

From global to regional inverse modelling of greenhouse gases

F Chevallier (LSCE, Gif-sur-Yvette, France)

This presentation discusses the potential introduction of surface fluxes (sources and sinks) in the control vector of the ECMWF 4D-Var . It starts from the example of the data assimilation systems set-up for methane (CH4) in MACC-II, before highlighting the various molecules whose surface fluxes are estimated through inverse modelling in this project. In each case, the inverse modelling work is distinct from the IFS that estimates initial conditions within a much shorter observation window (hours rather than months, years or decades). Merging the two types of work is an ambitious objective, which is made particularly challenging by the high sophistication of the prior models and inventories of the surface fluxes: any inverted flux map needs to pass stringent realism tests that up to now have favoured dedicated inversion tools compared to all-in-one systems. The presentation discusses this issue from the point of view of the atmospheric observations (a small and ambiguous signal), of the observation operator (flawed by various biases that significantly degrade inversion results), of the prior error statistics (for CO₂, the error correlation scales are short, which makes the inversion problem intrinsically of very large dimension; the temporal correlation scales are large which hampers short assimilation windows). The conclusion emphasizes the importance of well characterizing the prior flux errors and the need of redundancy in the inversion systems to compensate for internal biases. A long inversion window is the most straight-forward way to achieve this redundancy.

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Frédéric Chevallier

Laboratoire des Sciences du Climat et de l'Environnement
Gif-sur-Yvette
France



LSCE

LABORATOIRE DES SCIENCES DU CLIMAT
& DE L'ENVIRONNEMENT



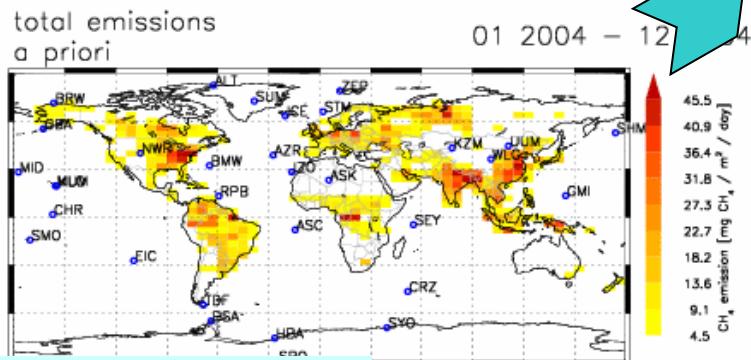
Roadmap of the talk

"The aim of the workshop is to see which existing methods could be used in the **ECMWF operational environment for atmospheric composition to improve the surface boundary conditions in terms of fluxes**, emissions, and point source releases. This could range from new on-line methods to better definitions of prescribed inventories.

I would therefore appreciate if you could discuss your work and ideas on greenhouse gas inversions within the above framework. Especially, **the potential use of flux increments in the 4D-Var control vector** would be of high relevance."

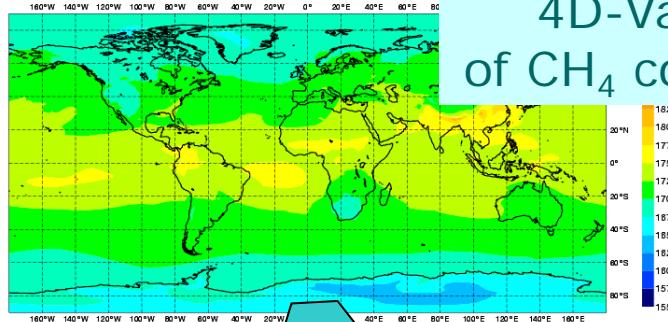
R. Engelen

The MACC CH₄ system



Prior information
about CH₄ fluxes

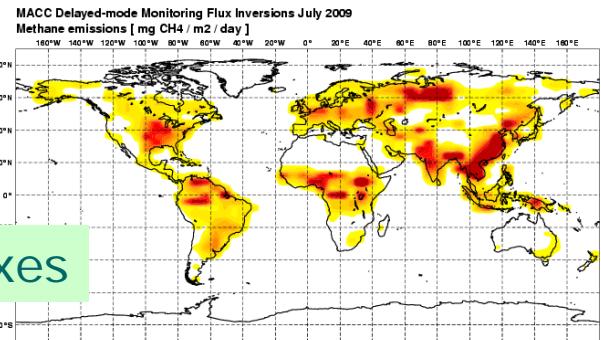
MACC Delayed mode Global Monthly Mean July 2009
Mean Column Methane Mixing Ratio [ppb] mean: 1709.21 max: 1869.40



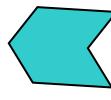
4D-Var analysis
of CH₄ concentrations



Satellite
observations
of CH₄

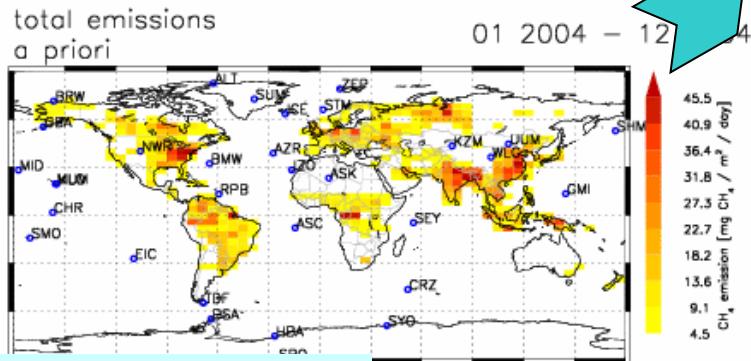


Optimized CH₄ fluxes



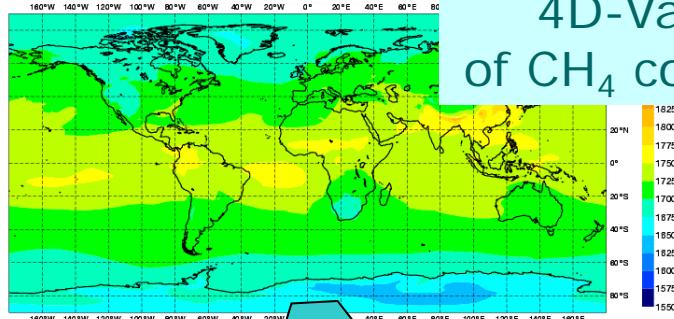
Surface
observations
of CH₄

The MACC-II CH_4 system

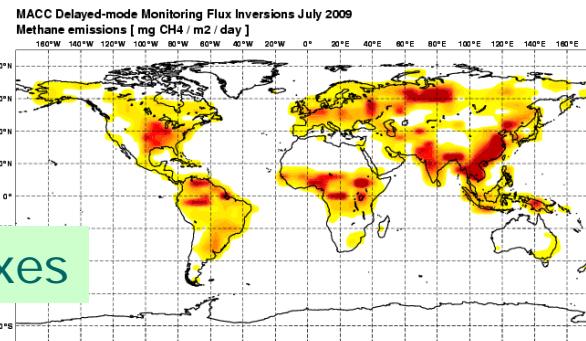


Prior information
about CH_4 fluxes

MACC Delayed mode Global Monthly Mean July 2009
Mean Column Methane Mixing Ratio [ppb] mean: 1709.21 max: 1869.40



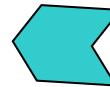
4D-Var analysis
of CH_4 concentrations



Optimized CH_4 fluxes

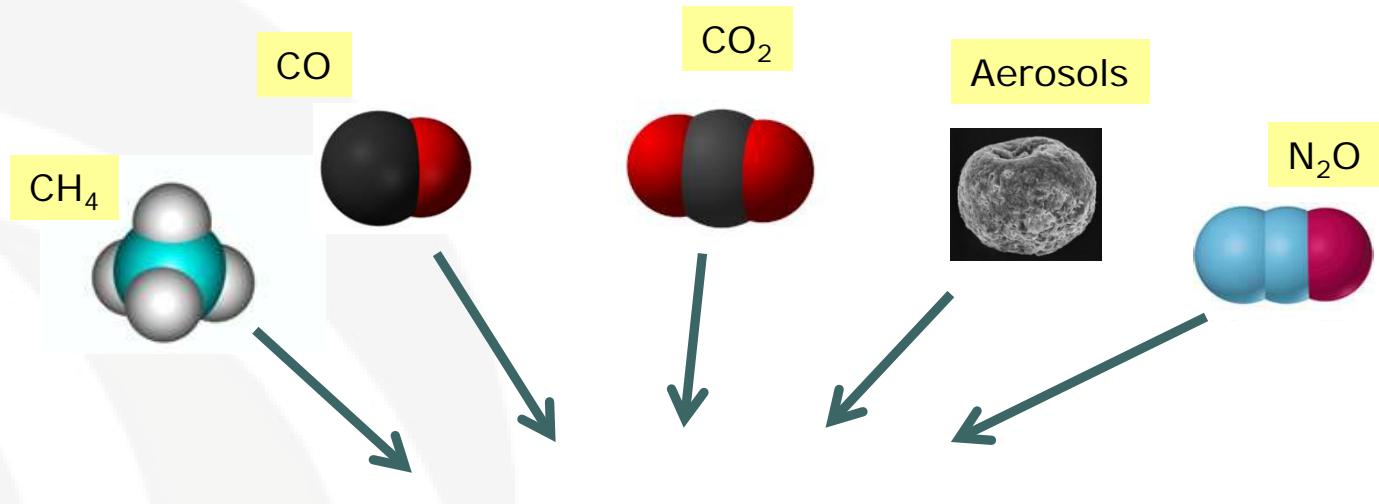


Satellite
observations
of CH_4

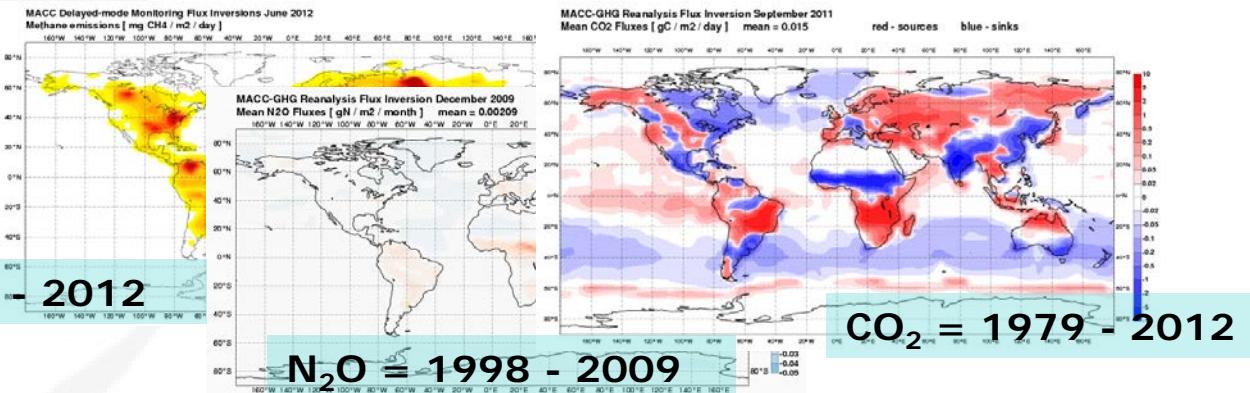


Surface
observations
of CH_4

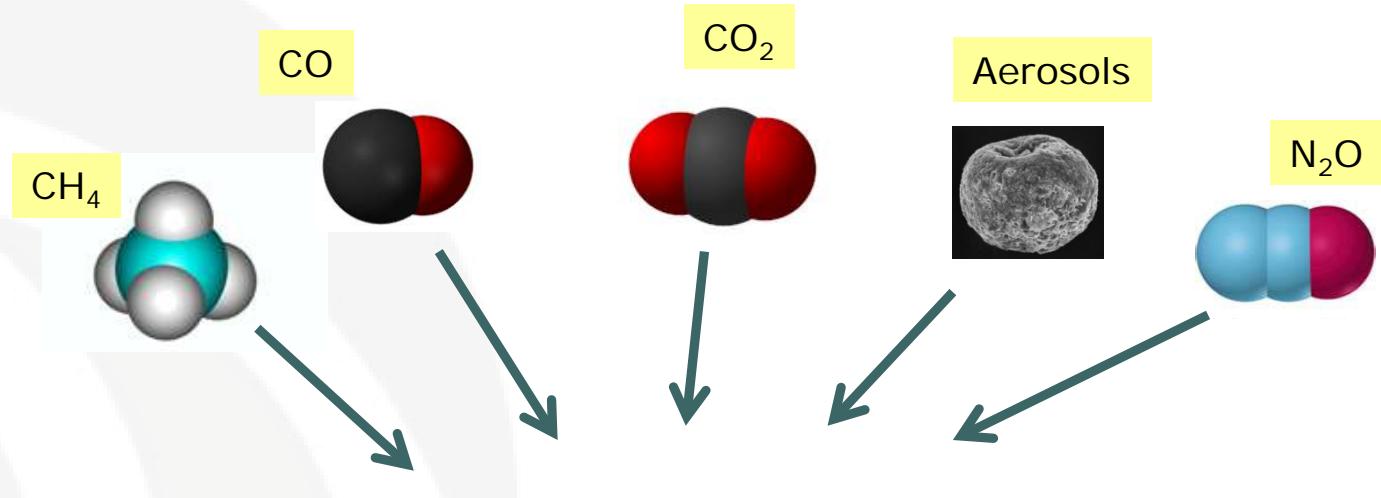
Atmospheric inversion in the MACC-II service



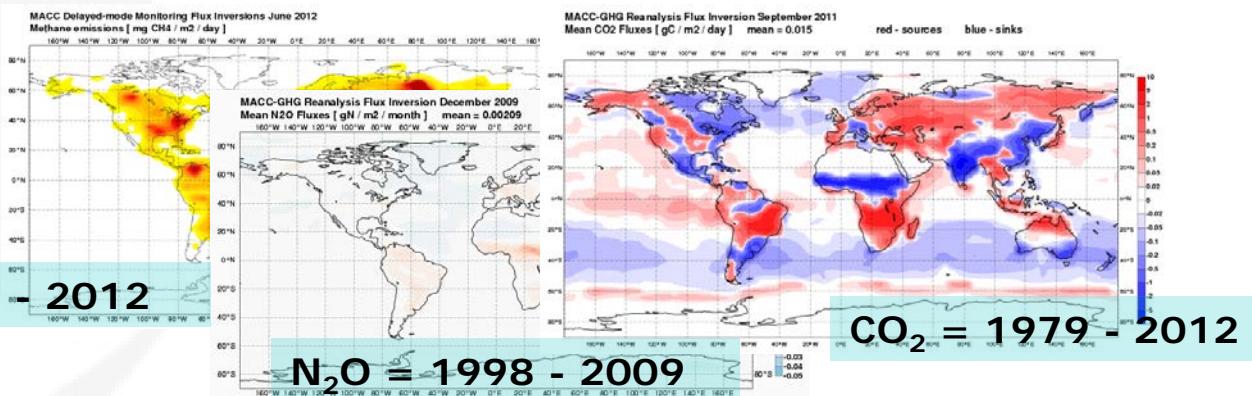
$$\nabla J(\mathbf{x}) = 2\mathbf{B}^{-1}(\mathbf{x} - \mathbf{x}_b) + 2\mathbf{H}^T\mathbf{R}^{-1}(\mathcal{H}(\mathbf{x}) - \mathbf{y})$$



Atmospheric inversion in the MACC-II service

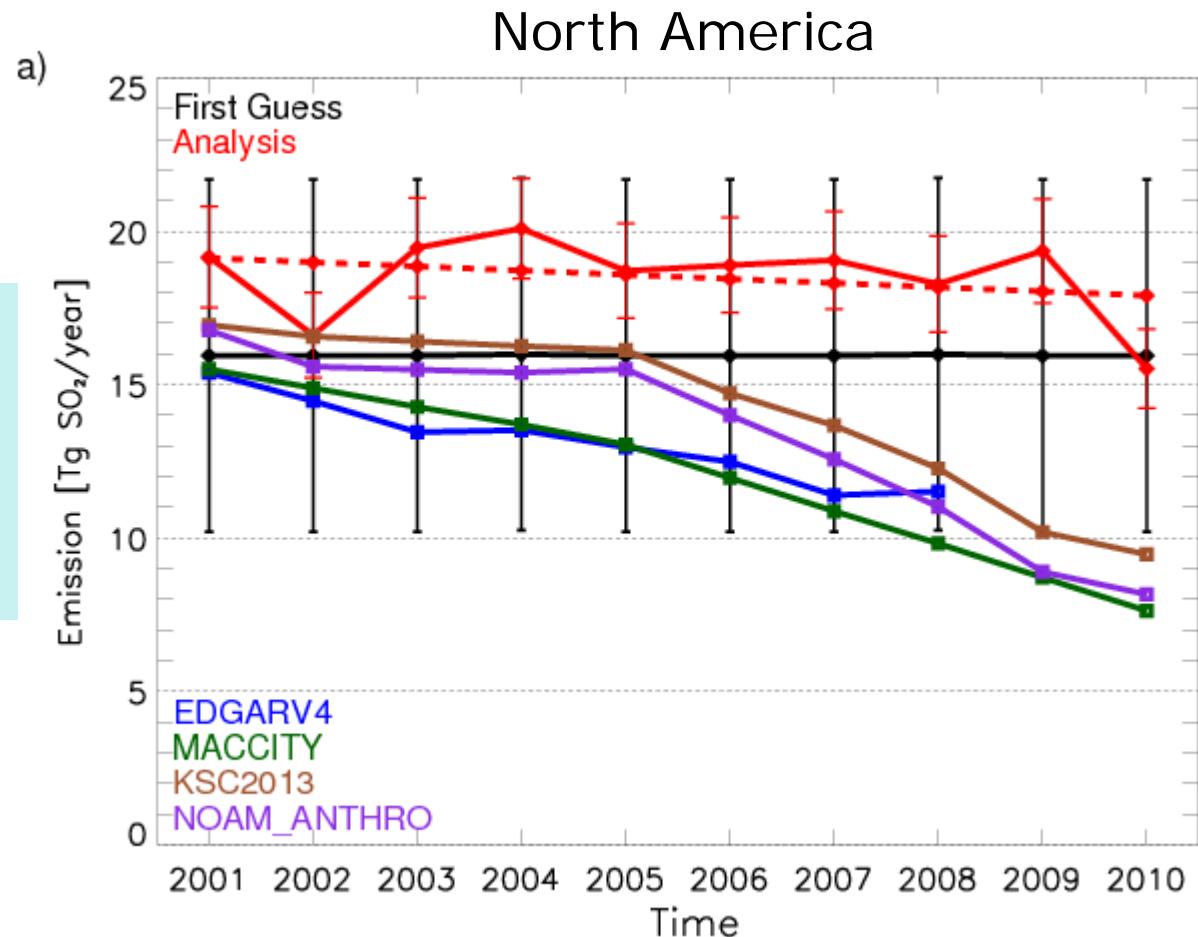


PYVAR,
TM5-4DVAR,
IFS? → $\nabla J(\mathbf{x}) = 2\mathbf{B}^{-1}(\mathbf{x} - \mathbf{x}_b) + 2\mathbf{H}^T\mathbf{R}^{-1}(\mathcal{H}(\mathbf{x}) - \mathbf{y})$

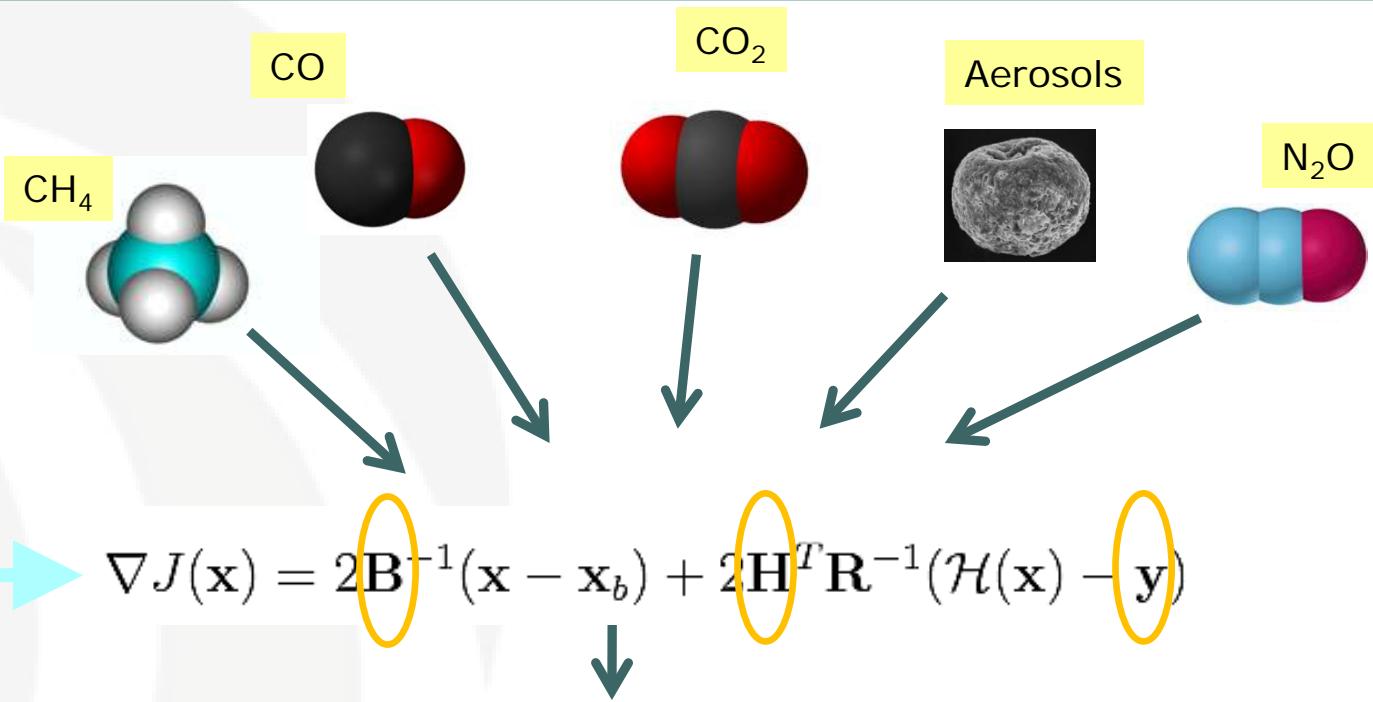


Towards meaningful flux increments

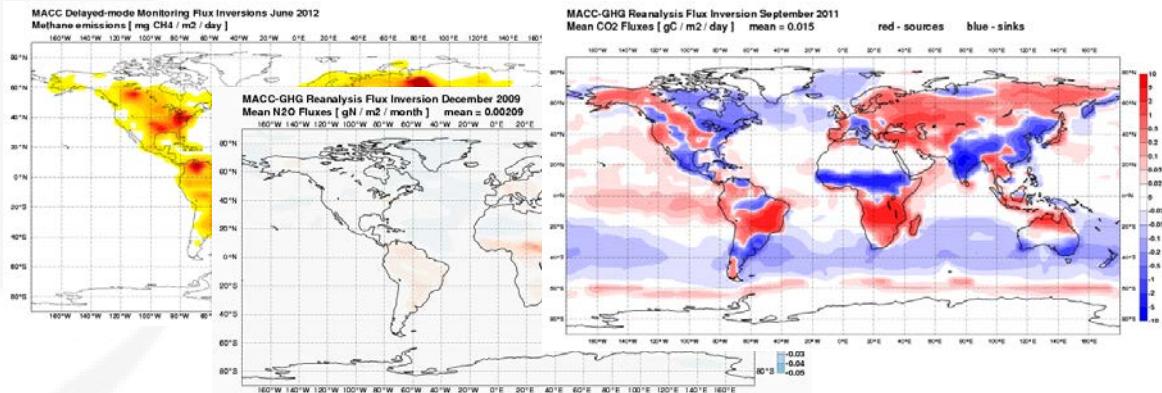
- Some regional emission budgets are very well documented.
- Stringent benchmark.



Outline



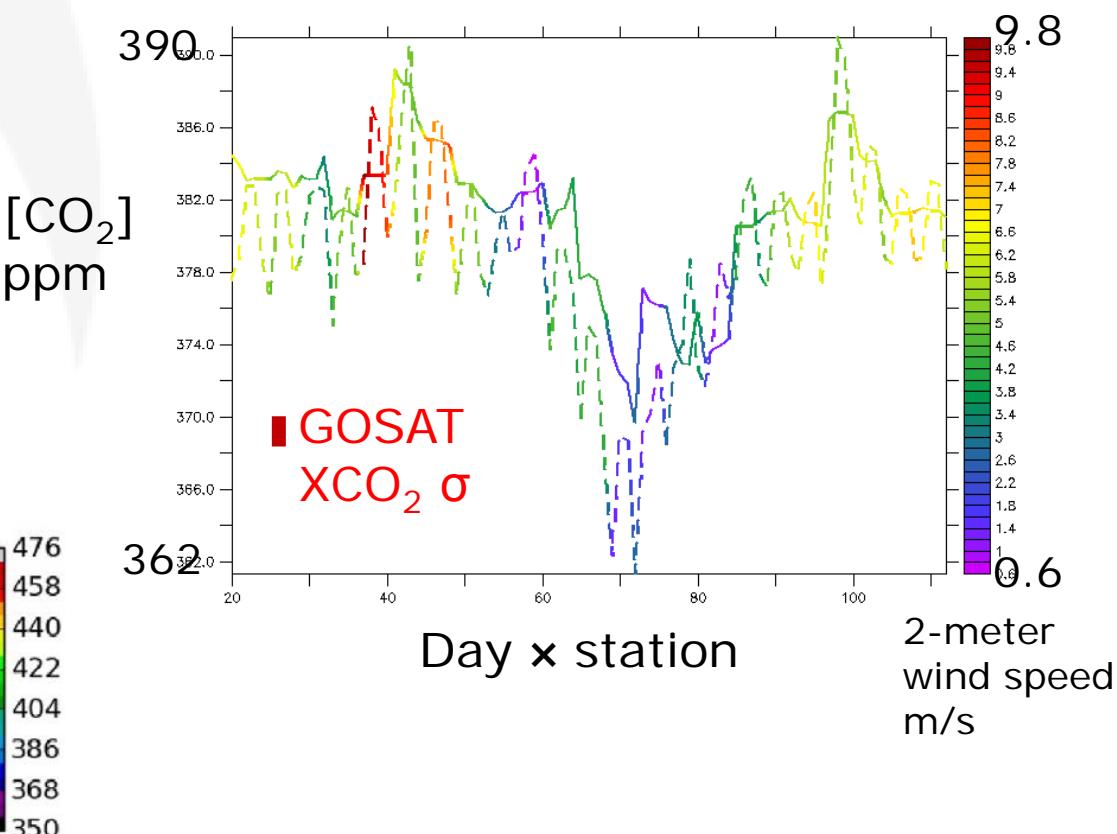
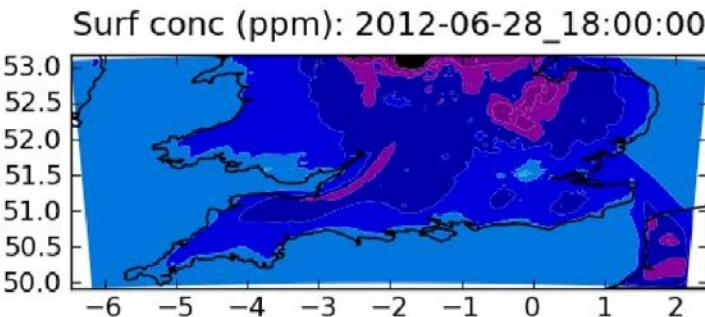
PYVAR,
TM5-4DVAR,
IFS?



$$\nabla J(\mathbf{x}) = 2\mathbf{B}^{-1}(\mathbf{x} - \mathbf{x}_b) + 2\mathbf{H}^T\mathbf{R}^{-1}(\mathcal{H}(\mathbf{x}) - \mathbf{y})$$

- y - CO₂

- July simulation of CO₂ at 4 sites in London (CHIMERE@2 km).
 - [CO₂] @ 15 UTC = UK fluxes from the past 36 h + Lateral boundaries
 - Sum of the two components (continuous line) and lateral boundaries only (dashed line).

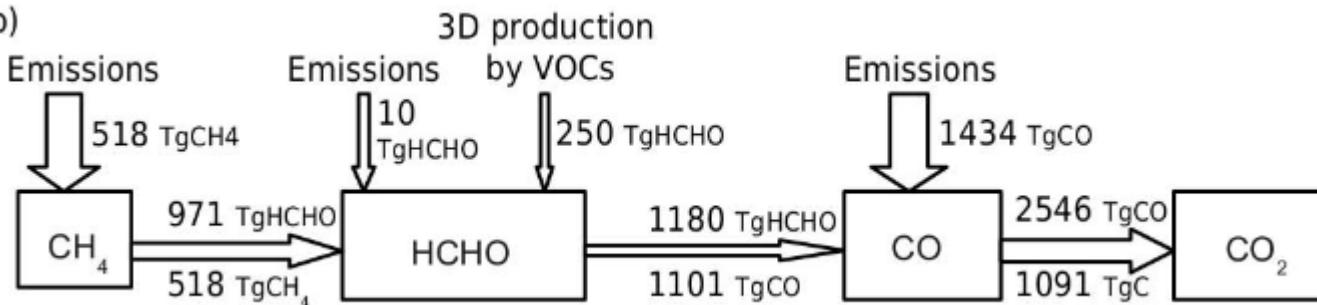


$$\nabla J(\mathbf{x}) = 2\mathbf{B}^{-1}(\mathbf{x} - \mathbf{x}_b) + 2\mathbf{H}^T\mathbf{R}^{-1}(\mathcal{H}(\mathbf{x}) - \mathbf{y})$$

- y - CO

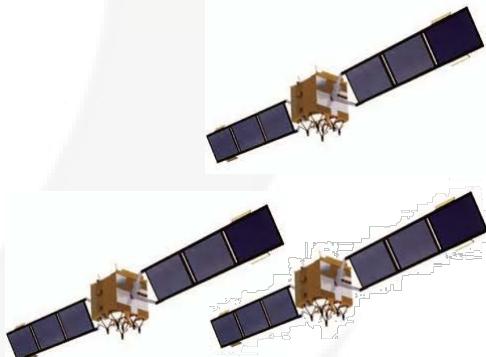
- Atmospheric production and loss: example of CO

b)



Fortems-Cheiney et al.
(2011, 2012)

TgCO/year



	USA	China	Canada	Western Europe	Global
EDGAR3.2+GFED2 (our prior)	105	108	8	44	1066
Posterior MOPITT+mcf	112	213	49	52	1467
Posterior MOPITT+OMI +mcf +ch4	132	151	54	58	1401
EDGAR 4.2+GFED3	60	96	12	22	1284

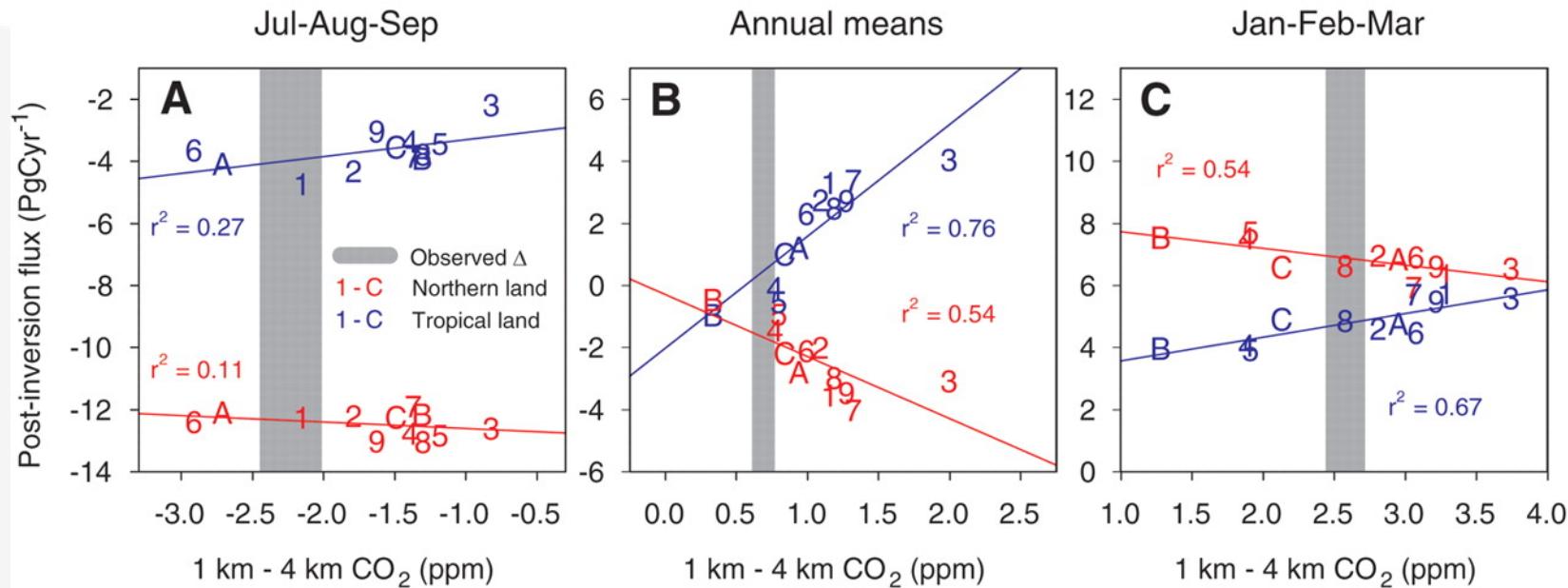
$$\nabla J(\mathbf{x}) = 2\mathbf{B}^{-1}(\mathbf{x} - \mathbf{x}_b) + 2\mathbf{H}^T\mathbf{R}^{-1}(\mathcal{H}(\mathbf{x}) - \mathbf{y})$$

– **y** –

- Mixture of signals:
 - Surface sources and sinks,
 - Transport,
 - Atmospheric production and loss.
- The signal from the surface fluxes does not necessarily dominate.
- All terms in the atmospheric mass budget ideally should be constrained.

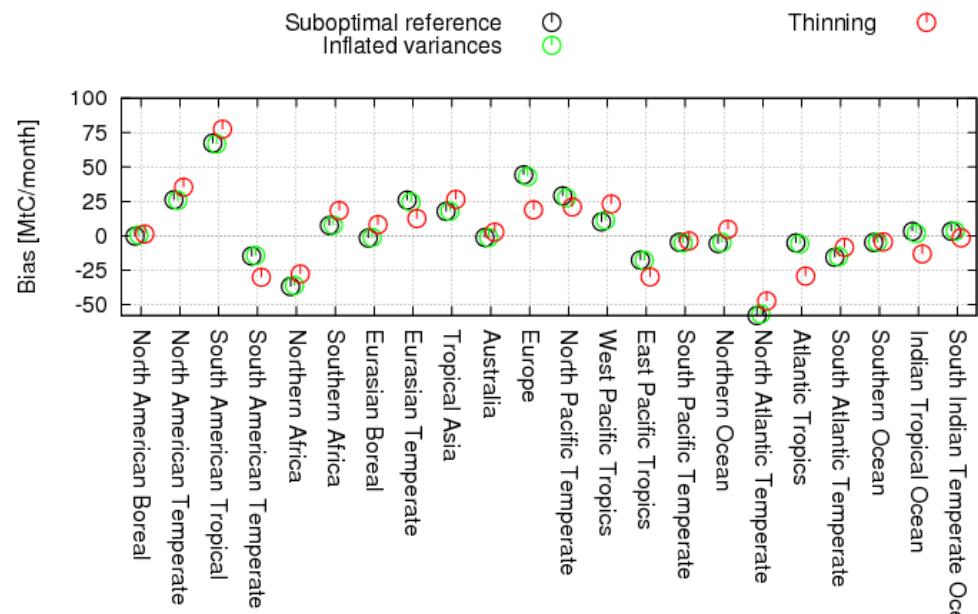
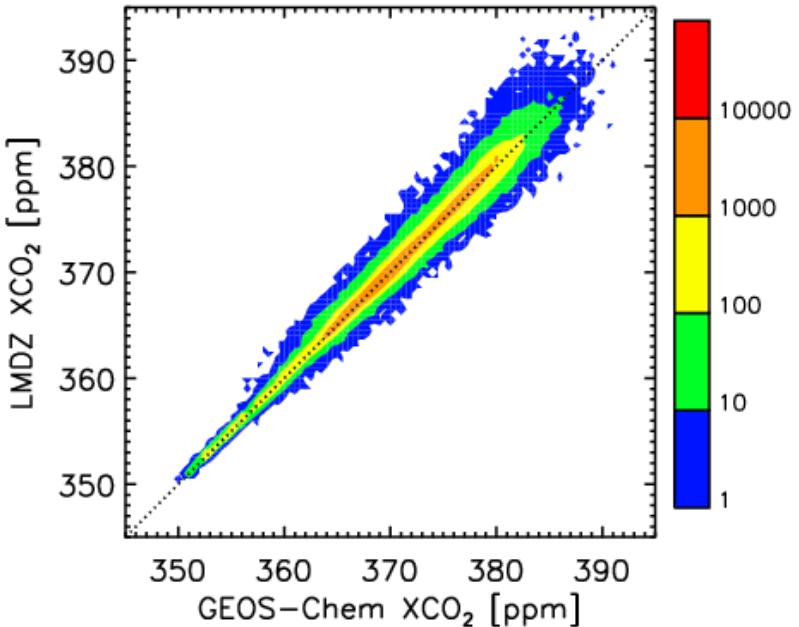
- H - long range transport

- About 15 global transport models to invert CO₂ fluxes with a standardized method (Stephens et al., Science, 2007).



- H - long range transport

- Inversion of CO_2 fluxes from simulated GOSAT XCO_2
 - True atmosphere represented by GEOS-Chem.
 - Inversion system uses LMDZ.
- LMDZ vs. GEOS-CHEM : bias = 0.0 ppm, std. dev. = 0.6 ppm
 - XCO_2 variability = 5.6 ppm (std. dev.)
- Inverted fluxes biased by 0.6 GtC/yr over Europe.

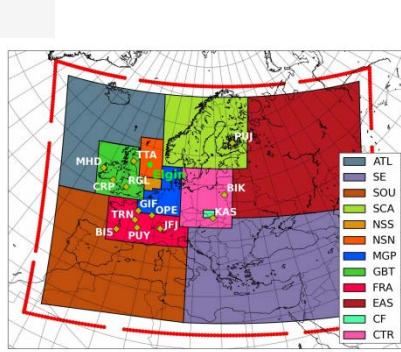


Chevallier, Feng, et al. (2010)

$$\nabla J(\mathbf{x}) = 2\mathbf{B}^{-1}(\mathbf{x} - \mathbf{x}_b) + 2\mathbf{H}^T\mathbf{R}^{-1}(\mathcal{H}(\mathbf{x}) - \mathbf{y})$$

– H – short-range transport

- Most likely (\mathbf{R}, \mathbf{B}) tuple given the atmospheric observations.
 - Application to CH_4 .
 - Link with boundary layer height (from ECMWF).



Berchet et al.
(ACP, 2013)

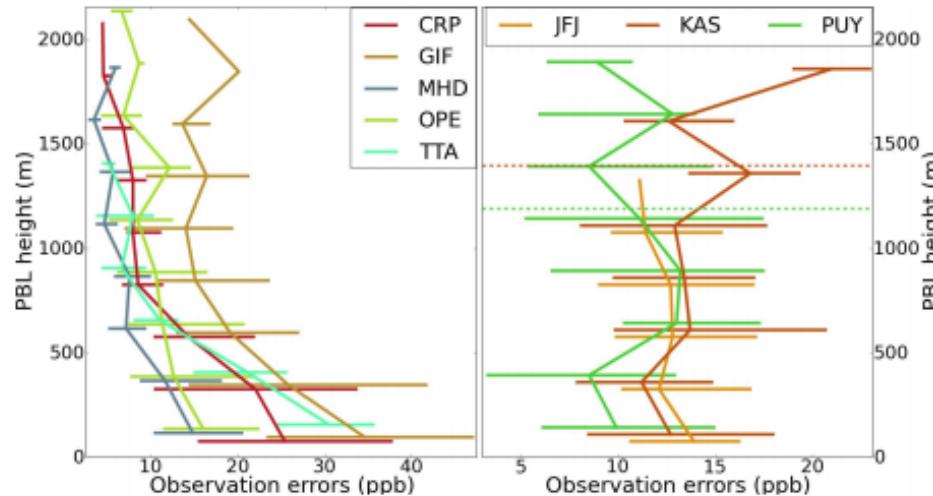


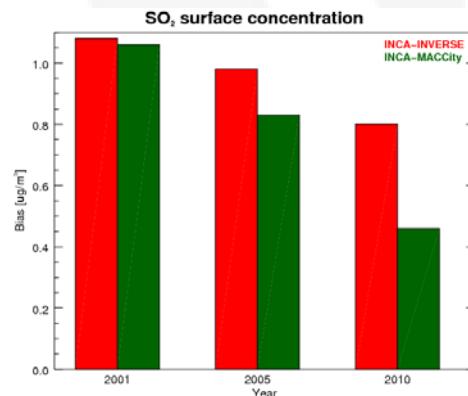
Fig. 3. Statistics of the errors projected along ECMWF-simulated PBL height for ML method: median and inter-quartile gap per 250m-high layer. (Left) sites with strong correlations as calculated in Table 2; not displayed site RGL exhibits the same patterns but with higher errors. (Right) Mountain sites with influence from the PBL less prevailing. Dashed lines refer to the station altitude in the model; JFJ is above the maximum simulated PBL height.

$$\nabla J(\mathbf{x}) = 2\mathbf{B}^{-1}(\mathbf{x} - \mathbf{x}_b) + 2\mathbf{H}^T\mathbf{R}^{-1}(\mathcal{H}(\mathbf{x}) - \mathbf{y})$$

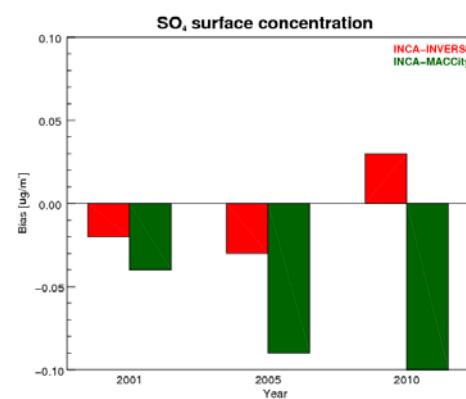
– H – chemistry

- Compare LMDZ-INCA simulations with SO_2 and SO_4 surface concentrations from the EMEP network:
 - Surface emissions from the MACCity inventory;
 - Surface emissions from the inversion of MODIS AODs (using a simplified chemistry mechanism);
 - Bias shown.

Sulfur dioxide
(SO_2)



Sulfate aerosols
(SO_4)



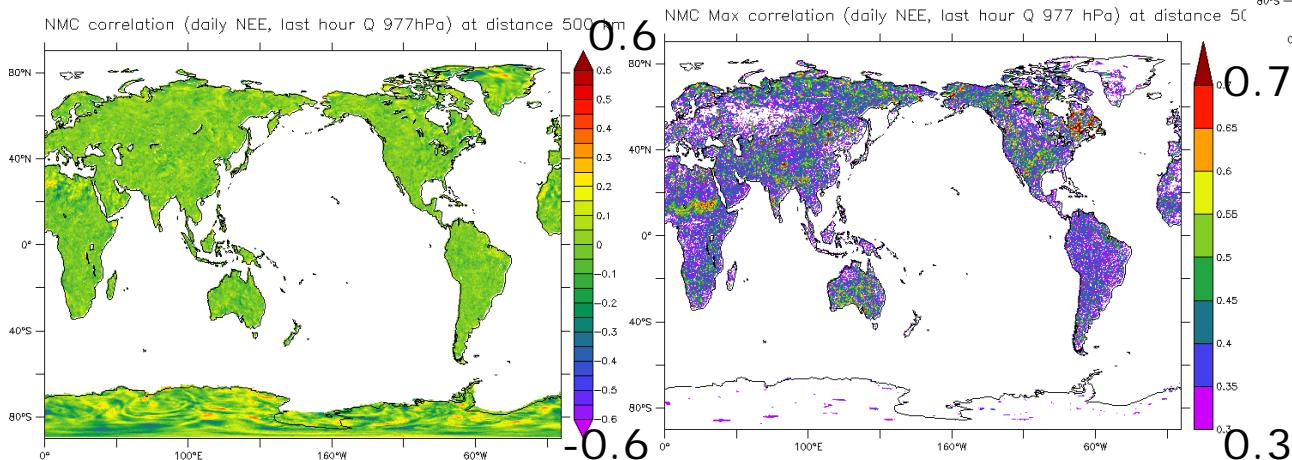
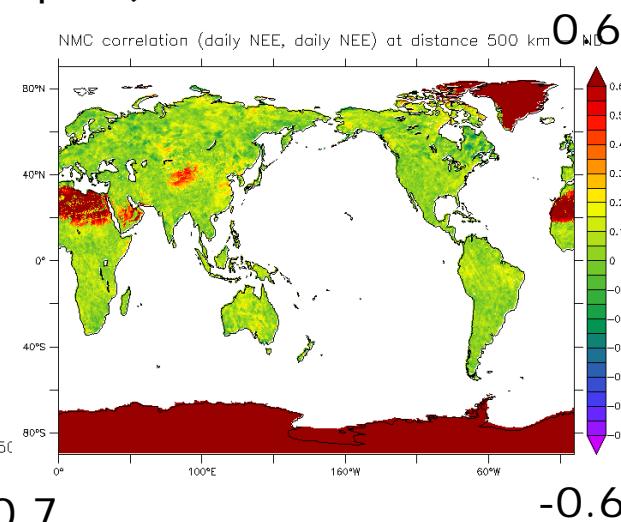
$$\nabla J(\mathbf{x}) = 2\mathbf{B}^{-1}(\mathbf{x} - \mathbf{x}_b) + 2\mathbf{H}^T\mathbf{R}^{-1}(\mathcal{H}(\mathbf{x}) - \mathbf{y})$$

— H —

- Transport models are flawed at all time scales, despite obvious skills.
 - The flaws are large enough to affect flux inversion.
- Chemistry issues as well.

– B – short window

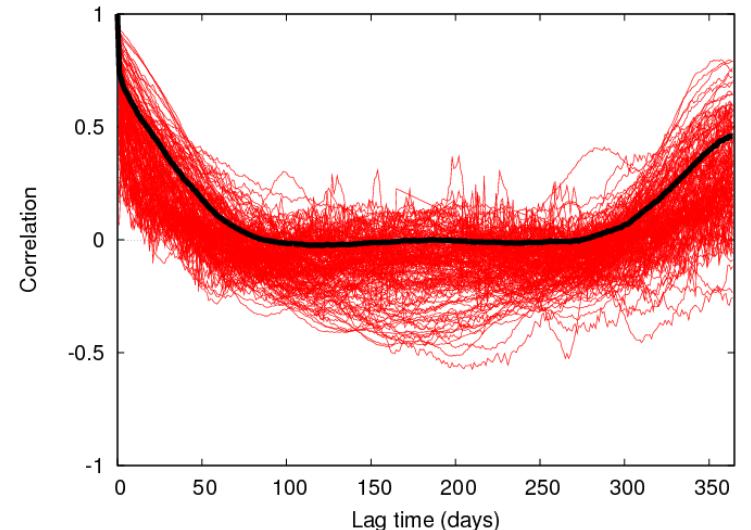
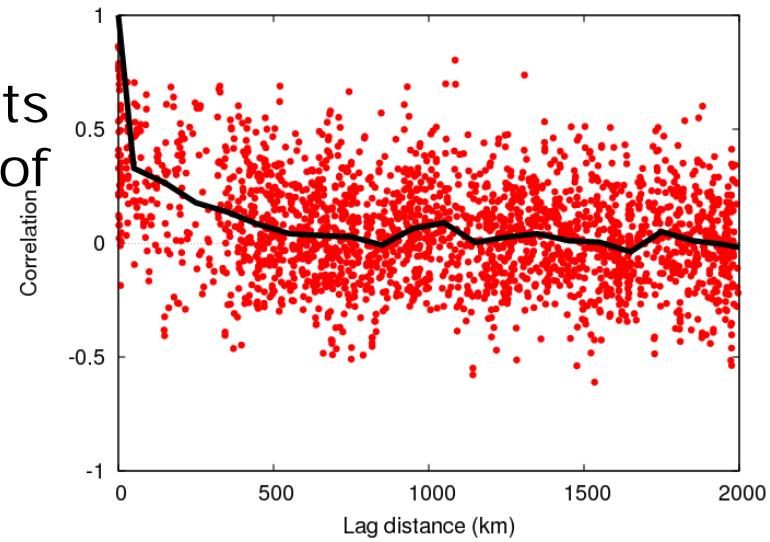
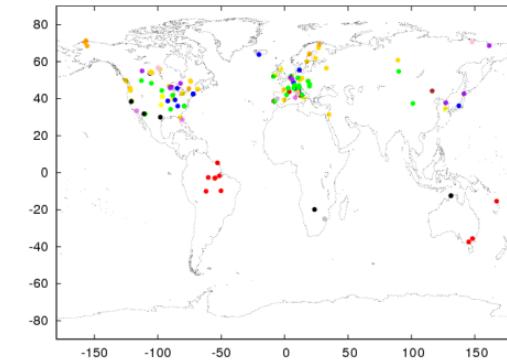
- Using the NMC method on the MACC-II NRT forecast to diagnose background error correlations (further to a discussion with W Peters)
 - Mean FCO₂ at ranges 12-36 h and 36-60 h (spin-up, ...)
 - 977 hPa [CO₂] at ranges 36 h and 60 h
 - November-December 2012, 15 km
- No isotropic correlations found.
- Some wind-dependent FCO₂ - [CO₂] correlations.



Correlations of the ensemble at lag distance 500 km

– B – error correlations

- Use daily-mean eddy-covariance flux measurements to assign the error statistics of the fluxes simulated by the ORCHIDEE model.
- Results:
 - Small spatial correlations,
 - Large temporal correlations.

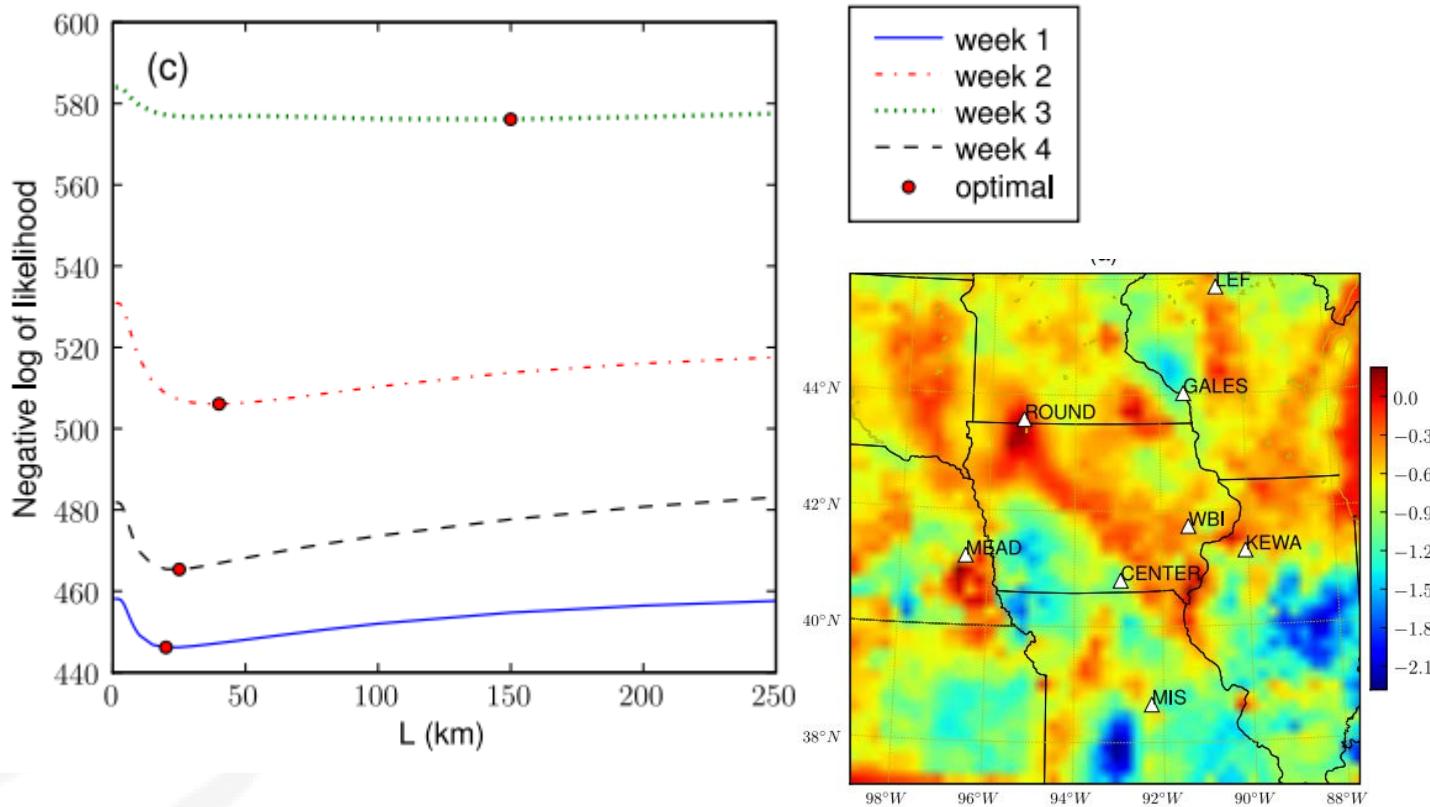


Chevallier et al. (2012)

– B – error correlations

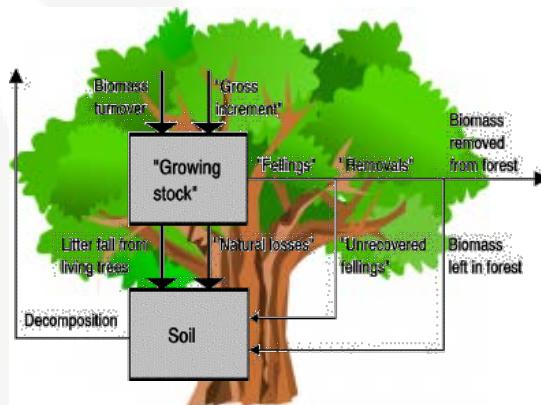
- Mesoscale regional inversion for NACP's Ring2.
 - Infer the characteristic correlation length of the SiBcrop model from $[CO_2]$ using maximum likelihood.
 - Small error correlations inferred.

Wu et al.
(Tellus B, 2013)



– B – parameter inversion

- Invert the parameters of a process model of the fluxes rather than the fluxes directly.
- Prior flux uncertainty $\mathbf{B} = \mathbf{B}_{\text{param}} + \mathbf{B}_{\text{struct}}$



– B – parameter inversion

- Using Fluxnet data to diagnose $\mathbf{B}_{\text{struct}}$ for the ORCHIDEE model.
 - When projected in the space of mole fractions, **the impact of model error ~ transport errors** ($L \sim 0$, std. = 1.3 ppm for surface CO₂; $L = 1200\text{km}$, std. = 0.5 ppm for XCO₂).

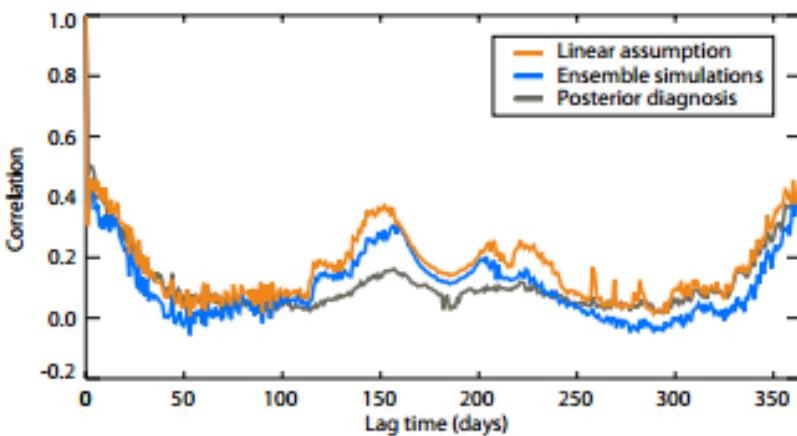


Fig. 2. All-site median of the autocorrelation of the observation error (i.e., model error + measurement error) \mathbf{R} , estimated at each site with three methods: prior diagnostics with the linear assumption (orange, $\hat{\mathbf{R}}^{\text{prior}}$ from Eq. 1), prior diagnostics with ensemble simulations (blue, $\hat{\mathbf{R}}^{\text{prior}}$ from Eq. 1), and posterior diagnostics (grey, $\hat{\mathbf{R}}^{\text{post}}$ from Eq. 3).

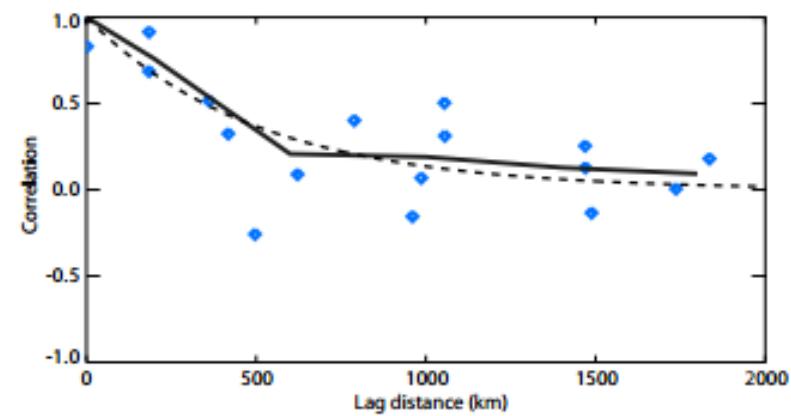


Fig. 3. Distance correlogram of the observation (model+measurement) error $\hat{\mathbf{R}}^{\text{prior}}$ estimated from Eq. (1), using pairs of distant sites for a same time. The value represented by each blue diamond includes all the common years of one site pair. The thick black line represents the overall median using 400-km bins, and the dotted line an exponential decay with an e-folding length of 500 km.

– B – parameter inversion

- Using Fluxnet data to diagnose $\mathbf{B}_{\text{struct}}$ for the ORCHIDEE model.
 - When projected in the space of mole fractions, **the impact of model error ~ transport errors** ($L \sim 0$, std. = 1.3 ppm for surface CO_2 ; $L = 1200\text{km}$, std. = 0.5 ppm for XCO_2).
- Mole fraction measurements are not the most effective measurements to constrain process parameters (Koffi et al., ACP, 2013).
 - Atmospheric concentrations are an observation of integrated flux.

$$\nabla J(\mathbf{x}) = 2\mathbf{B}^{-1}(\mathbf{x} - \mathbf{x}_b) + 2\mathbf{H}^T\mathbf{R}^{-1}(\mathcal{H}(\mathbf{x}) - \mathbf{y})$$

– B –

- Small spatial correlation lengths of the prior errors (at least for CO₂).
 - Flux increments peak in the vicinity of the measurements.
- Spreading the information via the generic parameters of a process model shifts the problem towards the model errors (within **R**).
- Long temporal correlation lengths.

Information offered by an air sample

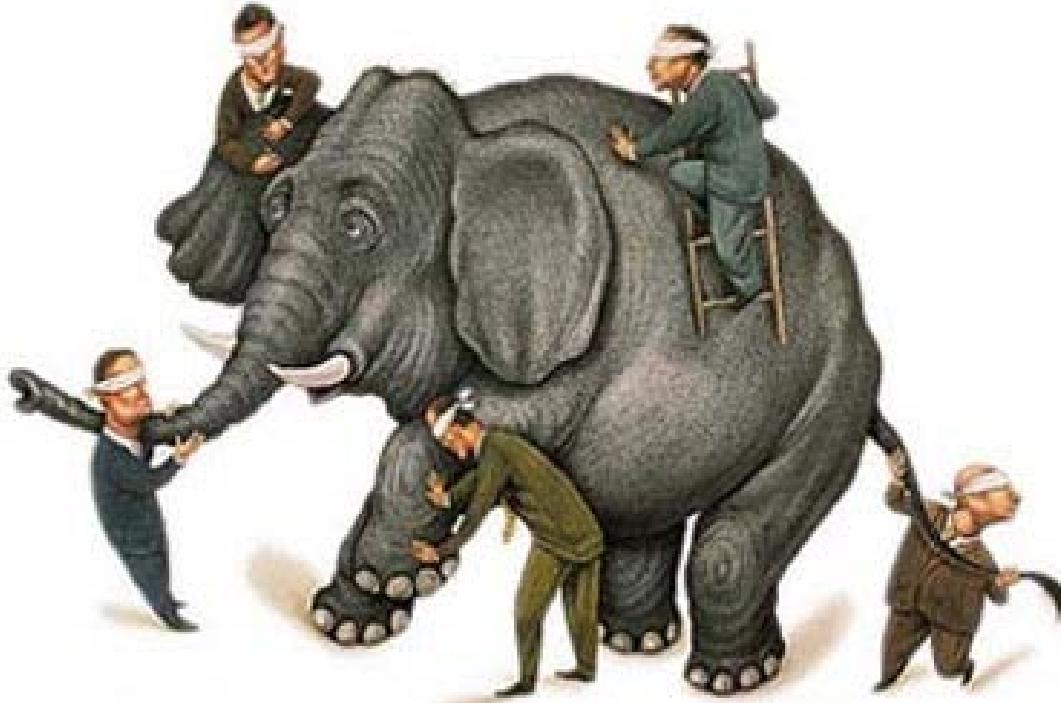


Information offered by an air sample



How atmospheric inverse modelling works

- Accumulating evidence about the fluxes:
 - long atmospheric windows,
 - combination of tracers.



Road map of the talk

"I would therefore appreciate if you could discuss your work and ideas on greenhouse gas inversions within the above framework. Especially, **the potential use of flux increments in the 4D-Var control vector** would be of high relevance."

- Need of specific systems with long assimilation windows (\geq weeks) to *properly* extract flux information from atmospheric measurements.
 - Dedicated systems run in // with the IFS.
 - Within shorter data assimilation windows, use other measurement types than atmospheric measurements.
 - Need to get the background errors right