



Co-ordinated by
ECMWF



**CO₂
Human
Emissions**

ENSEMBLE SIMULATIONS TO INFORM DATA ASSIMILATION -WP1+WP2+WP3 LINKAGES

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Nicolas Bousserez, Joe McNorton, Anna Agusti-Panareda,
Margarita Choulga, Gianpaolo Balsamo and more

ECMWF

The CHE project and its constraints

➤ Prototype **operational** CO₂ source inversion system (future Copernicus service).

Requirements:

- Support environmental decision-making and implementation of mitigation policies → posterior fluxes and their uncertainties, inform observational system requirements (e.g., satellite instrument design).
- Computational efficiency (high-resolution and fast).
- Multi-scale approach (from global to regional to local) → seamless integration of heterogeneous inversion systems.



Operational constraints will drive the methodological choice for the prototype and coordination across CHE's research activities.

ECMWF in the CO₂ community landscape

- Integrated system: online DA capabilities (i.e. joint meteorology/chemistry).
- Near real-time atmospheric composition DA and forecasting (CAMS).
- Ensemble DA system → can provide accurate transport fields together with their uncertainties as inputs for offline CO₂ inversions.
- The Object-Oriented Prediction System (OOPS) allows for modular implementation of DA methods → ideal testbed for testing new DA algorithms (Variational, Ensemble-variational).

ECMWF contribution to CHE

- Coordination of the different WP activities toward building a prototype operational CO₂ inversion system (WP5).
- Support for OSSEs → Tier 1, Tier 2 global nature run simulations.
- **Transport error estimation → ensemble of CO₂ forward model simulations (focus of this presentation).**
- Development and testing of a global anthropogenic CO₂ inversion system based on the IFS.

A global CO₂ source inversion prototype for the IFS

- Leverage online capabilities (joint meteorology/chemistry/emission DA).
- Non-intrusive approach → consistency with existing variational framework.
- Computational efficiency → addition of the CO₂ source optimization should not increase significantly the cost of the analysis.
- Maximize the use of existing operational IFS products (e.g., Ensemble Data Assimilation (EDA)).

Formalism and Notations

- Bayesian framework:

$$p(x|y) \underset{\text{posterior}}{=} \frac{\overset{\text{likelihood}}{p(y|x)} \overset{\text{prior}}{p(x)}}{\int p(y|x)p(x)dx}$$

Dimensions:

B	: nxn
H	: mxn
R	: mxm
x^b	: n
y	: m

- Maximum a posteriori (normal distribution):

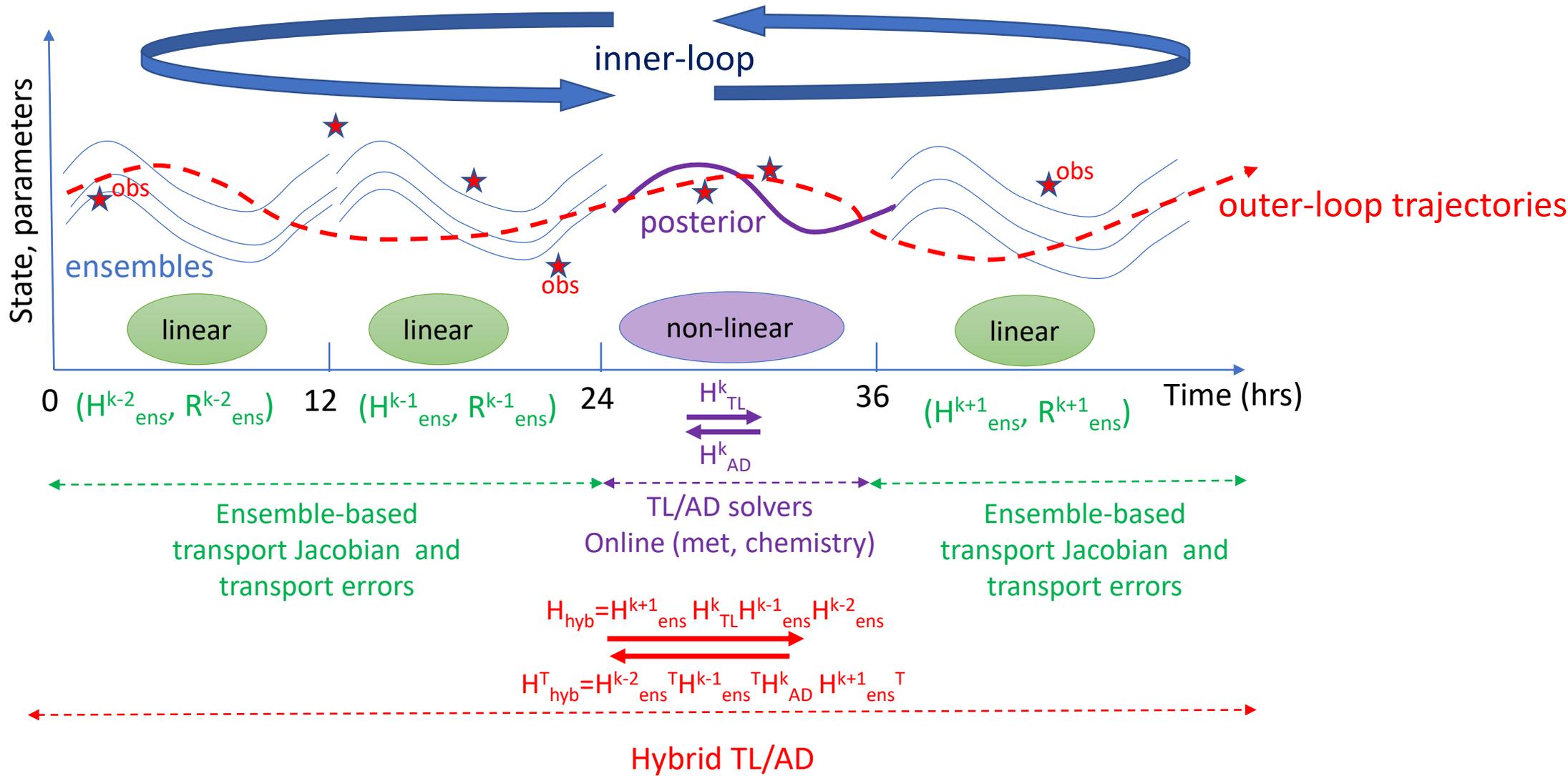
$$\begin{aligned} \mathbf{x}^a &\equiv \underset{\mathbf{x}}{\text{Arg max}} p(\mathbf{x}|\mathbf{y}) \\ &\underset{\text{posterior mode}}{=} \underset{\mathbf{x}}{\text{Arg min}} J(\mathbf{x}) \end{aligned}$$

High-dimensional problems → gradient-based iterative minimization using TL/AD models (e.g., 4D-Var).

$$\text{with: } J(\mathbf{x}) \equiv \frac{1}{2} (\underbrace{H\mathbf{x}}_{\text{forward model}} - \underbrace{\mathbf{y}}_{\text{data}})^T \underbrace{\mathbf{R}^{-1}}_{\text{model-data error covariance}} (H\mathbf{x} - \mathbf{y}) + \frac{1}{2} (\mathbf{x} - \underbrace{\mathbf{x}^b}_{\text{prior}})^T \underbrace{\mathbf{B}^{-1}}_{\text{prior error covariance}} (\mathbf{x} - \mathbf{x}^b)$$

$$\mathbf{P}^a \underset{\text{posterior error covariance}}{=} (\nabla^2 J)^{-1}(\mathbf{x}_a) = (\mathbf{B}^{-1} + \underbrace{\mathbf{H}^T}_{\text{Adjoint (AD)}} \mathbf{R}^{-1} \underbrace{\mathbf{H}}_{\text{Tangent linear (TL)}})^{-1}$$

Hybrid long-window 4D-Var (Kalman smoother)



The transport error problem

- Online DA system(i.e., joint meteorology assimilation): transport error implicitly accounted for in **B** matrix → nothing to do!
- Offline DA systems: transport error is represented in **R** matrix (observational error) → requires ensemble of transport simulations.
- Sampling noise due to small ensemble (a filtering approach is necessary).
- An overlooked issue in long-window offline 4D-Var approaches:
 - Online DA is non-linear → 4D-Var window necessarily short (~1 day).
 - Offline DA systems for CO₂ inversion use long-window 4D-Var (weeks to months to multi-years).
 - 4D-Var assumes gaussian transport error distributions → for a long integration time this might not be valid!

Configuration of Ensemble Simulations

Simulations performed at:

- TCo3099 (~**25km**) resolution with 137 vertical levels.
- 1 month (January 2015).
- **1** hourly output.
- Cycling 24 hour forecasts with analysis initialisation.
- **50** Ensemble Members.

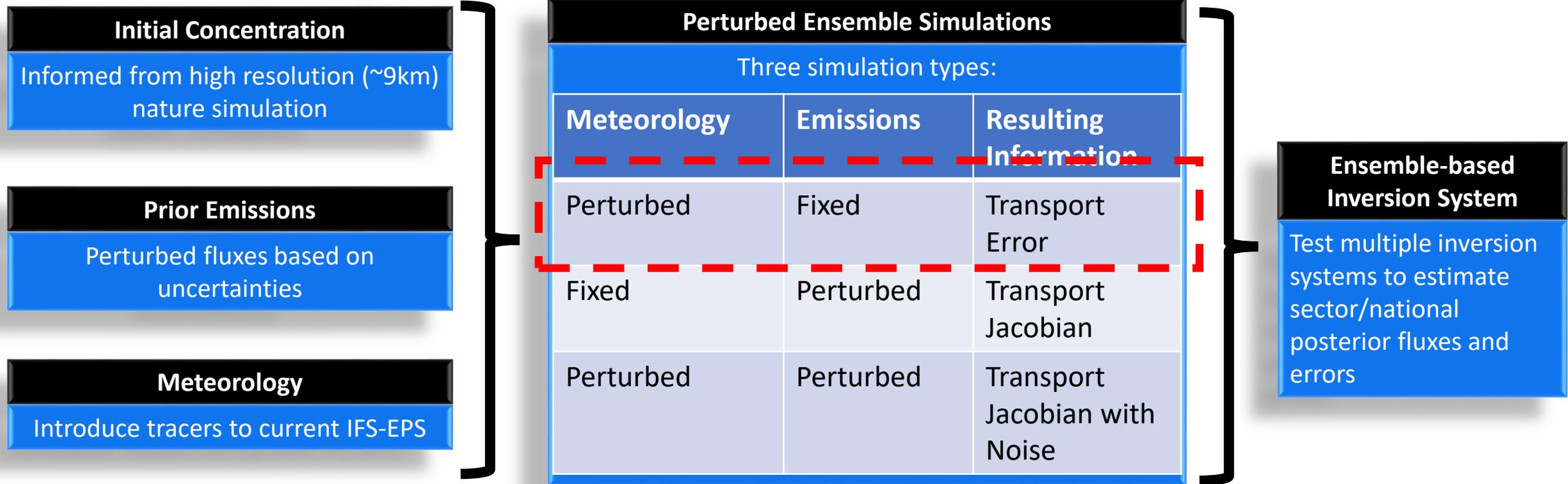
Fluxes:

- EDGAR_2015 anthropogenic emissions gridded onto TCo399 (using **2010 monthly scaling factors**).
- GFAS fire emissions and Takahashi ocean emissions.
- Biogenic fluxes are online generated using CTESSEL.
- A biogenic CO₂ flux adjustment scheme (BFAS) is used to mitigate large-scale model bias.

Perturbations:

- Anthropogenic emissions perturbed using **WP-3** uncertainties per sector & country for 7 ECMWF sectors (see Margarita Choulga's poster).
- Biogenic emissions are member specific, forced by meteorology.

Ensemble Simulations

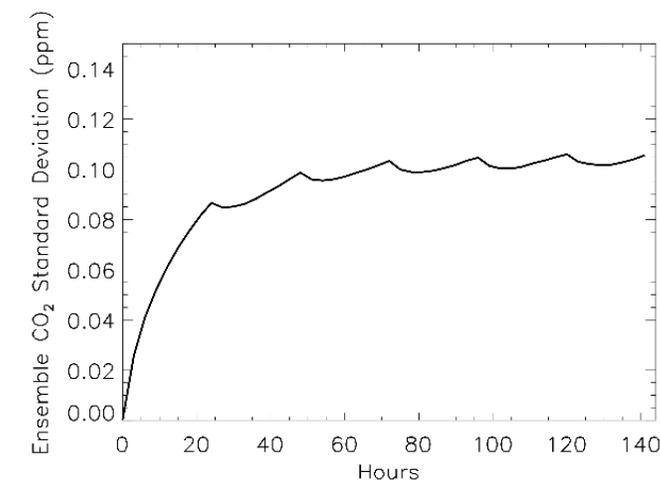
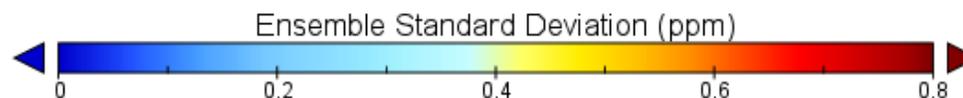
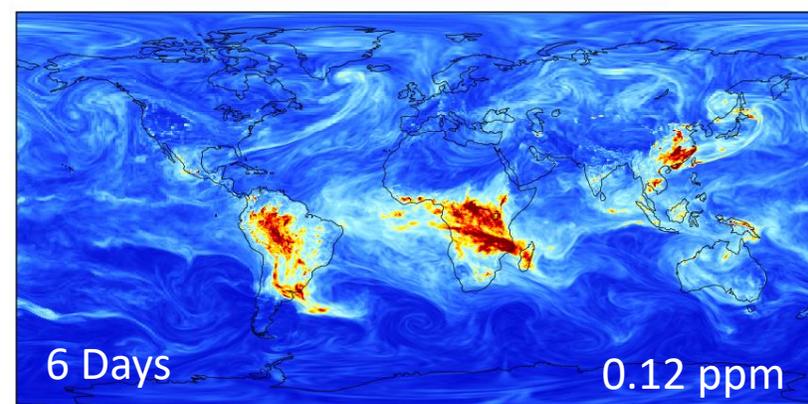
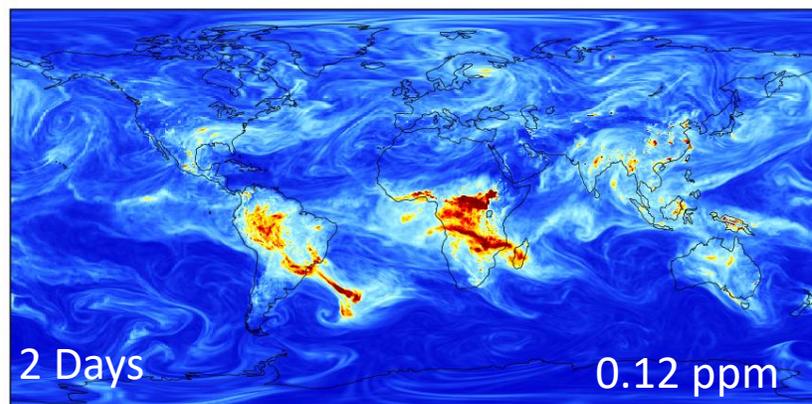
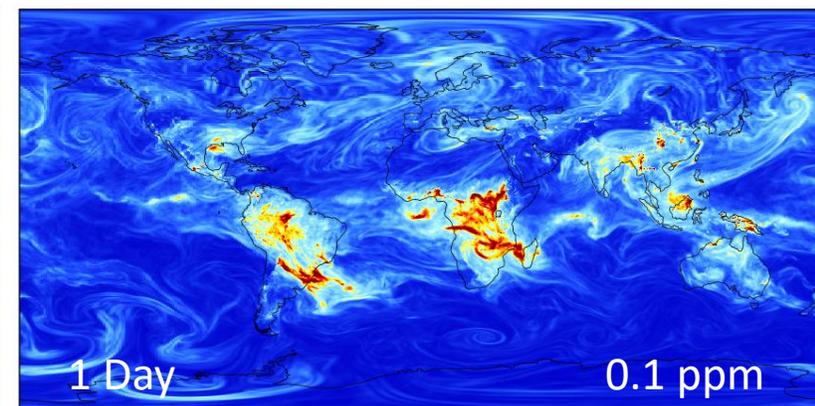
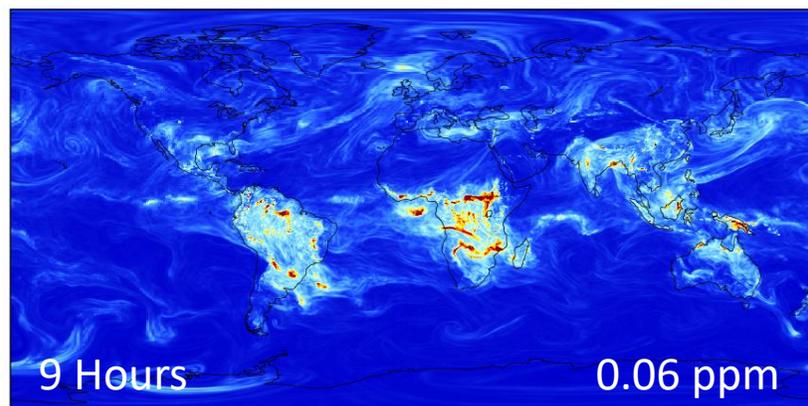
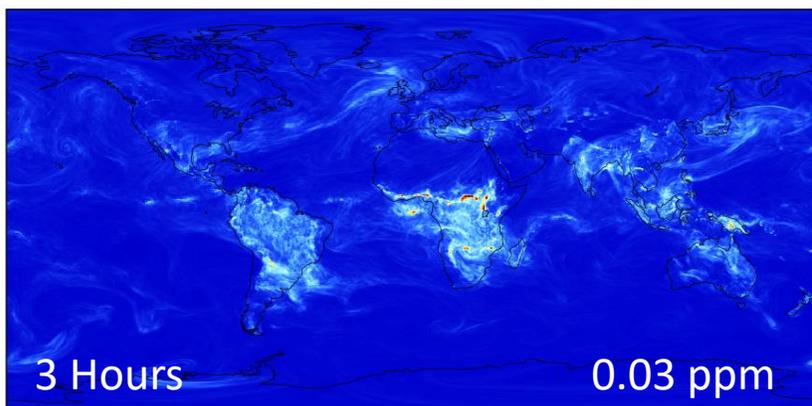


Ensemble-based Inversion System

Test multiple inversion systems to estimate sector/national posterior fluxes and errors

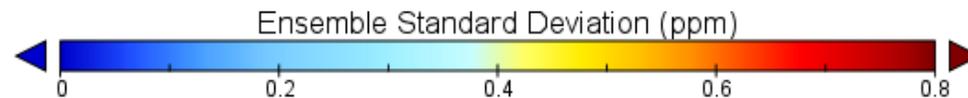
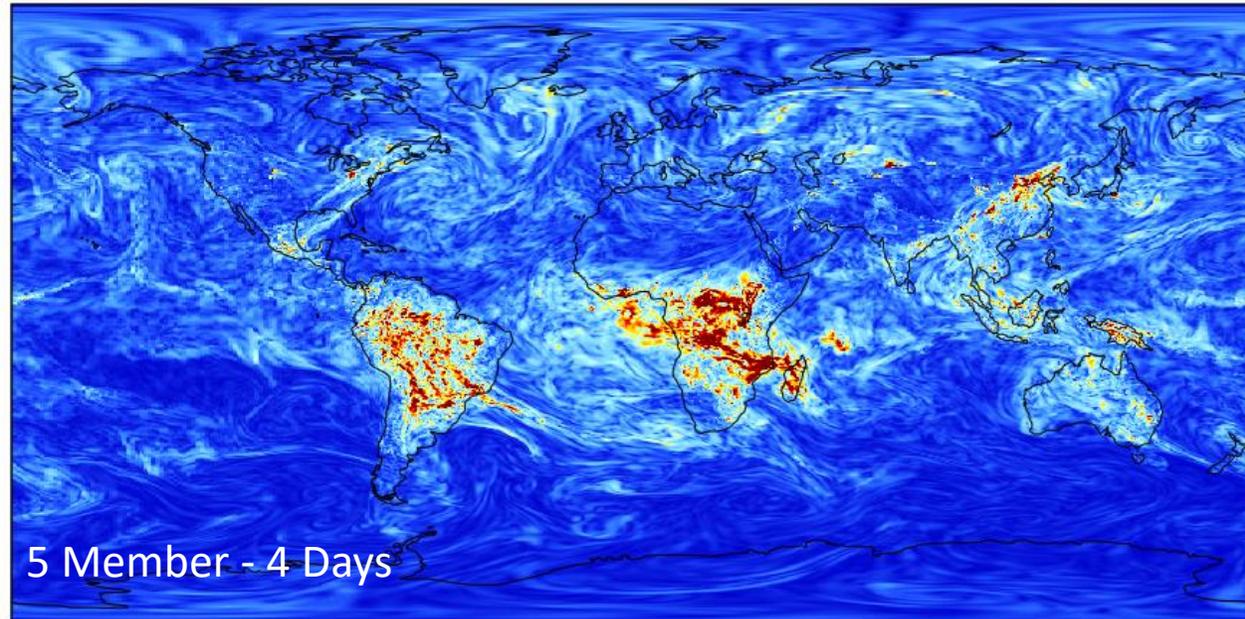
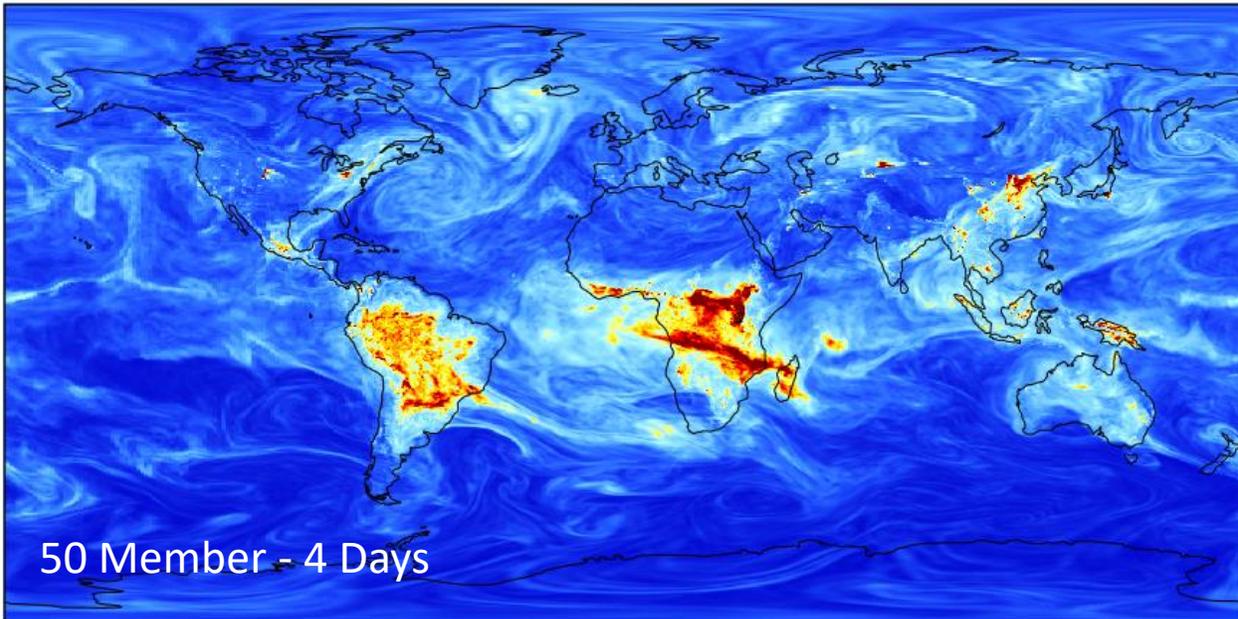
Model Transport Error – global

Meteorology	Emissions
Perturbed	Fixed



- Global transport error in XCO₂ stabilises after 2-3 days.
- Stabilization results from the impact of diffusion over longer time-scales.

Model Transport Error – ensemble size

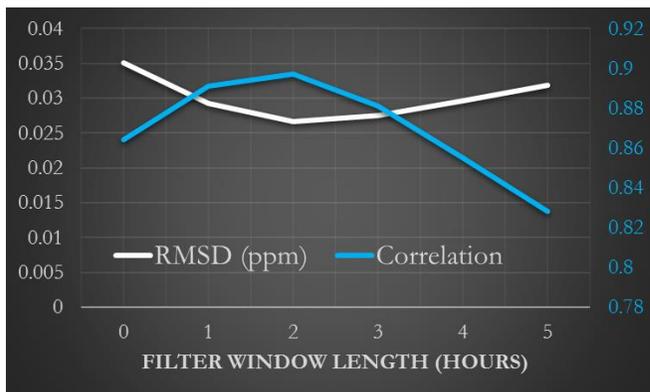
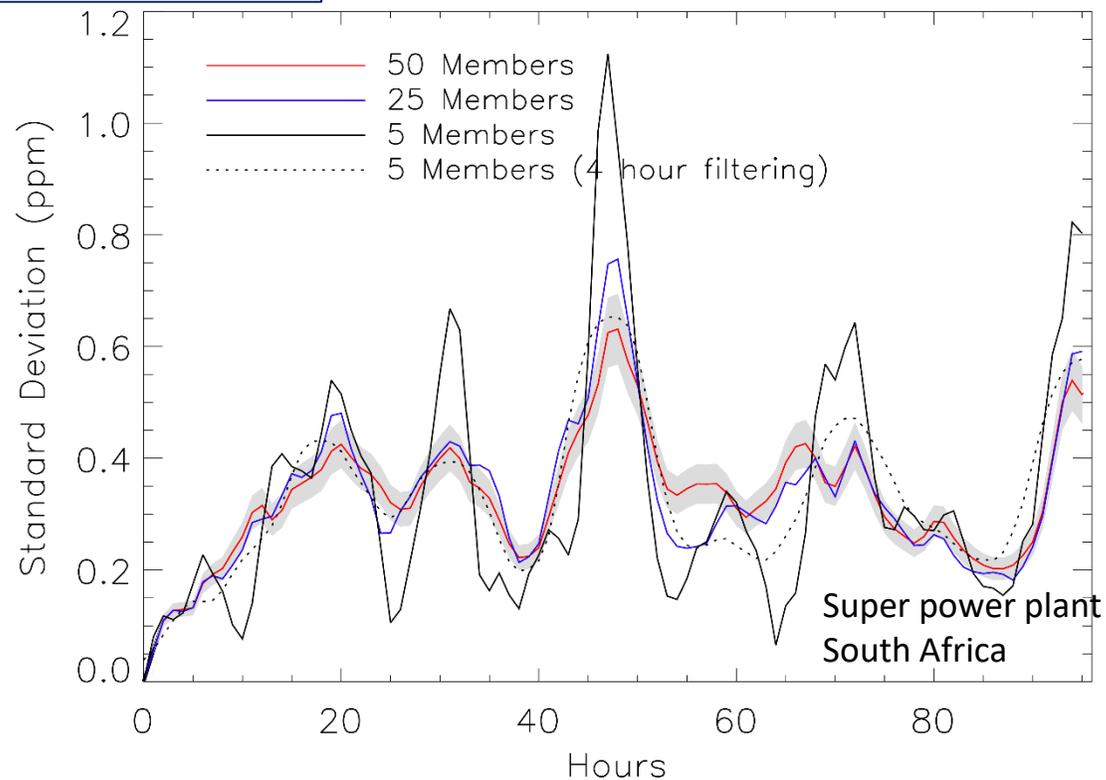
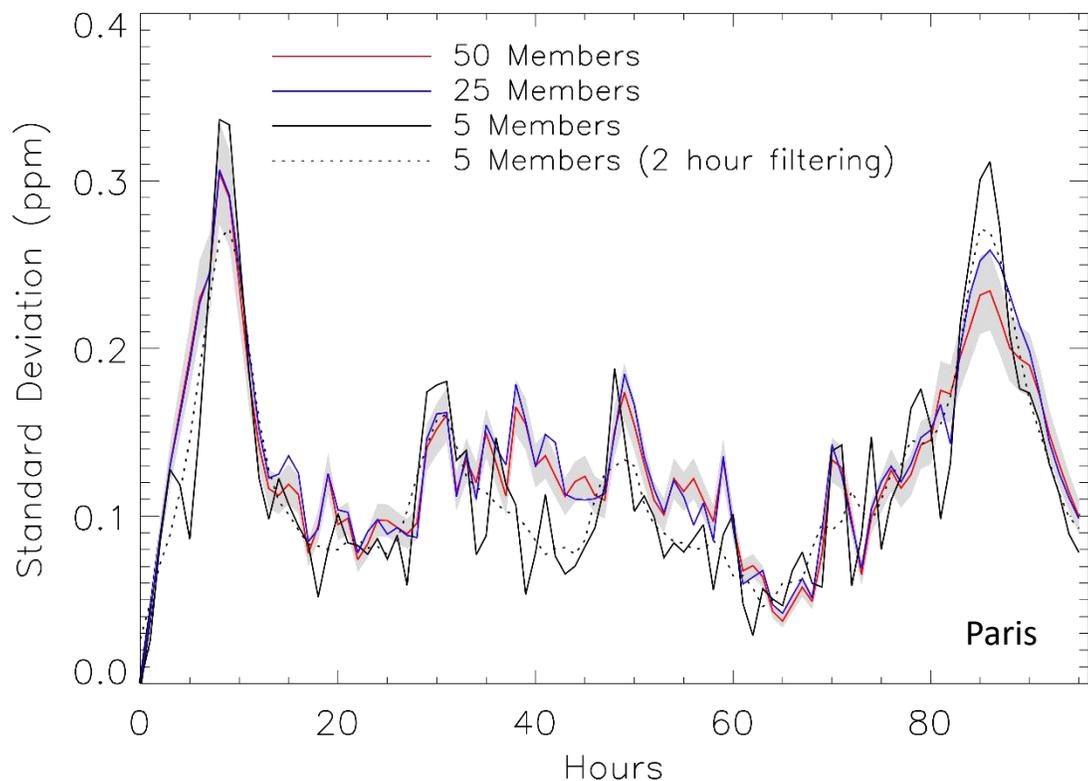


- Reducing ensemble size increases significantly transport error noise.

Model Transport Error – temporal filter

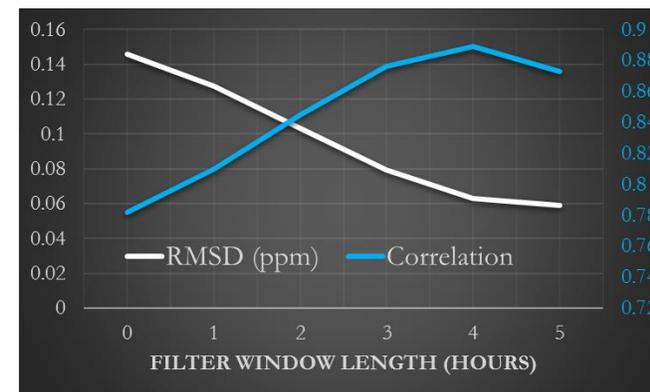
Meteorology	Emissions
Perturbed	Fixed

Filter= n hours centered average



Agreement between 50 (reference) and 5 member ensemble using different time-windows for the filter.

Optimum :
2 hour filter



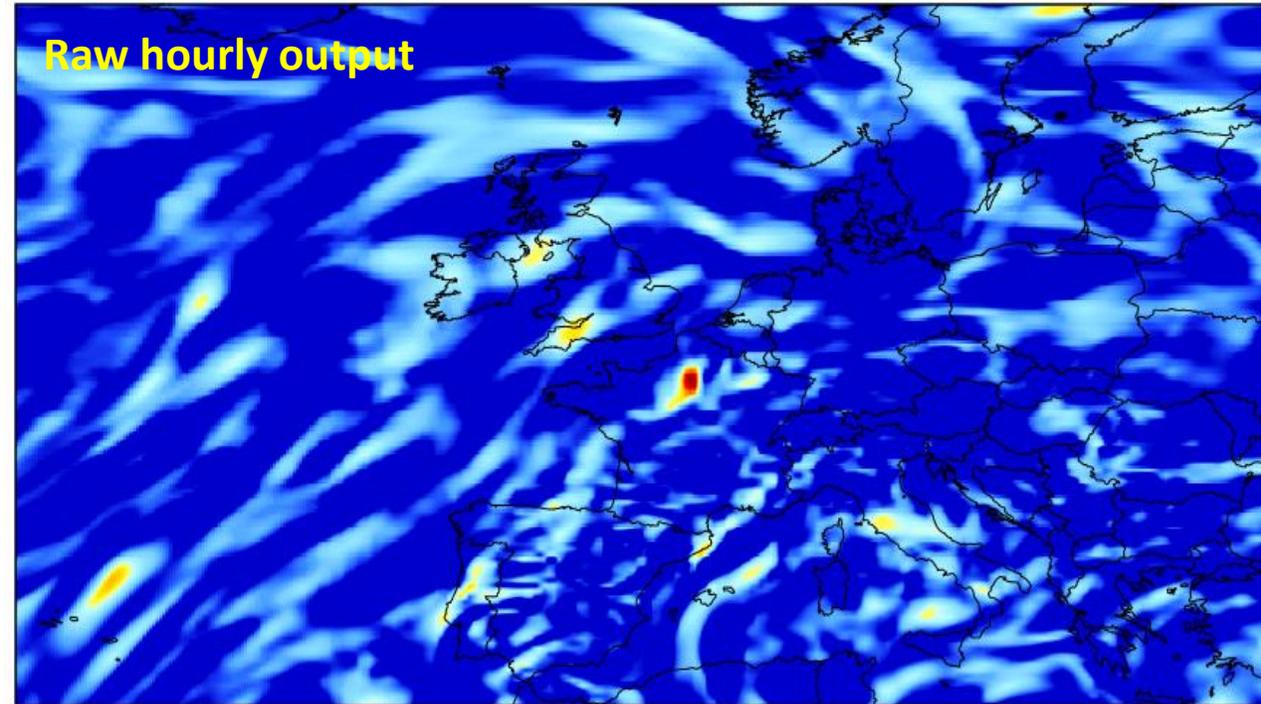
Optimum :
4 hour filter

Model Transport Error Correlations

Animations showing XCO₂ correlations with respect to Paris XCO₂ for 50 member ensemble.

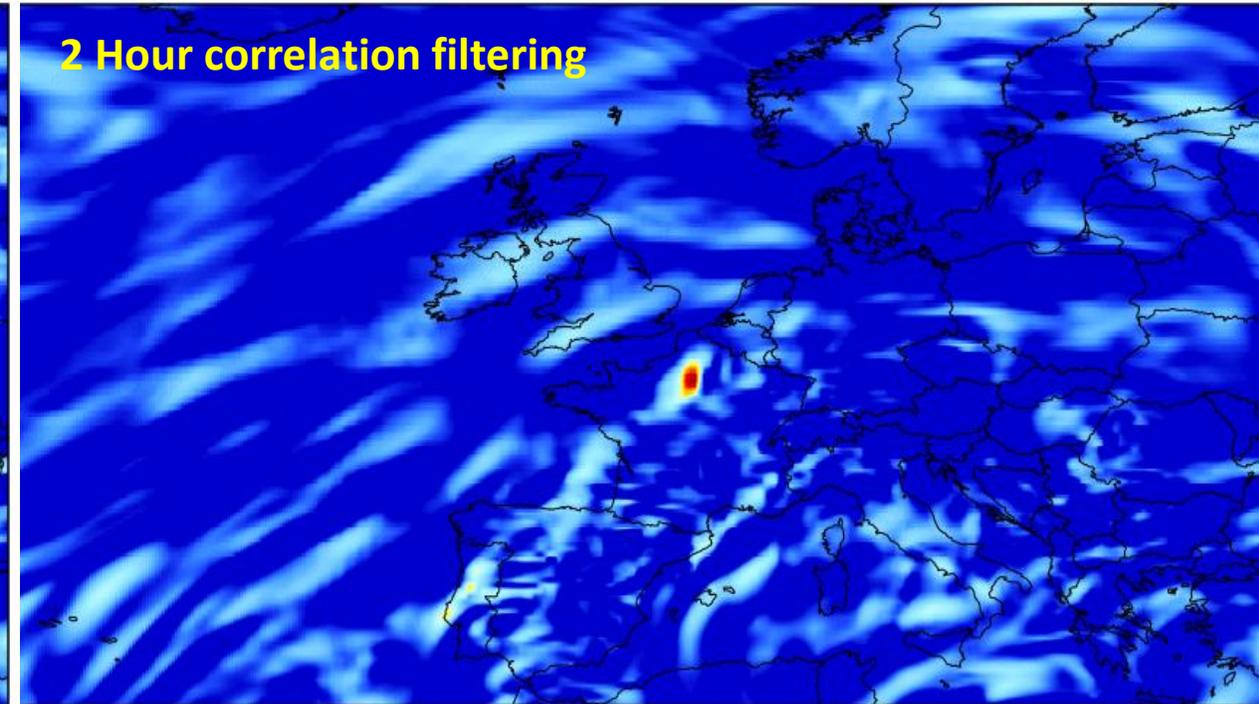
Time: 9

Raw hourly output



Time: 9

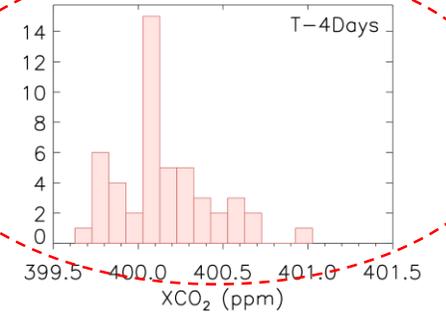
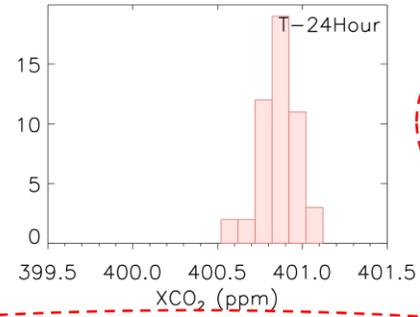
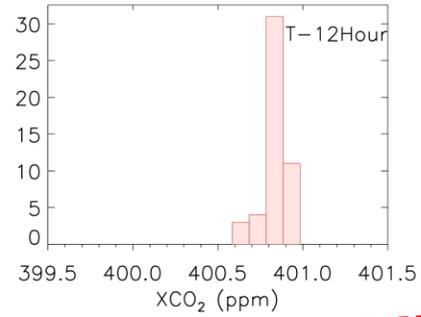
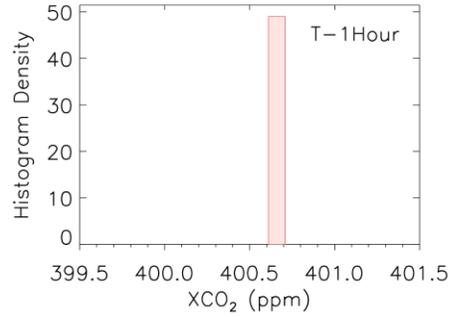
2 Hour correlation filtering



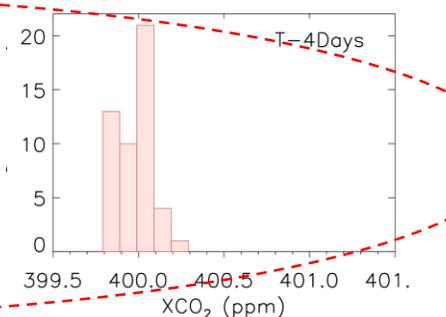
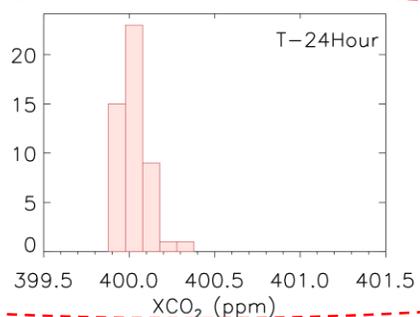
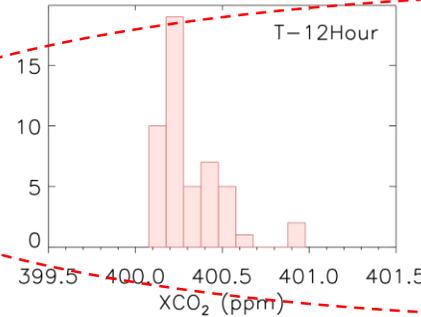
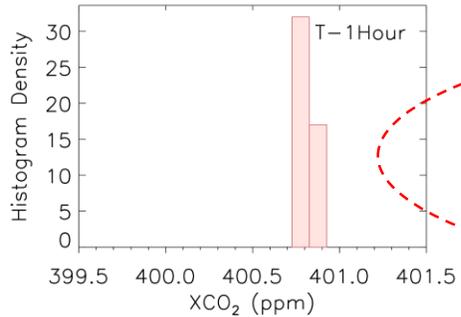
- The spurious noise in the raw correlations is removed with a 2-hour window smoothing.
- 2-hour window smoothing maintains heterogeneous structures.

Validity of the Gaussian assumption

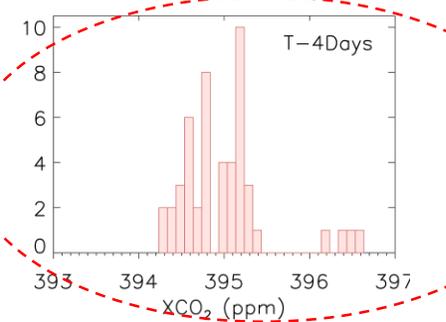
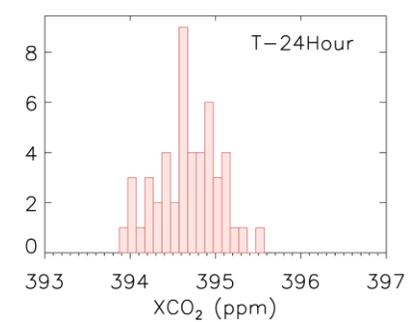
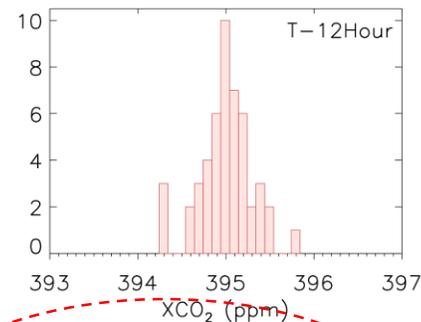
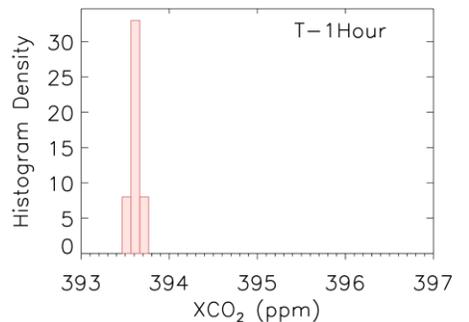
New York



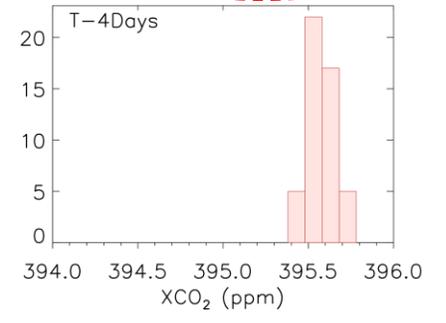
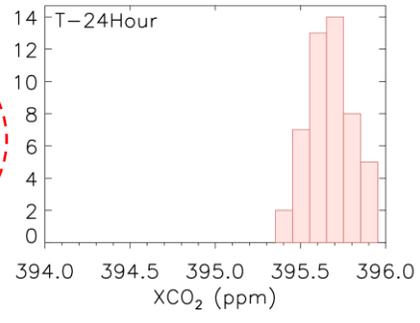
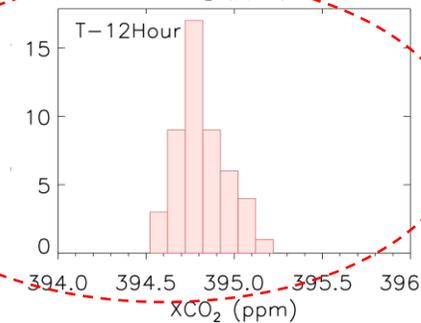
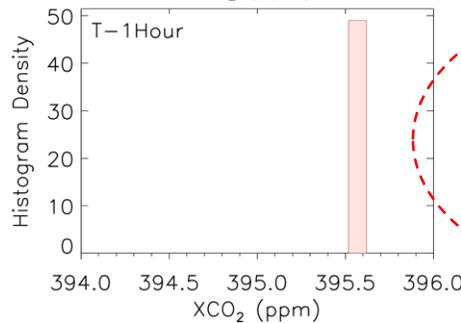
Paris



South Africa
Power
station

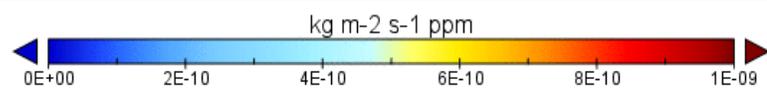
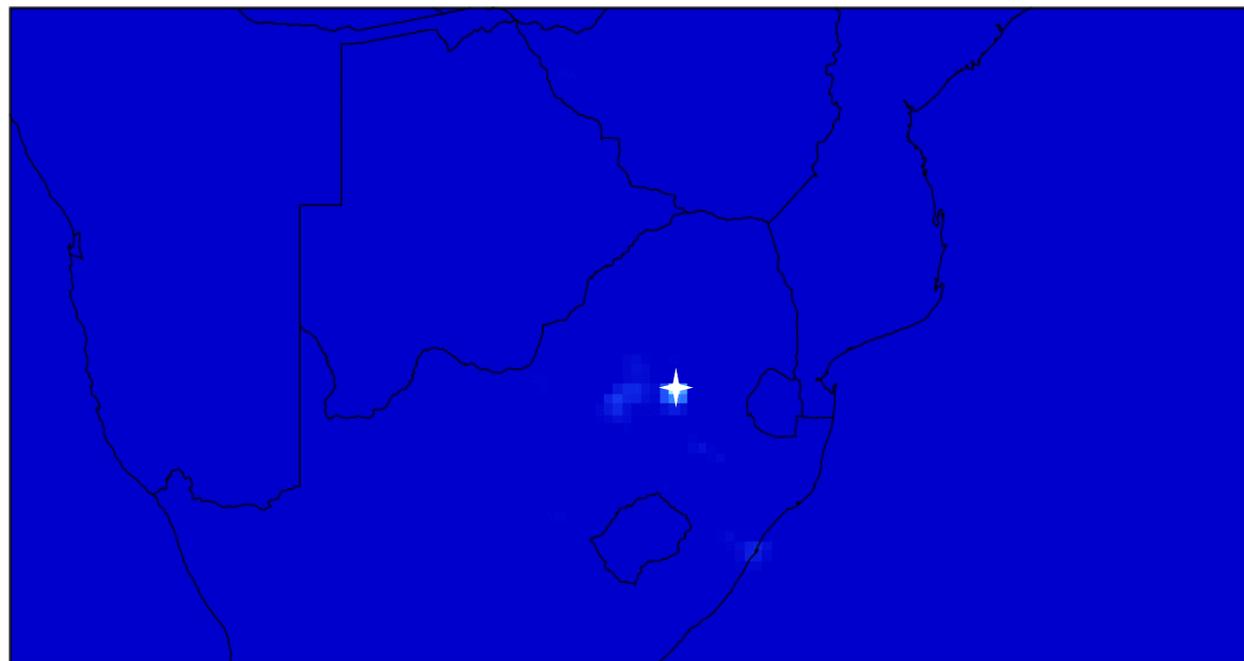


Sydney



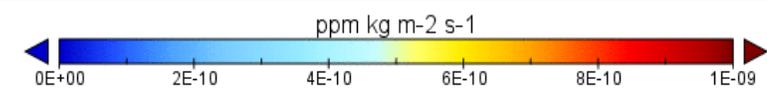
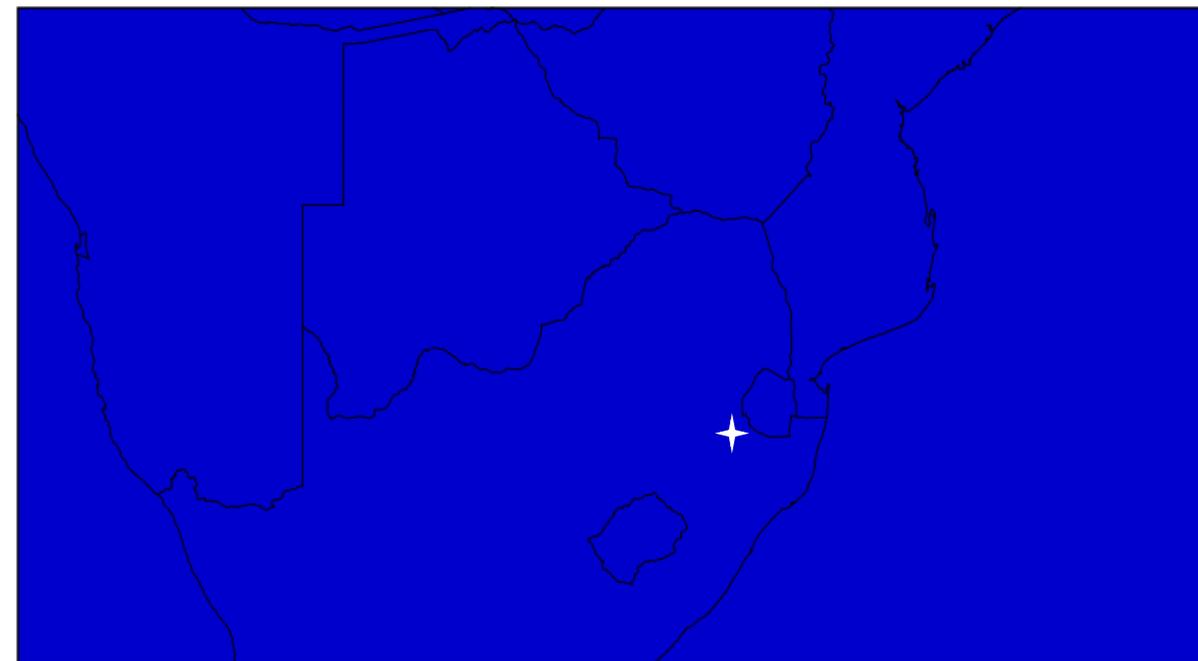
Flux-column relationship

Time: 1



Covariances between point source and XCO₂ columns
 (~forward sensitivities)

Time: 1



Covariances between point XCO₂ column and sources
 (~backward sensitivities)

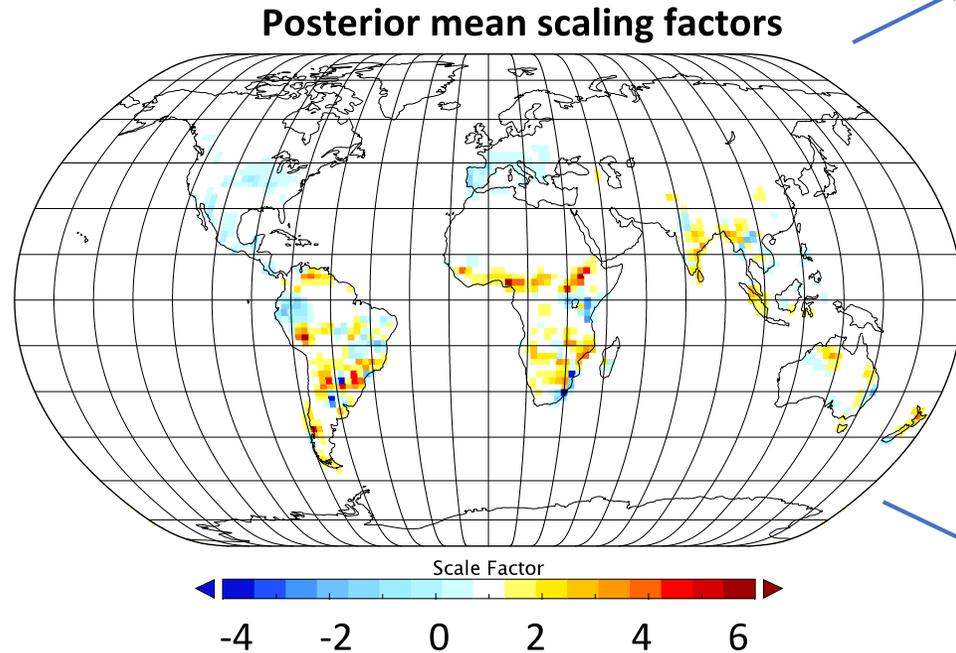
Improved inversion diagnostics and optimization performance

- Posterior diagnostics will include:
 - Posterior error covariances.
 - Effective resolution of the inversion (i.e., what are the spatiotemporal flux patterns being constrained by the observations?)
- New highly parallel stochastic optimization algorithm will be implemented and tested in the IFS to improve computational performance.
- This framework is currently tested in NASA's JPL CMS-Flux system (CO₂) and has been successfully applied to CH₄ GOSAT-based inversions (Bousserez and Henze, 2018).

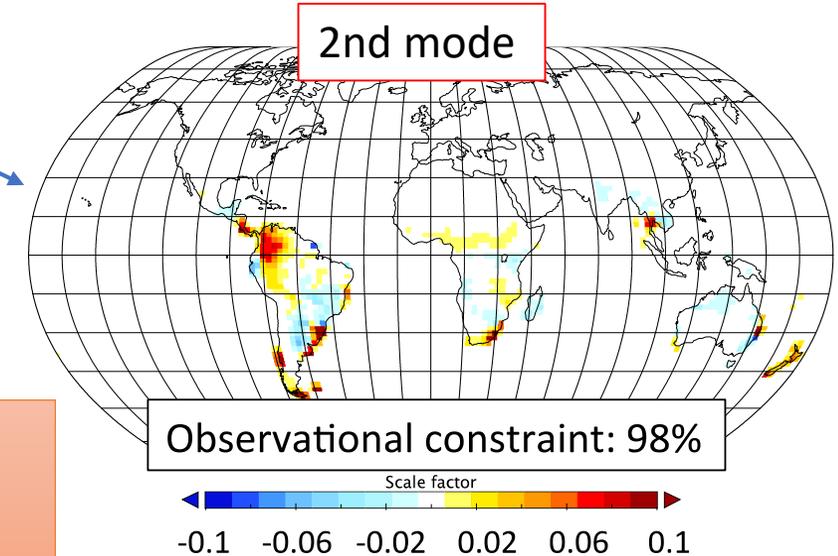
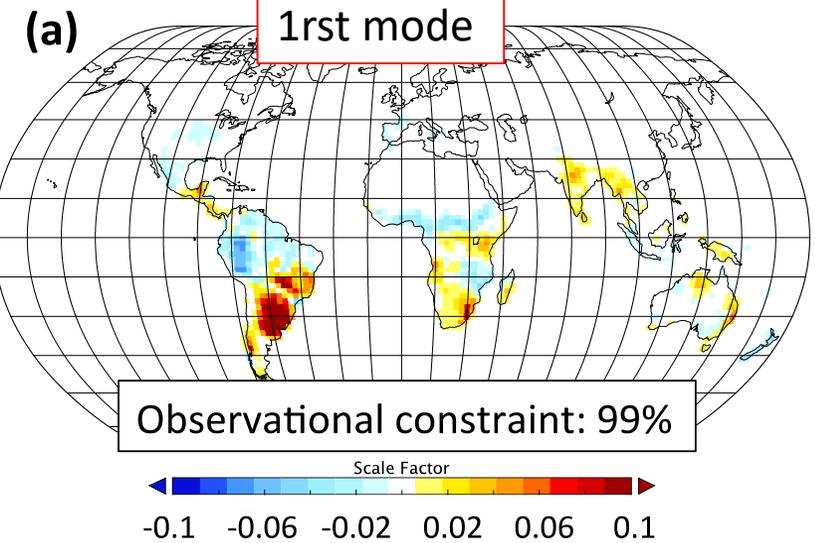
What are the observational constraints on the CO₂ fluxes?

Test Case: OCO-2 data, January-only, 2015

- Flux estimates are computed for ocean, land, and fossil fuel using FRODO with 150 ensembles.
- A priori fluxes follow Liu et al., 2017 and Bowman et al., 2017.
- Flux uncertainty is simply 50%.
- What patterns are constrained by the inversion?

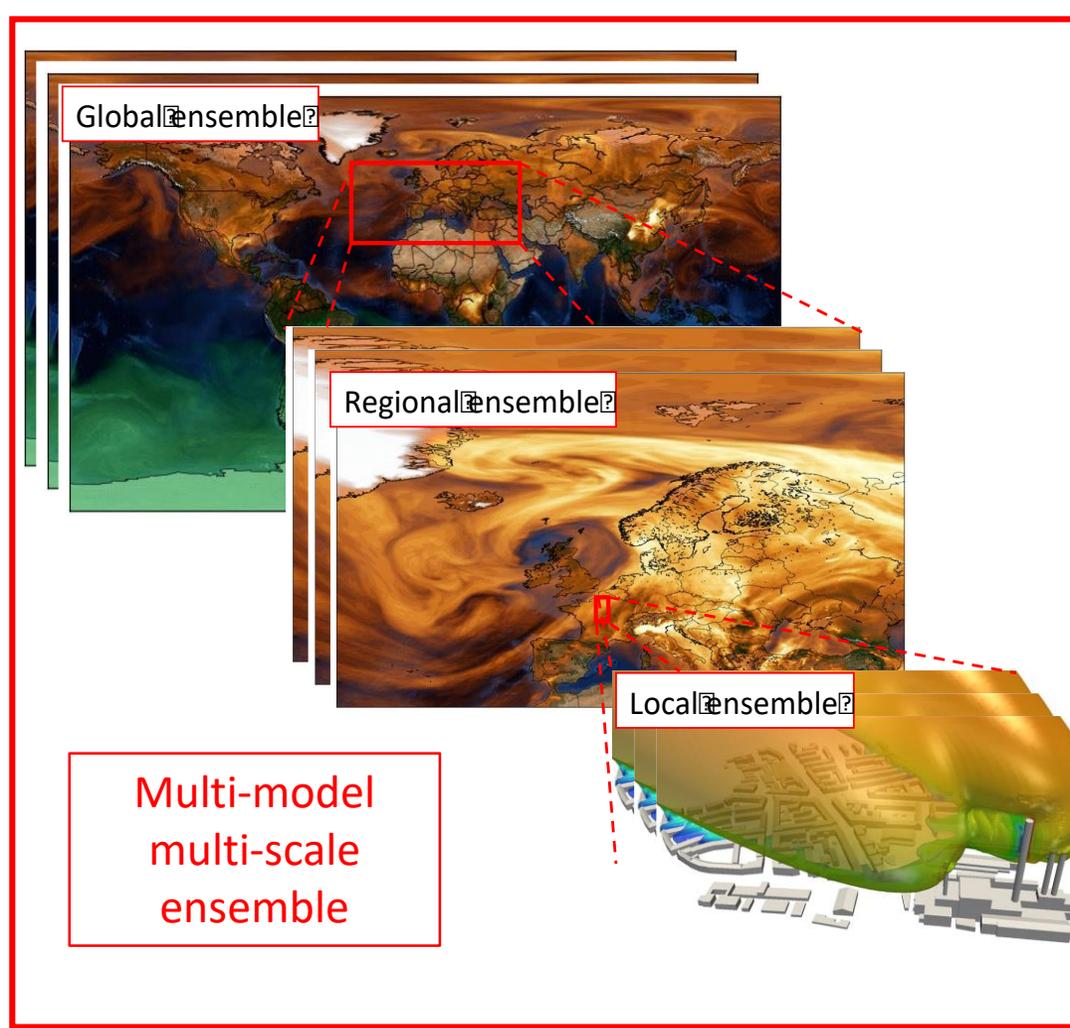


Independently constrained flux patterns

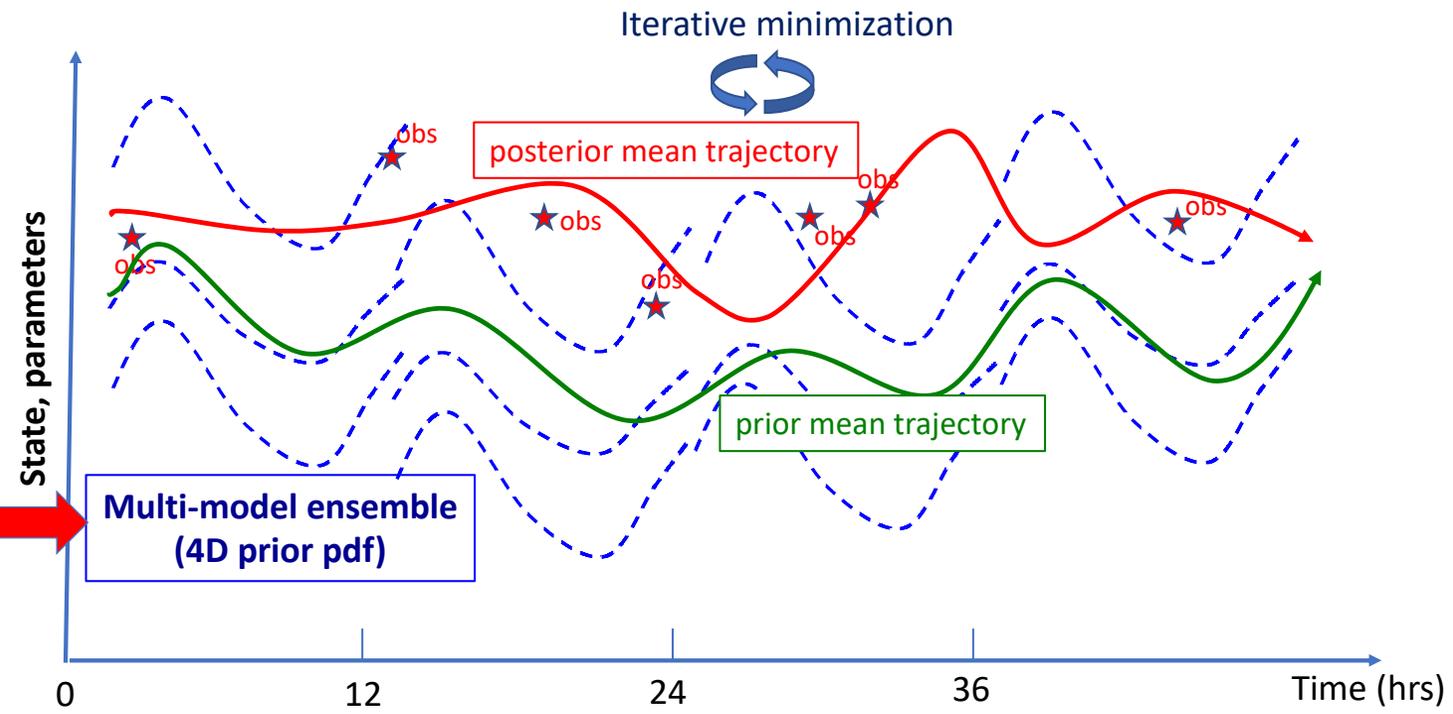


Ongoing collaboration with NASA-JPL (Carbon Monitoring System (CMS) project) using the Fast Randomized and Optimal method for Diagnostics and Optimization (FRODO) (Bousserez and Henze, 2018).

How can we optimize the synergy between CHE activities toward building a multi-scale CO₂ inversion system?



Multi-scale, multi-model ensemble DA system (EnVar)

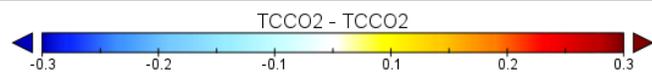
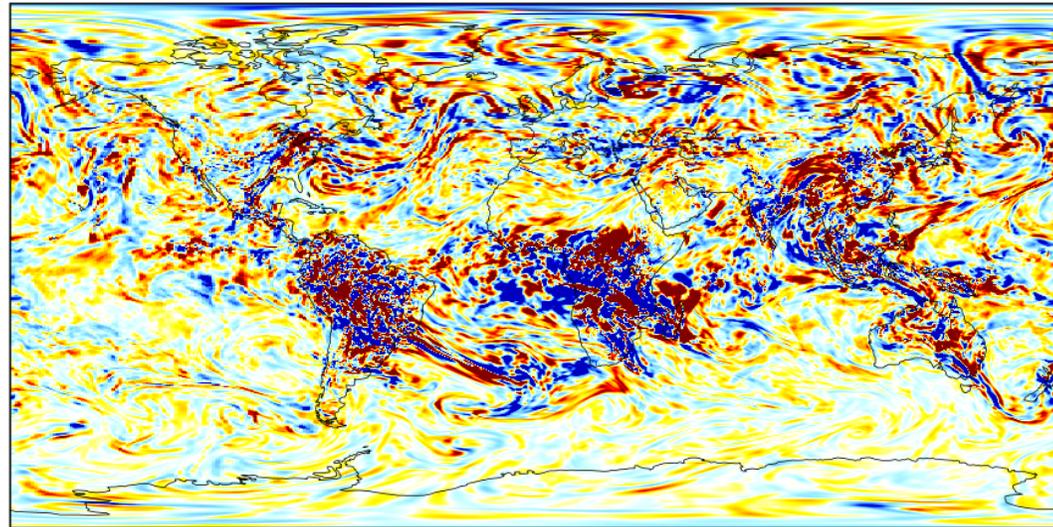
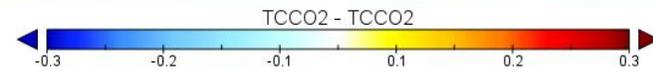
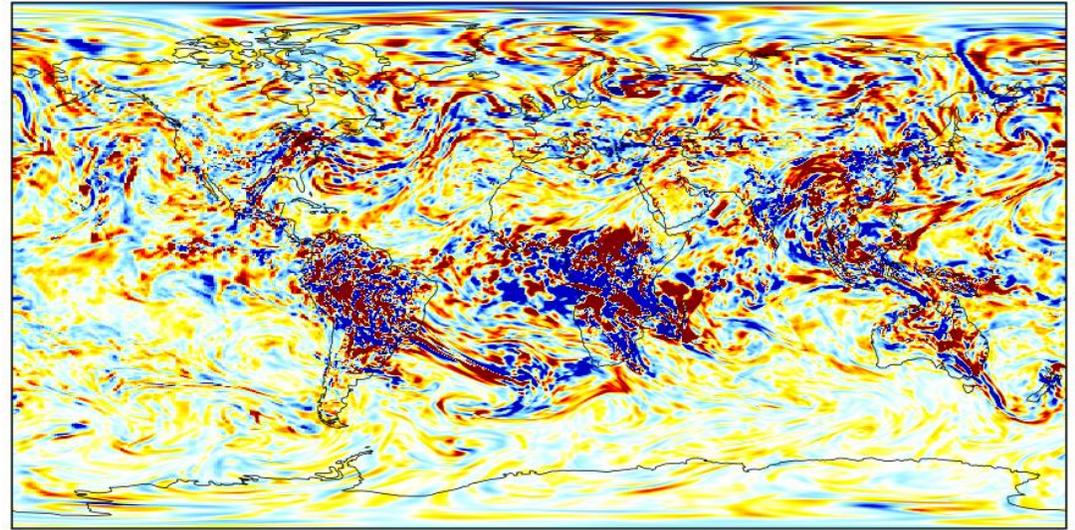
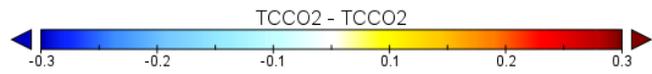
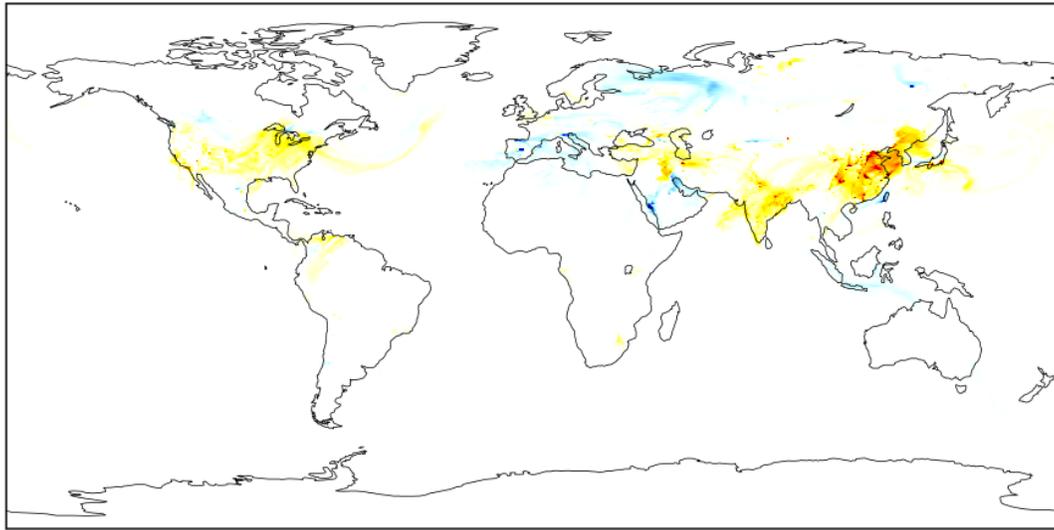


- Each model provides an ensemble of prior forward simulations.
- Prior error flux/state covariance matrix is built from the set of all (multi-model) ensemble forward simulations.
- Posterior mean fluxes are linear combinations of prior ensemble fluxes → multi-model, multi-scale.
- Conceptually simple, provides an efficient framework for collaborations (partners can work on their ensemble of simulations (almost) independently).

Conclusion

- ECMWF is working on a hybrid ensemble-variational system for global anthropogenic CO₂ source inversion.
- IFS ensembles have been used to quantify transport errors and flux-observations sensitivities.
- Transport errors stabilize after 2-3 days.
- Ensemble-based transport error covariances require sampling noise filtering → preliminary tests with a temporal filter show encouraging results.
- Gaussian assumption on transport errors → errors can become quickly (~day) non-gaussian.
- A paper on transport errors in global CO₂ inversions is in preparation.
- Ensemble-based sensitivities would provide a computationally tractable approach for network design studies (adjoint-based methods are costly).
- Improved diagnostic and computational tools are being tested in a global inversion system (NASA JPL's CMS-Flux) before implementation in the global IFS prototype.
- Volunteers to participate to an experiment with a multi-model ensemble-variational approach? Collaboration would only require to provide an ensemble of perturbed (flux/transport) forward CO₂ simulations. Come talk to us if interested...

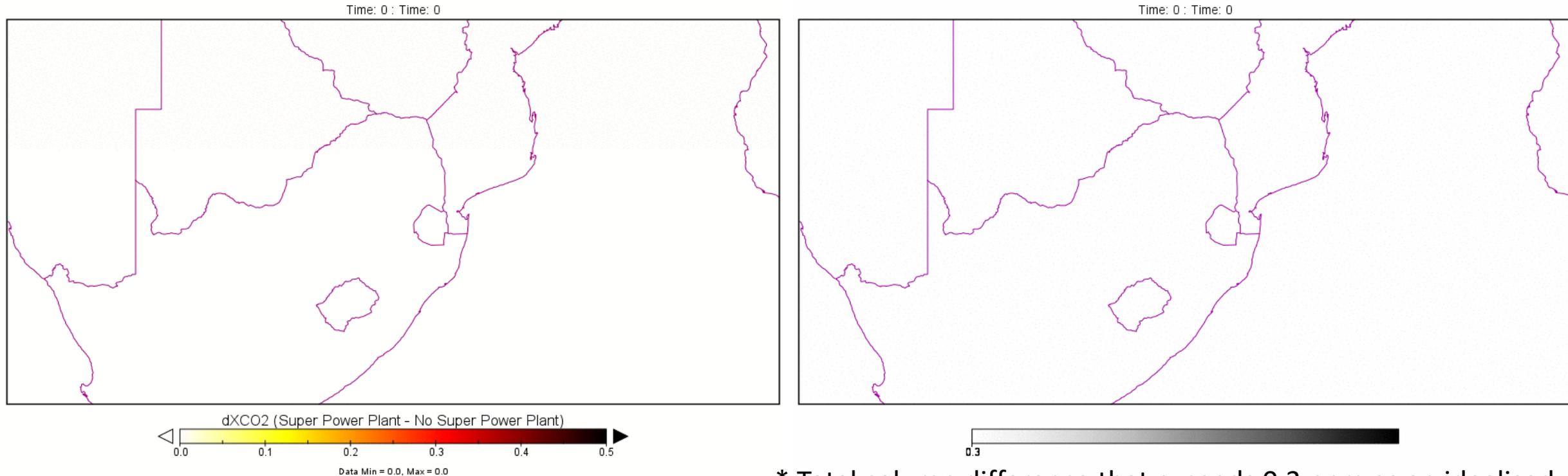
Backup slides



Testing the XCO₂ atmospheric signal from the super power station.

To establish an idealised detection threshold limit two simulations are compared with the following configuration :

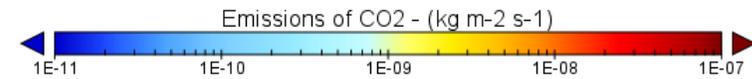
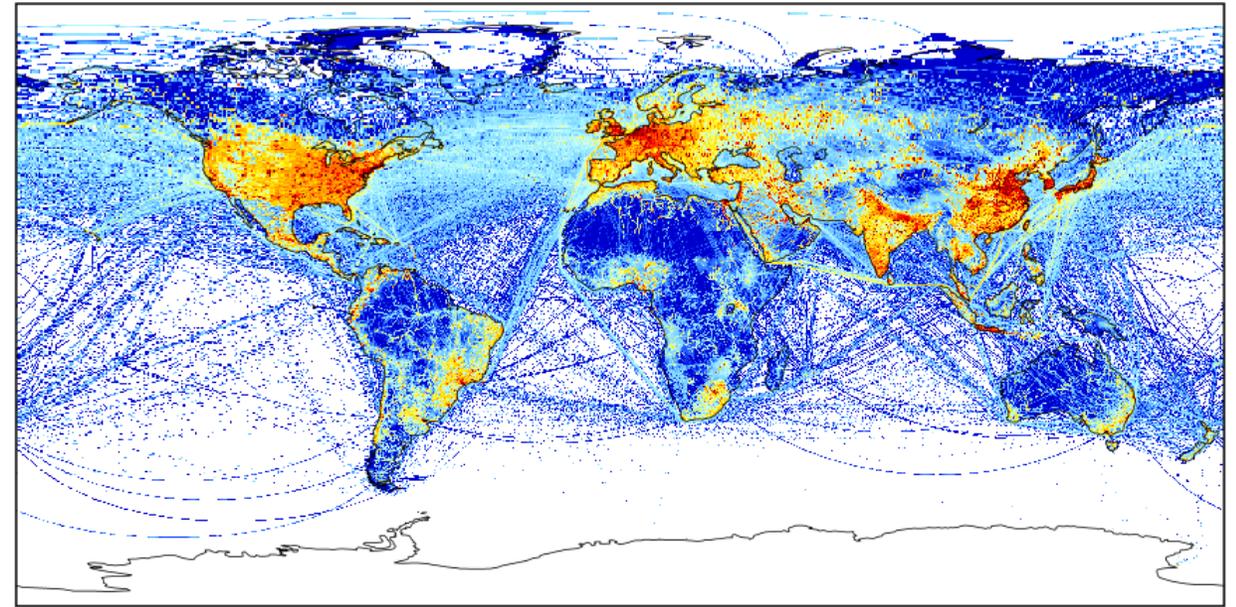
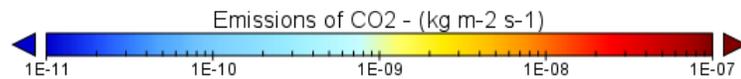
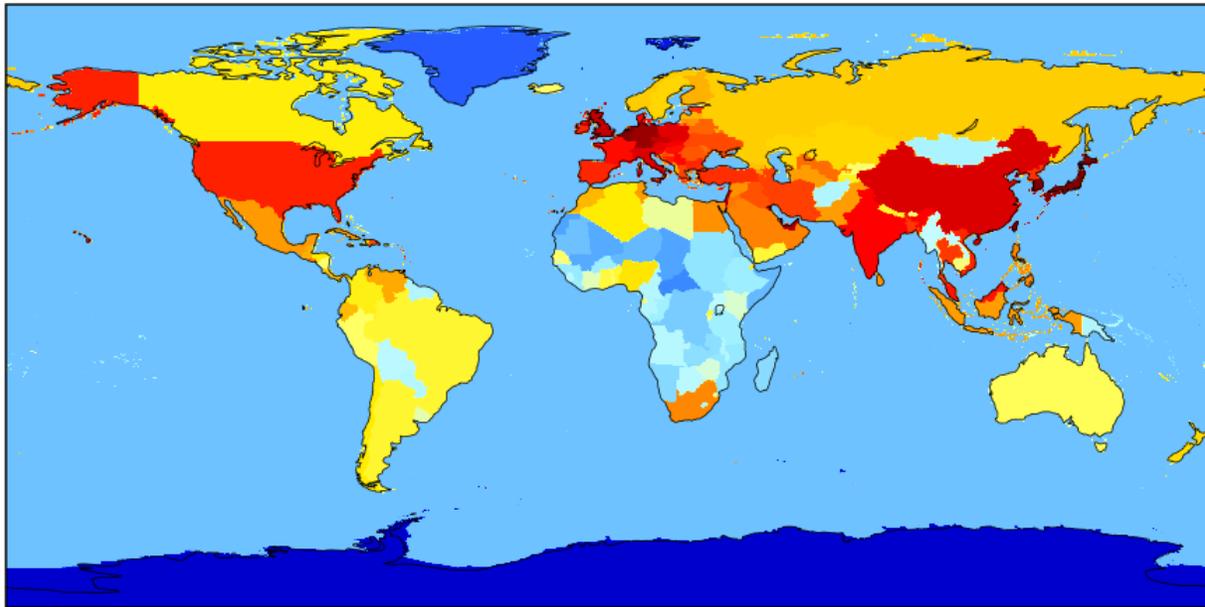
- ~25 km resolution
 - 137 levels
 - 3 hourly output
- (i) Using fully resolved EDGARv4.3.2-2015 monthly emissions (EDGARv4.2-2010 scaling factors applied).
- (ii) Using the same emissions with “super” emitters ($>8.3 \times 10^{-6} \text{ kg m}^{-2} \text{ s}^{-1}$).



* Total column difference that exceeds 0.3 ppm as an idealised constant observation limit.

Representativeness error in the prior model

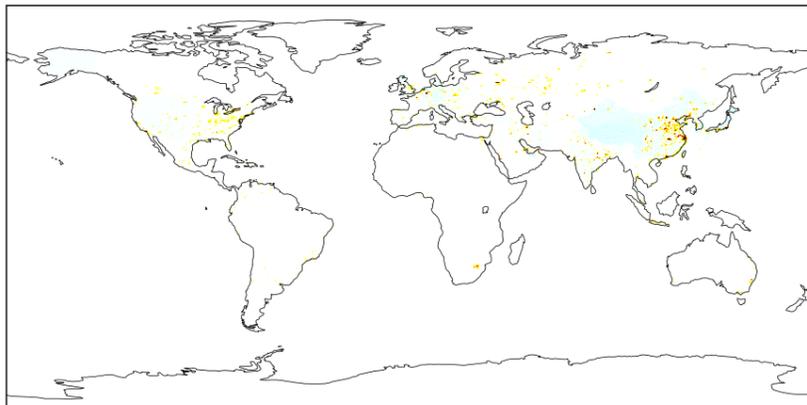
To assess the importance of accurate spatial distribution in the prior two simulations performed with (i) uniformly smoothed emissions per country and (ii) EDGARv432-2015 resolved emissions.



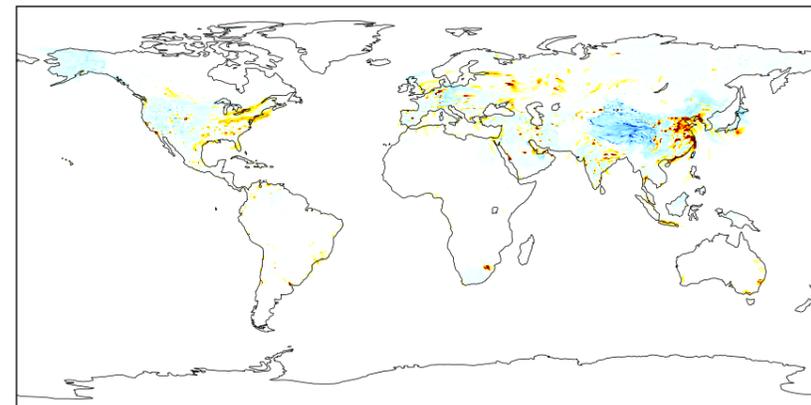
T = 0



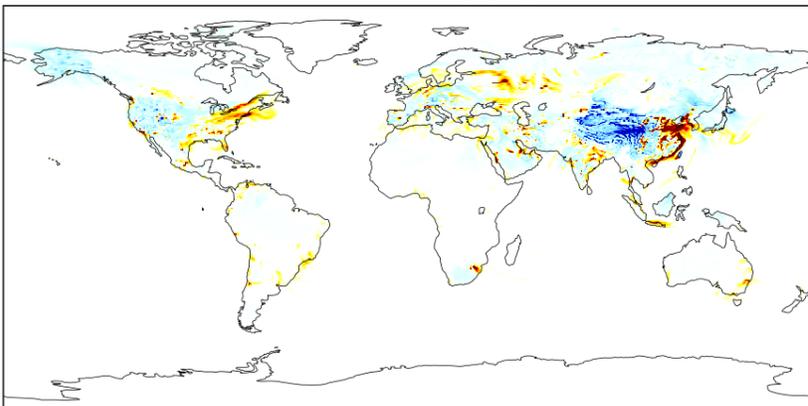
T = 3 hours



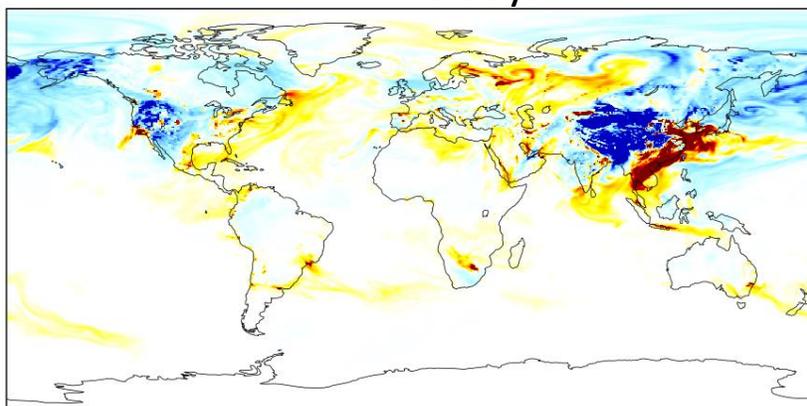
T = 12 hours



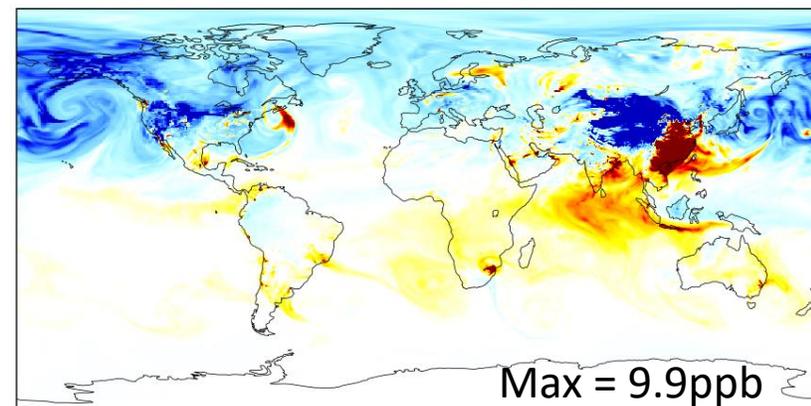
T = 24 hours



T = 10 days



T = 1 month



XCO2 (Resolved - Smoothed Emissions, ppm)

