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Canada

Atmospheric composition coupled model developments and surface flux estimation

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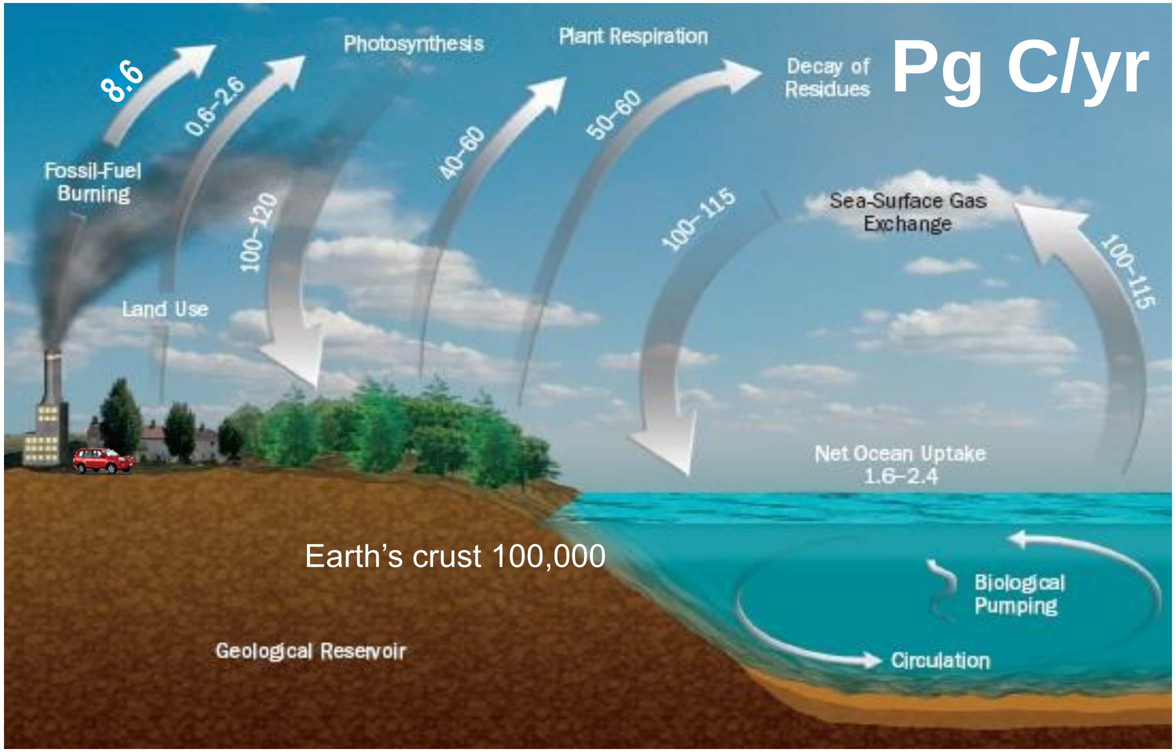
OUTLINE

1. The carbon cycle: a coupled data assimilation problem
2. Meteorology/constituent coupling in models
   - Sources of coupling in online constituent transport models
   - Impacts of constituents on meteorological forecasts
3. Data assimilation for constituents and surface fluxes
   - Inverse modelling with a Chemistry Transport Model (CTM)
   - Constituent transport model error
   - Impact of meteorological uncertainty on constituent forecasts
   - Coupled meteorological, constituent state, flux estimation
4. Challenges of greenhouse gas surface flux (emissions) estimation

1. The carbon cycle: a coupled data assimilation problem

The Global Carbon Cycle

http://www.scidacreview.org/0703/html/biopilot.html



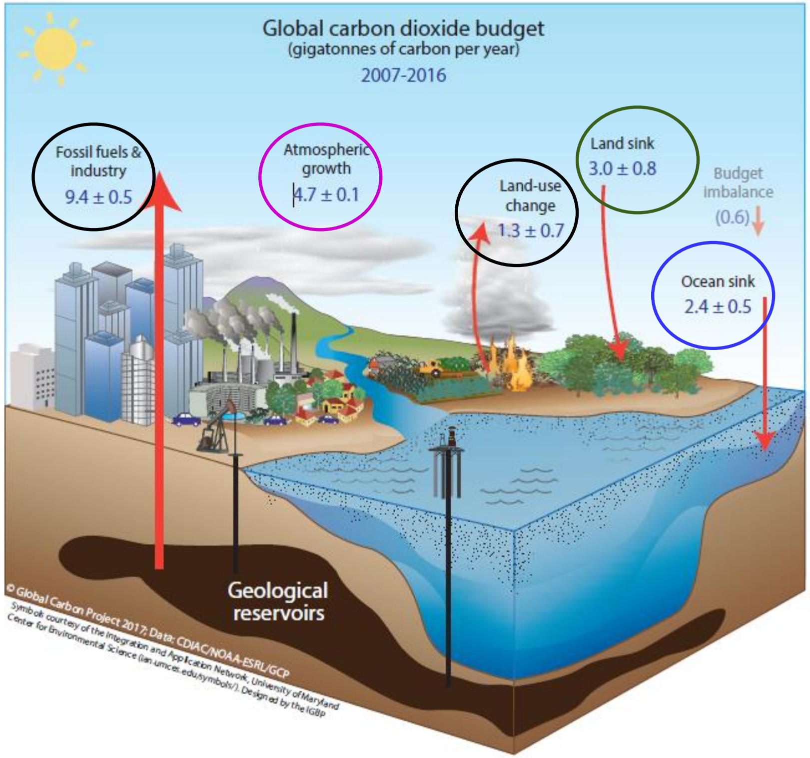
1 Pg = 1 Gt = 10^{15} g

Net surface to atmosphere flux for biosphere or ocean is a small difference between two very large numbers

- The natural carbon cycle involves CO_2 exchange between the terrestrial biosphere, oceans/lakes and the atmosphere.
- Fossil fuel combustion and anthropogenic land use are additional sources of CO_2 to the atmosphere.

Net perturbations to global carbon budget

LeQuéré et al. (2018, ESSDD)

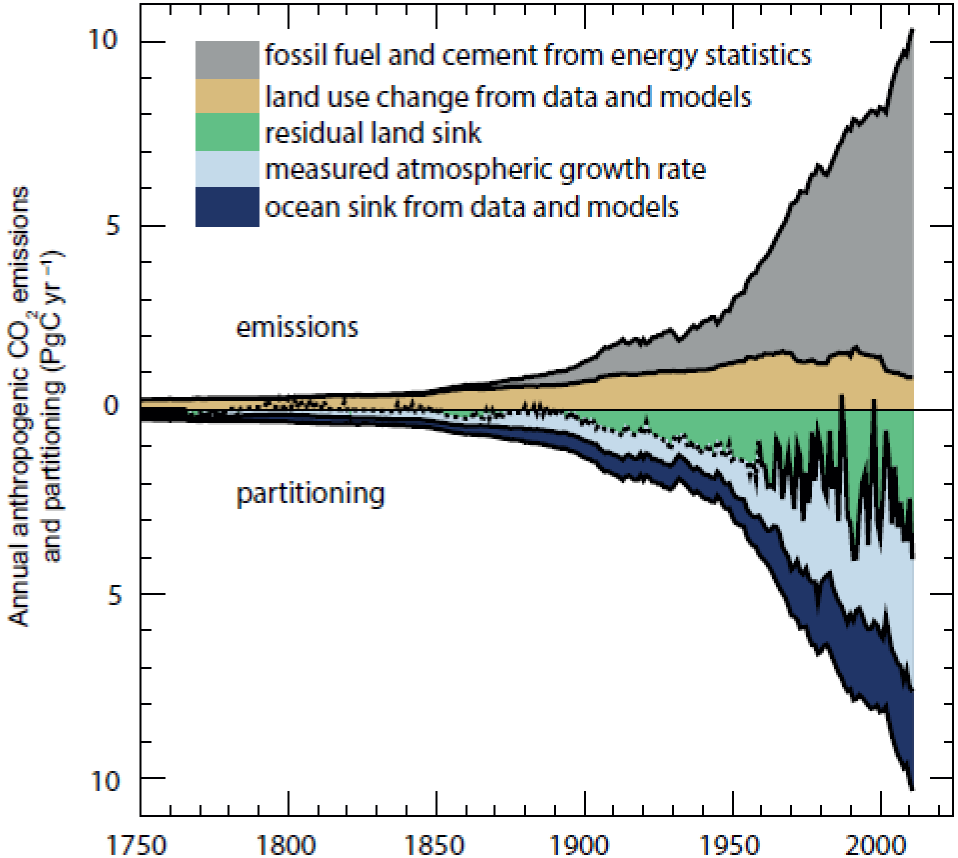


- Based on 2005-2014
- 44% of emissions remain in atmosphere
- 28% is taken up by terrestrial biosphere
- 22% is taken up by oceans

1 Pg = 1 Gt = 10^{15} g

Interannual variability

IPCC AR5 WG1 2013

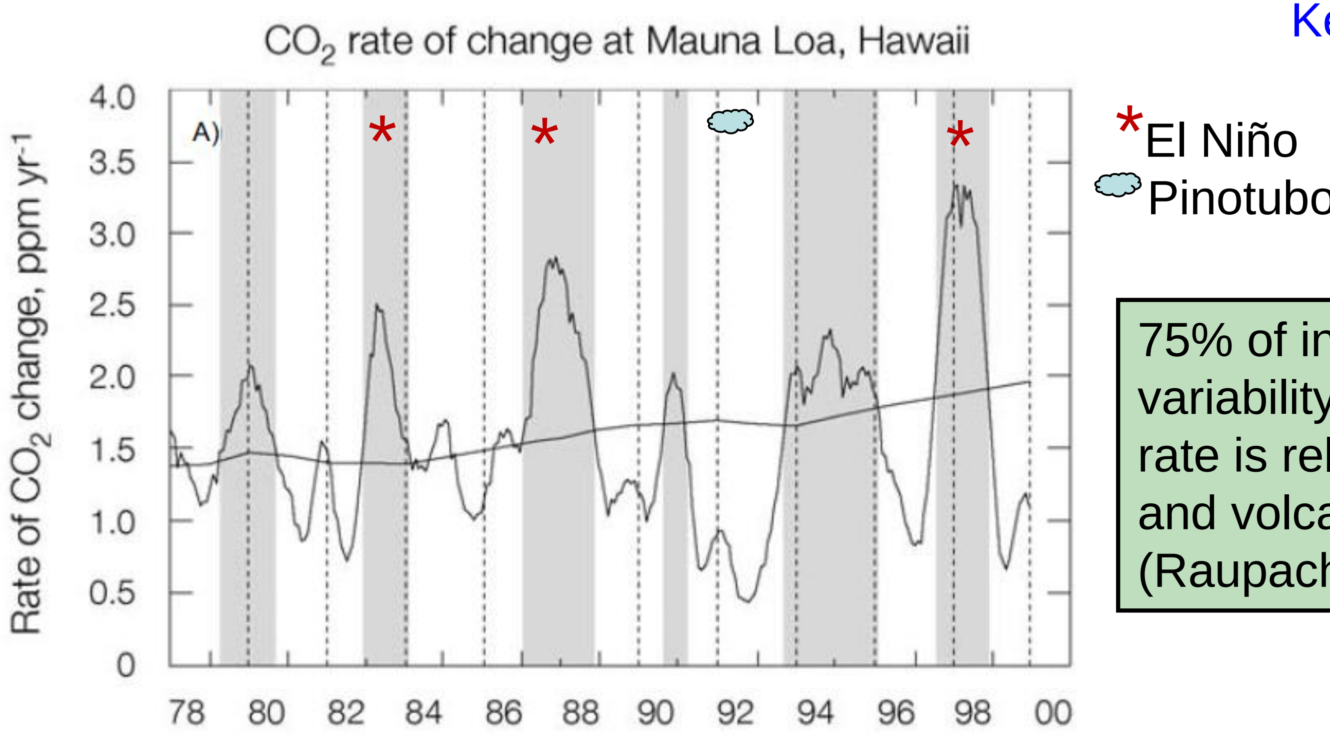


We need to better understand biospheric sources and sinks

The largest uncertainty and interannual variability in the global CO_2 uptake is mainly attributed to the terrestrial biosphere

Interannual variability in atmospheric CO_2 due to climate

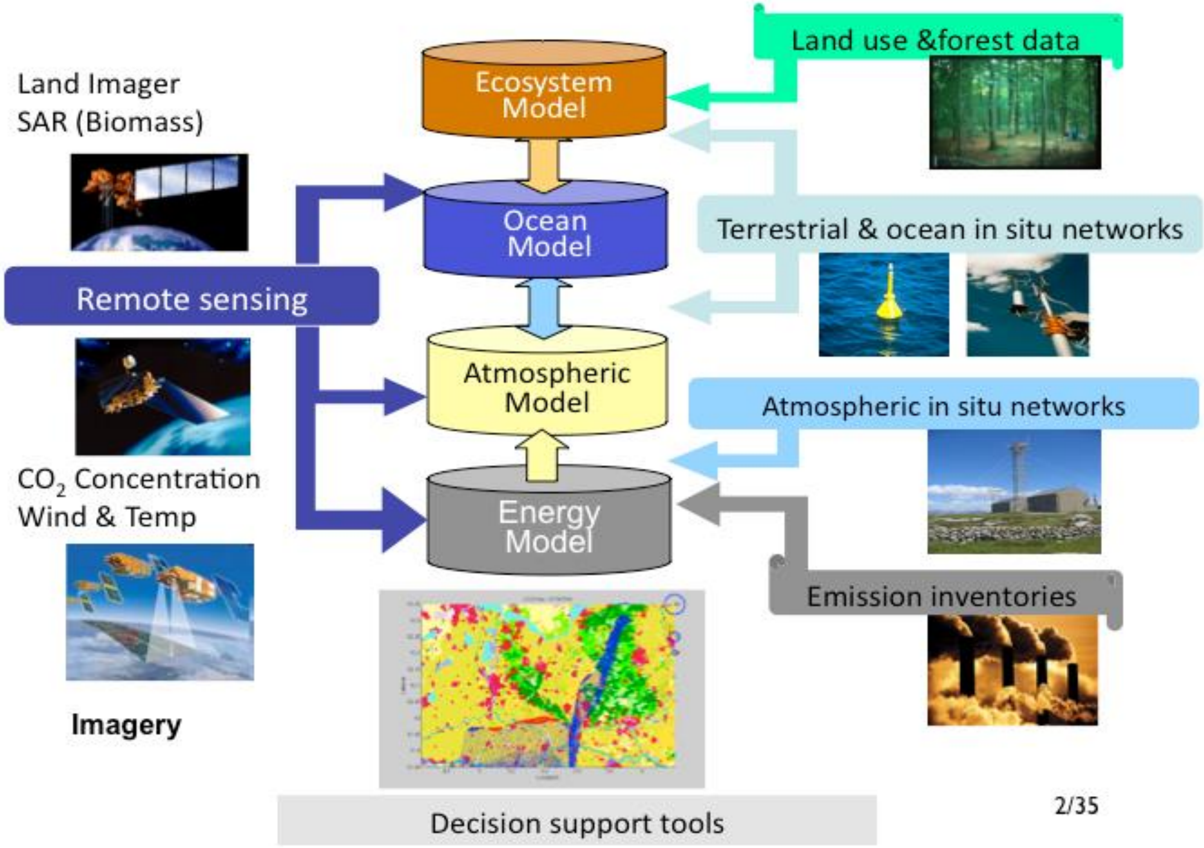
Keeling et al. (2005)



75% of interannual variability in CO_2 growth rate is related to ENSO and volcanic activity (Raupach et al. 2008)

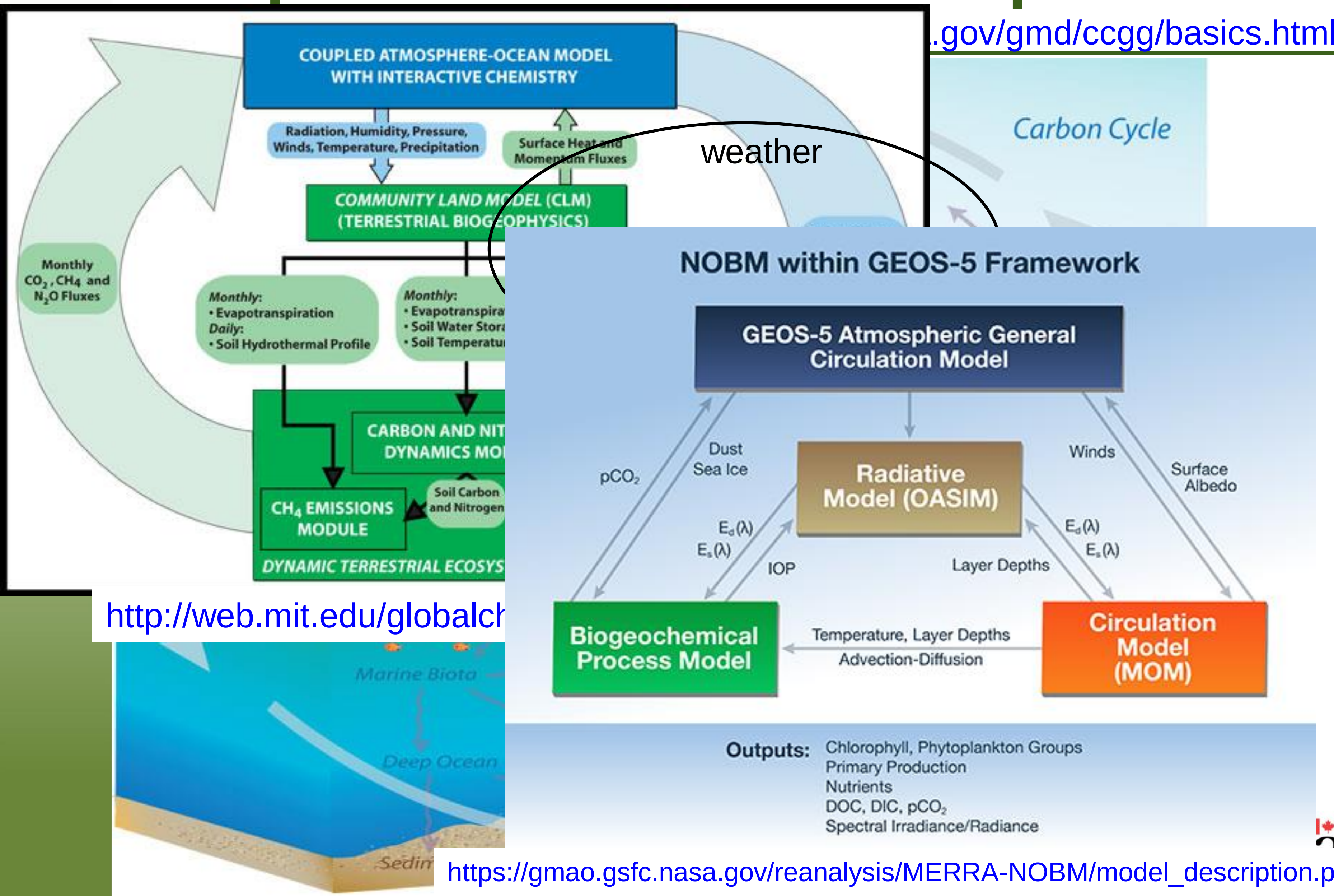
- Tropical CO_2 flux goes from uptake to release in dry, warm ENSO.
- More CO_2 uptake by plants with more diffuse sunlight and cooler temperatures after volcanic eruptions.

Coupled Carbon Data Assimilation Systems



http://www.globalcarbonproject.org/misc/JournalSummaryGEO.htm

Coupled land/ocean/atmosphere



.gov/gmd/ccgg/basics.html

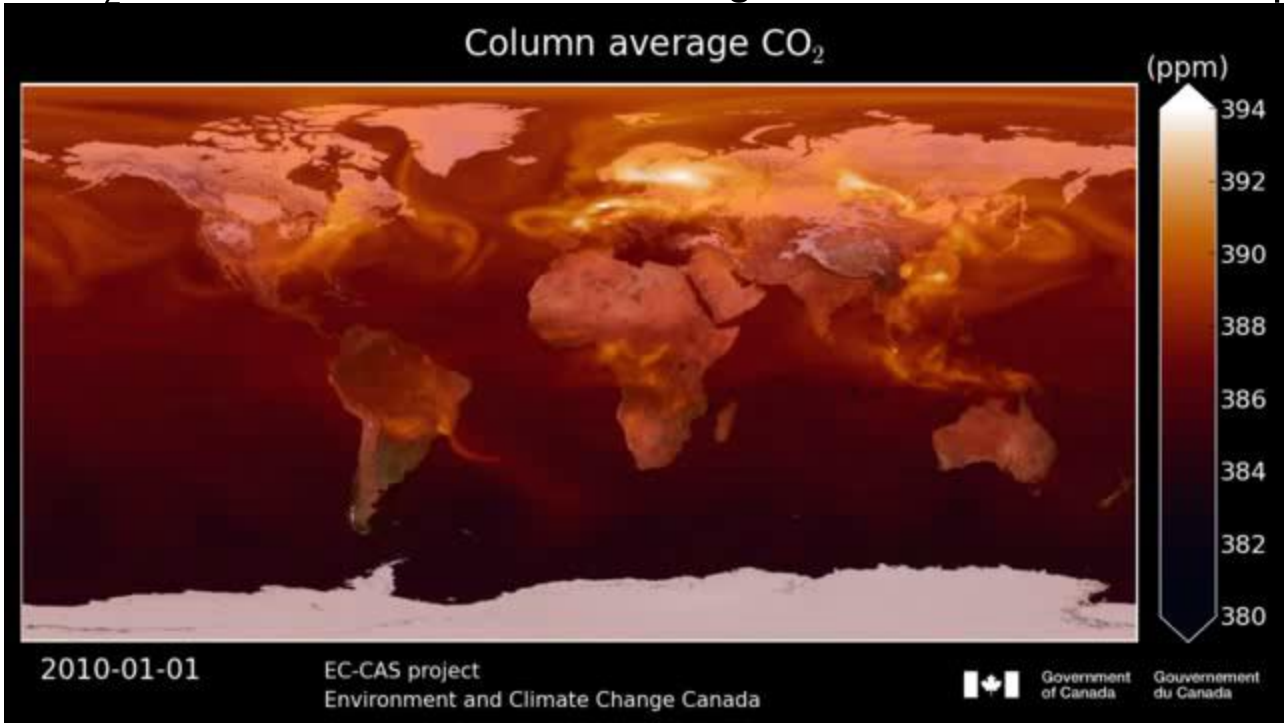
http://web.mit.edu/globalch

https://gmao.gsfc.nasa.gov/reanalysis/MERRA-NOBM/model_description.php

CO_2 Time scales

Video by Mike Neish (ECCC)

Simulation of CO_2 with GEM-MACH-GHG using NOAA CarbonTracker optimized fluxes

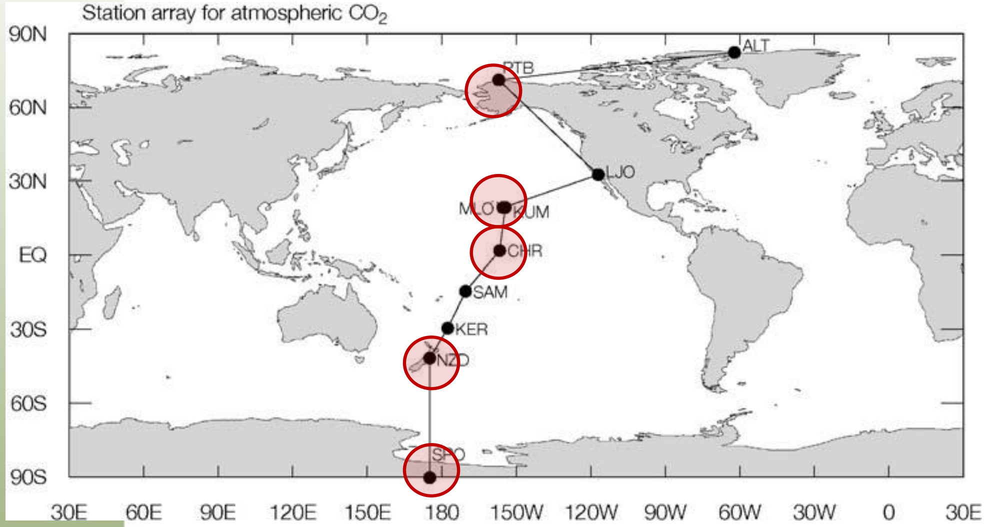


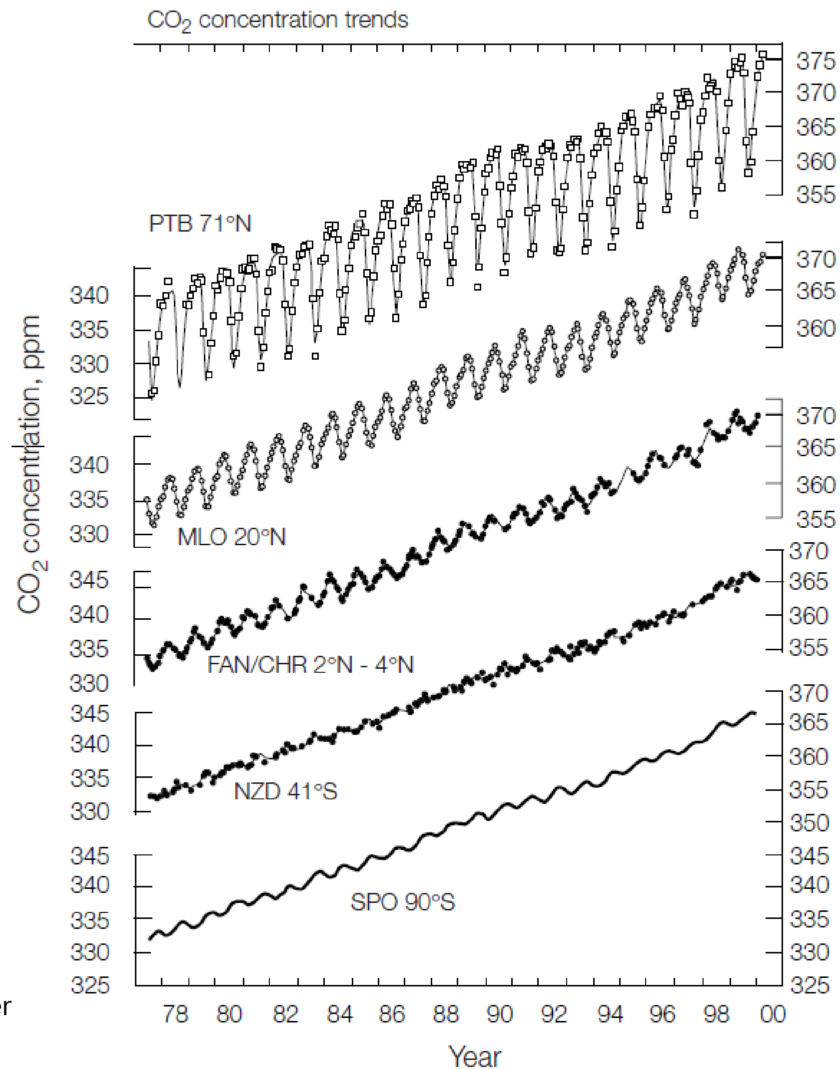
Colour bar range is 3.5% of mean

- Diurnal, synoptic, seasonal, annual
- Hemispheric gradient
- Signals are mixed by middle of Pacific ocean

Atmospheric CO_2 observations

Keeling et al. (2005)



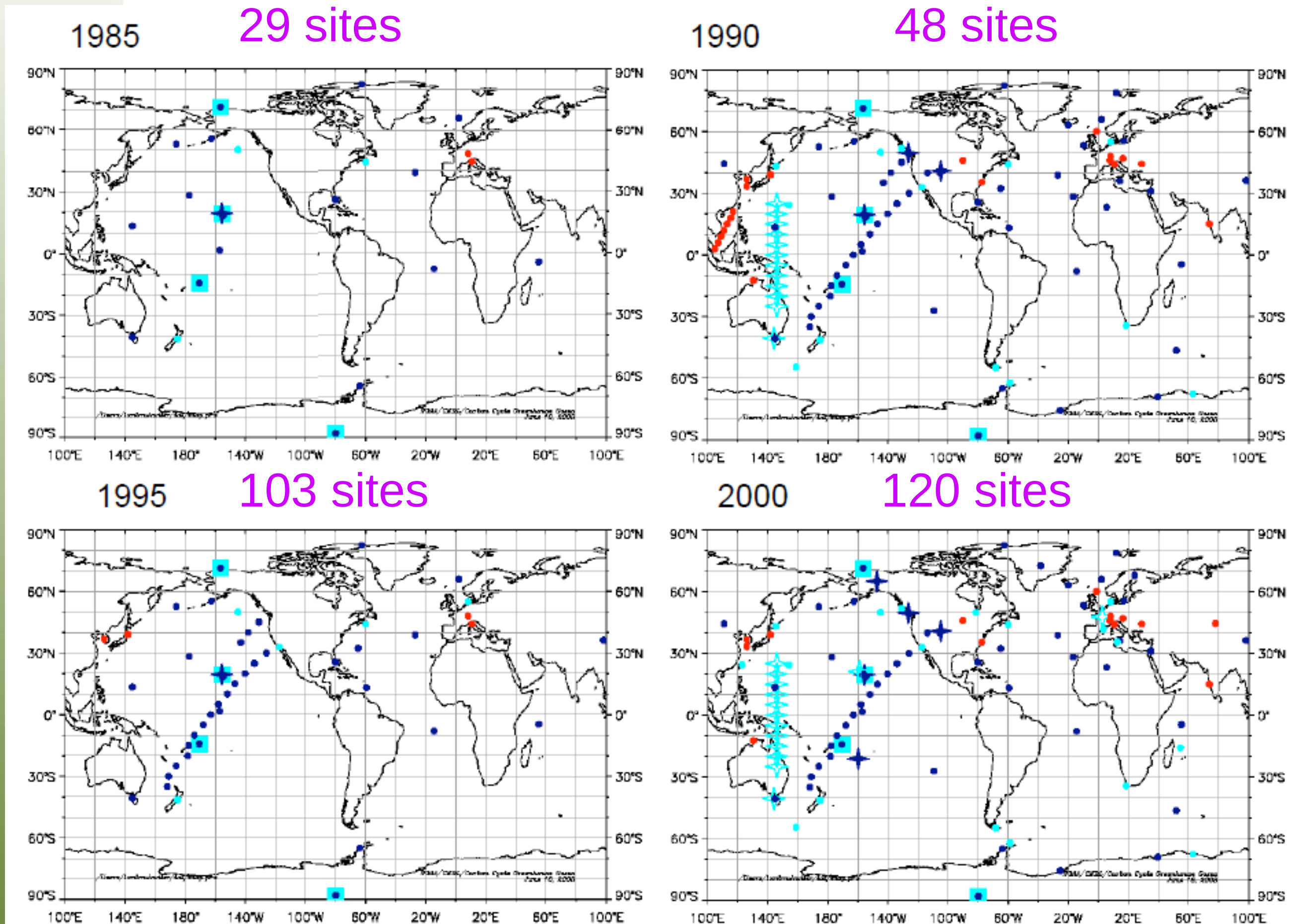


Time signals:

- Linear trend
- Seasonal cycle
  - Amplitude ↓ with latitude

Evolution of the in situ obs network

Bruhwiler et al. (2011)



- Routine flask samples
- Continuous obs
- Not used flask obs
- Aircraft sampling

- **Original goal**: Long term monitoring of background sites
- **Later on**: Add continental sites to better constrain terrestrial biospheric fluxes at continental scales

Increasing in situ measurements

https://www.icos-ri.eu/greenhouse-gases

2018 ECCC GHG network
Hourly obs of CO_2, CH_4, CO

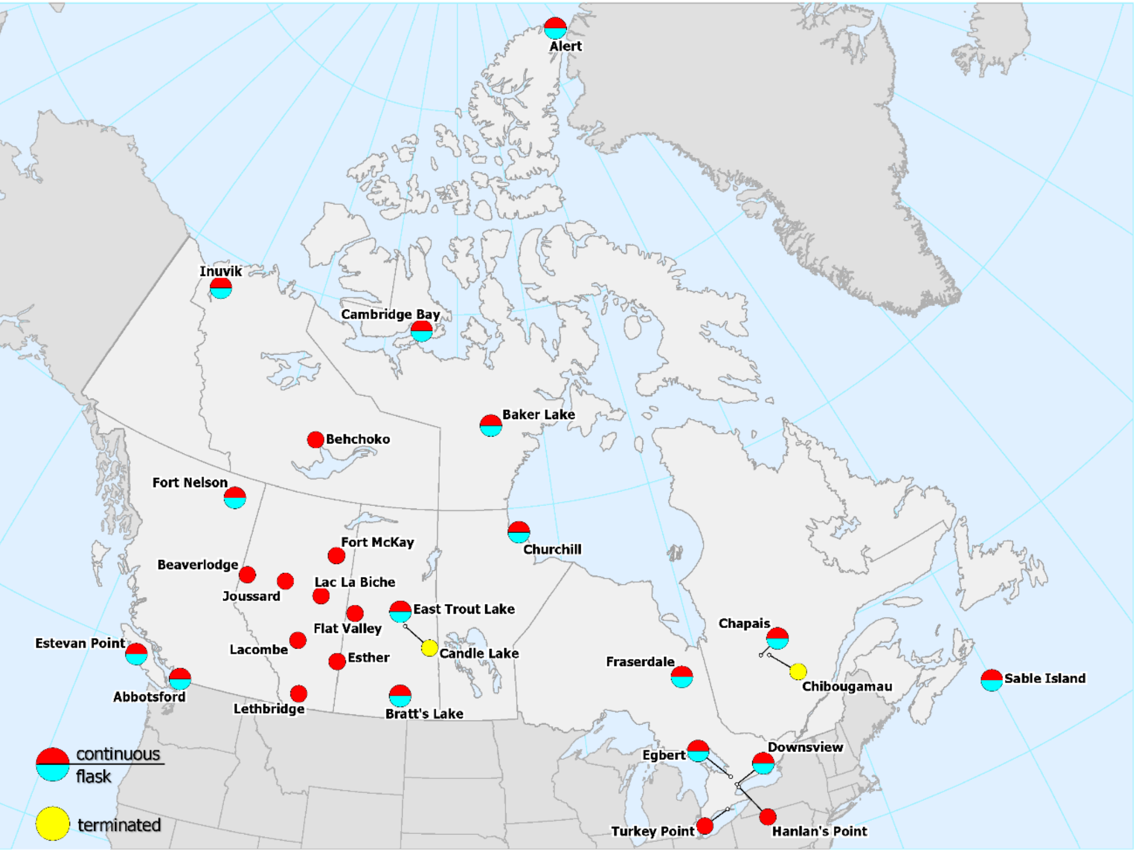
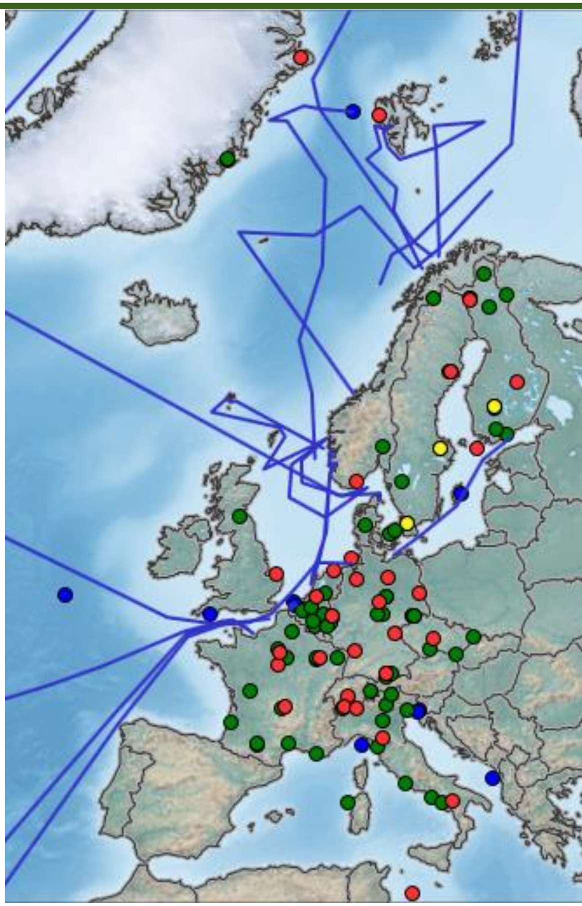


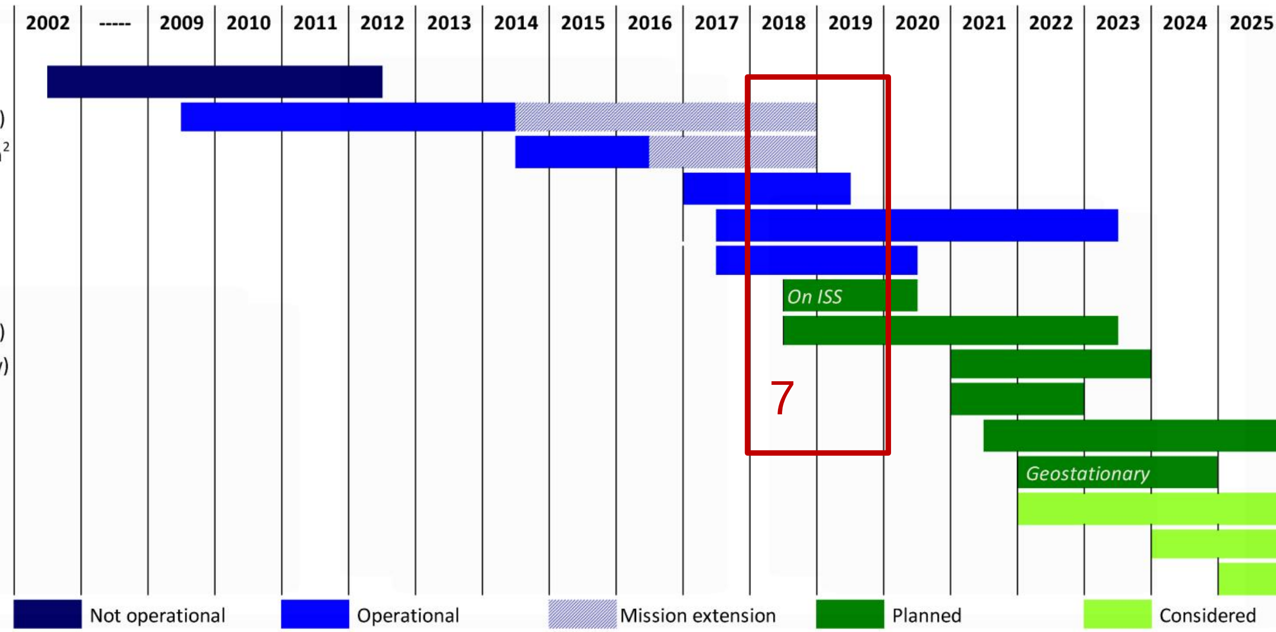
Figure courtesy of Elton Chan (ECCC)



ICOS network has stations in 12 countries: atmospheric (30+), ecosystem flux (50+) , ocean measurements (10+)

GHG Mission Timeline

Satellite, Instrument (Agencies)	CO_2	CH_4	Swath	Sample
ENVISAT SCIAMACHY (ESA)	●	●	960 km	30x60 km^2
GOSAT TANSO-FTS (JAXA-NIES-MOE)	●	●	3 pts	10.5 km (d)
OCO-2 (NASA)	●		10.6 km	1.3x2.3 km^2
TanSAT (CAS-MOST-CMA)	●		20 km	1x2 km^2
Sentinel 5P TROPOMI (ESA)		●	2600 km	7x7 km^2
Feng Yun 3D GAS (CMA)	●	●		10 km (d)
OCO-3 (NASA)	●		11 km	~4 km^2
GOSAT-2 TANSO-FTS (JAXA-MOE-NIES)	●	●	5 pts	10.5 km (d)
MERLIN (DLR-CNES)		●	100 m	0.14 km (w)
MicroCarb (CNES)	●		13.5 km	40 km^2
MetOp Sentinel-5 series (Copernicus)		●	2670 km	7x7 km^2
GEOCARB (NASA)	●	●		4x4 km^2
Feng Yun 3G (CMA)	●	●		1x1 km^2
GOSAT-3 (JAXA-MOE-NIES)	●	●		
CO2 Monitoring series (Copernicus)	●	●		2x2 km^2



- A broad range of GHG missions will be flown over the next decade.
- Most are "science" missions, designed to identify optimal methods for measuring CO_2 and CH_4, not "operational" missions designed to deliver policy relevant GHG products focused on anthropogenic emissions

WMO/UNEP - Integrated Global Greenhouse Gas Information System (IG3IS)

WORLD METEOROLOGICAL ORGANIZATION
Weather · Climate · Water

UN environment

https://public.wmo.int/en/resources/bulletin/integrated-global-greenhouse-gas-information-system-ig3is

Objective: Provide timely actionable GHG information to stakeholders

1. Support of Global Stocktake and national GHG emission inventories
   - Establish good practices and quality metrics for inverse methods and how to compare results to inventories
   - Reconcile atmospheric measurements and model analyses (inverse modelling) with bottom up inventories
2. Detection and quantification of fugitive methane emissions
   - Extend methods used by EDF, NOAA and others to identify super emitters in N.American oil and gas supply chain to countries and other sectors: offshore platforms, agriculture, waste sector
3. Estimation and attribution of subnational GHG emissions
   - Urban GHG information system using atmospheric monitoring, data mining and (inverse) models, Provide sector-specific information to stakeholders

ECMWF and CO_2 monitoring

https://www.che-project.eu/

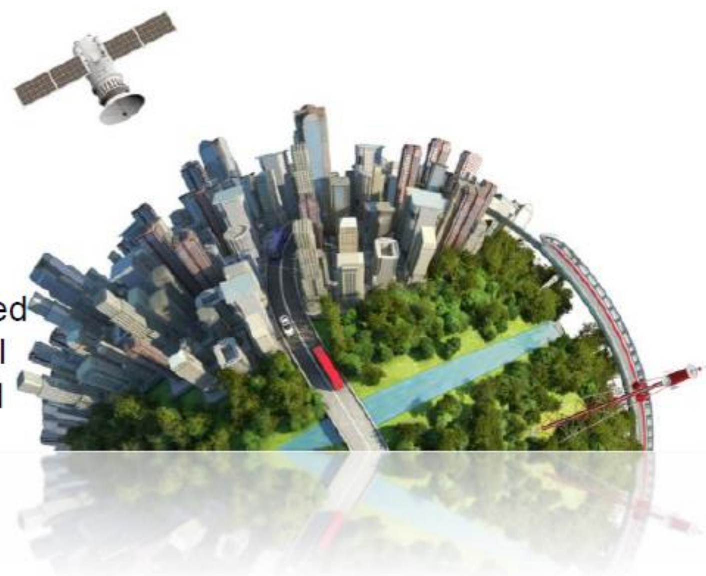
Slide from Gianpaolo Balsamo presentation at CHE workshop Feb. 2018

CHE-CO2 Human Emission Project (& its numbers)

Aim:
Build European monitoring & verification support capacity for anthropogenic CO2 emissions

How:
Monitoring/Verification System (MVS) driven by Earth observations, from remote sensing and in situ, combined with enhanced modelling systems, that includes CO2 fossil fuel emissions, along with other natural and anthropogenic CO2 emissions & transport.

Why:
To support the Paris Climate Agreement and its implementation



Project Duration:
39 month

Project Funding:
3.75 ME (1.25 ME/year)

Consortium Numbers
22 partners Institutes

Work Content Numbers
7 work-packages:
5-Science development, 1-International liaison, 1-Management & Coms
7 Milestones
45 Deliverables

344.25 Person Month
(Eq 8.8 FTE)

3 Project Reviews
(M15, M27Tech, M39)

ECMWF · AIRBUS · cmcc · DLR · Empa · EUMETSAT · iLab · Lund University · NILU · SPASCIA · SRON · ThalesAlenia Space · TNO innovation for life · UEA · University of Leicester · Wageningen

The carbon cycle data assimilation problem

- Estimating surface fluxes (emissions):
  - By following the movement of carbon.
  - Ultimately, we want to be able to attribute distributions to source sectors (e.g. fossil fuel, natural, etc.)
- Multiple spheres are coupled:
  - atmosphere, ocean, constituents, terrestrial biosphere
  - Assimilation window lengths vary from hours to years
- Multiple time scales:
  - interannual, seasonal, synoptic, diurnal
- Multiple spatial scales:
  - global, regional, urban
- Long lifetime species: CO_2 (~5-200 years), CH_4 (~12 years)

2. Meteorology and constituent coupling in atmospheric models

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

species

moist air

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

Density moist air

Diffusion coefficient

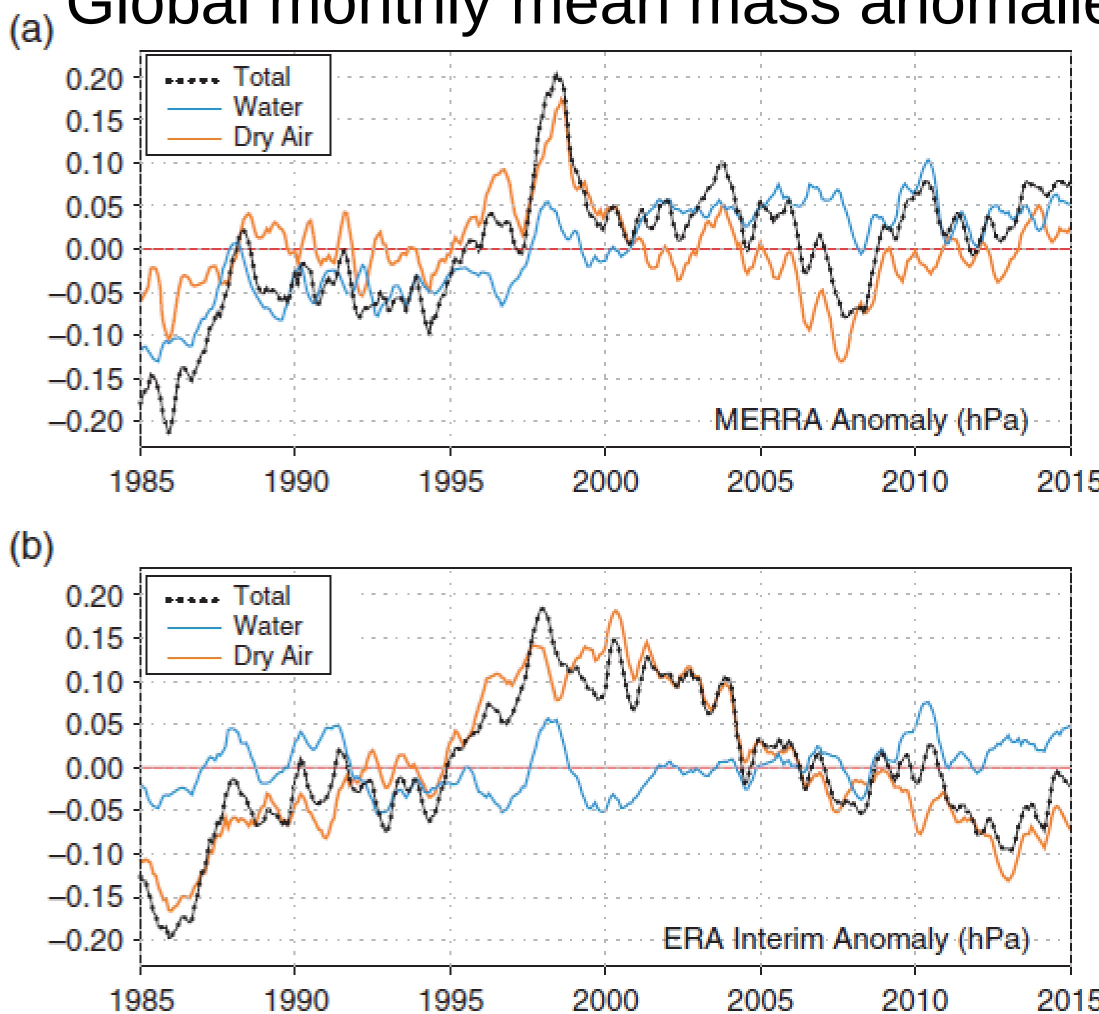
emission, dry deposition, wet deposition, photochemistry, gas/particle partitioning, etc.

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

Lack of global dry air conservation

Takacs et al. (2015)

Global monthly mean mass anomalies

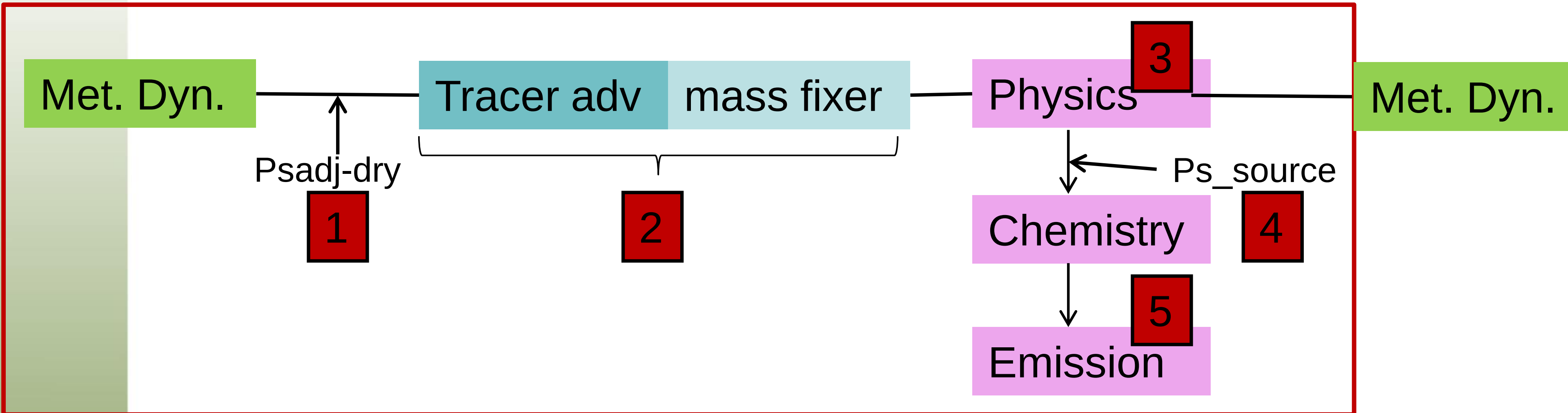


Dry air mass is not conserved because:

1) Model conserves moist air mass
2) Model continuity eq does not account for sources
3) Analysis increments of surface P and water vapour are not consistent

Conserving tracer mass in GEM

One time step



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.

Processes that couple meteorological and chemistry variables

Meteorological impacts on constituents:

- Surface pressure, water vapour through dry air mass
- Wind fields through advection
- Temperature through chemical reaction rates
- Temperature through photosynthesis, respiration
- Convection schemes: transport constituents
- Boundary layer parameterizations: transport constituents

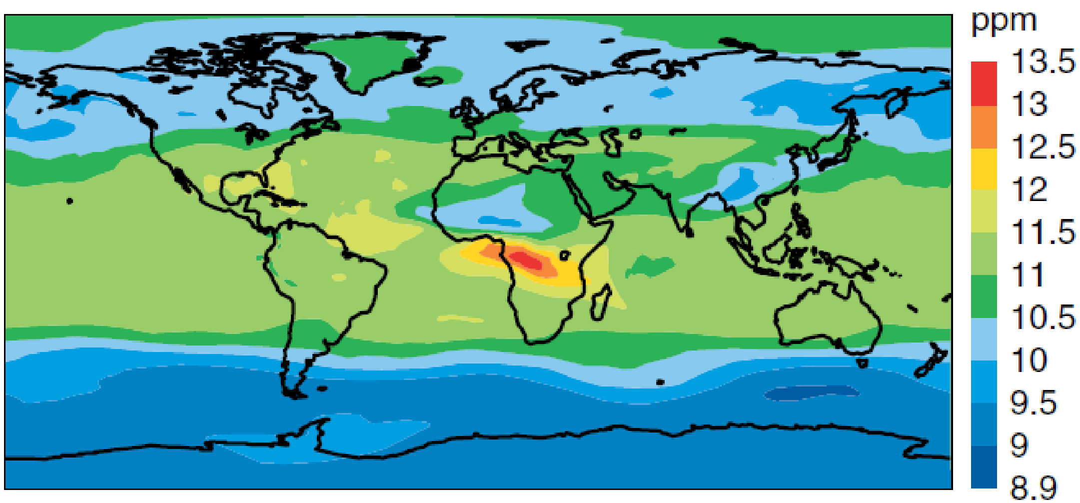
Constituent impacts on meteorology:

- Forecast model's radiation calculation
- Assimilation of constituents could potentially impact
  - Temperature analyses through improved radiance assimilation
  - Wind field analyses through coupling in dynamics, covariances

CO_2 and radiance assimilation

Engelen and Bauer (2012)

August 2009 mean CO_2 minus 377 ppm, ~210 hPa



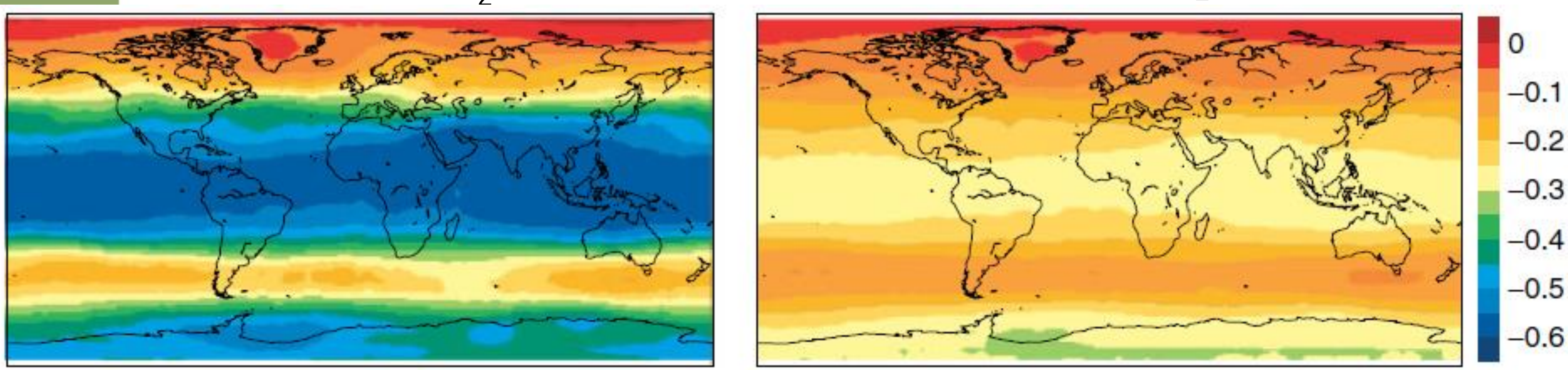
Bias correction has less work to do if CO_2 is a 3D field.

Impact on temperature analyses/forecasts is positive at 200 hPa in tropics, neutral elsewhere

AIRS ch. 175 ~200 hPa

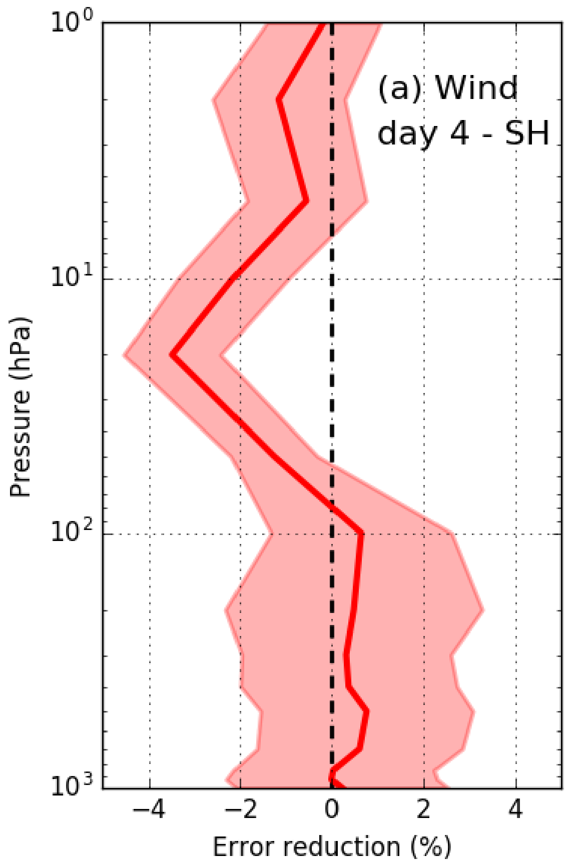
Bias correction Aug. 2009

Constant CO_2 | Variable CO_2

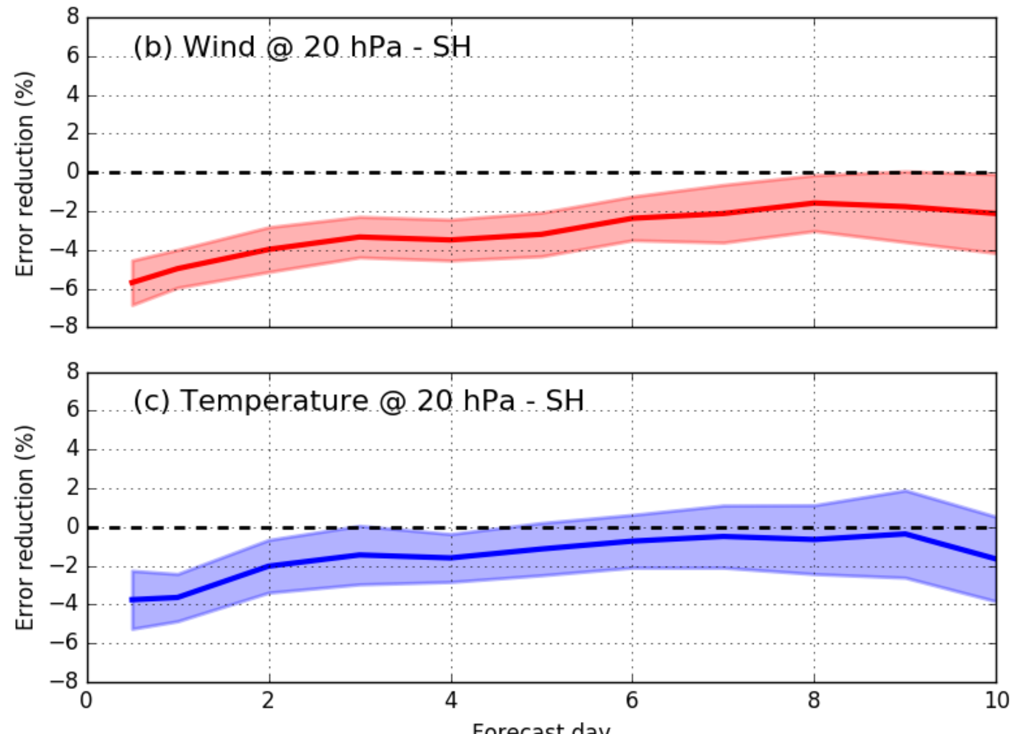


Impact of assimilating CO_2 , CH_4 on wind fields

Massart (WMO WWRP e-news Jan. 2018)



Impact of IASI CO_2 and CH_4 retrievals with EnKF for Jan-Feb 2010 is positive in stratospheric southern hemisphere

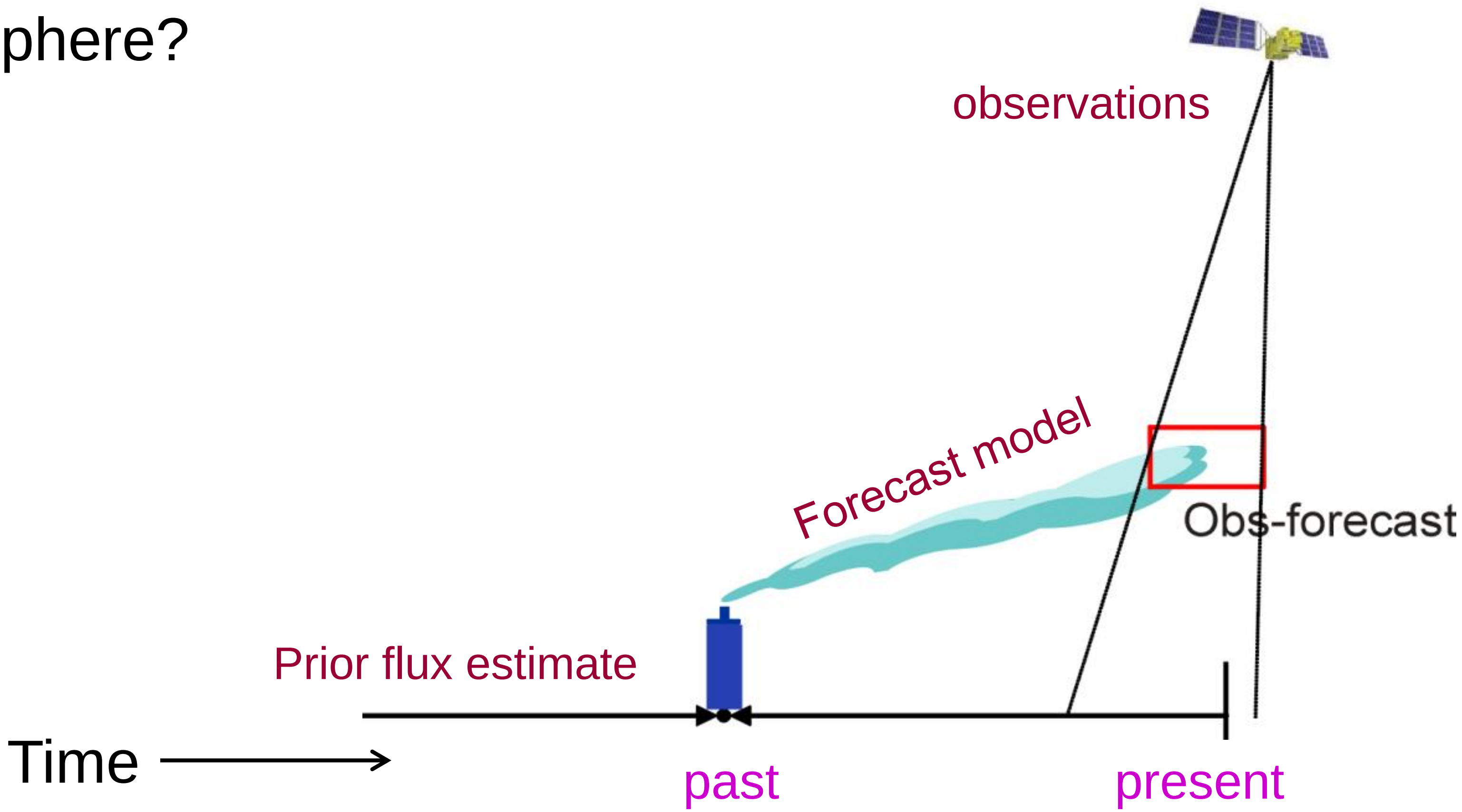


Pa

3. Data assimilation: Constituent/flux estimation

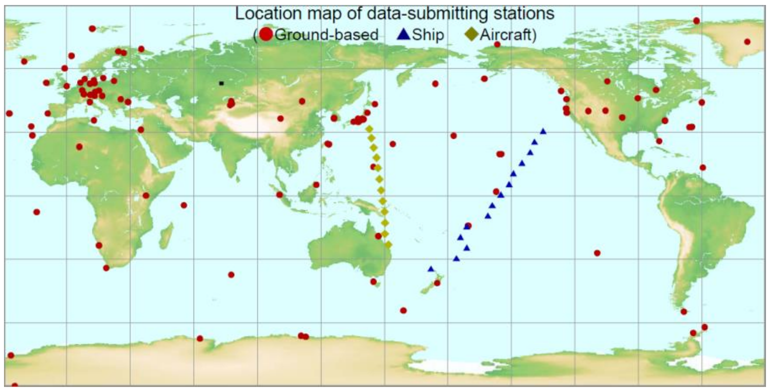
The surface flux estimation problem

Using atmospheric observations from the present, what was the past flux of GHG from the surface to the atmosphere?



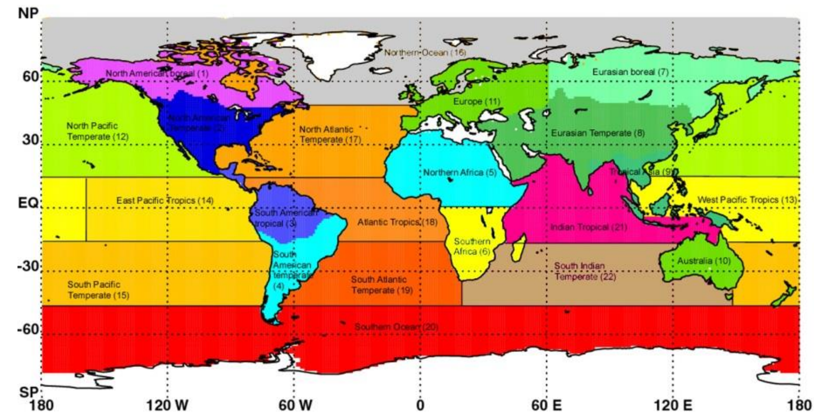
The standard inverse modeling approach

World Data Centre for Greenhouse Gases (WDCGG)

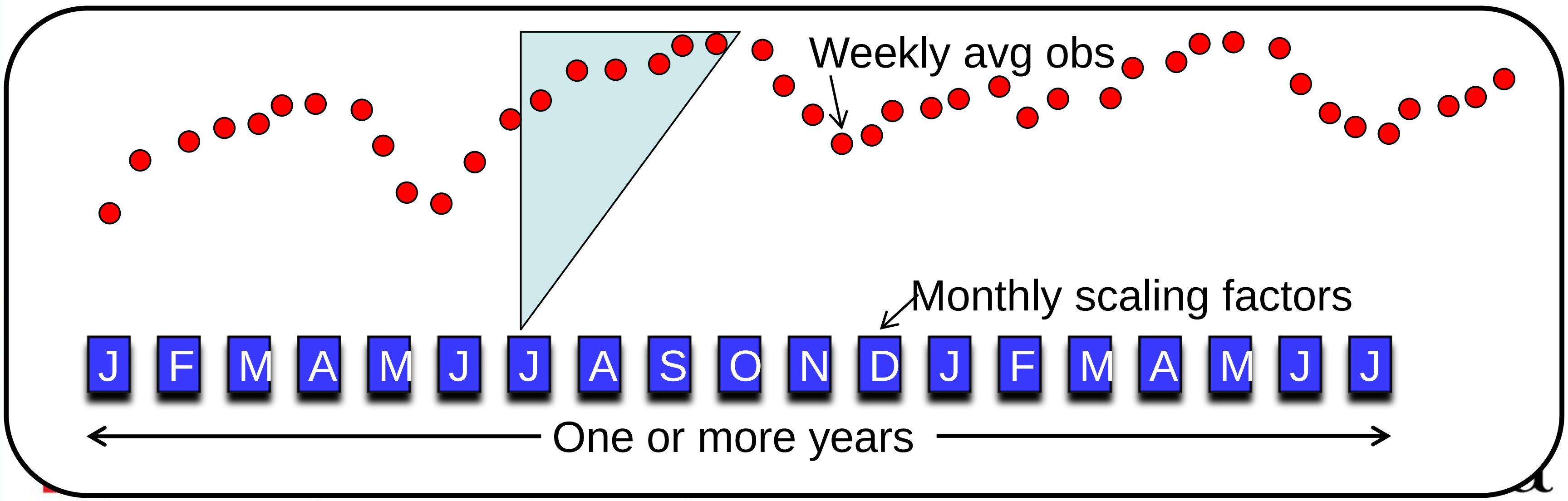


http://gaw.kishou.go.jp/cgi-bin/wdcgg/map_search.cgi

22 TransCom regions



http://transcom.project.asu.edu



The standard inverse problem for carbon flux estimation

flux Prior flux conc obs

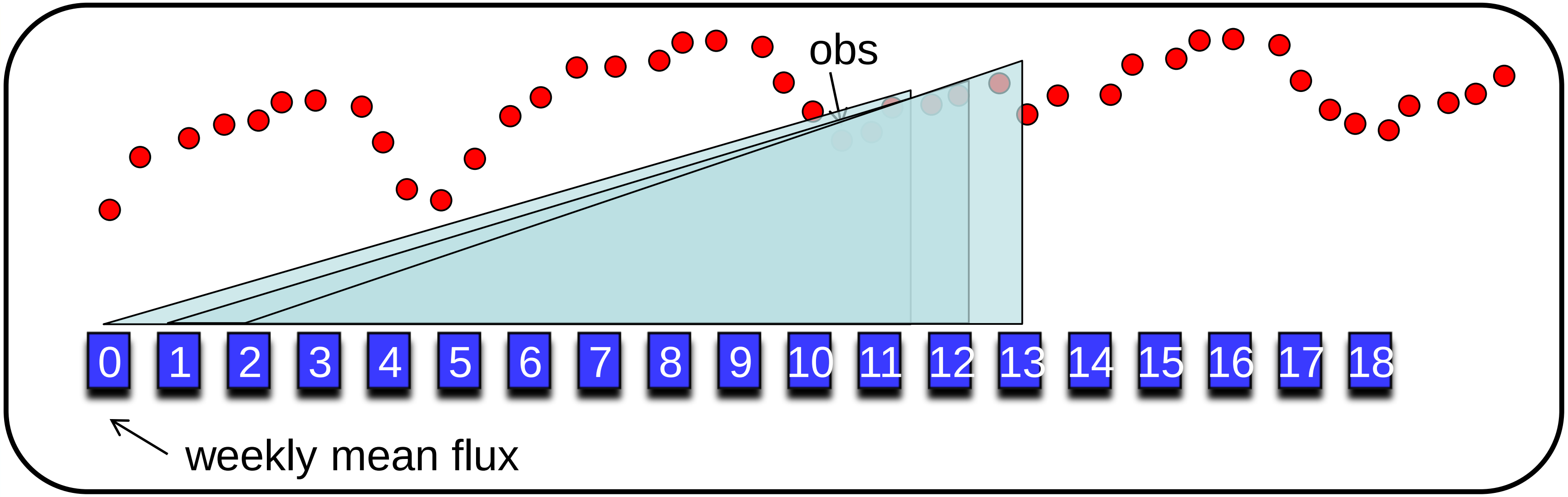
$$J(\mathbf{s}) = \frac{1}{2}(\mathbf{s}-\mathbf{s}^b)^T\mathbf{B}^{-1}(\mathbf{s}-\mathbf{s}^b) + \sum_{k=0}^{N}\frac{1}{2}(\mathbf{c}_k^{obs} - H[\mathbf{c}_k(\mathbf{s})])^T\mathbf{R}^{-1}(\mathbf{c}_k^{obs} - H[\mathbf{c}_k(\mathbf{s})])$$

Spatial interpolation Forecast model

- In flux inversions, if one solves for surface fluxes only, the transport model is needed to relate the surface flux to the observation
  - Can solve inverse problem with 4D-Var
  - Extension for imperfect tracer initial conditions, add a term
- Assumptions
  - Anthropogenic and biomass burning emissions are perfectly known
  - Observations and forecast errors are unbiased
  - Prior flux error covariance is known (correctly modelled)
  - Model-data mismatch covariance is known (correctly modelled)
  - Perfect model assumption since forecast model is used as a strong constraint

Fixed Lag Kalman Smoother

Peters et al. (2005, JGR)

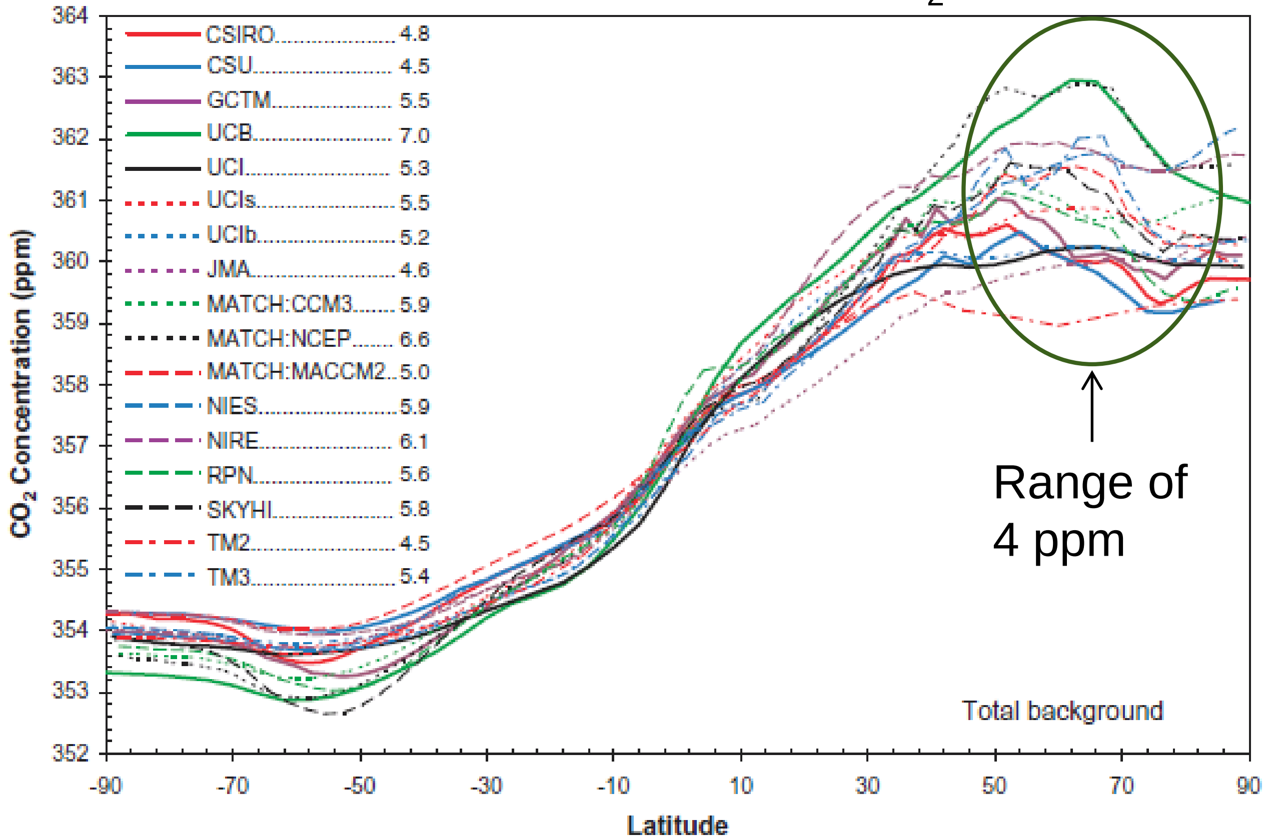


- e.g. CarbonTracker NOAA, CT-Europe, CT-Asia
- State vector: 5-12 sets of weekly-mean fluxes
- Lag: 5-12 weeks
- Forecast step: Persistence, static prior covariances
- Perfect model: transport model in observation operator

Transport model is not perfect

Gurney et al. (2003, Tellus)

Zonal mean annual mean CO_2



Even with the same surface fluxes, different models give different CO_2.

Transport model errors are an important source of error in surface flux inversions (Chevallier et al., 2014, 2010; Houweling et al.,2010; Law et al., 1996)

Forecast or "Transport error"

1) Transport model

$$\mathbf{c}_{k+1} = T_k(\overset{\text{met state}}{\mathbf{x}_k}, \underset{\text{chem state}}{\mathbf{c}_k}) + \mathbf{G}_k \overset{\text{2D flux}}{\mathbf{s}_k}$$

2) True evolution

$$\mathbf{c}_{k+1}^{\text{true}} = T_k(\mathbf{x}_k^{\text{true}}, \mathbf{c}_k^{\text{true}}) + \mathbf{G}_k \mathbf{s}_k^{\text{true}} + \underset{\text{Model error}}{\epsilon_k^{\text{mdl}}}$$

Forecast error: (1) – (2)

$$\epsilon_{k+1}^{c} = \frac{\partial T_k}{\partial \mathbf{x}} \epsilon_k^x \Big|_{\mathbf{x}_k} + \frac{\partial T_k}{\partial \mathbf{c}} \overset{\text{Chem error}}{\epsilon_k^c} \Big|_{\mathbf{c}_k} + \mathbf{G}_k \overset{\text{Flux error}}{\epsilon_k^s} - \epsilon_k^{\text{mdl}} + \text{Higher order terms}$$

Meteor. state error $\epsilon_k^x = \mathbf{x}_k - \mathbf{x}_k^{\text{true}}$

Constituent error $\epsilon_k^c = \mathbf{c}_k - \mathbf{c}_k^{\text{true}}$

Flux error $\epsilon_k^s = \mathbf{s}_k - \mathbf{s}_k^{\text{true}}$

Sources of constituent transport model error

- If constituent state, meteorological state and fluxes are perfect, the constituent forecast can still be wrong due to model error. For CO_2, sources of model error are:
  - Boundary layer processes (Denning et al. 1995)
  - Convective parameterization (Parazoo et al. 2008)
  - Synoptic scale and frontal motions (Parazoo et al. 2008)
  - Mass conservation errors (Houweling et al. 2010)
  - Interhemispheric transport (Law et al. 1996)
  - Vertical transport in free atmosphere (Stephens et al. 2007, Yang et al. 2007)
  - Chemistry module, if present. (CO_2 is a passive tracer; CH_4, CO use parameterized climate-chemistry with monthly OH)
- Comparing CO_2 simulations to observations reveals model errors due to meteorological processes → leading to feedback on meteorological model

Dealing with model error: variational approach

$$J(\mathbf{s},\mathbf{u}) = \frac{1}{2}(\mathbf{s}-\mathbf{s}^b)^T\mathbf{B}^{-1}(\mathbf{s}-\mathbf{s}^b) + \sum_{k=0}^{N}\frac{1}{2}(\mathbf{c}_k^{obs} - H[\mathbf{c}_k(\mathbf{s})])^T\mathbf{R}^{-1}(\mathbf{c}_k^{obs} - H[\mathbf{c}_k(\mathbf{s})]) + \boxed{\sum_{k=0}^{N}\frac{1}{2}\mathbf{u}_k^T\mathbf{Q}^{-1}\mathbf{u}_k}$$

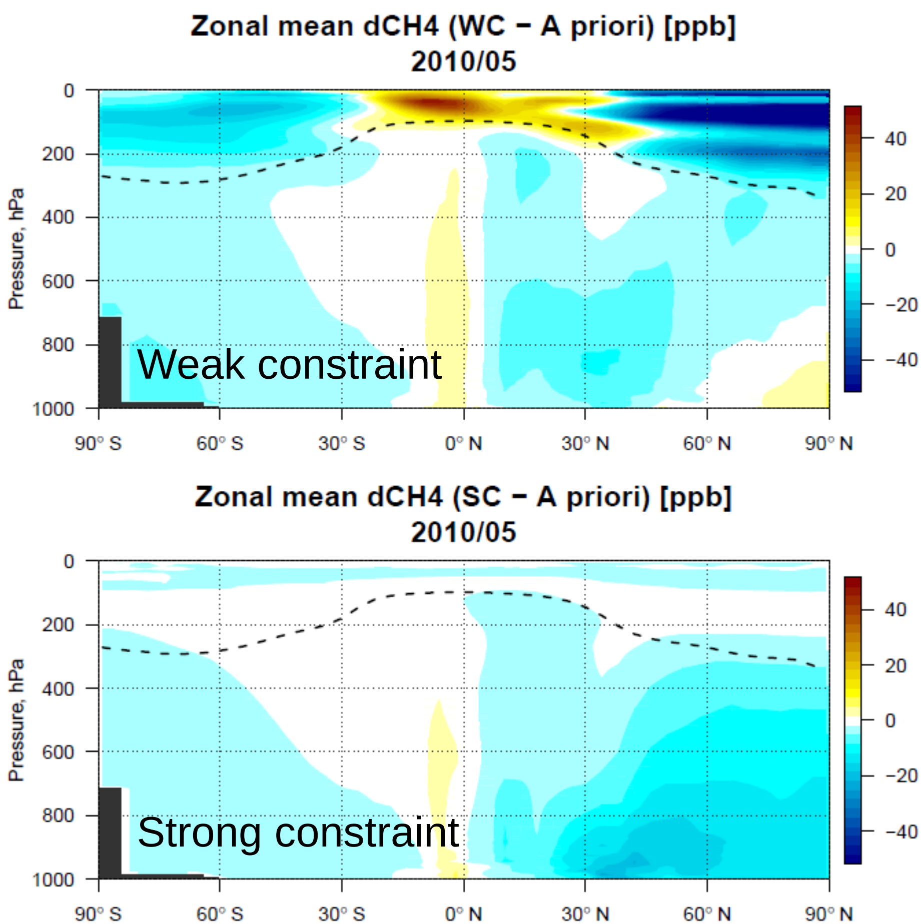
$$\boxed{\mathbf{c}_{k+1} = T_k(\mathbf{x}_k,\mathbf{c}_k) + \mathbf{G}_k\mathbf{s}_k + \mathbf{u}_k}$$

- Use constituent observations to constrain both fluxes and model errors, $\mathbf{u}$ (3D fields of mixing ratio)

Application of weak constraint 4D-Var to GOSAT CH_4 assimilation

Stanevich et al. (2018, ACPD*)

*To be submitted



- GEOS-Chem 4° x 5°
- 3-day forcing window
- Forcing over whole domain
- Weak constraint solution better matches independent observations

Solving for fluxes only misattributes model errors to flux increments

Dealing with model error: Coupled constituent and flux estimation

$$\begin{aligned} \mathbf{c}_{k+1}^t &= T_k(\mathbf{x}_k^t, \mathbf{c}_k^t) + \mathbf{G}_k \mathbf{s}_k^t + \boldsymbol{\epsilon}_k^c \\ \mathbf{s}_{k+1}^t &= \Phi_k \mathbf{s}_k^t + \boldsymbol{\epsilon}_k^s \end{aligned}$$

$$\mathbf{c}_k^{obs} = H_k(\mathbf{c}_k)$$

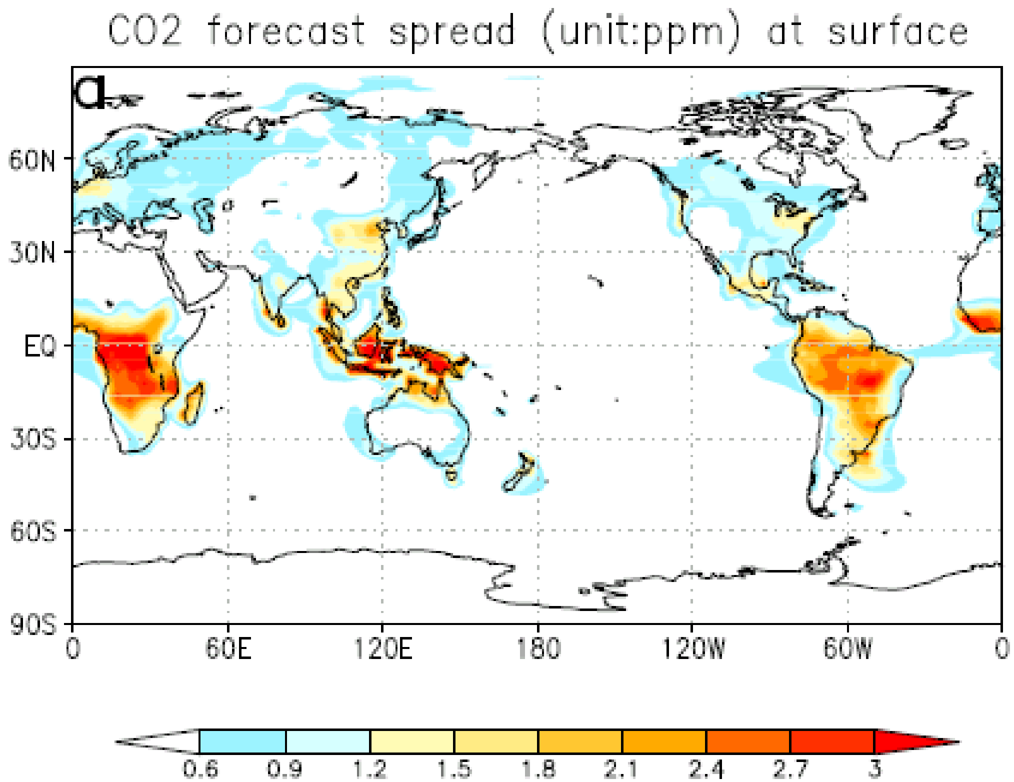
$$\mathbf{z}_{k+1}^t = \mathbf{F}_k \mathbf{z}_k^t + \boldsymbol{\epsilon}_k^z$$

$$\mathbf{z}_k = \begin{bmatrix} \mathbf{c}_k \\ \mathbf{s}_k \end{bmatrix}, \quad \boldsymbol{\epsilon}_k^z = \begin{bmatrix} \boldsymbol{\epsilon}_k^c \\ \boldsymbol{\epsilon}_k^s \end{bmatrix}, \quad \mathbf{F}_k = \begin{bmatrix} T_k & \mathbf{G}_k \\ \mathbf{0} & \Phi_k \end{bmatrix}$$

- Flux forecast model is persistence: $\Phi_k = I$
- Chinese Tan-Tracker: GEOS-Chem, 5 week lag, weekly fluxes (Tian et al. 2014, ACP)
- Fixed interval Ens. Kalman smoother, 3-day window (Miyazaki et al. 2011, JGR)

Errors in meteorological analyses

Liu et al. (2011, GRL)



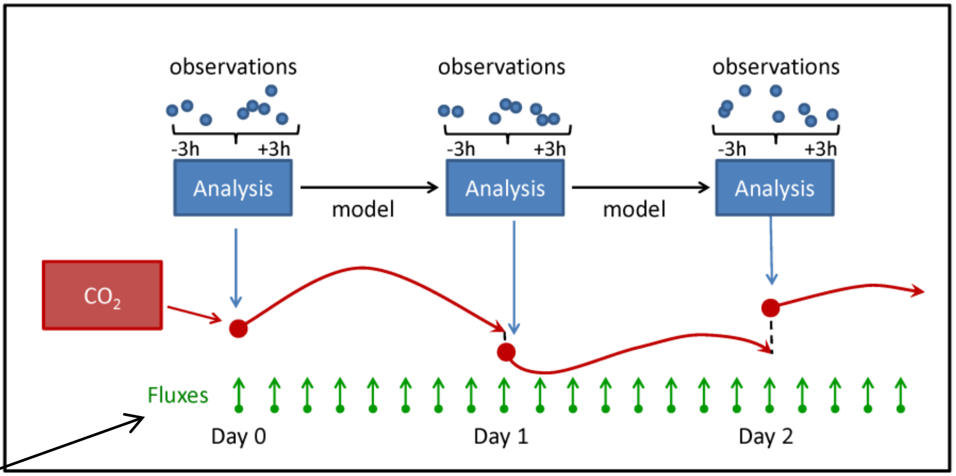
Uncertainty in CO_2 due to errors in wind fields is 1.2–3.5 ppm at surface and 0.8–1.8 ppm in column mean fields.

Global annual mean of natural fluxes is ~2.5 ppm

Using same sources/sinks, same model, same initial condition, CO_2 forecasts are still different due to errors in wind fields.

Coupled global weather and greenhouse gas models

Initial CO_2 on
1 Jan 2009 from
CarbonTracker

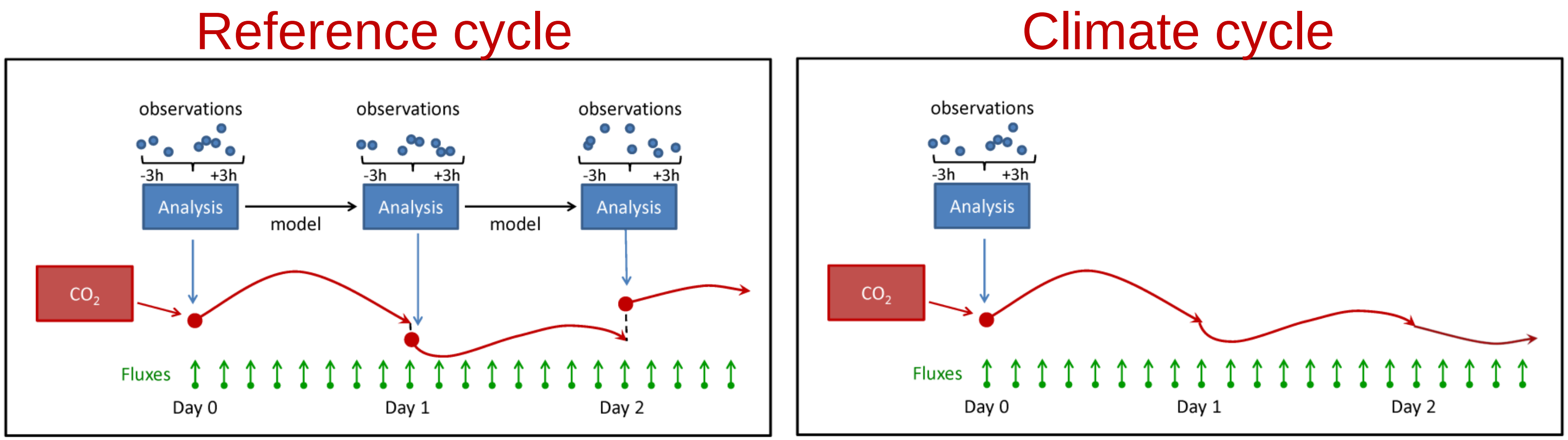


Sub-daily fluxes (biospheric, ocean, anthropogenic, biomass burning)
3-hourly CT2013B fluxes from NOAA CarbonTracker

Coupled systems using global models:

- ECMWF CAMS (Agusti-Panareda et al. 2014)
- NASA GMAO (Ott et al. 2015)
- ECCC (Polavarapu et al. 2016)

Experimental design: predictability

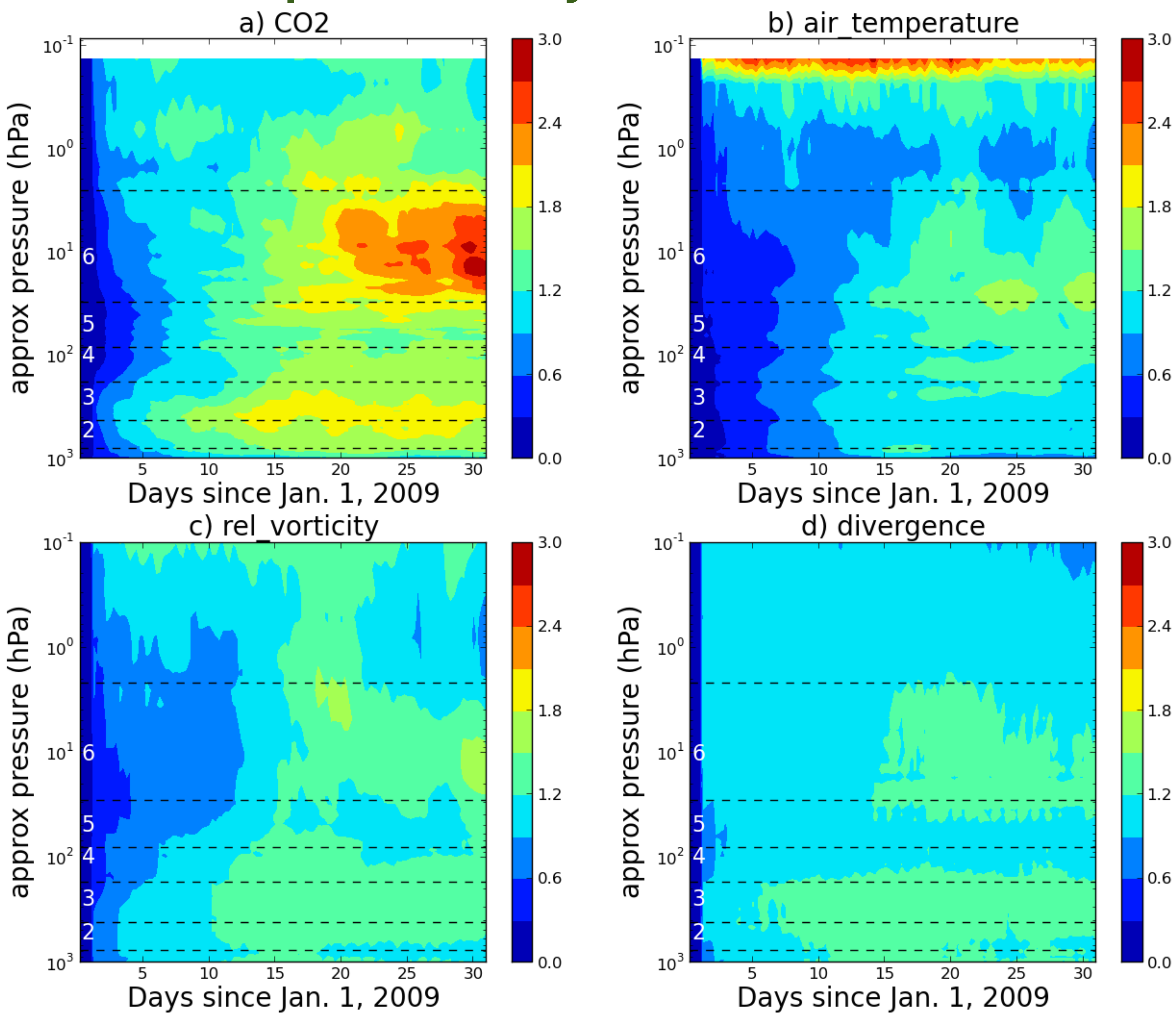


- Analyses constrain CO_2 transport using observed meteorology even with no CO_2 assimilation
- What if we don't use analyses (after the initial time) and replace them with 24h forecasts? → Climate cycle
- Climate cycle will drift from control cycle which uses analyses

Predictability error definition used

- Drift of climate cycle from reference cycle:
  - $E=(CO_2^{clim}-CO_2^{ref})$
- A measure of variability:
  - P = Global mean (zonal standard deviation (E))
- Normalize by variability in full state itself (at initial time):
  - P_0 = Global mean (zonal standard deviation ($CO_2^{ref}(t_0)$))
- Define Normalized Predictability error:
  - $N=P/P_0$
  - Dimensionless
  - Can compare different variables, (e.g. T, vorticity, divergence)
  - N<<1 for small variability relative to state itself
  - Global measure (including tropics)

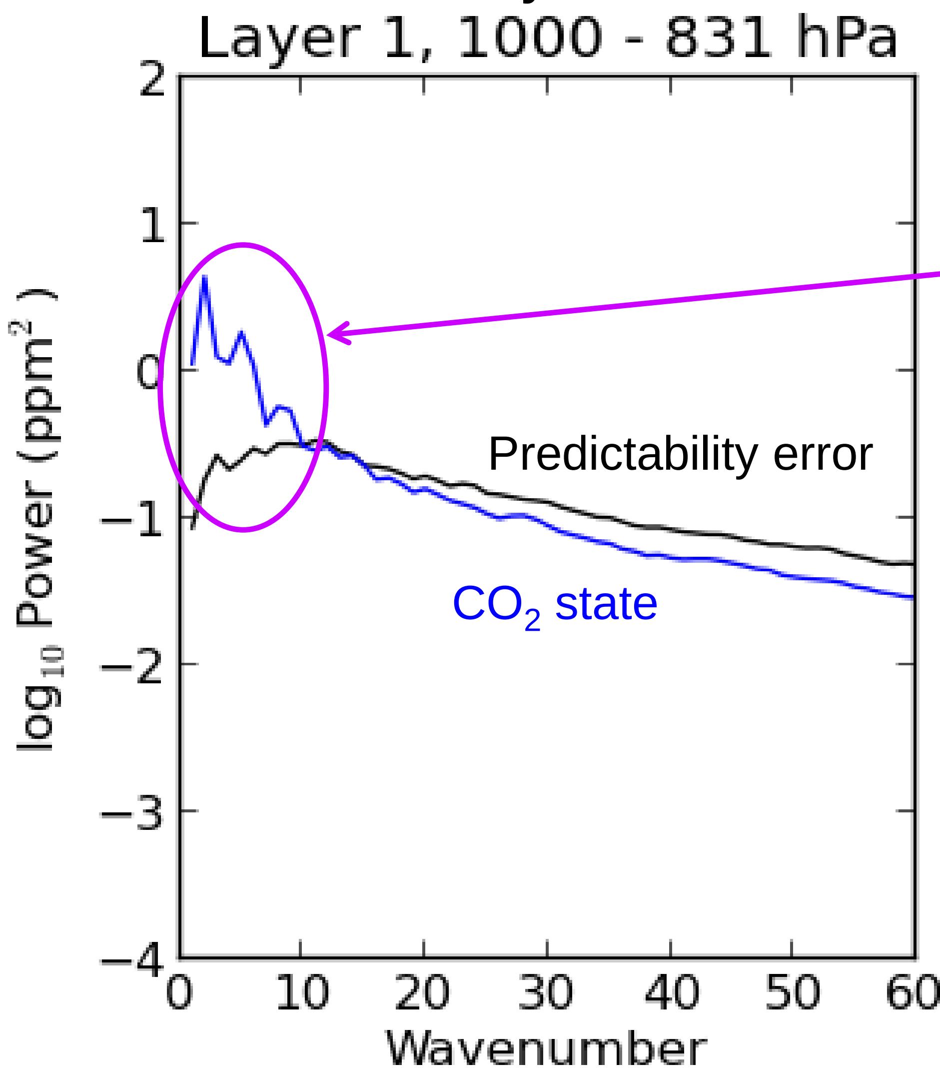
Normalized predictability error for Jan 2009



Climate time scales: seasonal

- CO_2 predictability is short ~2 days in the free troposphere and follows pattern of wind field predictability. CO_2 predictability increases near the surface and in the lower stratosphere
- Can we see predictability on longer (sub-seasonal to seasonal) time scales?
- Do a spherical harmonic decomposition of drift E and average over one month of spectra, and over 12 model levels

July 2009

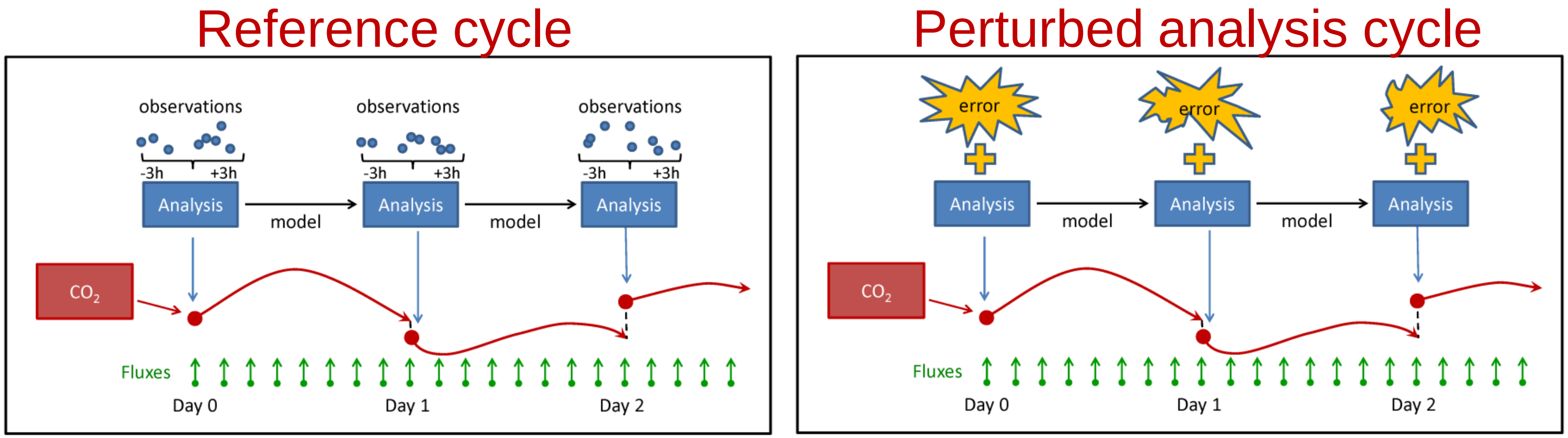


Largest scales are predictable in July

Where does this predictability come from?

- CO_2 surface fluxes
- Land/ocean surface

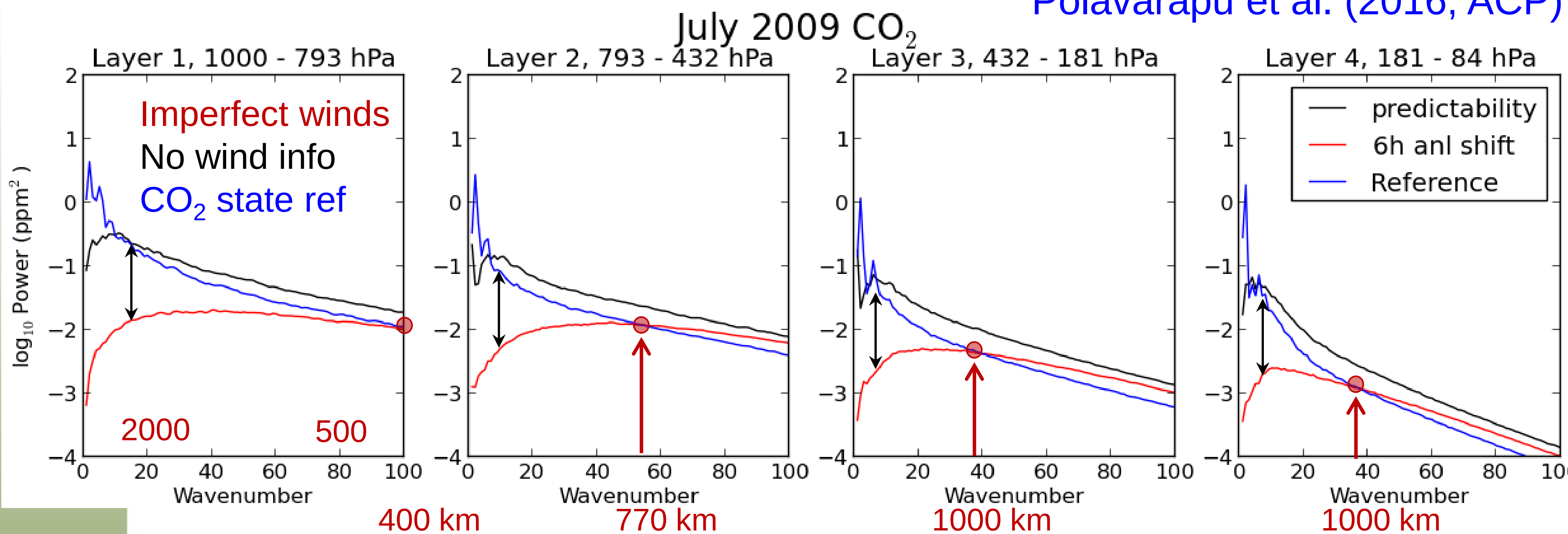
Experimental design: analysis error



- Meteorological analyses keep our CO_2 transported by realistic wind fields. 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

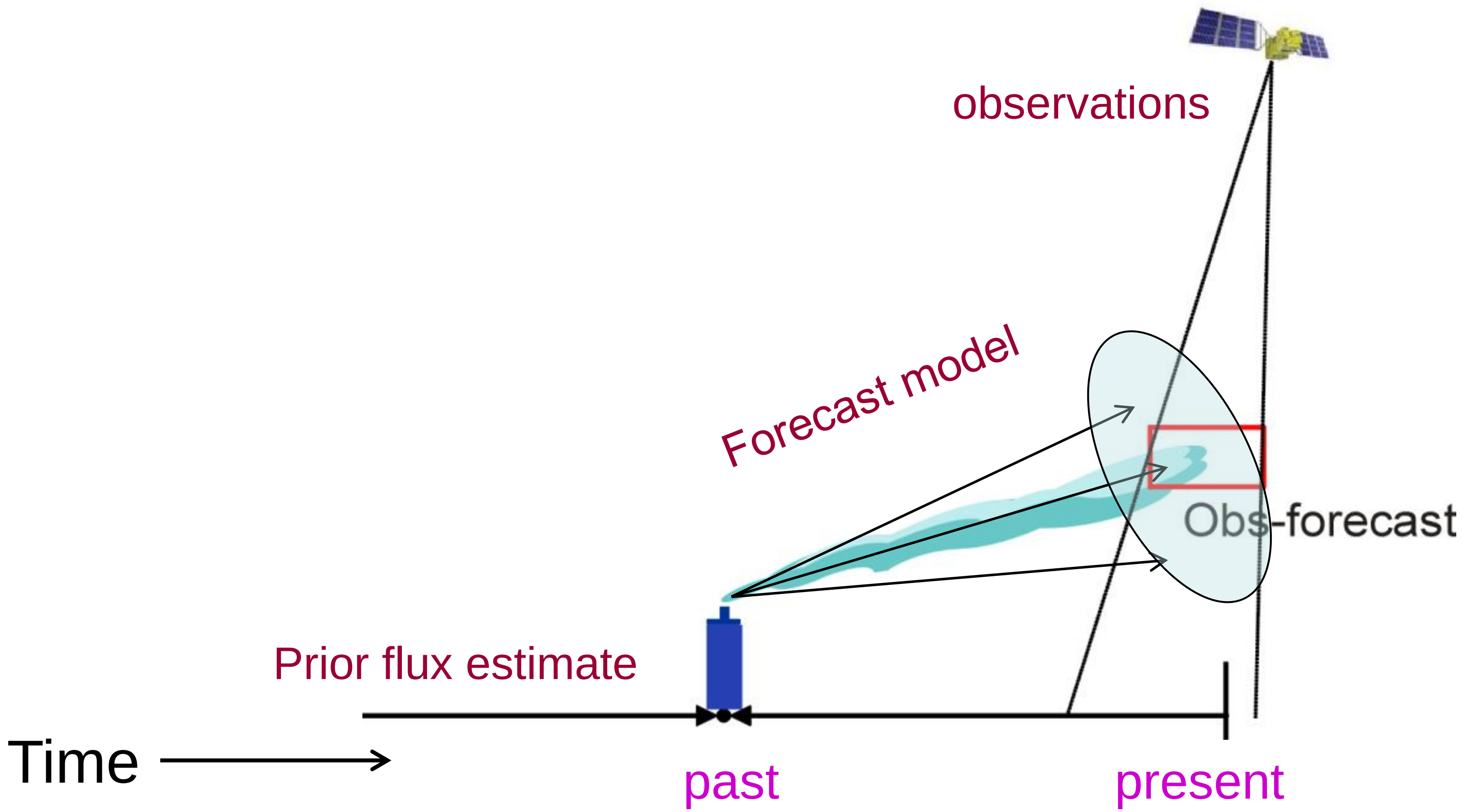
Polavarapu et al. (2016, ACP)



- 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 meteorological analysis uncertainty.* This spatial scale increases with altitude.

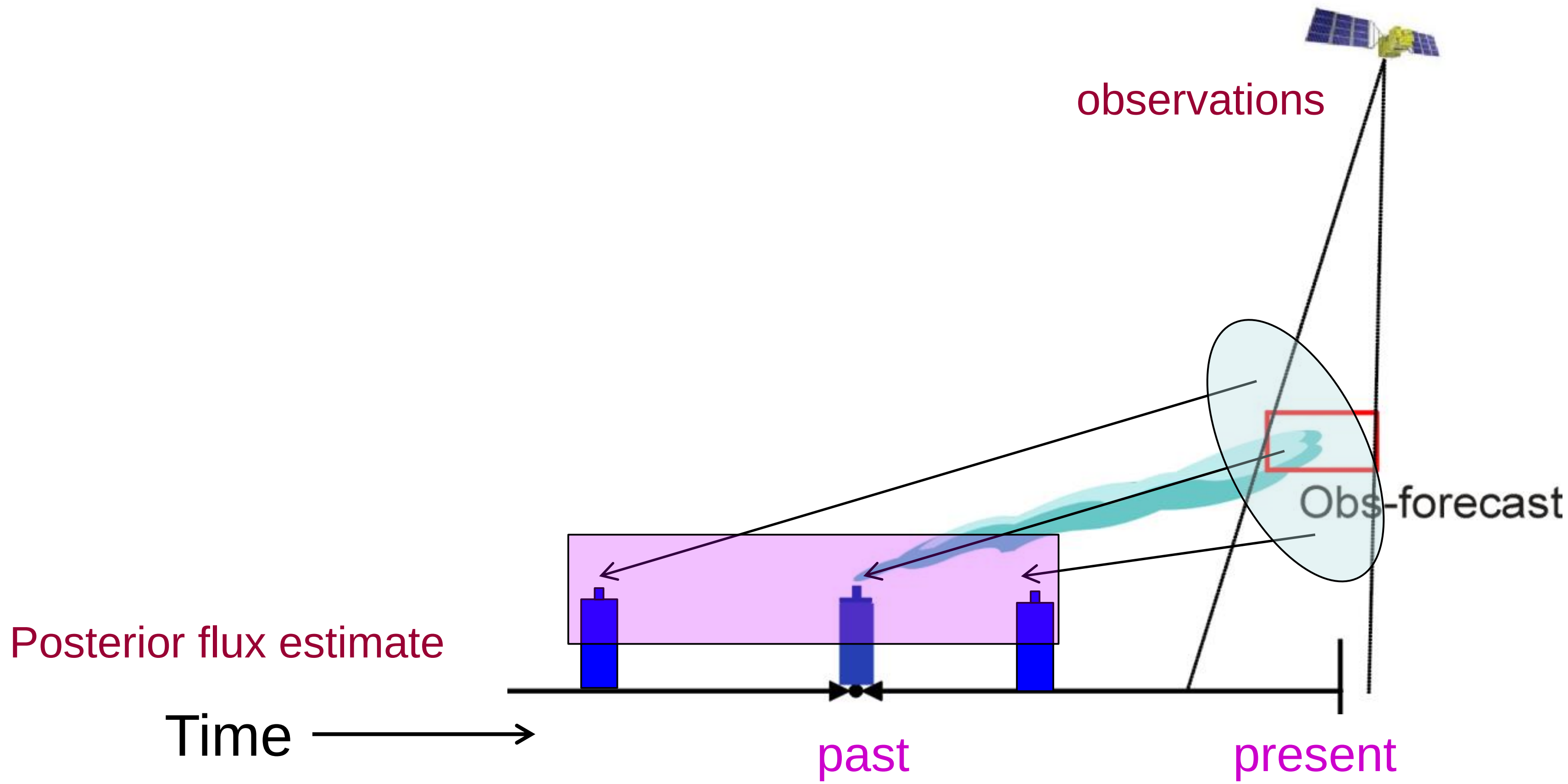
Spatial scales seen in fluxes

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



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.



Implications on flux inversions

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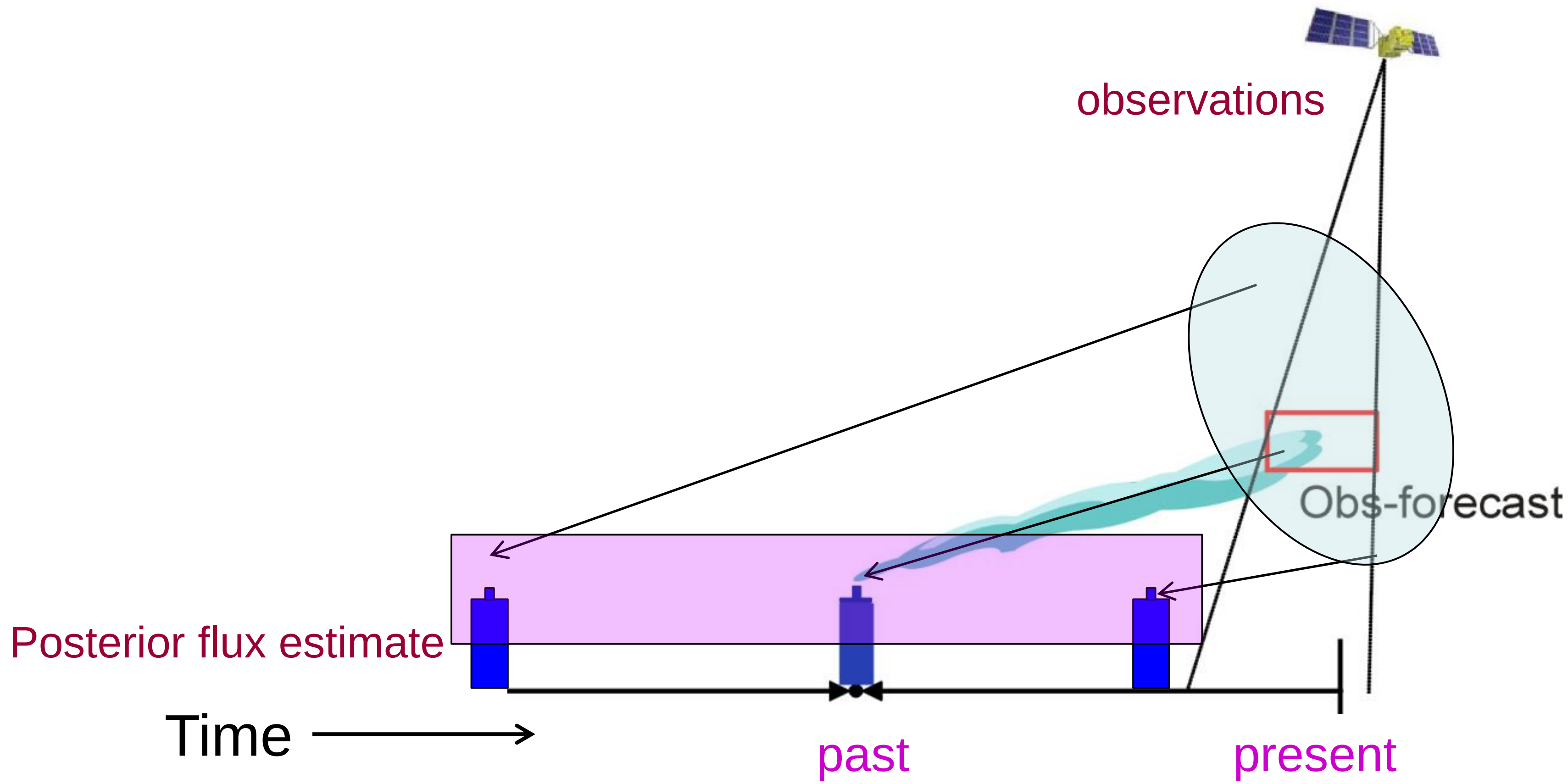


Coupled meteorology, constituent and flux estimation

- Assimilate meteorology and chemistry observations
- State vector (x, c, s): meteorology, chemistry, fluxes
- Meteorological uncertainties (e.g. boundary layer, convection) can be simulated with an EnKF
- Demonstrated w LETKF with a 6h window (Kalnay group)
  - OSSEs w SPEEDY model: Kang et al. (2011, JGR; 2012, JGR)
- Flux estimates obtained through cross covariances with CO_2 state estimates through ensemble→ requires a good state estimate constrained by lots of observations
- How to deal with differing assimilation window lengths: 6h – meteorology, CO_2 state, weeks/months for fluxes?

Challenges of GHG data assimilation

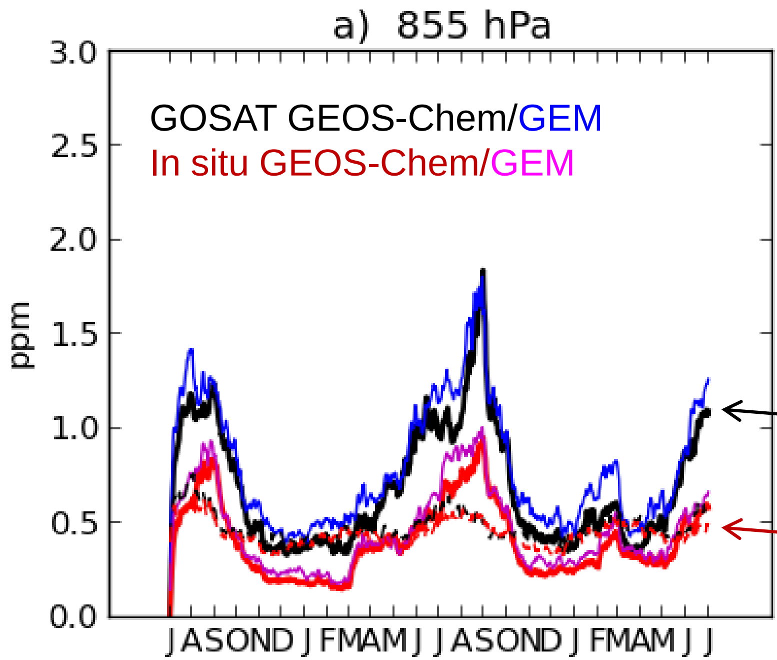
- Multiple time scales: diurnal, synoptic, seasonal, interannual
- Multiple spatial scales: Global, regional, urban
- Multiple systems: Atmosphere, ocean, constituents, biosphere. How to deal with different assimilation window lengths?
- Multiple chemical species may be needed to attribute components of fluxes to natural or anthropogenic origin
- New satellite observations: need to improve bias corrections, develop inter-satellite bias corrections
- Need independent obs for validation, anchoring bias corrections
- Moving to near-real-time systems

EXTRA SLIDES

Spatial scales of fluxes seen in CO_2

Polavarapu et al. (2018, ACP)

Zonal standard deviation of ΔCO_2 (global mean)



Compare:

CO_2 ($flux^{prior}$, met^{ref}) – CO_2 ($flux^{post}$, met^{ref})

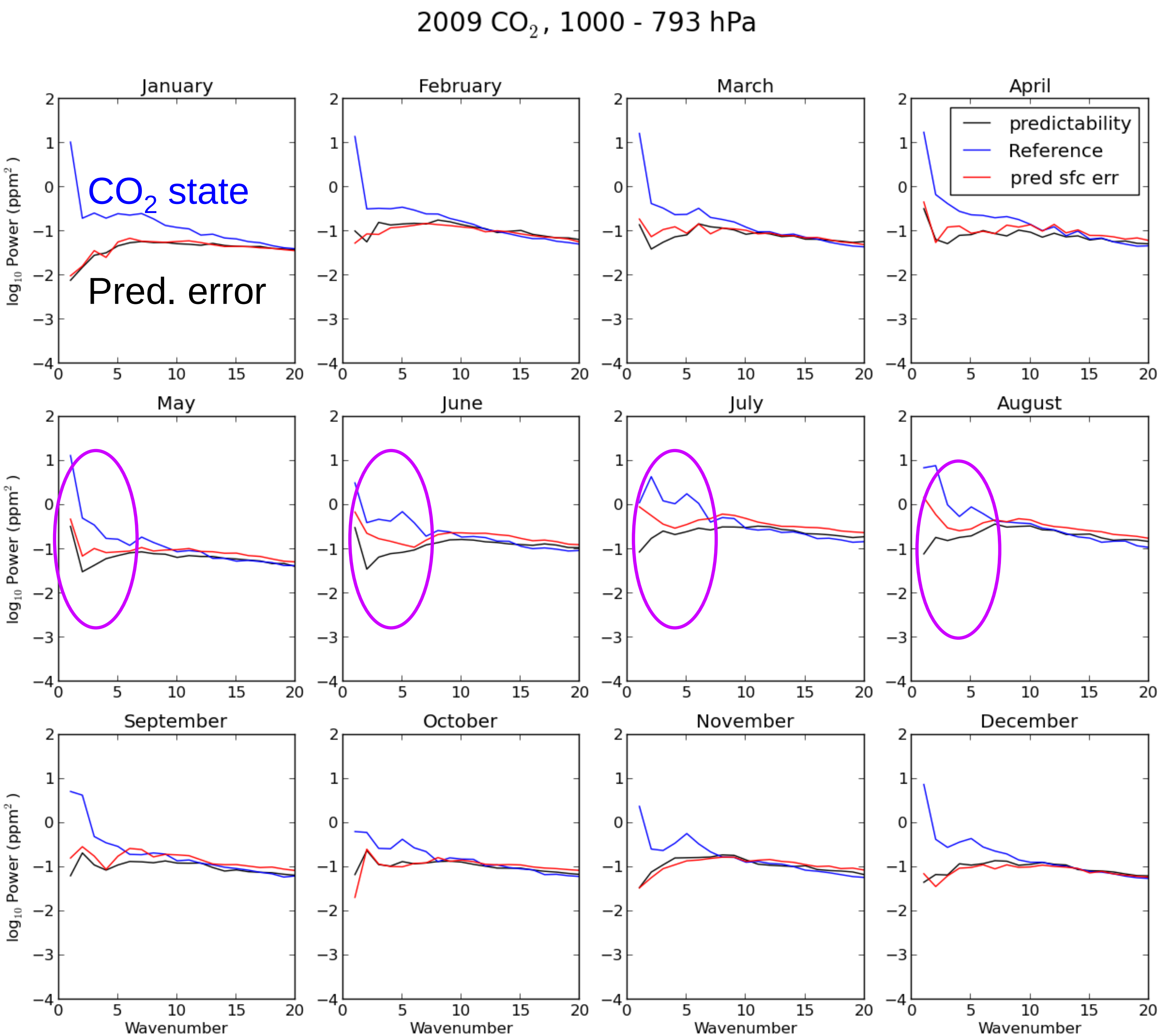
and

CO_2 ($flux^{post}$, met^{ref}) – CO_2 ($flux^{post}$, met^{pert})

Posterior fluxes from GOSAT assimilation

Posterior fluxes from flask obs assimilation

- Impact of updated fluxes on CO_2 exceeds CO_2 uncertainty due to meteorological uncertainty most seasons, if GOSAT data is used
- This occurs only in boreal summer, if flask data is used



Land and ocean surface affects CO_2 predictability

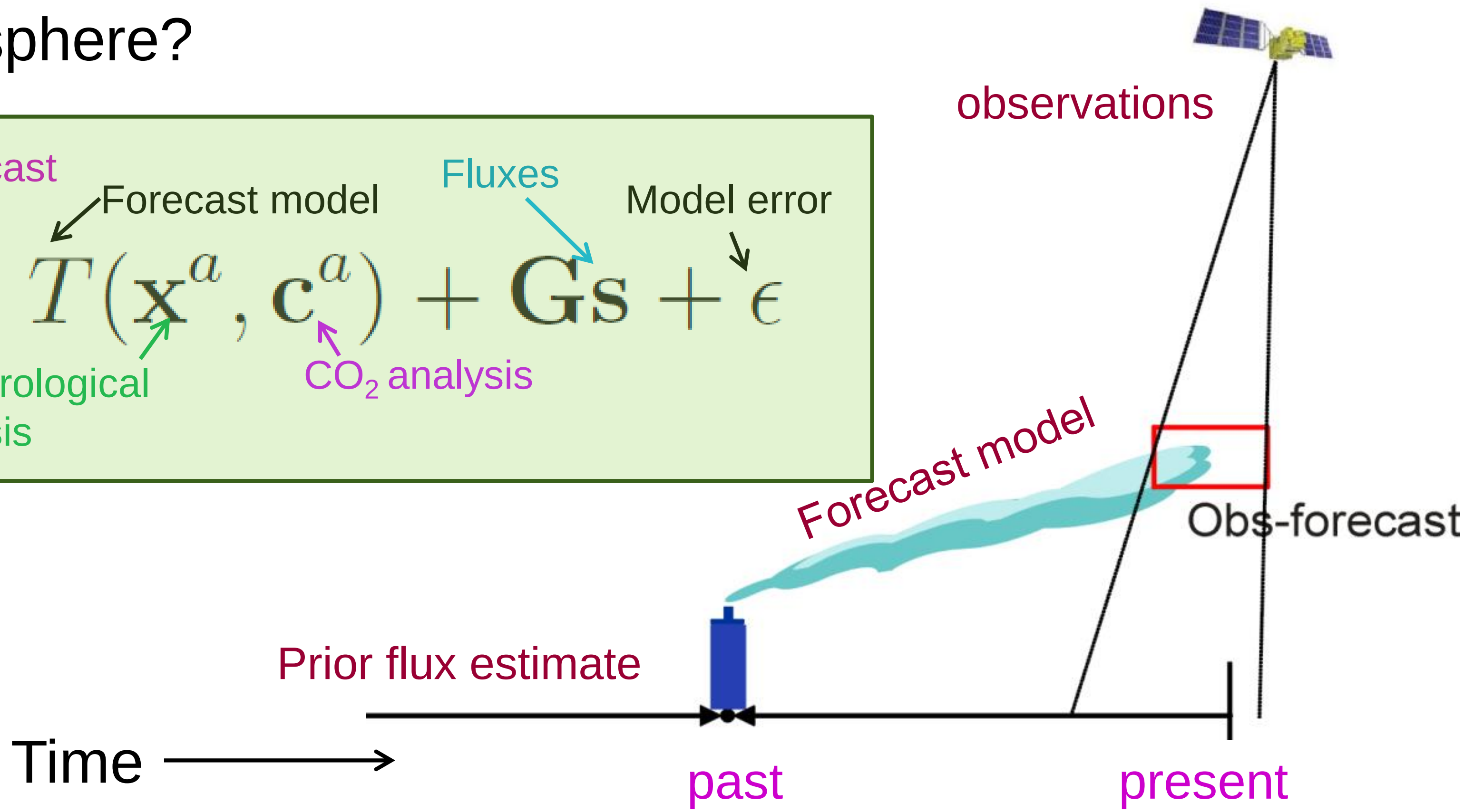
The flux estimation problem

Using atmospheric observations from the present, what was the past flux of GHG from the surface to the atmosphere?

CO_2 forecast — Forecast model — Fluxes — Model error

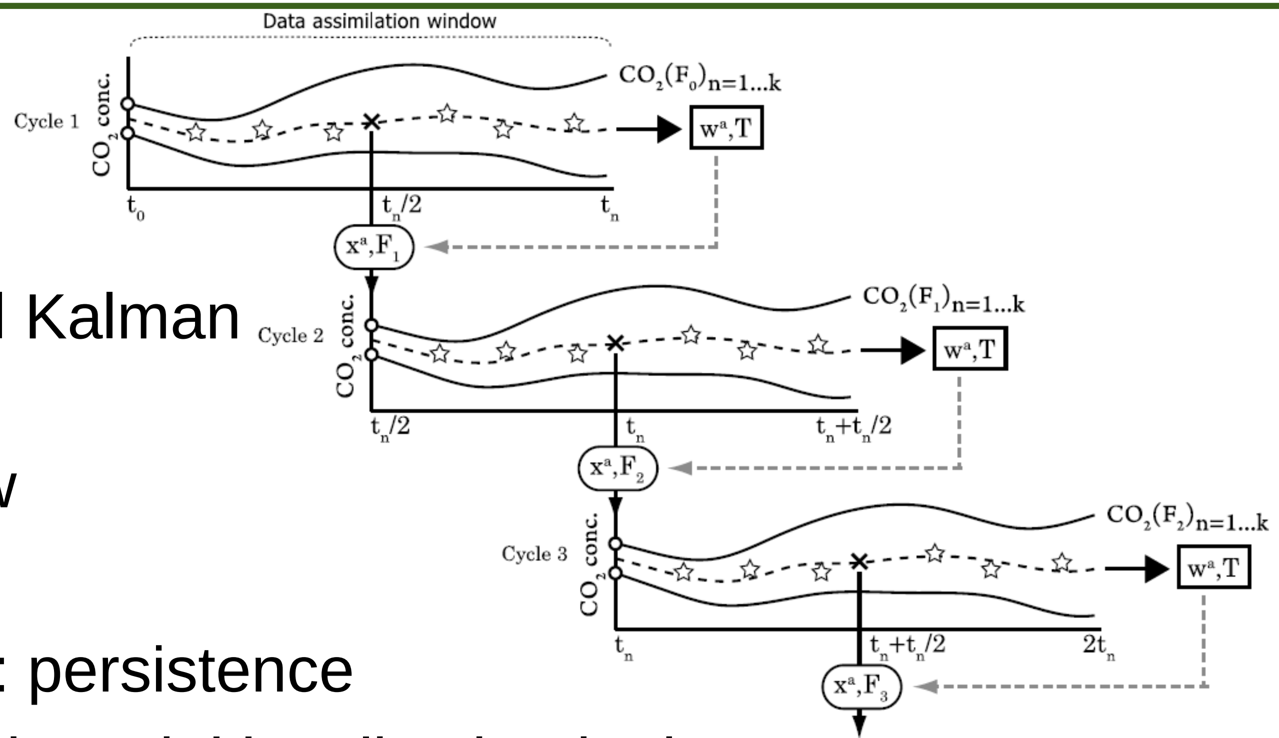
$$\mathbf{c}^f = T(\mathbf{x}^a, \mathbf{c}^a) + \mathbf{G}\mathbf{s} + \epsilon$$

Meteorological analysis — CO_2 analysis



Dealing with model error: Coupled state/flux estimation

Miyazaki (2011, JGR)

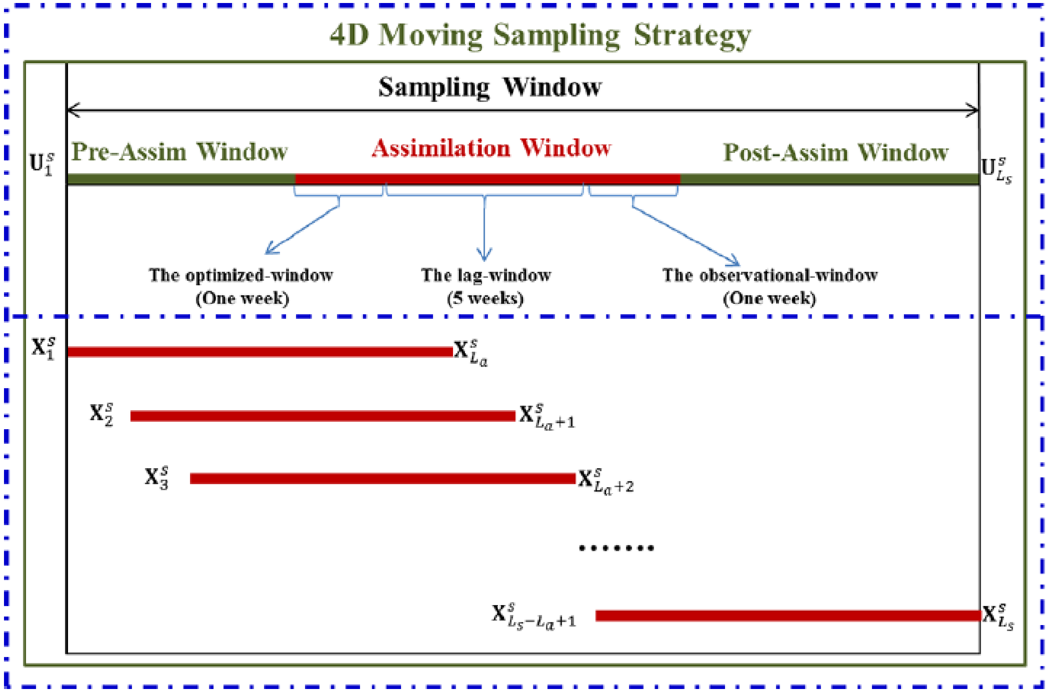


- Fixed interval Kalman smoother
- 3-day window
- 48 members
- Flux forecast: persistence
- Temporal and spatial localization is done.
- CO_2 mass not conserved due to analysis increments

Coupled state/flux estimation

Tian et al. (2014, ACP)

- EnVar, GEOS-Chem
- State vector: CO_2, λ
- Flux forecast: persistence

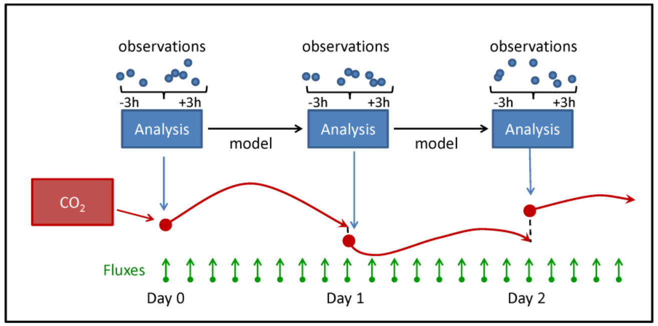


- Temporal and spatial localization is done.
- CO_2 mass not conserved due to analysis increments

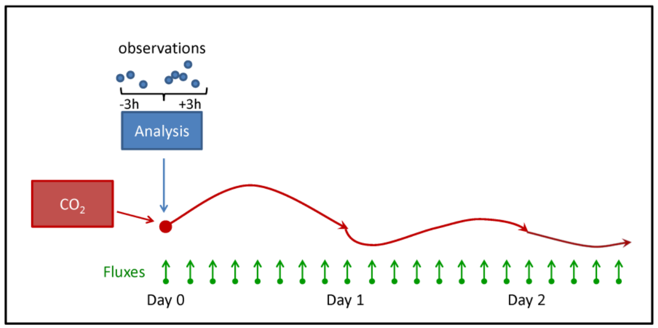
Predictability of CO_2 in a regional model

Jinwoong Kim (ECCC)

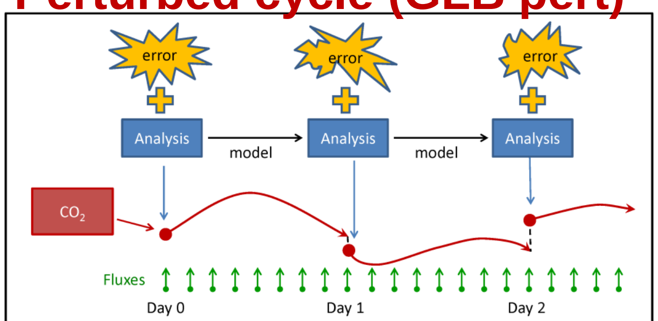
Reference cycle (GLBref)

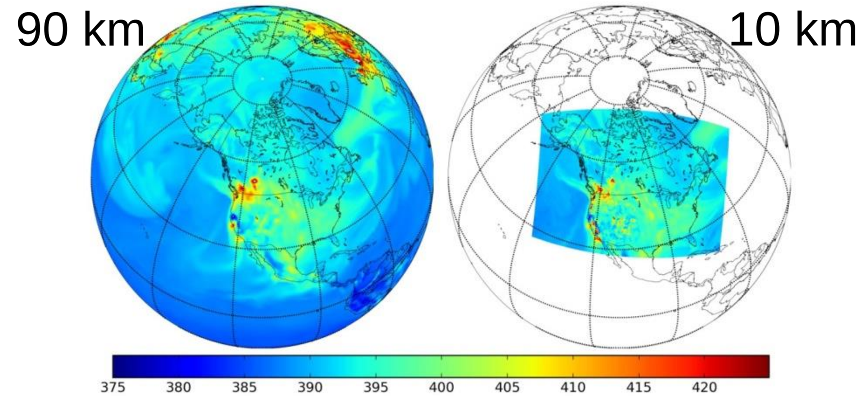


Climate IC (GLBclim)



Perturbed cycle (GLB pert)



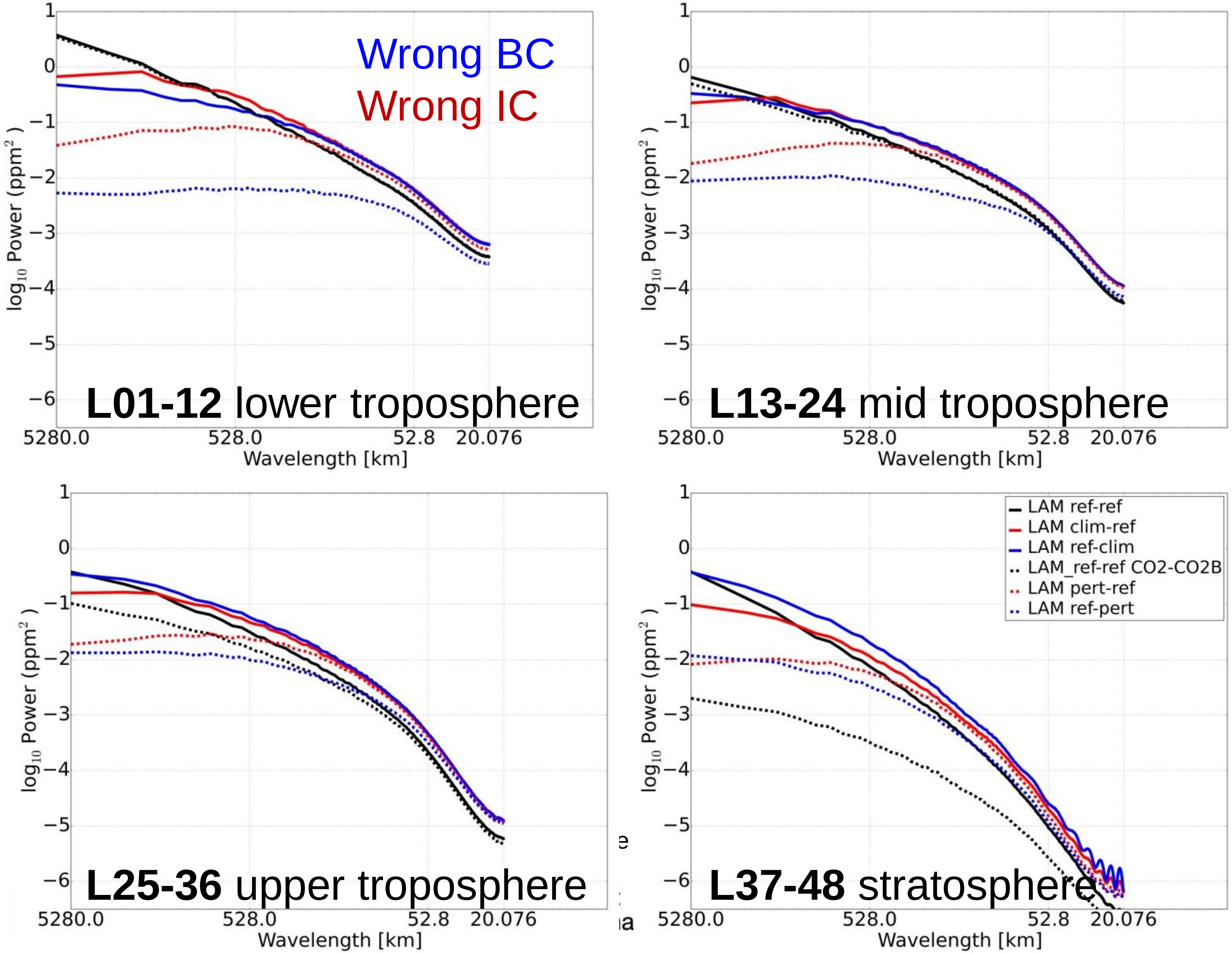


	Reg. IC	LBC
LAM ref-ref	Analysis	GLBref
LAM clim-ref	Forecast	GLBref
LAM ref-clim	Analysis	GLBclim
LAM clim-clim	Forecast	GLBclim
LAM pert-ref	Perturbed Analysis	GLBref
LAM ref-pert	Analysis	GLBpert
LAM pert-pert	Perturbed Analysis	GLBpert

Predictability of CO_2 in a regional model

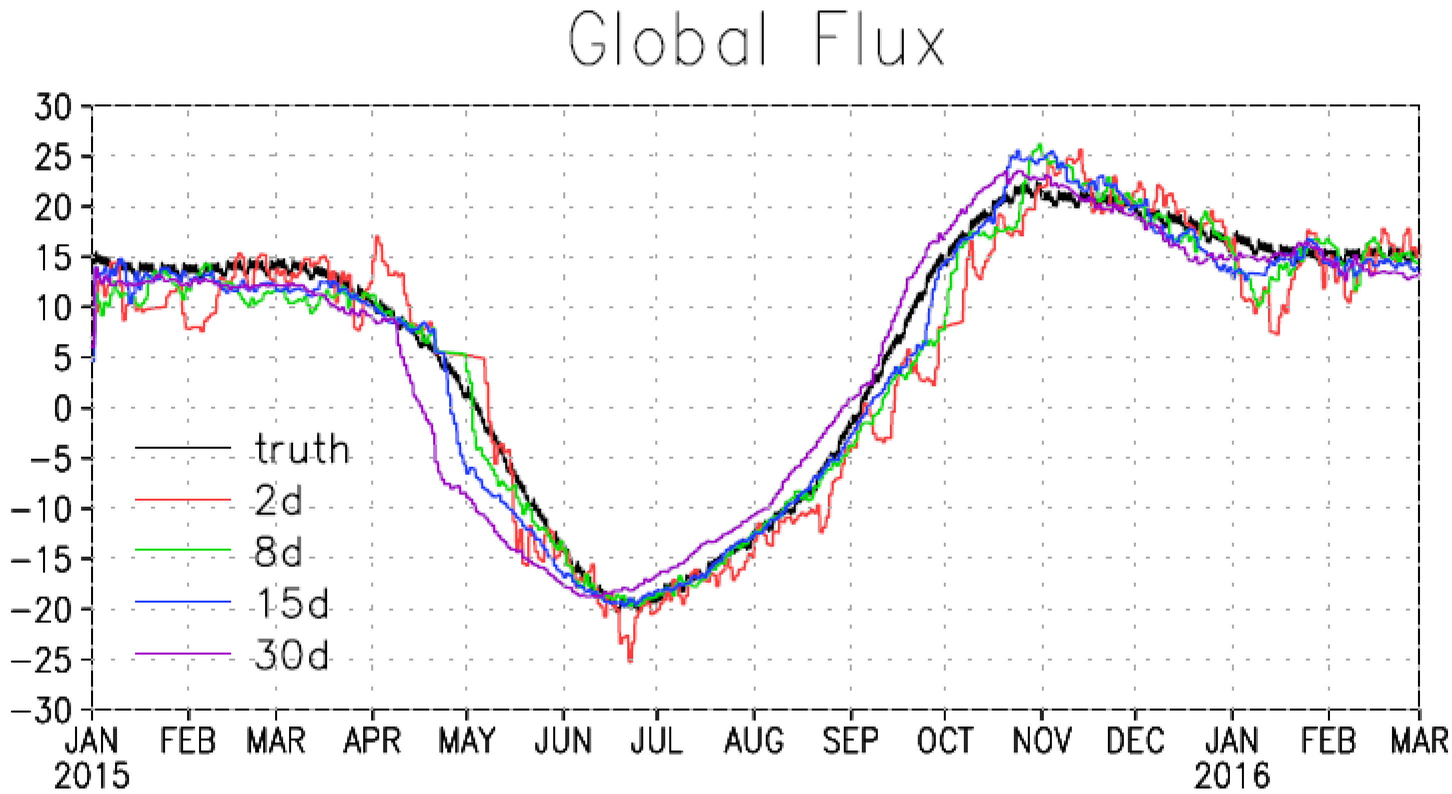
Jinwoong Kim (ECCC)

June 2015 monthly mean spectra



Optimal window length for CO_2 flux

Liu et al. (2018, GMDD)



With an assimilation window of 1 day, the optimal observation window is 8 days based on OSSEs with GEOS-Chem and OCO-2 data. LETKF with GEOS-Chem coupled CO_2 state and flux estimation was used.

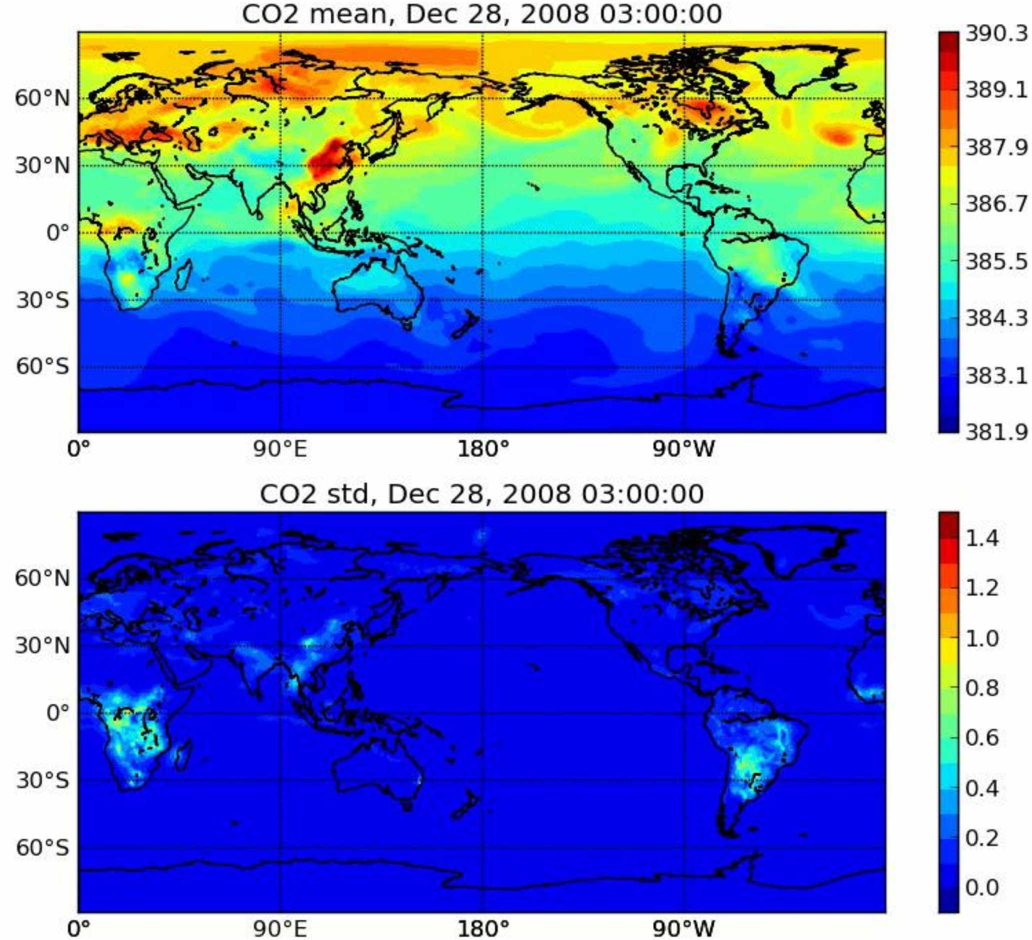
Evolution of ensemble spread

Animation of column mean CO_2

Dec. 28, 2008 to Jan. 23, 2009

Ensemble mean

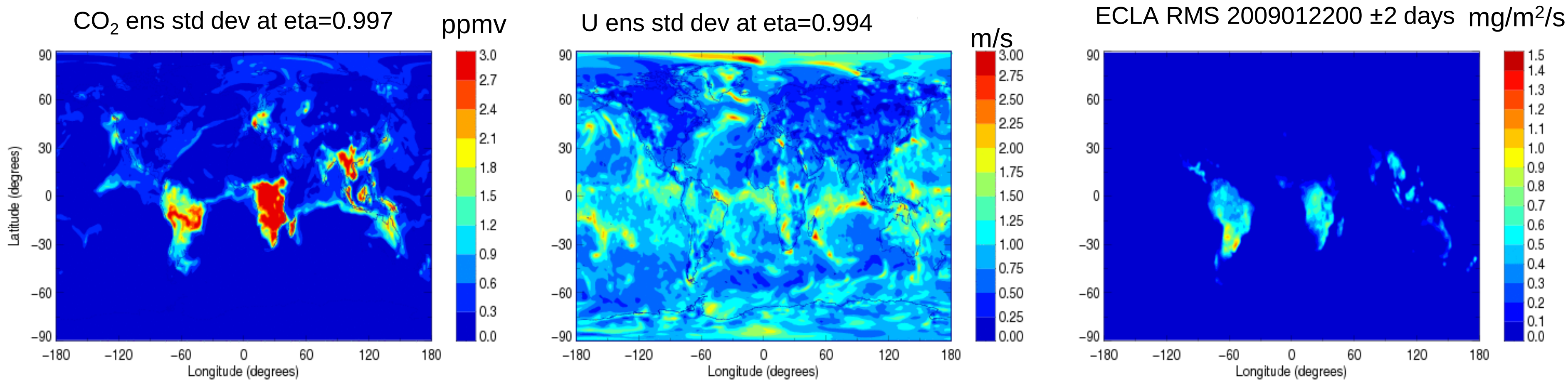
Ensemble spread



Environ
Climate

How does uncertainty in winds affect CO_2 spread?

2009012206 2009012206



- CO_2 spread (left) does not mainly resemble spread in winds (middle) but rather the spatial variability of biospheric fluxes (right)
- Only where tracer gradients exists does uncertainty in winds matter

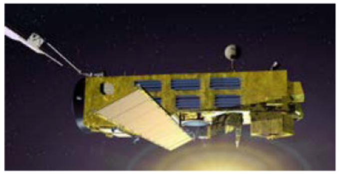
Ensemble Kalman Filter – first look

- No tracer assimilation, only passive advection
- Testing with 64 ensemble members, 0.9° grid spacing
- Start on 28 Dec 2008. Run for 4 weeks to 23 Jan 2009
- All members have same initial CO_2 and same fluxes. Spread is due to spread in winds only.
- Winds differ among ensemble members due to differences in: model parameters (convection scheme, parameters involved in PBL model, diffusion of potential temperature, etc.), observation error perturbations
- How does uncertainty in winds affect CO_2 spread?

Remote Sensing of CO_2 and CH_4 using Reflected Sunlight: The Pioneers

Slide from Dave Crisp, JPL

- **SCIAMACHY (2002-2012)** – First sensor to measure O_2, CO_2, and CH_4 using reflected NIR/SWIR sunlight
  - Regional-scale maps of X_{CO2} and X_{CH4} over continents



- **GOSAT (2009 …)** – First Japanese GHG satellite
  - FTS optimized for hgh spectral resolution over broad spectral range, yielding CO_2, CH_4, and chlorophyll fluorescence (SIF)

- **OCO-2 (2014 …)** – First NASA satellite to measure O_2 and CO_2 with high sensitivity, resolution, and coverage
  - High resolution imaging grating spectrometer small (< 3 km^2) footprint and rapid sampling (10^6 samples/day)

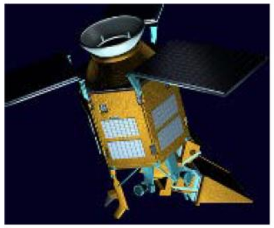
- **TanSat (2016 …)** - First Chinese GHG satellite
  - Imaging grating spectrometer for O_2 and CO_2 bands and cloud & aerosol Imager
  - In-orbit checkout formally complete in August 2017

Remote Sensing of CO_2 and CH_4: The Next Generation

Slide from Dave Crisp, JPL

In orbit Checkout

- **Feng Yun 3D (2017)** – Chinese GHG satellite on an operational meteorological bus
  - GAS FTS for O_2, CO_2, CH_4, CO, N_2O, H_2O
- **Sentinel 5p (2017)** - Copernicus pre-operational Satellite
  - TROPOMI measures O_2, CH_4 (1%), CO (10%), NO_2, SIF
  - Imaging at 7 km x 7 km resolution, daily global coverage

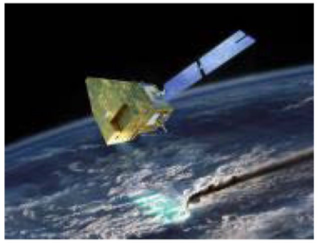


- **Gaofen 5 (2018)** - 2nd Chinese GHG Satellite
  - Spatial heterodyne spectrometer for O_2, CO_2, and CH_4
- **GOSAT-2 (2018)** – Japanese 2nd generation satellite
  - CO as well as CO_2, CH_4, with improved precision (0.125%), and active pointing to increase number of cloud free observation
- **OCO-3 (2019*)** – NASA OCO-2 spare instrument, on ISS
  - First CO_2 sensor to fly in a low inclination, precessing orbit

Slide from Dave Crisp, JPL

Future GHG Satellites

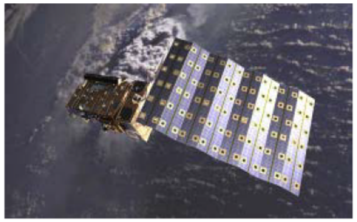
- **CNES/UK MicroCarb (2021+)** – compact, high sensitivity
  - Imaging grating spectrometer for O_2 A, O_2 $^1\Delta_g$, and CO_2
  - ~1/2 of the size, mass of OCO-2, with 4.5 km x 9 km footprints



- **CNES/DLR MERLIN (2021+)** - First CH_4 LIDAR (IPDA)
  - Precise (1-2%) X_{CH4} retrievals for studies of wetland emissions, inter-hemispheric gradients and continental scale annual CH_4 budgets

- **NASA GeoCarb (2022*)** – First GEO GHG satellite
  - Imaging spectrometer for XC_{O2}, X_{CH4}, X_{CO} and SIF
  - Stationed above North/South America

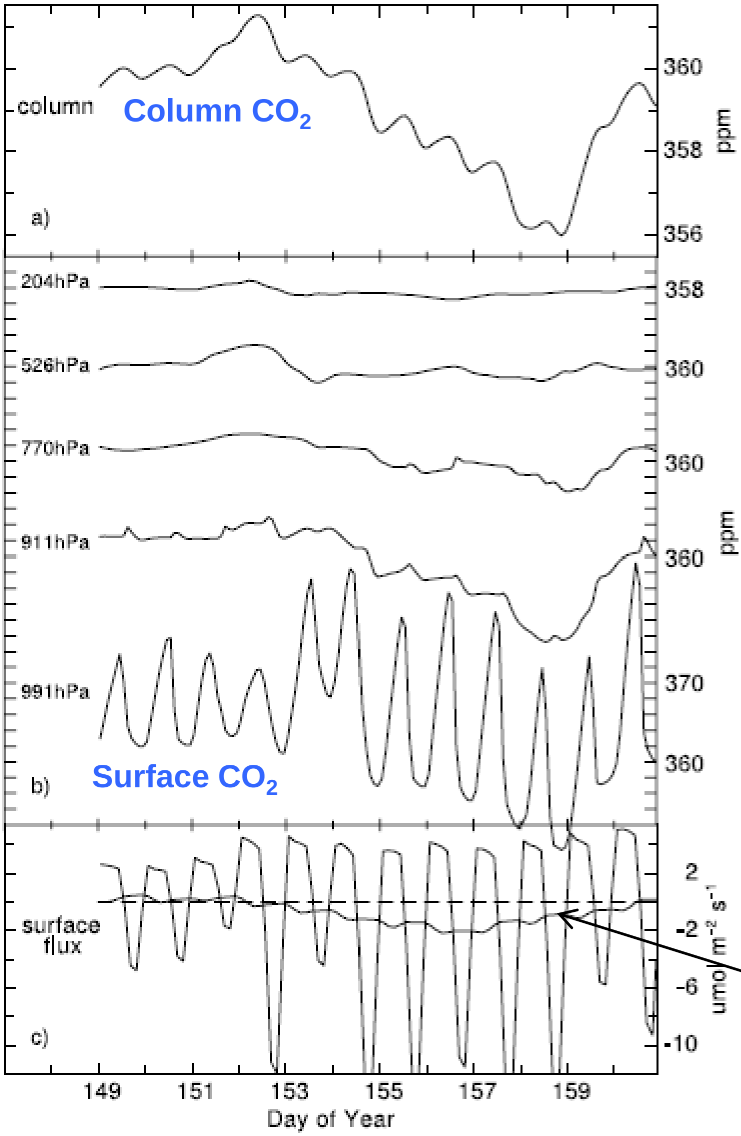
- **Sentinel 5A,5B,5C (2022)** - Copernicus operational services for air quality and CH_4
  - Daily global maps of X_{CO} and X_{CH4} at < 8 km x 8 km



CO_2 Variations with height

Park Falls: 29 May-10 June, 1996

Olsen and Randerson (2004, JGR)



Diurnally varying surface fluxes

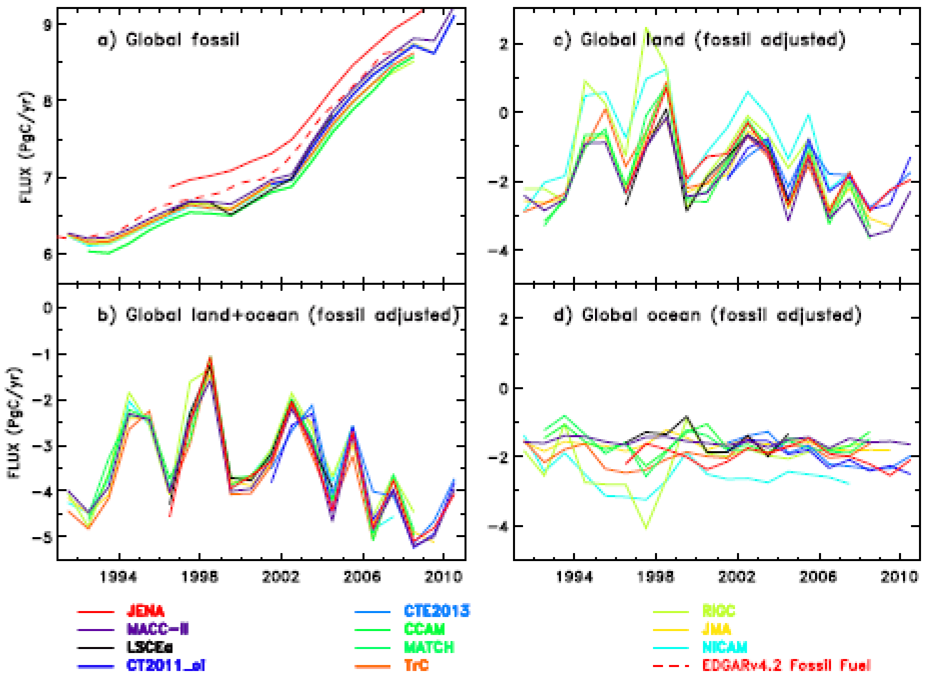
5-day running mean surface fluxes

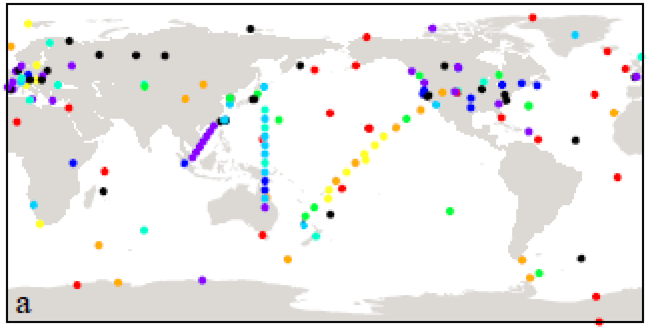
- Diurnal variations, linked to surface sources and sinks, are strongly attenuated in the free troposphere
- Diurnal variations in column CO_2 are less than 1 ppm
- Large changes in the column reflect the accumulated influence of the surface sources and sinks on timescales of several days

Canada

Inversions using surface network

Peylin et al. (2013)





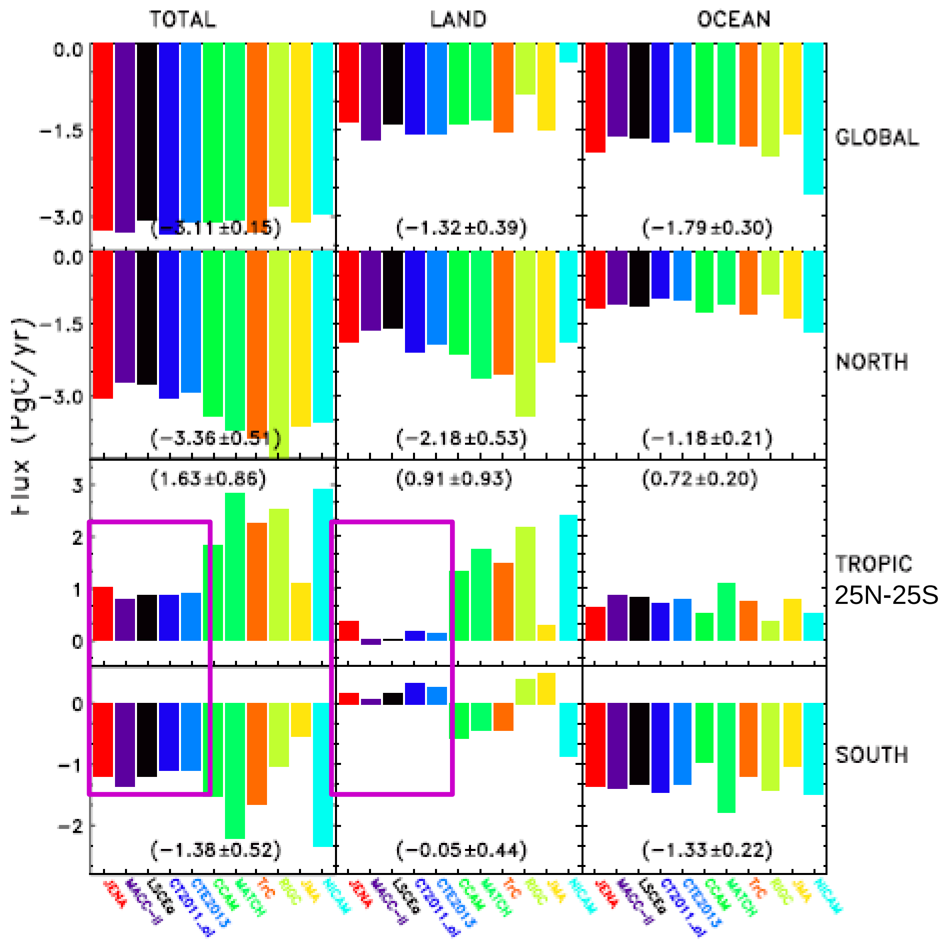
1 5-6
2 7-8
3 9
4 10
11

- Inversion methods differ in:
  - Methodology
  - Observations
    - Sfc: 100 flask + continuous
  - A priori fluxes
  - Transport models
- Interannual variability is similar and due to land

Spatial information

Peylin et al. (2013)

- Good agreement on global fluxes and partition into land and ocean



Not as good agreement on spatial distributions even for very large regions (only 3 latitude bands)

Flux inversions using GOSAT data

Houweling et al. (2015, ACP)