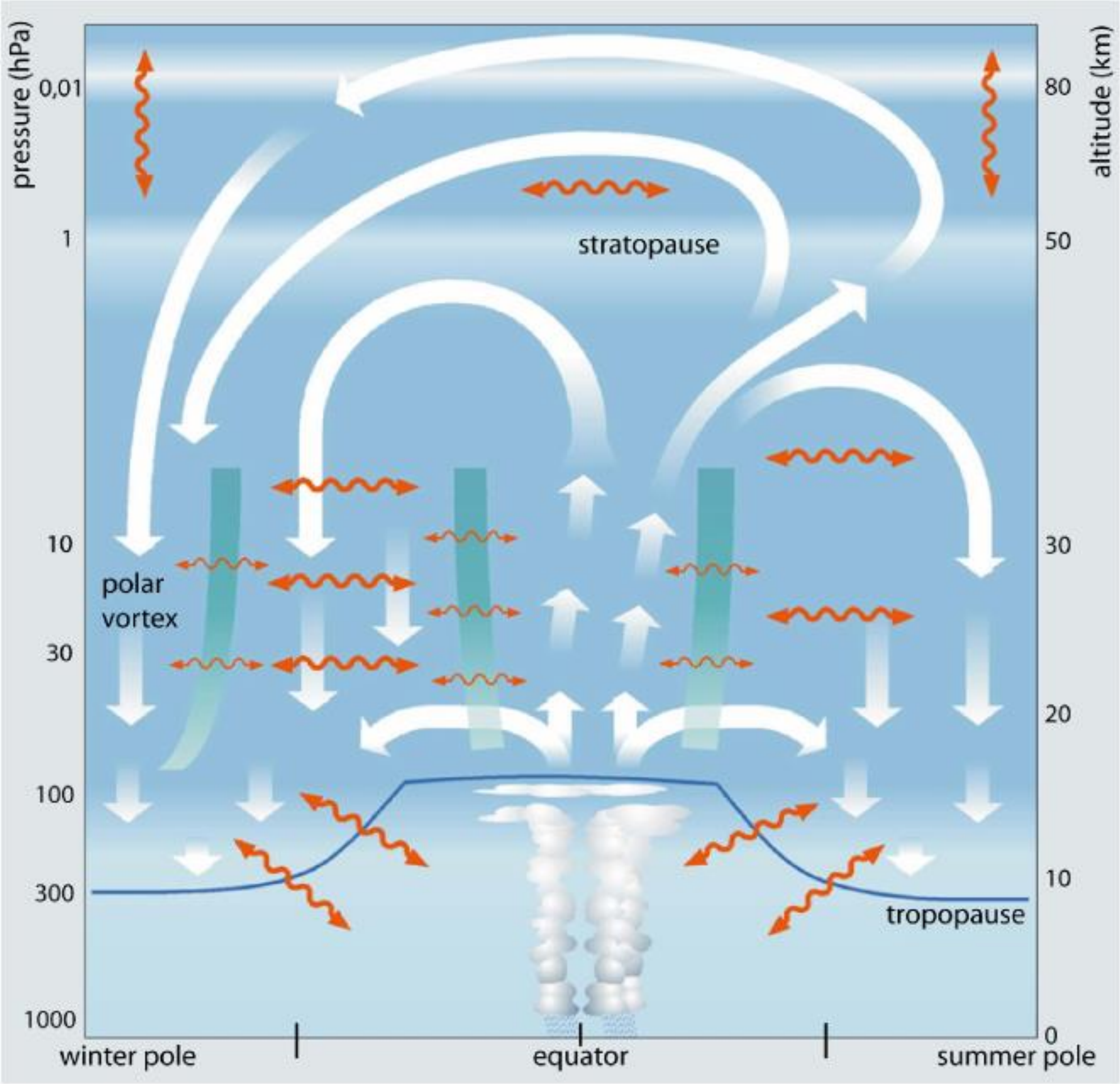
Outline

- Brewer Dobson circulation (BDC): what is?
- Long-term Changes in the BDC in the literature.
- Nitrous oxide in the stratosphere.
- Data: models, reanalyses.
- Early time-series results
- Dynamical Linear Model (DLM)
- Early fit results
- Conclusions
- References

Brewer-Dobson circulation (BDC)



From Bonisch et al., *ACP* 2011

Mostly wintertime in the stratosphere

Combined effect of residual circulation (white arrows) and mixing (red wavy arrows)

Induced by tropospheric wave activity (gravity, planetary waves,..)

Transports trace gases to stratosphere (O_3). Exchanges momentum and heat with the troposphere.

Changes in the BDC: state of the art

Global BDC is predicted to accelerate in Chemistry-Climate Models (CCM), as a consequence of the increasing GHG (Butchart, *RG* 2014)

CCM also predict a deceleration of the BDC mostly in the southern hemisphere, as a result of the ozone recovery (decrease of CFCs; Polvani et al., *JGR* 2019, Abalos et al., *JGR* 2019).

No direct observation of BDC => indirect measure through time-series of temperature and long-lived tracers.

Observed long-lived tracers trends (HCl, HNO3): acceleration of the BDC in the southern hemisphere (Strahan et al., *GRL* 2020).

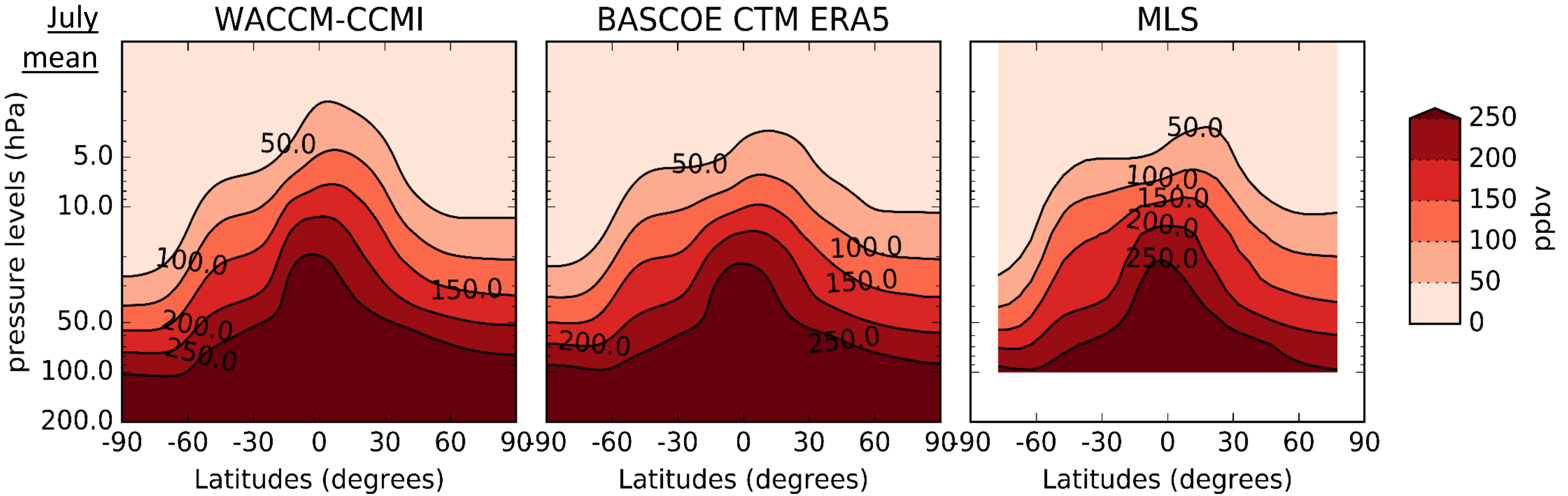
Temperature trends: global acceleration of the BDC (1980-2018). In particular, acceleration in 1980-1999 and deceleration in 2000-2018. Changes mostly driven by the southern hemisphere (Fu et al., *ERL* 2019).

Contrasting results between CCMs and observations => need for further investigation

Nitrous oxide (N2O) in the stratosphere

N2O is produced in the troposphere and transported in the stratosphere in the Tropics, where is destroyed by photodissociation (no other sink).

Long-lived tracer (~120 years): good for transport studies in the stratosphere.



Data

WACCM (Whole Atmosphere Community Climate Model, Garcia et al., *JAS* 2017).

- State of the art Chemistry-Climate Model (period: 1990-2014).
- 3 realizations of the CCMI (Chemistry-Cliamte Model Initiative) version with modified gravity waves parameterization.
- Longitude-latitude grid of 2.5°x1.9° and 66 vertical levels from the surface to about 140 km.
- QBO is nudged to observations.

BASCOE CTM: (Belgian Assimilation System for Chemical ObsErvation Chemistry-Transport Model, Chabrillat et al., *ACP* 2018).

- Chemistry-Transport Model: kinematic transport and explicit solver for stratospheric chemistry (period: 1996/7-2014.)
- Driven by 5 dynamical reanalyses: ERA5, ERA-Interim, JRA-55, MERRA, MERRA-2.
- Common longitude-latitude grid 2°x2.5°. Vertical resolution depends on the reanalysis.

BRAM3: (BASCOE Reanalysis of Aura MLS version 3, Errera et al., *ACP* 2019).

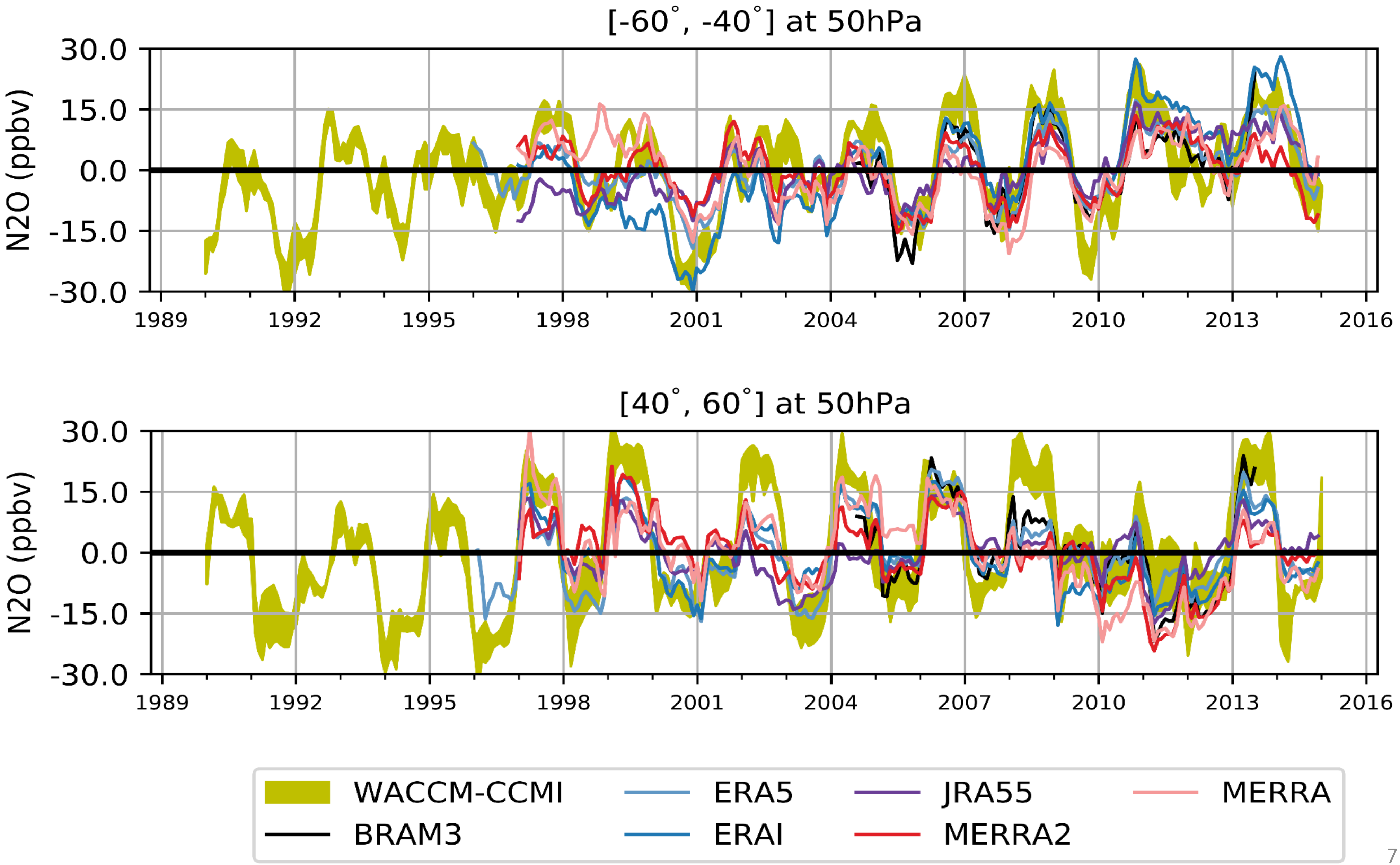
- Chemical reanalysis: assimilates the N2O product of Aura MLS (640 Hz radiometer, period : 2004/08-2013/07).
- Dynamics driven by ERA5. Horizontal resolution of 2°x2.5° with 42 vertical levels.

Time series

N2O anomalies at mid-latitude

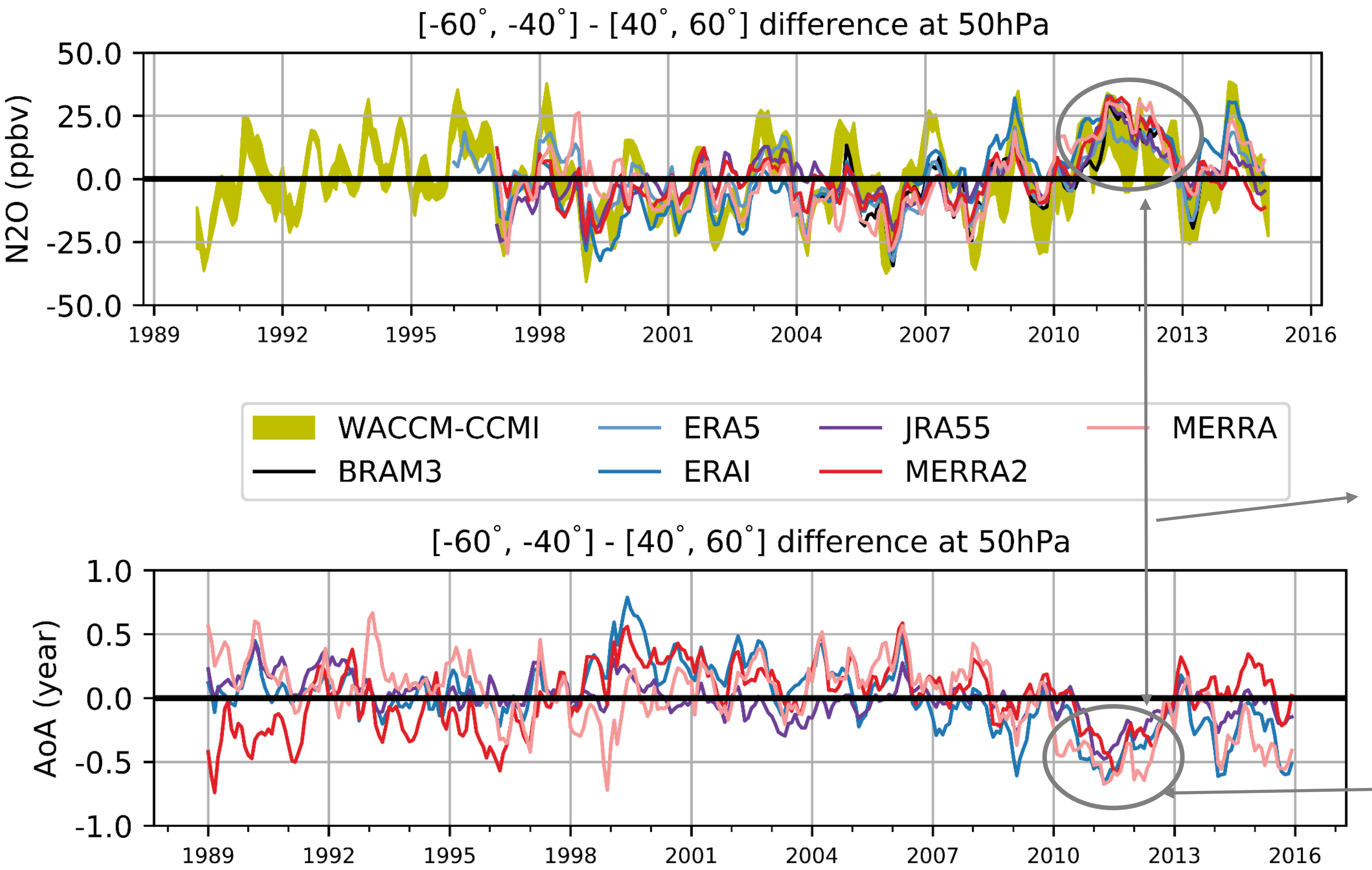
Southern mid-latitudes

Northern mid-latitudes



Time series

Differences between N2O anomalies in Southern and Northern mid-latitudes.



N2O is inversely proportional to AoA

Differences between mean AoA anomalies in Southern and Northern mid-latitudes.

QBO disruption in 2010-2011

Dynamical Linear Model (DLM)

Regression tool based on the <u>Bayesian inference</u> (Alsing, *JOOS*, 2019, Ball et al., *ACP* 2018).

$$P(\vartheta|d) \propto P(d|\vartheta) \cdot P(\vartheta)$$

ϑ= unknown parameters; *d*=data

<u>*P(θ|d)*</u>: **posterior probability**.

<u>*P(θ)*</u>*:* **prior assumption**.

<u>*P(d| θ)*</u>*:* likelihood of getting the data as a function of different values of the parameters *θ* and given the **<u>modeling assumptions</u>**.

1. Set your prior beliefs about the parameters *θ*, get *P(θ).*
2. Set your modeling assumptions, used to derive *P(d| θ).*
3. Use Bayes' theorem to get the posterior *P(θ|d).*
4. Plug the posterior into a Monte Carlo sampler to draw samples from the posterior.

Once the model is specified, there are <u>no further approximations</u> when recovering parameters. All uncertainties, autoregressive terms, missing data are <u>treated exactly</u>.

Dynamical Linear Model (DLM)

Atmospheric time-series

$$\begin{aligned} y_t = &\boxed{\beta_{1,t} z_{1,t} + \beta_{2,t} z_{2,t} \ldots + \beta_{n,t} z_{n,t}} \\ &+ \boxed{\beta_{1,t}^{12} \sin(2\pi t/12) + \beta_{2,t}^{12} \cos(2\pi t/12) \\ &+ \beta_{1,t}^{6} \sin(2\pi t/6) + \beta_{2,t}^{6} \cos(2\pi t/6)} \\ &+ \mu_t \\ &+ z_t^{AR} \\ &+ \epsilon_t . \end{aligned}$$

Regressors (QBO, ENSO, solar cycle….)

12- and 6-months
seasonal cycles

Linear term

Autoregressive process

Allows us to specify the likelihood *P(d|ϑ).*

Dynamical Linear Model (DLM)

$$y_t = \boxed{\beta_{1,t} z_{1,t} + \beta_{2,t} z_{2,t} \ldots + \beta_{n,t} z_{n,t}}$$
$$+ \beta^{12}_{1,t} \sin(2\pi t/12) + \beta^{12}_{2,t} \cos(2\pi t/12)$$
$$+ \beta^{6}_{1,t} \sin(2\pi t/6) + \beta^{6}_{2,t} \cos(2\pi t/6)$$
$$+ \mu_t$$
$$+ z^{AR}_t$$
$$+ \epsilon_t .$$

$z_{i,t}$ = regressor time series (QBO, ENSO, solar cycle…)

σ_{reg}: how much can the regressors amplitude vary.

$$\sigma_{reg} \rightarrow 0$$

Constant coefficients (MLR)

$$\beta_{i,t} = \beta_{i,t-1} + w_t$$

$$w_t \sim N(0, \sigma_{reg})$$

Regressor coefficients are time-dependent

Dynamical Linear Model (DLM)

$$
\begin{aligned}
y_t = &\beta_{1,t} z_{1,t} + \beta_{2,t} z_{2,t} \ldots + \beta_{n,t} z_{n,t} \\
&+ \boxed{\beta_{1,t}^{12} \sin(2\pi t/12) + \beta_{2,t}^{12} \cos(2\pi t/12) \\
&+ \beta_{1,t}^{6} \sin(2\pi t/6) + \beta_{2,t}^{6} \cos(2\pi t/6)} \\
&+ \mu_t \\
&+ z_t^{AR} \\
&+ \epsilon_t .
\end{aligned}
$$

Seasonal coefficients are <u>time-dependent</u>

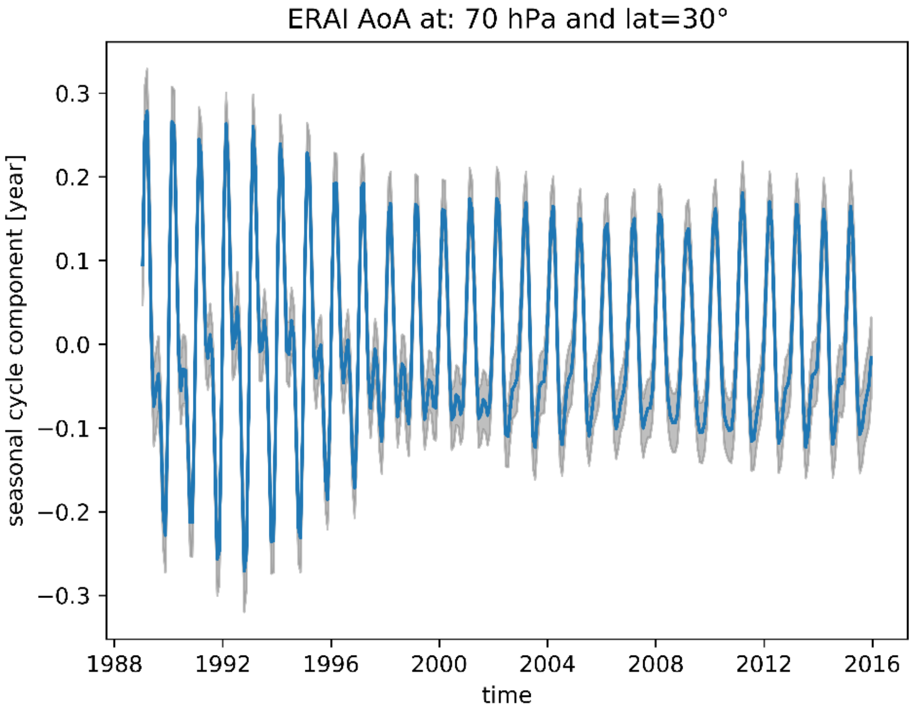
σ_{seas}: how can the amplitude of the seasonal cycle vary.

$$\beta_{i,t}^{(k)} = \beta_{i,t-1}^{(k)} + w_t$$

$$w_t \sim N(0, \sigma_{seas})$$

$\sigma_{seas} \rightarrow 0$

Constant coefficients (MLR)

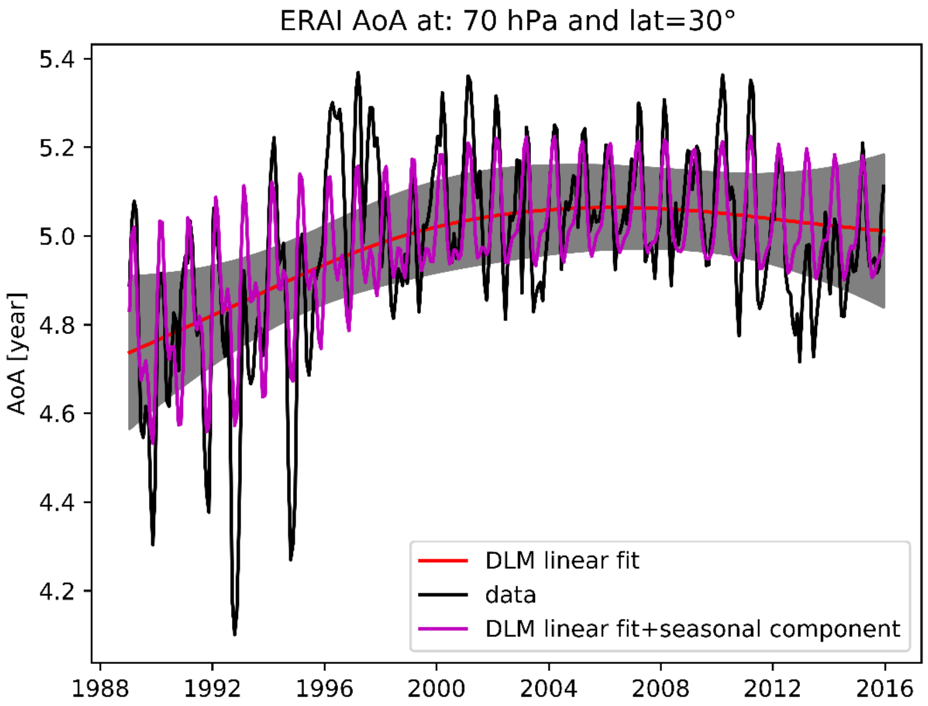


Dynamical Linear Model (DLM)

$$\begin{aligned} y_t = &\beta_{1,t} z_{1,t} + \beta_{2,t} z_{2,t} \ldots + \beta_{n,t} z_{n,t} \\ &+ \beta_{1,t}^{12} \sin(2\pi t/12) + \beta_{2,t}^{12} \cos(2\pi t/12) \\ &+ \beta_{1,t}^{6} \sin(2\pi t/6) + \beta_{2,t}^{6} \cos(2\pi t/6) \\ &+ \mu_t \\ &+ z_t^{AR} \\ &+ \epsilon_t . \end{aligned}$$

The linear trend is <u>time-dependent</u>

$$\mu_t = \mu_{t-1} + \alpha_t$$
$$\alpha_t = \alpha_{t-1} + w_t$$
$$w_t \sim N(0, \sigma_{trend})$$



σ_{trend}: how smooth/wiggly the trend can be.

$\sigma_{trend} \to 0$ → MLR

Dynamical Linear Model (DLM)

$$
\begin{aligned}
y_t = & \beta_{1,t} z_{1,t} + \beta_{2,t} z_{2,t} \ldots + \beta_{n,t} z_{n,t} \\
& + \beta_{1,t}^{12} \sin(2\pi t/12) + \beta_{2,t}^{12} \cos(2\pi t/12) \\
& + \beta_{1,t}^{6} \sin(2\pi t/6) + \beta_{2,t}^{6} \cos(2\pi t/6) \\
& + \mu_t \\
& + z_t^{AR} \\
& + \epsilon_t .
\end{aligned}
$$

$$z_t^{AR} = \rho z_{t-1}^{AR} + N(0, \sigma_{AR})$$

ρ: autoregressive coefficient

σ_{AR}: how strong the autoregressive process can be.

Dynamical Linear Model (DLM)

DLM priors parameters: $\vartheta = \{\beta_{k,t}^{(reg)}, \beta_{i,t}^{(seas)}, \alpha_t, \mu_t, \rho, \sigma_{seas}, \sigma_{reg}, \sigma_{trend}, \sigma_{AR}\}$

Prior for the "hyper-parameters": $\boldsymbol{\sigma_{XX}}$ All the other parameters are derived by σ_{XX} .

For the sigmas, the priors are half-positive normals:

$$
\begin{aligned}
\sigma_{\mathrm{trend}} &\sim \mathrm{HalfNormal}(0, \sigma_{\mathrm{trend}}^{\mathrm{prior}}) \\
\sigma_{\mathrm{seas}} &\sim \mathrm{HalfNormal}(0, \sigma_{\mathrm{seas}}^{\mathrm{prior}}) \\
\sigma_{\mathrm{z}} &\sim \mathrm{HalfNormal}(0, \sigma_{\mathrm{z}}^{\mathrm{prior}}) \\
\sigma_{\mathrm{Ar1}} &\sim \mathrm{HalfNormal}(0, \sigma_{\mathrm{AR1}}^{\mathrm{prior}}),
\end{aligned}
$$

The σ^{prior} can be set by the user.

Dynamical Linear Model (DLM)

The code can be downloaded at: https://github.com/justinalsing/dlmmc, Alsing, *JOOS* 2019

3000 iterations, first 1000 discarded.
144 CPUs, ~12-13hrs for the largest dataset (25 years of monthly zonal mean).

A priori values:

- $\sigma_{trend}^{prior} = 0{,}0001$
- $\sigma_{seas}^{prior} = 0{,}01$
- $\sigma_{reg}^{prior} = 0$
- $\sigma_{AR}^{prior} = 0{,}5$

trend [data units/time units]: difference (delta) of the fit distributions between the end and start date, normalized by the number of years.
trend=(μ@date2 – μ@date1)/(# of years)

uncertainty on the trend: from the distribution of delta values (2000 values), it is the percentage of those values that are positive/negative ➔approximates the posterior probability that the overall change in the fit is positive/negative (no assumptions about the shape of the distribution).

Dynamical Linear Model (DLM)

In a nutshell:

Choose your DLM model (which features are on/off, e.g. QBO off)

Load in your data and your regressors (if any)

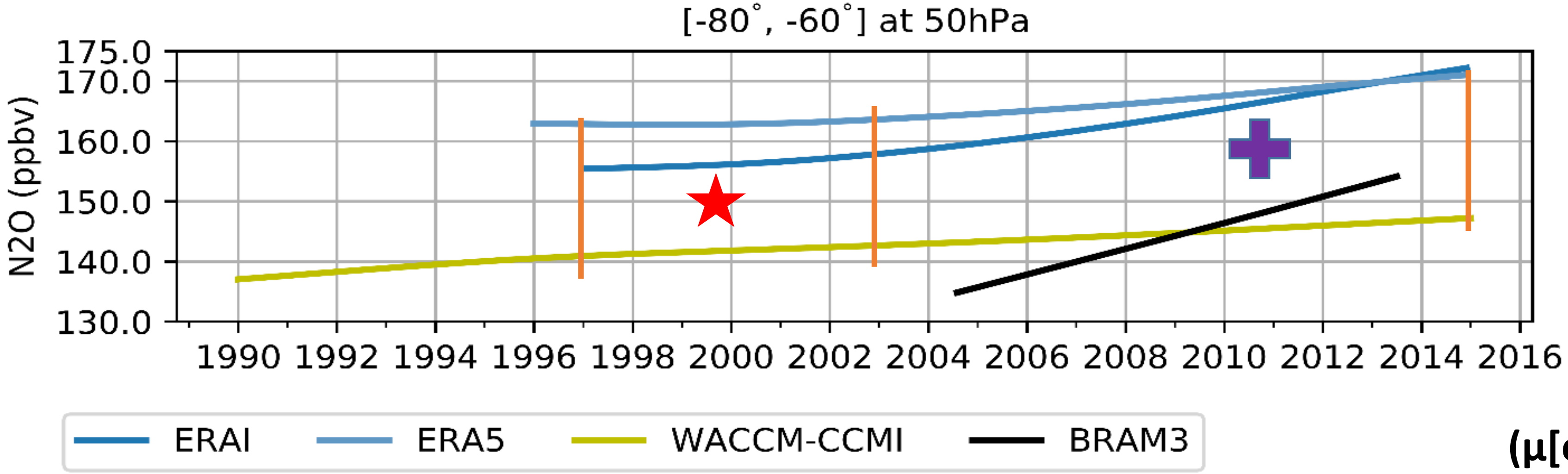
Choose the priors for the hyper-parameters σ

DLM sampler

Samples from the posterior probability of all model components (fit, seasonal cycle, regressors…)

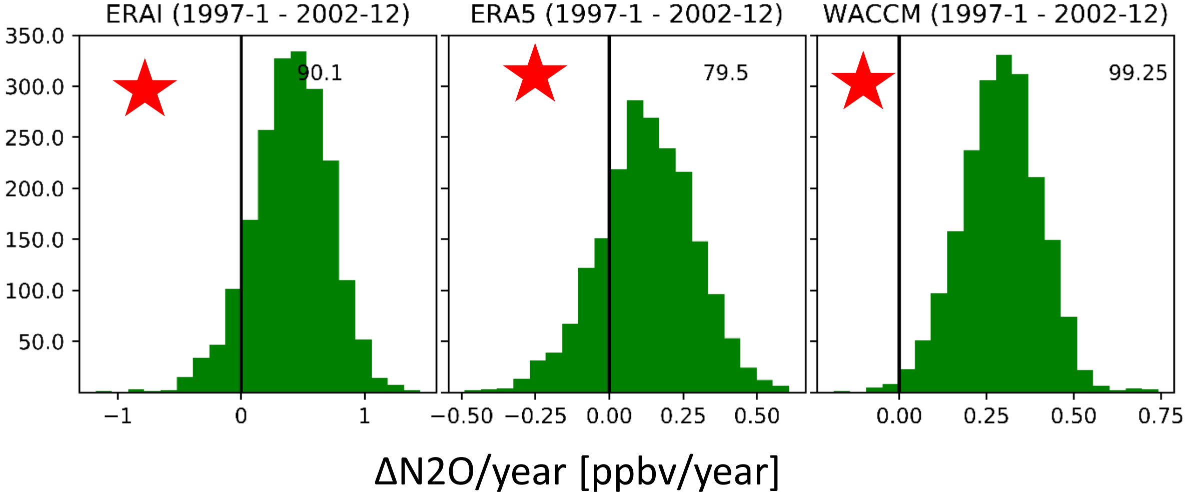
Above the Antarctic

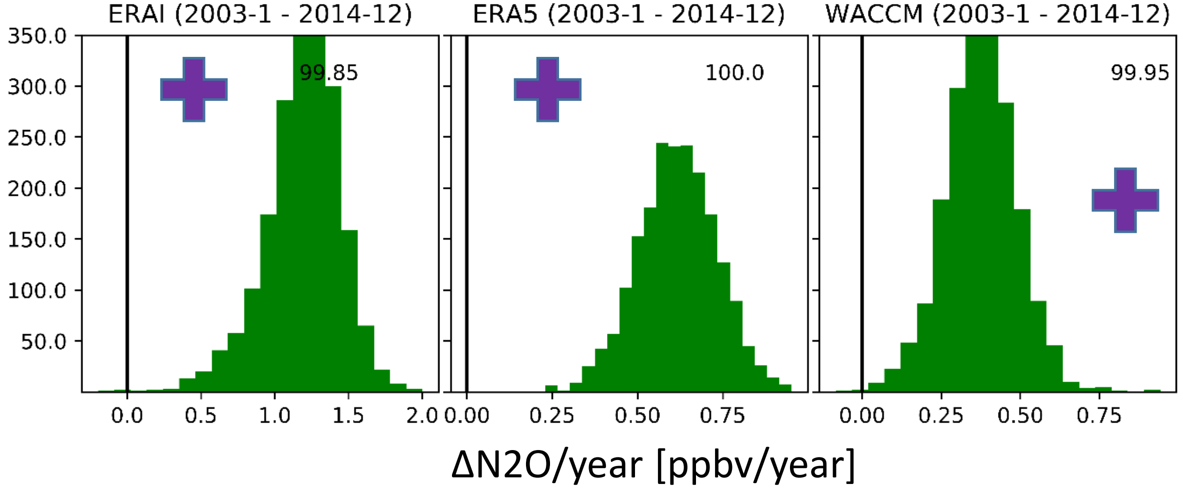
Preliminary fit results



Linear component of the DLM (μ_t).

(μ[end] – μ[start])/nyears



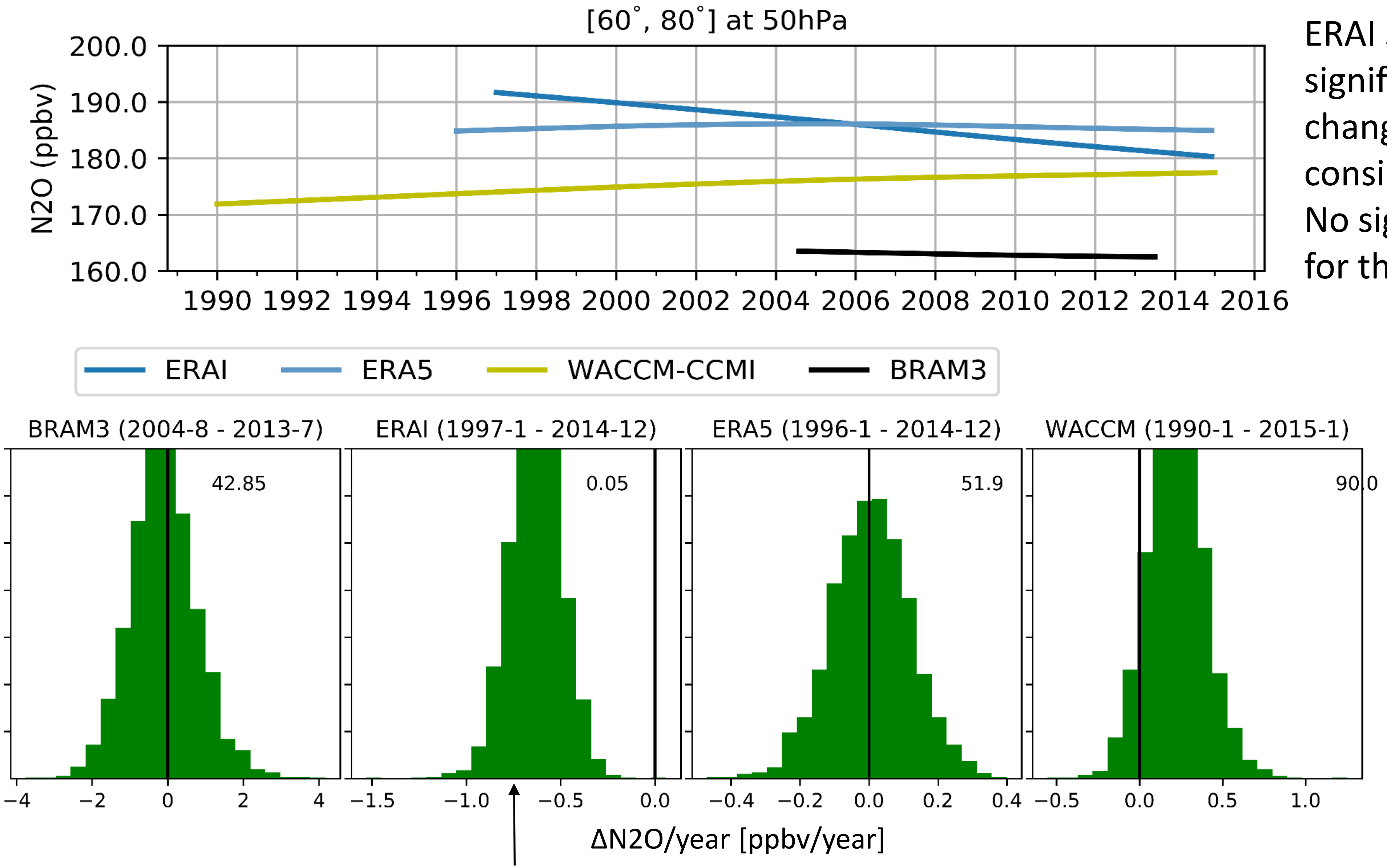


Number in the panels: posterior probability of positive changes.

ERA5 and ERAI: slope of the fit is steeper after beginning of 2000's ➔ the fitted change is significant.

Above the Arctic

Preliminary fit results



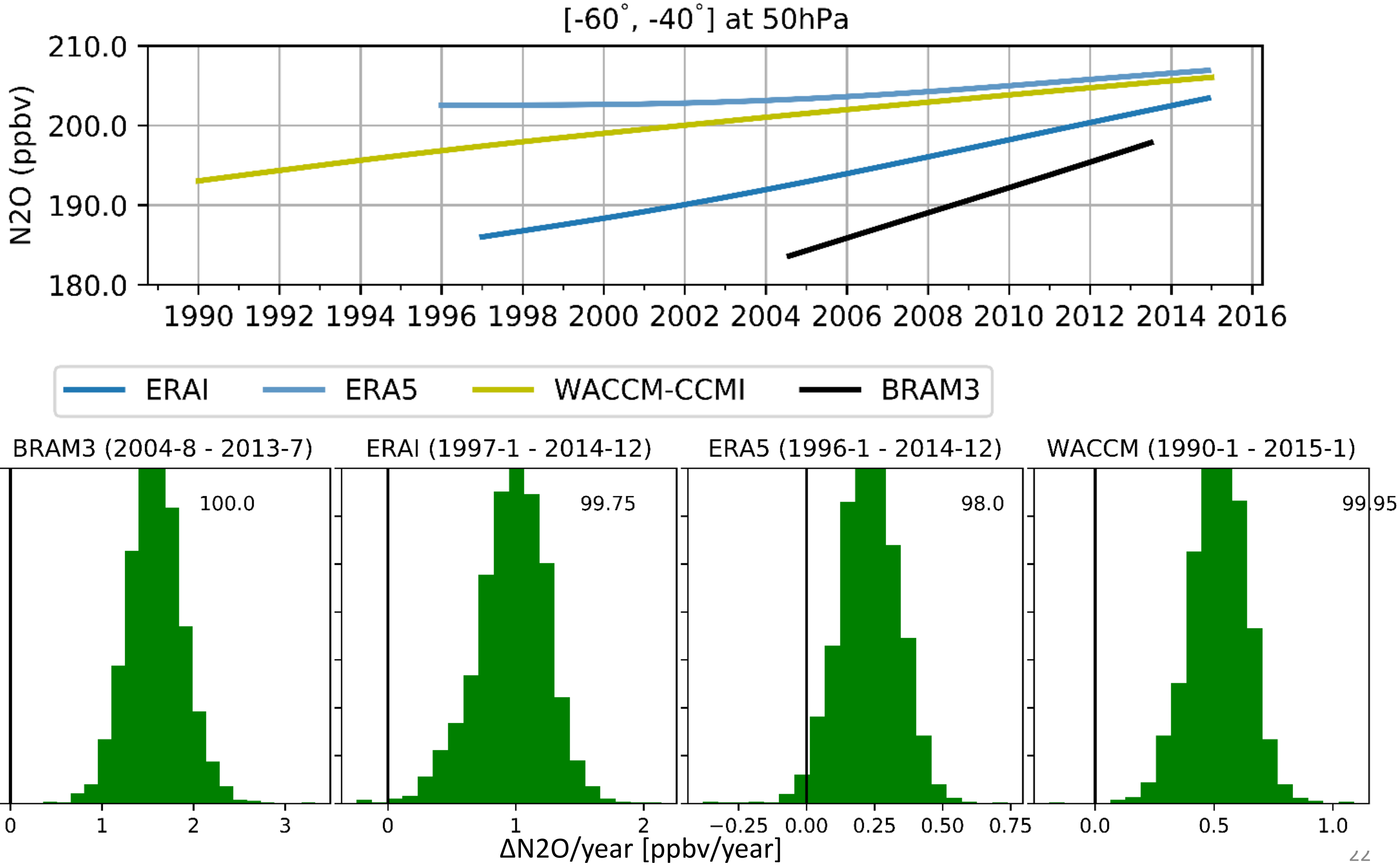
ERAI shows significant negative change between the considered dates.
No significant change for the others.

ERAI: 99.95% probability that the changes are negative

Preliminary fit results

Southern mid-latitudes

Positive significant change in all datasets

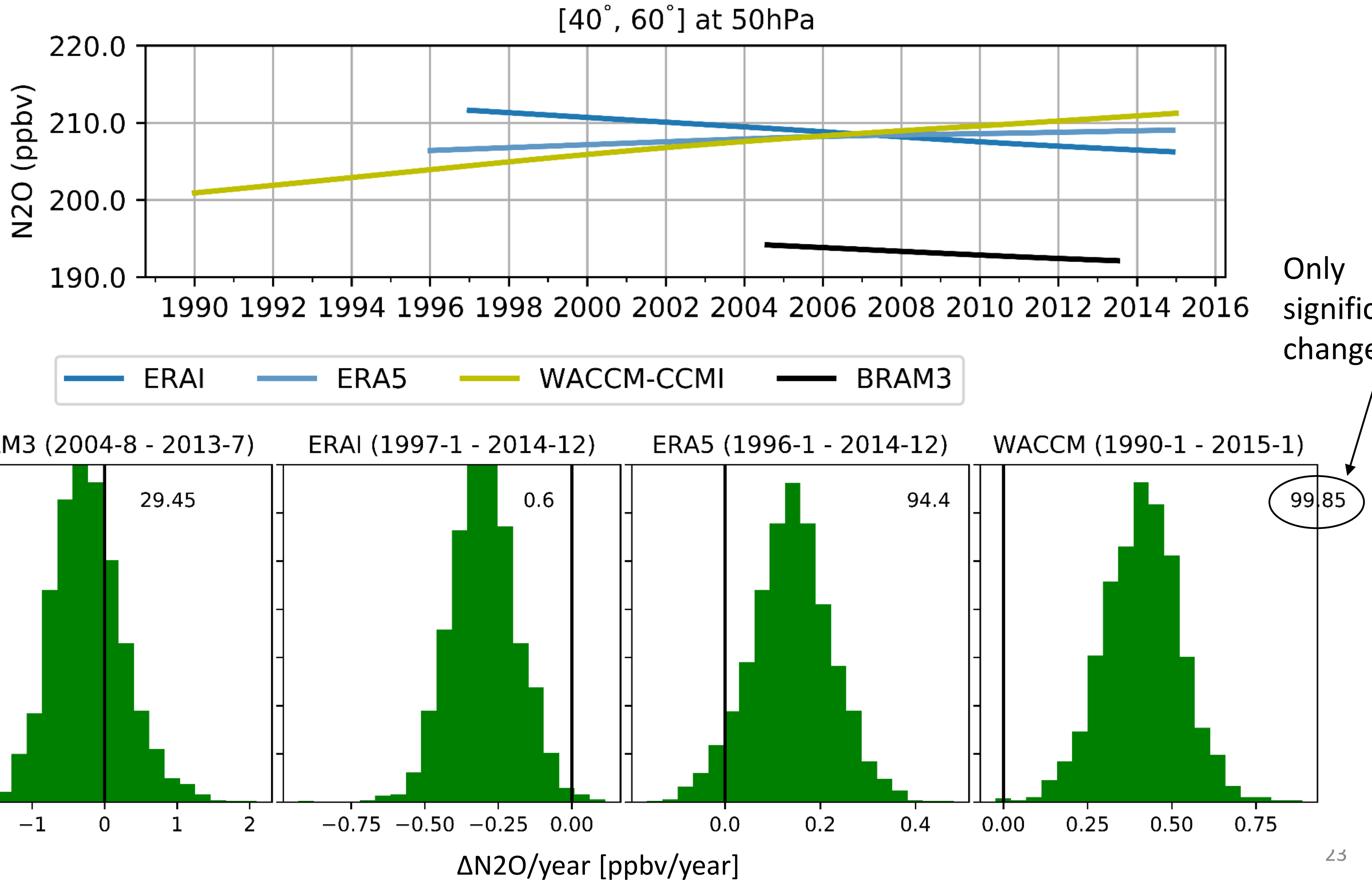


Preliminary fit results

Northern mid-latitudes

Negative significant change in ERAI (99,4%)

Only significant change



Conclusions (work in progress)

- **Time-series**: inter-hemispheric differences in N2O anomalies in the middle latitudes. Driven by circulation anomalies after unusual QBO (Strahan et al., *GRL* 2020).
- **DLM linear fit**: Above the Antarctic, the change of slope in the dynamical reanalyses can be related to transport changes due to the ozone hole recovery (Fu et al., *ERL* 2019).
- **DLM linear fit**: for ERA5 and BRAM3, inter-hemispheric differences in the extra-tropics: positive significant changes in the SH, non-significant in the NH.
- **DLM linear fit**: positive changes in the SH and negative in the NH, both significant. Corresponds to detected trends in mean AoA for similar period (Chabrillat et al., *ACP* 2018).
- **DLM linear fit**: WACCM show a global positive change in N2O.
- Exploit groundbased FTIR observations from NH (Jungfraujoch), SH (Lauder) and Tropics (Paramaribo).

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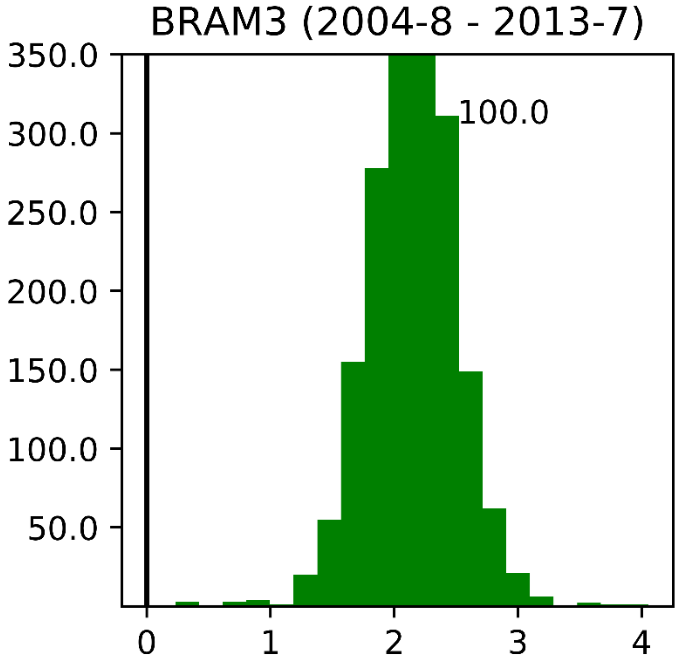
Posterior probability in BRAM3 above the Antarctic



Differences btw DLM and MLR

MLR:

- Assumptions about the noise.
- Post-hoc corrections for correlated residuals.
- De-seasonalize first.
- The parameters are estimated with approximate error bars.
- Piecewise linear trend is not ideal for describing real trends: in advance we don’t know the behavior of the data.
- Regressors and seasonal coefficients are constant in time.

How does DLM handle missing data?

- Missing data are set to NaN.
- Then, they are set as the mean of the rest of the values, but with enormous error bars (1e20).

QBO impact on transport (and then on tracer anomalies)

- Before 2011 there was longer easterly QBO phase (Strahan et al, 2015).
- In the SH this creates negative anomaly of N_2O, that lasted in the mid-latitudes through recirculation (AoA anomalies, Ploeger and Birner, 2016).