Environment and Climate Change Canada / Environnement et Changement climatique Canada

COUPLING OF METEOROLOGY AND TRACERS IN DATA ASSIMILATION SYSTEMS

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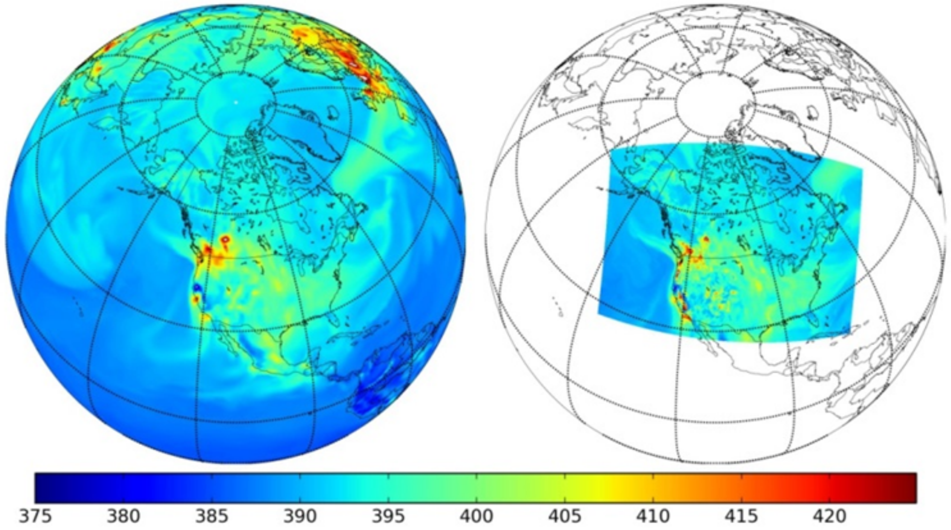
Canada

PERSONAL UPDATES

CO_2 near surface
Jan 4. 2010 20 UTC



Global model
- 0.9° × 0.9°
- Lid at 0.1 hPa
- CO_2, CH_4, CO
- 3DVar CO_2 DA

Model details in Polavarapu et al. (2016, ACP)

Regional model
- 10 km grid
- Lid at 0.1 hPa
- CO_2, CH_4, CO

Model details in Kim et al. (2020, GMD), CO_2 flux inversion Jinwoong Kim talk

- Retired from ECCC July 1, 2022
- Working a few hours per week now (institutional memory)
  - Contract renewed yearly
  - Focus on state estimation of GHG (CO_2) with operational global weather forecast model. Currently: 3D-Var. Future: Add CH_4, EnVar? Coupled state/flux estimation?

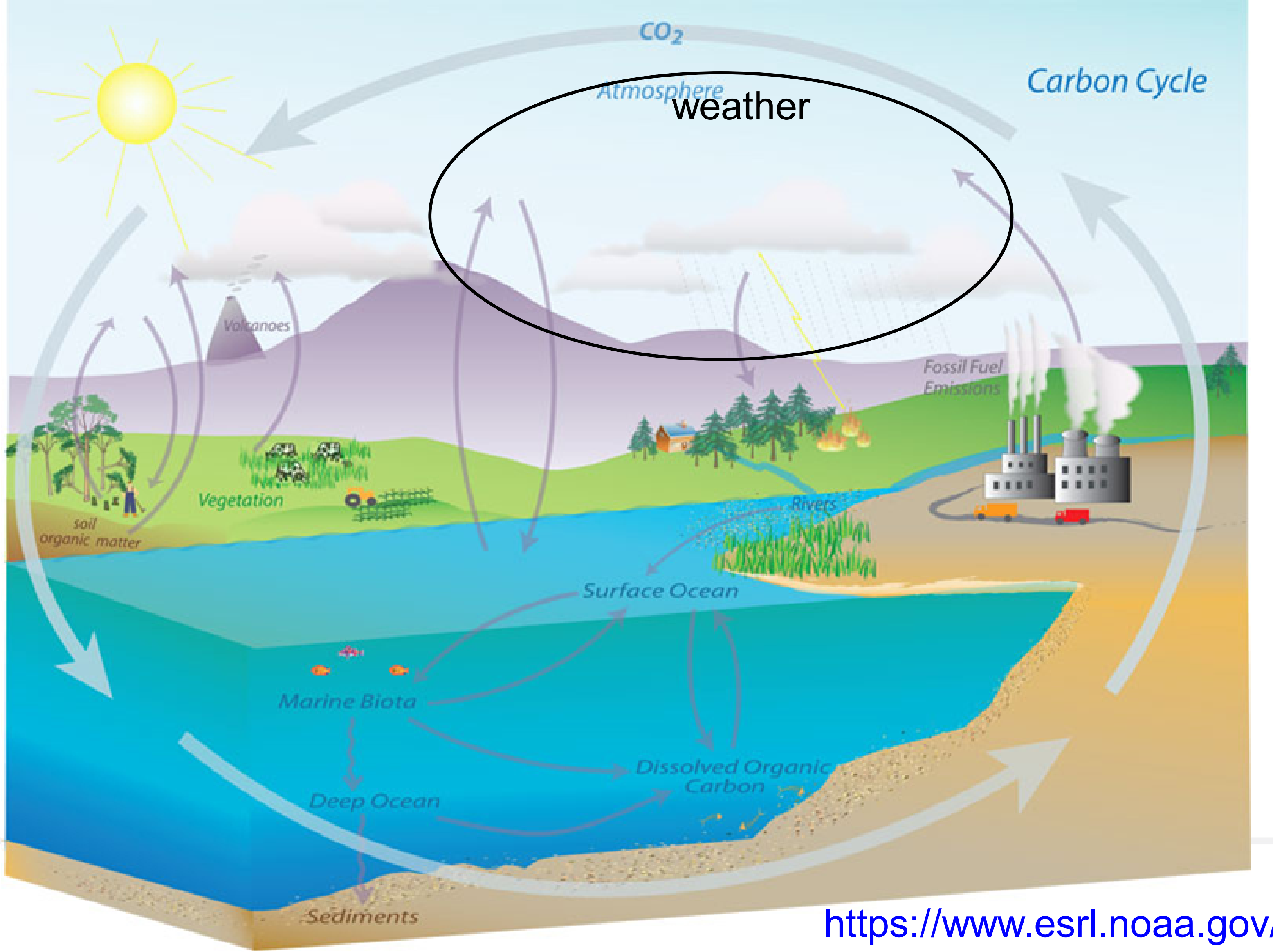
OUTLINE

Coupling of meteorology and tracers (CO_2)

1. In the forecast model
   - Conserving tracer mass
   - Diagnostic: spatial scales of CO_2 uncertainty due to uncertain meteorology
2. In flux inversion
   - Diagnostic: Change in CO_2 state due to fluxes versus uncertain meteorology
3. In CO_2 3D-Var data assimilation
   - Diagnostic: Global mass evolution?

1. THE FORECAST MODEL

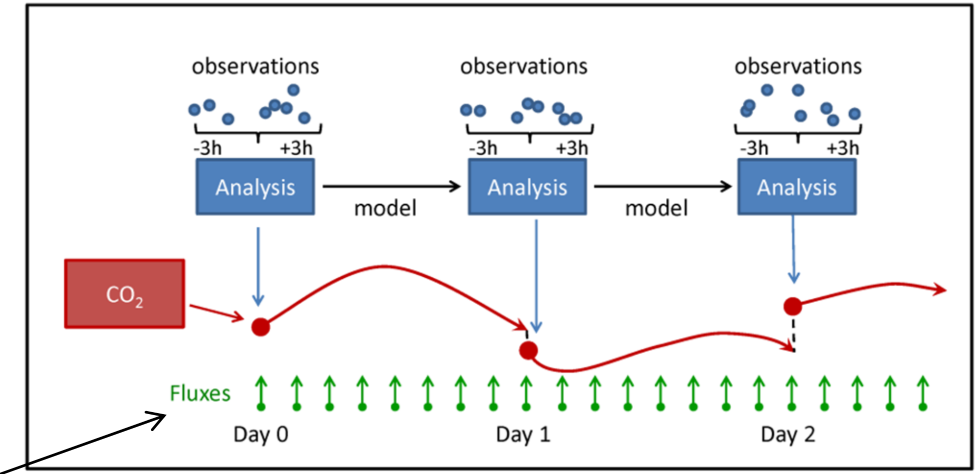
COUPLED LAND/OCEAN/ATMOSPHERE



https://www.esrl.noaa.gov/gmd/ccgg/basics.html

COUPLED GLOBAL WEATHER AND GREENHOUSE GAS MODELS

Initial CO_2 on 1 Jan 2009 from CarbonTracker



Sub-daily fluxes (biospheric, ocean, anthropogenic, biomass burning)
3-hourly fluxes from NOAA CarbonTracker (CT2013B, CT2019B)

Global coupled weather-GHG models include:

- ECMWF CAMS (Agusti-Panareda et al. 2014)
- ECCC (Polavarapu et al. 2016)
- NASA GMAO (Weir et al. 2021)
- NOAA GML (Bruhwiler, BIRS presentation 2023)

COUPLED METEOROLOGY AND CHEMISTRY

- Meteorological model equations (momentum, thermodynamic, equation of state)
- Species continuity equation for mixing ratio: $c = \frac{m_c}{m_a}$ (mass m_c of species; m_a moist air)

$$\frac{\partial c}{\partial t} + (\mathbf{U} \cdot \nabla)c = \frac{1}{\rho_a} \nabla \cdot (\rho_a K \nabla c) + \sum_i S_i$$

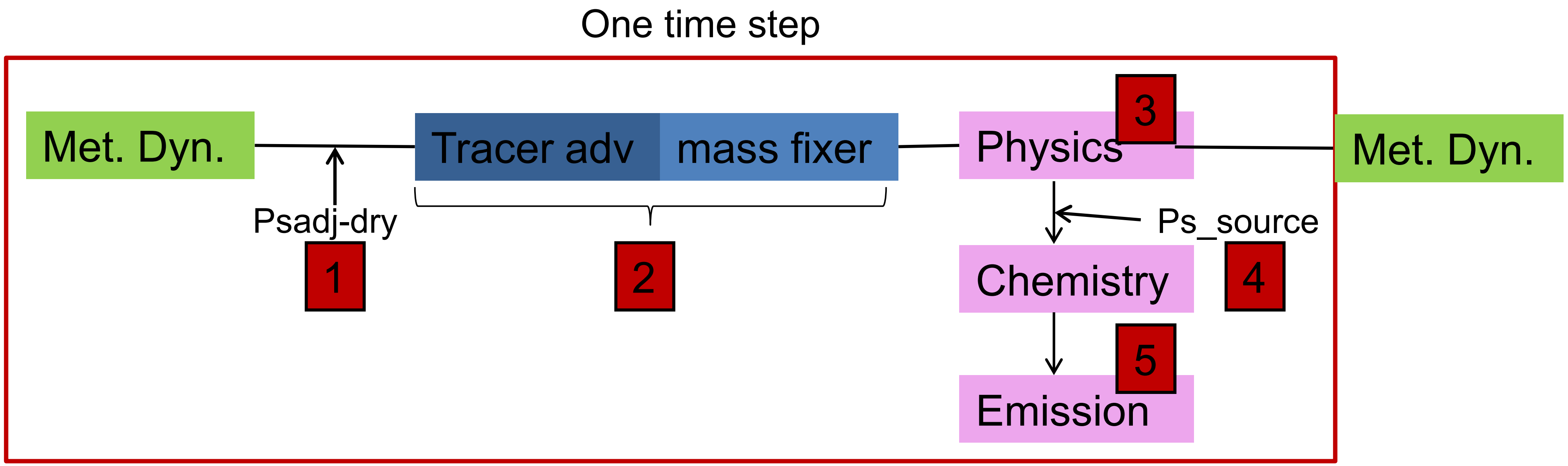
ρ_a: Density moist air

K: Diffusion coefficient

S_i: emission, dry deposition, wet deposition, photochemistry, gas/particle partitioning, etc.

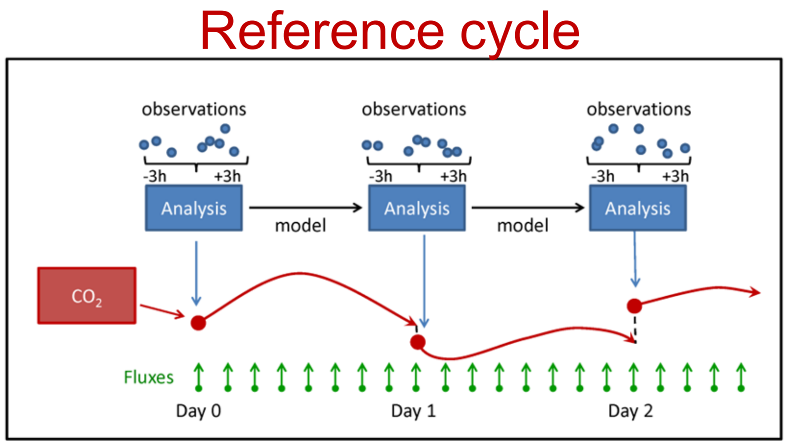
- For greenhouse gases: tracer mass conservation desired
- Tracer variable: dry air mixing ratio is desired

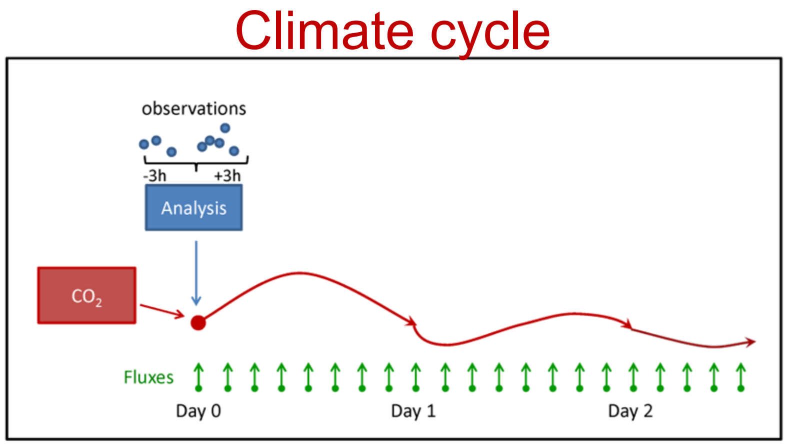
CONSERVING TRACER MASS IN GEM



1. The model loses mass during the dynamics step, so psadj-dry adjusts the global dry air mass so it is conserved. The tracer mixing ratio is not adjusted even though the dry air mass is not locally conserved.
2. Tracer mass is changed during advection so the mass fixer is applied for global conservation. This requires knowledge of the dry air mass field (Ps, q)
3. During Physics, water vapour (q) is changed so dry air is changed so tracer needs adjusting.
4. Mass change due to change in q from physics is added to Ps.
5. Emission is added so the tracer mass changes. q and Ps are needed.

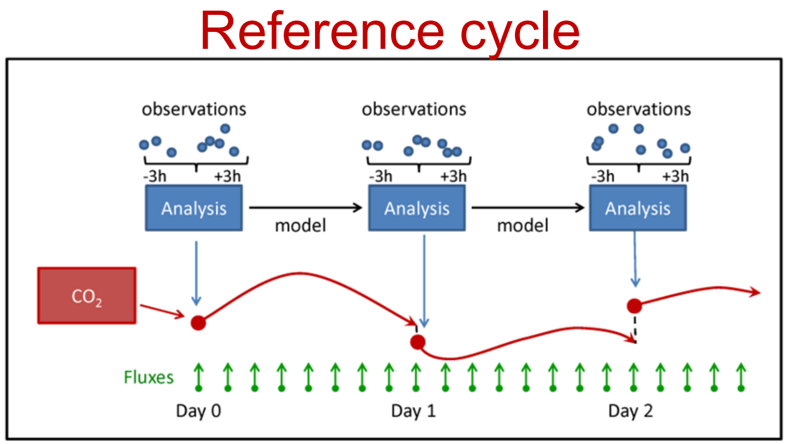
EXPERIMENTAL DESIGN: PREDICTABILITY

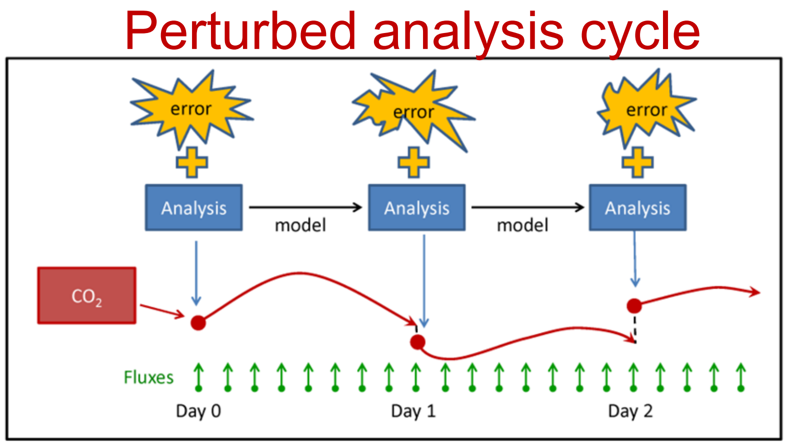




- Analyses constrain CO_2 transport using observed meteorology even with no CO_2 assimilation
- What if we don't use analyses (after the initial time) and replace them with 24h forecasts? → Climate cycle
- Climate cycle will drift from control cycle which uses analyses

EXPERIMENTAL DESIGN: ANALYSIS ERROR

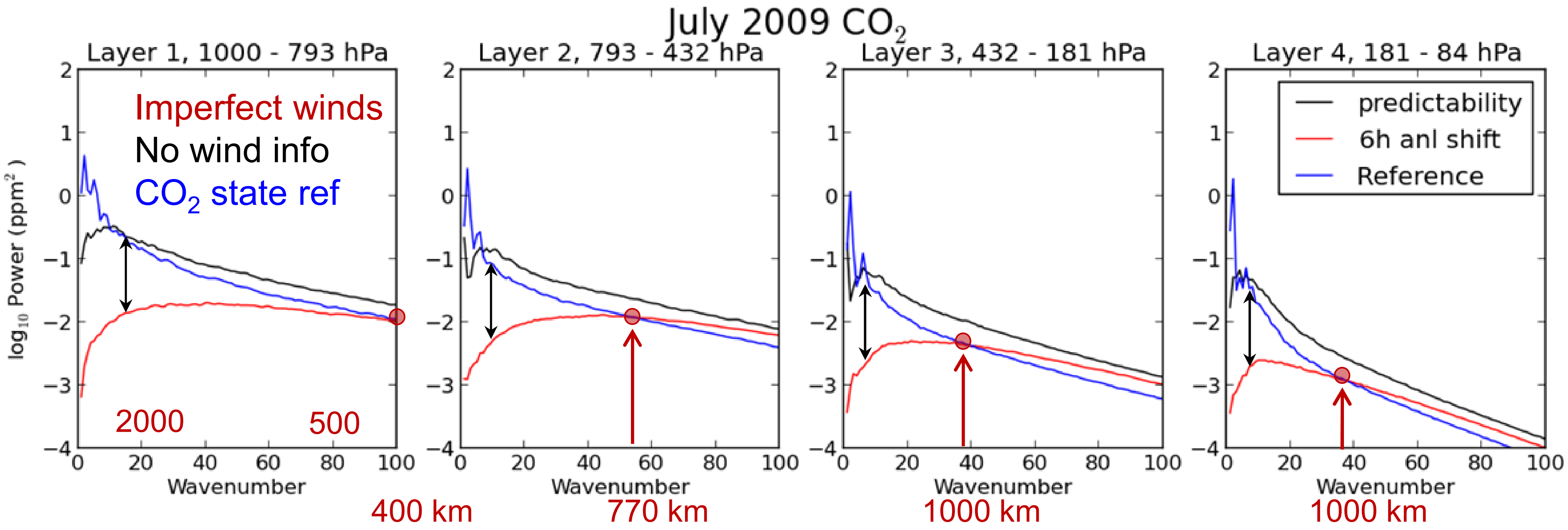




- Climate cycle is an extreme case. In reality analyses keep our cycle close to observations. But analyses are not perfect. What is the impact of analysis error on CO_2 spatial scales?
- Experiment: Perturb reference analyses by error
- Analysis error proxy: Cycle with analysis 6h early

IMPACT OF METEOROLOGICAL ANALYSIS UNCERTAINTY

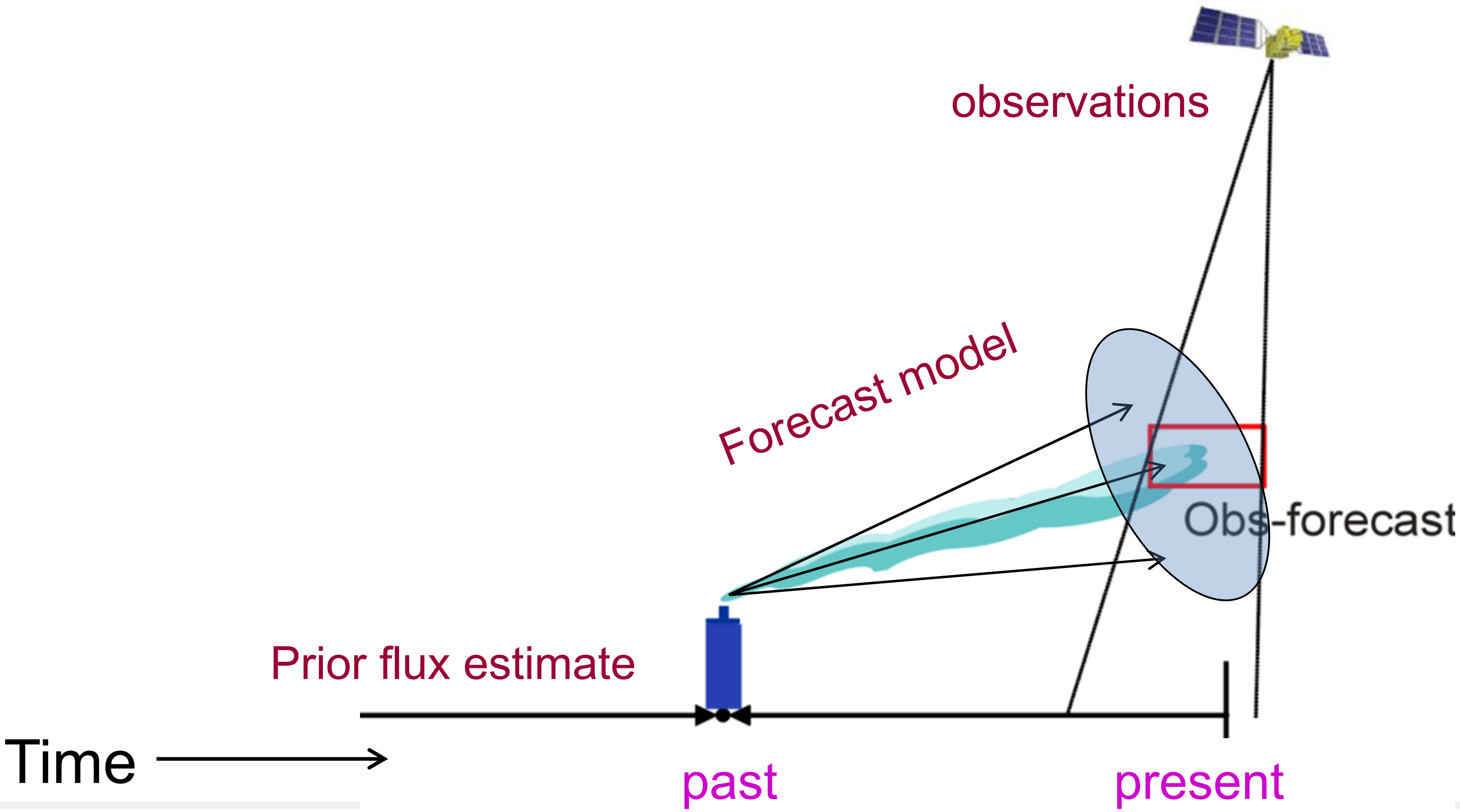
Polavarapu et al. (2016, ACP)



- Error spectra asymptote to predictability error spectra. For smaller spatial scales, we don't gain much over predictability error.
- For some wavenumber, the power in this error equals that in the state itself (red arrows). *There is a spatial scale below which CO_2 is not resolved due to analysis uncertainty.* This spatial scale increases with altitude.
- CO_2 predictability on regional scale in limited area domain (Kim et al. 2021, JGR)

IMPLICATIONS ON FLUX INVERSIONS

If CO_2 can be reliably simulated only for large spatial scales, this translates to flux uncertainties which are unaccounted for.



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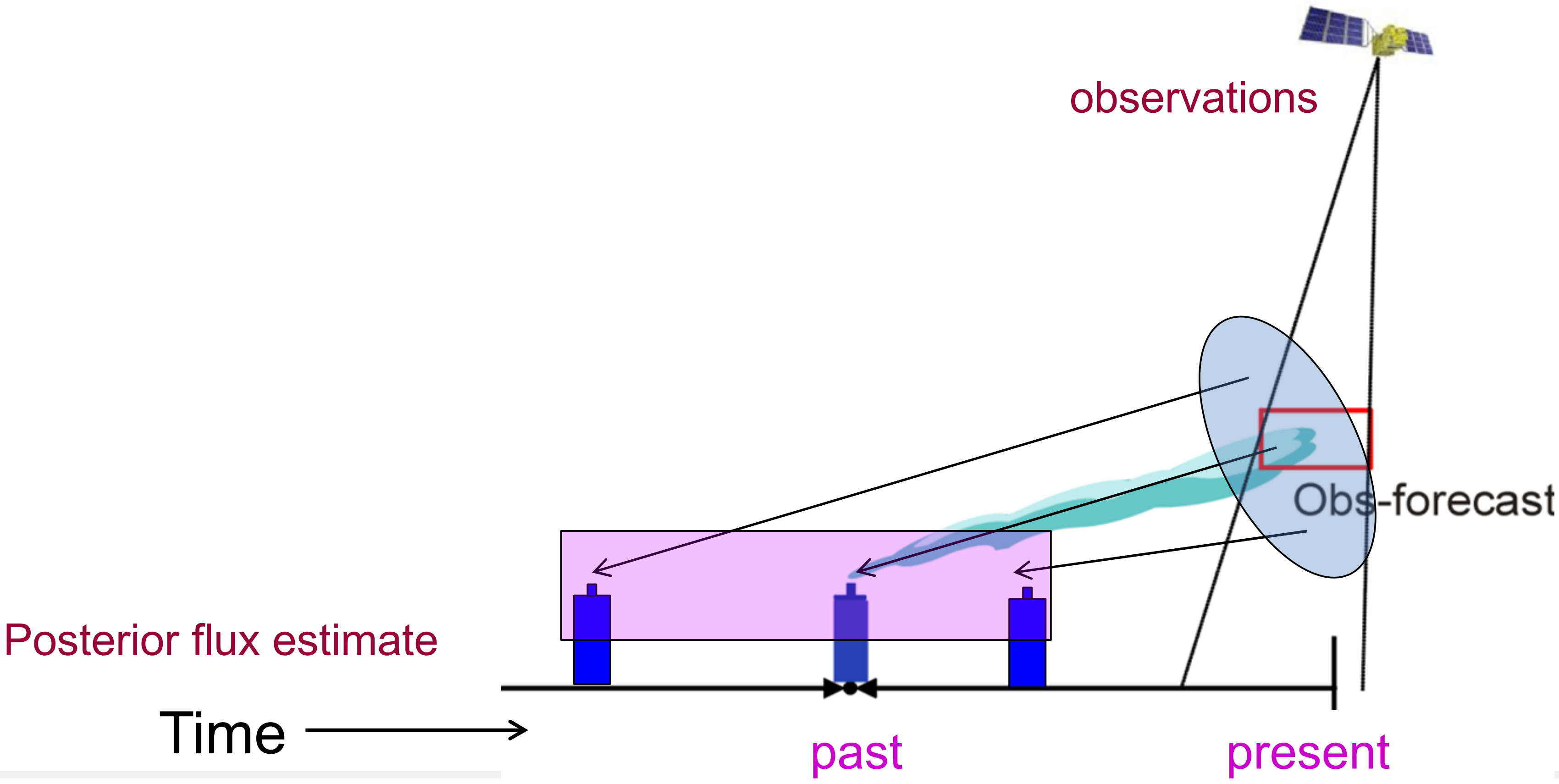

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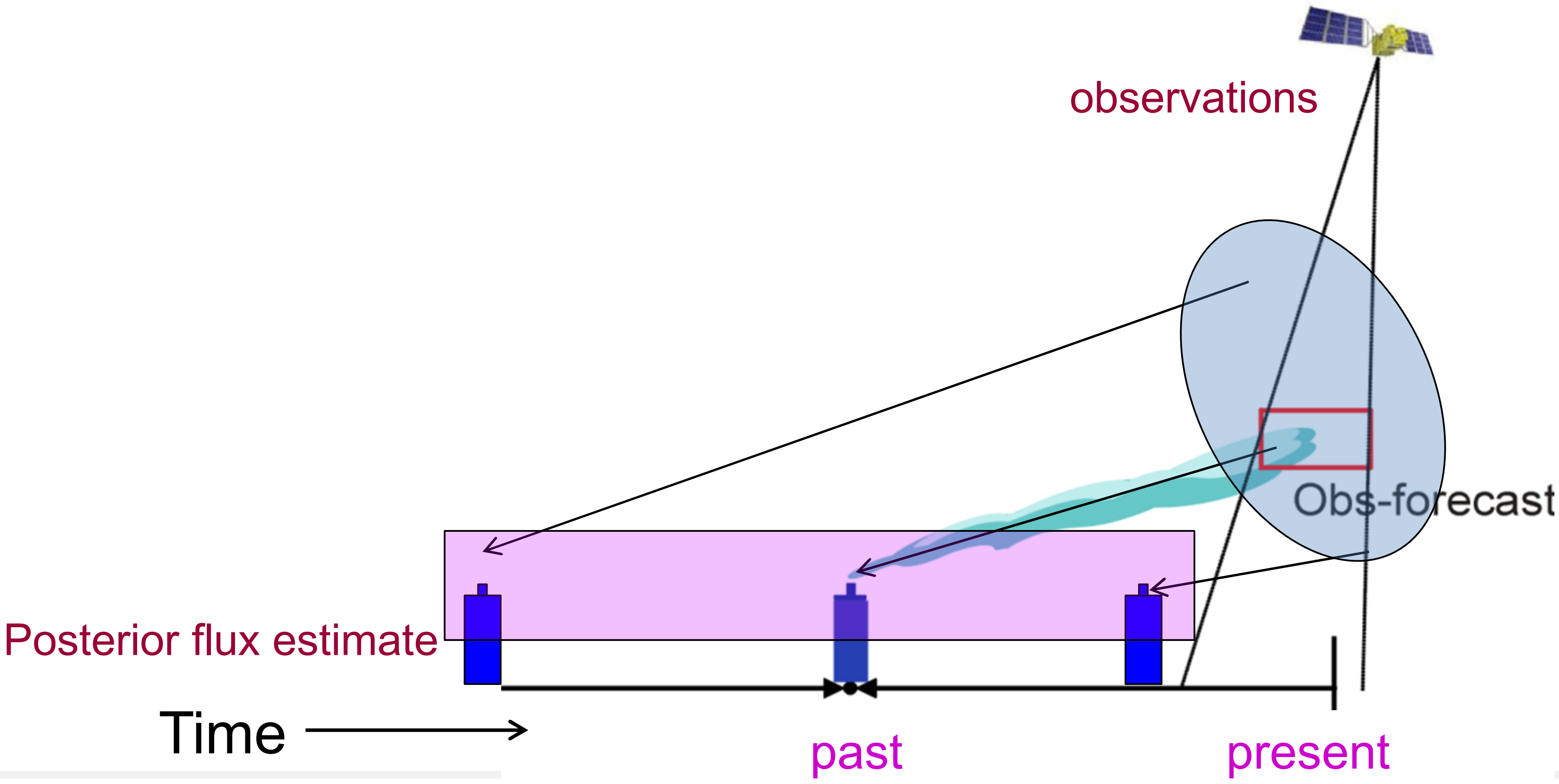
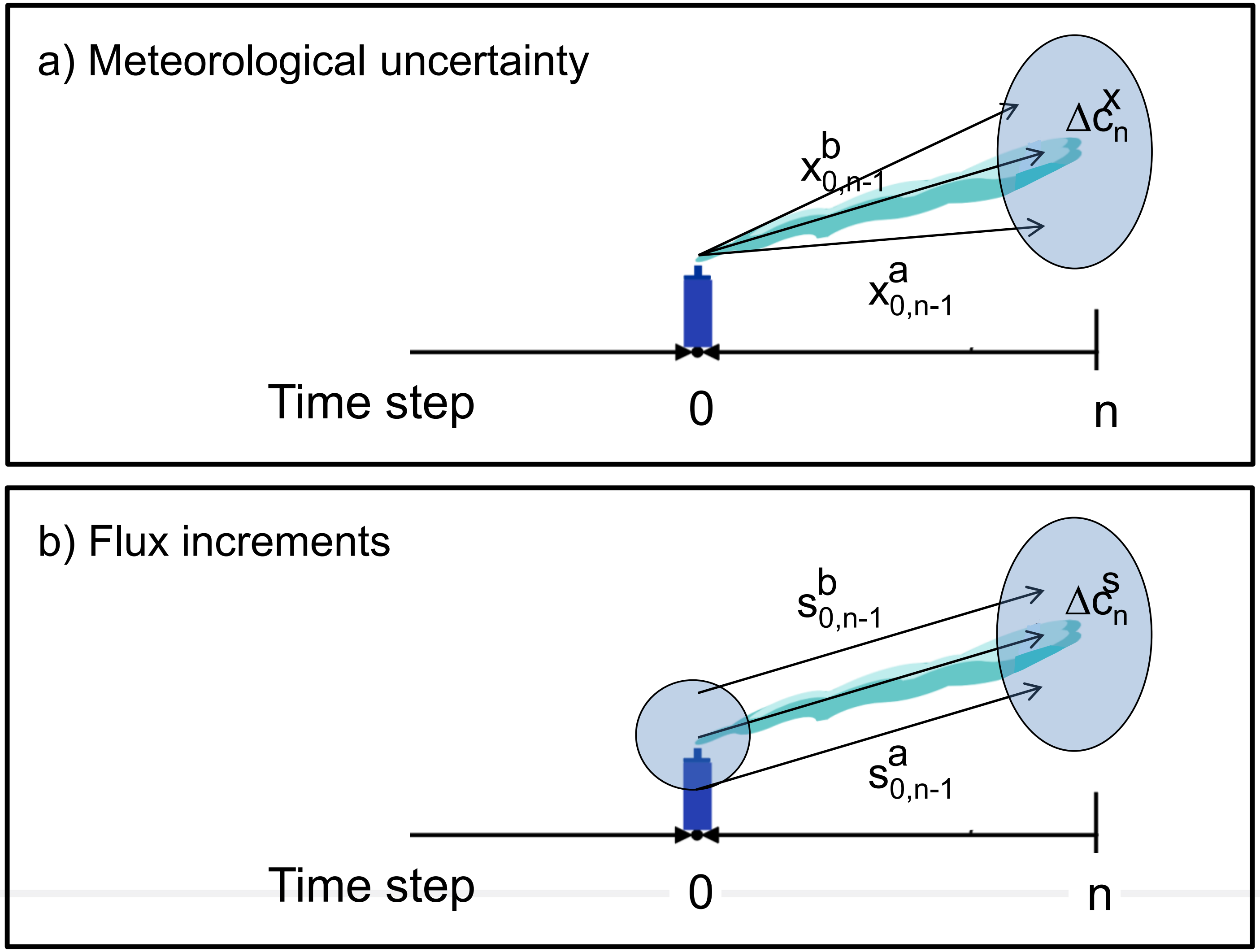
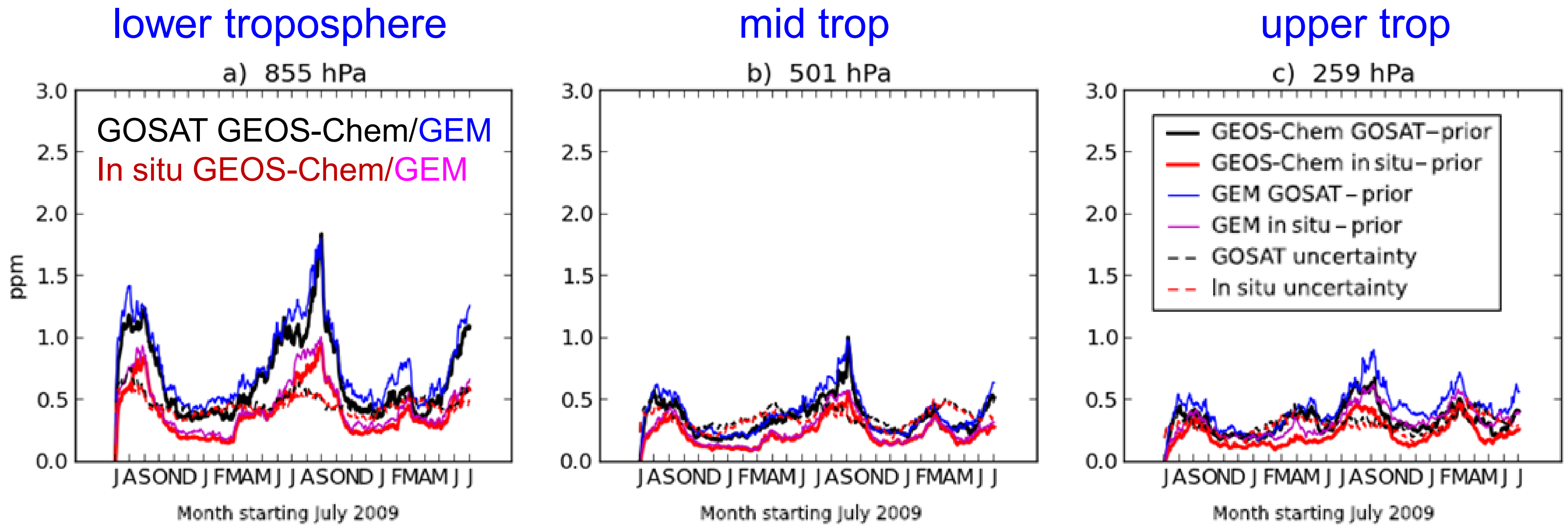


2. INVERSE MODELING

Does the change in CO_2 induced by updated flux estimates exceed the uncertainty in CO_2 due to imperfect meteorology?



CHANGE IN CO_2 DUE TO FLUX ESTIMATION



Once the flux signal has diffused to large-scale structures (~3 months in troposphere), there will be no contribution to zonal std-dev. So zonal std-dev reflects shorter time scales than zonal mean.

- CO_2 change due to GOSAT flux increments exceeds change in CO_2 due to perturbed met analyses except in boreal winter in lower trop.
- CO_2 change due to insitu flux increments exceeds change in CO_2 due to perturbed met analyses only in boreal summer in lower trop.

Polavarapu et al. (2018, ACP)

3. DATA ASSIMILATION

3D-VAR ESTIMATION OF CO_2 STATE

CO_2 state; CO_2 obs; Observation error covariance matrix; Forecast error covariance matrix

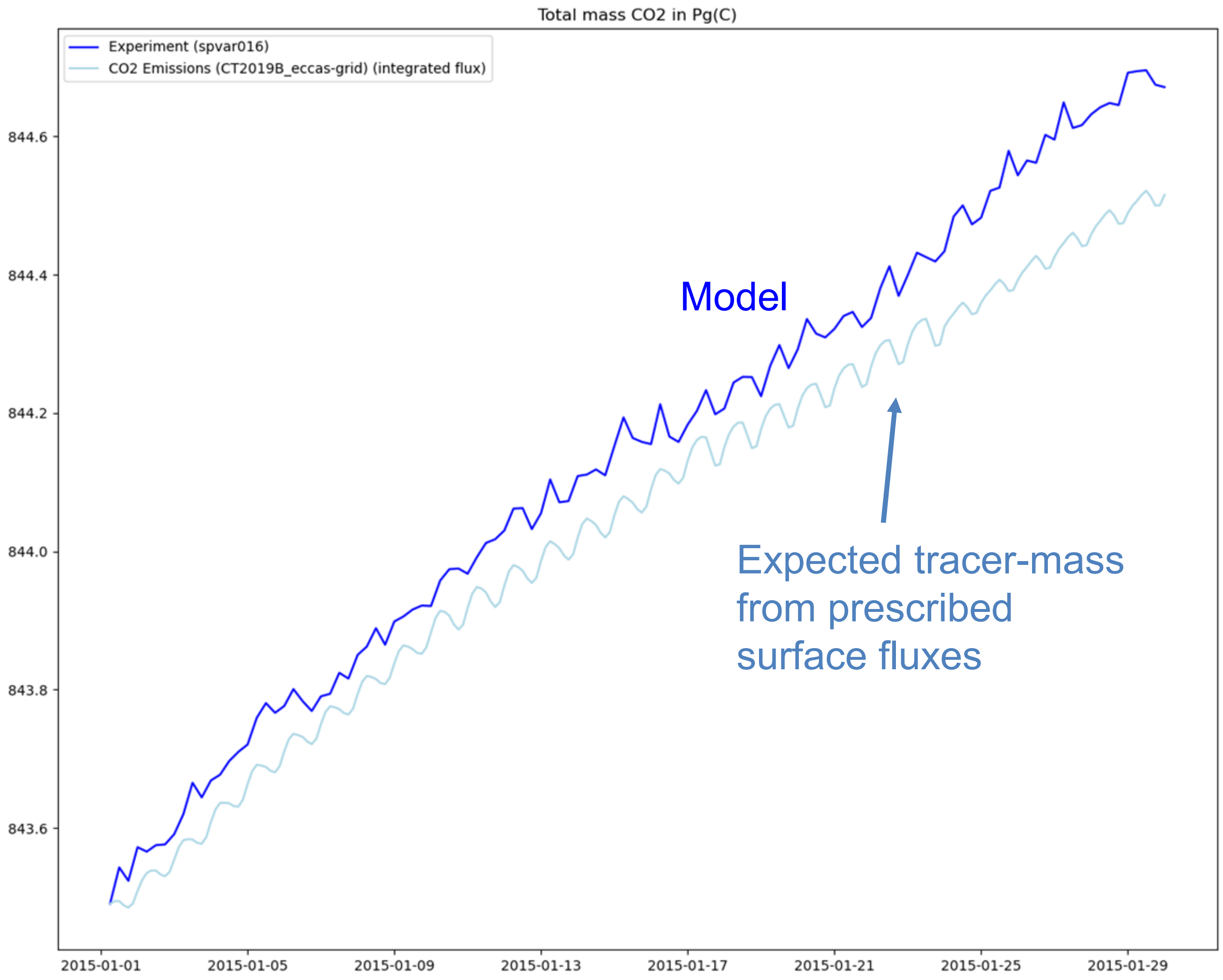
$$J_{\mathrm{MAP}}(\mathbf{x}) = \frac{1}{2}(\mathbf{z} - \mathbf{H}\mathbf{x})^{\mathrm{T}}\mathbf{R}^{-1}(\mathbf{z} - \mathbf{H}\mathbf{x}) + \frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^{\mathrm{T}}\mathbf{P}^{-1}(\mathbf{x} - \boldsymbol{\mu}).$$

Spatial interpolation; 6h forecast of CO_2

- January 1-30, 2015, 6h update cycle
- **Model**: GEM-MACH-GHG 400x200 global uniform
- **CO_2 observations**: aircraft, surface, tower continuous obs from NOAA Obspack at all times (day and night) obspack_co2_1_GLOBALVIEWplus_v6.1_2021-03-01
- **Obs errors:** from CT_MDM values in ObsPack
- **Prior fluxes**: CT2019B posterior fluxes
- **Initial state**: Jan. 1, 2015 0 UTC from CT2019B molefractions
- **Background error covariance matrix**: From O_3 assimilation for correlations, standard deviations vary with height for 3 zonal bands: NE, TR, SE.

Previous work was with EnKF for simulated CO observations (Khade et al. 2021, GMD)

Global CO_2 mass evolution in Jan 2015

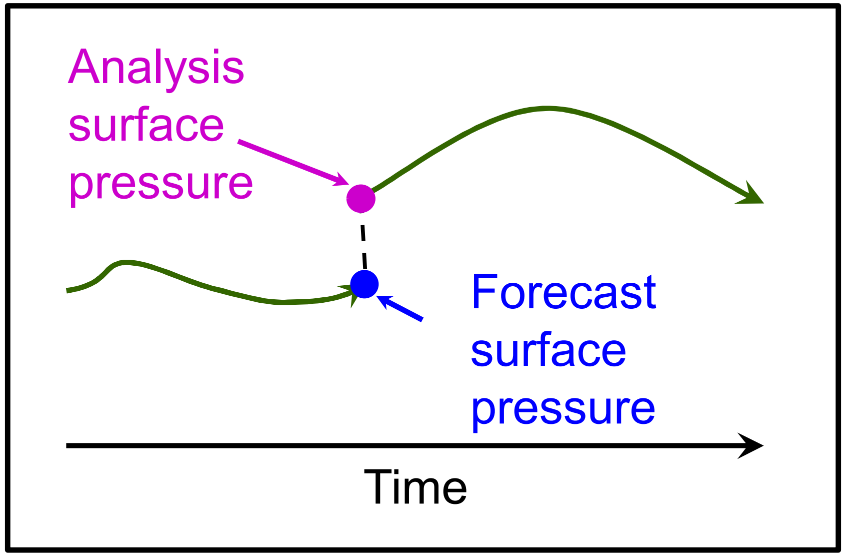


Time series of CO_2 global mass show departures from the mass expected from prescribed CO_2 surface fluxes. This is because:

1) The global dry-air mass changes in the model when a new meteorological analysis is inserted every 6 h
2) Assimilating CO_2 observations will create adjustments to the CO_2 state and hence the global CO_2 mass

DEALING WITH DRY AIR MASS CHANGES AT ASSIMILATION WINDOW INTERFACES

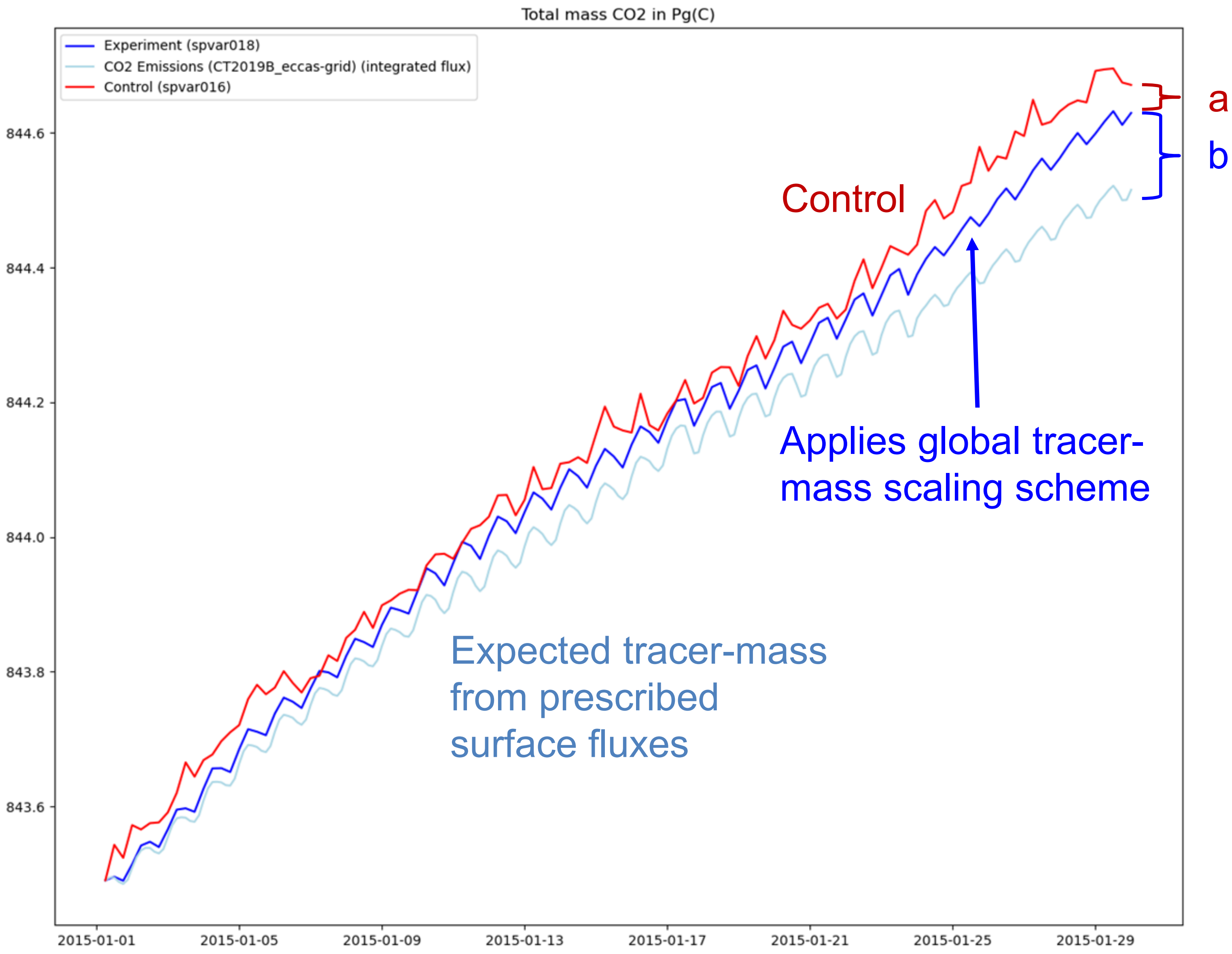
If we can account for the change in dry-air mass across the temporal boundary between analysis cycles, then we can compare the magnitude of global mass change in CO_2 due to dry-air mass changes in the model to the change due to assimilating CO_2 observations.



We want to adjust the analysis mixing ratio field by a global constant, ϵ:

$$\tilde{c}_{i,k}^{dry,a} = c_{i,k}^{dry,a} + \epsilon = c_{i,k}^{dry,f} + \Delta c_{i,k}^{dry,a} + \epsilon$$

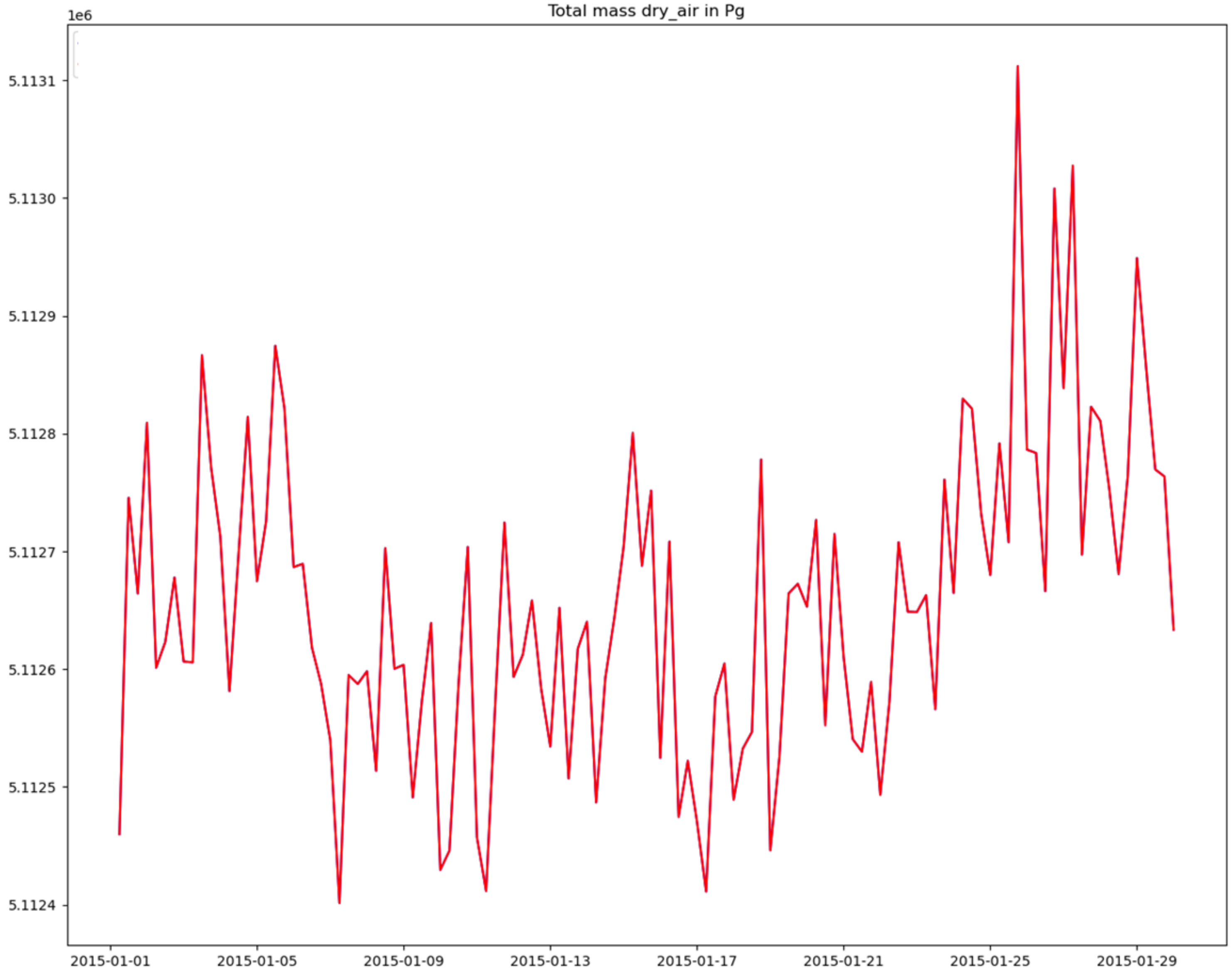
Global CO_2 mass due to analysis increments



a) Mass change due to dry-air mass adjustments
b) Mass added through CO_2 data assimilation

The change in mass due to global dry-air mass adjustments (a) can exceed that due to assimilation of CO_2 data (b)

Global dry air mass in GEM



Jan 1 Jan 29

Trenberth and Smith (2005, J.Clim):

Global dry air mass

$(5.132 \pm 0.005) \times 10^{18}$ kg

Global water vapor:

$(1.25 \pm 0.1) \times 10^{16}$ kg

Y-axis range is 0.0007×10^{18} kg

Ticks are 0.0001×10^{18} kg

SUMMARY

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Feedback?

Contact: saroja.polavarapu@ec.gc.ca, Teams, Zoom, etc.

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