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

1 Pg = 1 Gt = 10$^{15}$ g
Net perturbations to global carbon budget

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
The largest uncertainty and interannual variability in the global CO$_2$ uptake is mainly attributed to the terrestrial biosphere.

We need to better understand biospheric sources and sinks.
Interannual variability in atmospheric CO$_2$ due to climate

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

- [https://www.esrl.noaa.gov/gmd/ccgg/basics.html](https://www.esrl.noaa.gov/gmd/ccgg/basics.html)
- [https://web.mit.edu/globalchange/www/tem.html](https://web.mit.edu/globalchange/www/tem.html)
CO₂ Time scales

Simulation of CO₂ with GEM-MACH-GHG using NOAA CarbonTracker optimized fluxes

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

Colour bar range is 3.5% of mean
Atmospheric CO₂ 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)

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

29 sites to 48 sites to 103 sites to 120 sites
Increasing in situ measurements

2018 ECCC GHG network
Hourly obs of CO₂, CH₄, CO

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

Figure courtesy of Elton Chan (ECCC)

https://www.icos-ri.eu/greenhouse-gases
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.
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 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 CO₂ monitoring

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)
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:

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

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

Density of moist air

Diffusion coefficient

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

mass

species

moist air
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.

**Constant CO$_2$**

Bias correction Aug. 2009

**Variable CO$_2$**

AIRS ch. 175 ~200 hPa
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
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

Weekly avg obs

Monthly scaling factors

One or more years
The standard inverse problem for carbon flux estimation

- 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

- 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

Peters et al. (2005, JGR)
Transport model is not perfect

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).

Gurney et al. (2003, Tellus)
Forecast or "Transport error"

1) Transport model
\[ c_{k+1} = T_k(x_k, c_k) + G_k s_k \]

2) True evolution
\[ c_{k+1}^{\text{true}} = T_k(x_k^{\text{true}}, c_k^{\text{true}}) + G_k s_k^{\text{true}} + \epsilon_k \]

Forecast error: (1) – (2)
\[ \epsilon_{k+1}^c = \left( \frac{\partial T_k}{\partial x} x_k + \frac{\partial T_k}{\partial c} c_k \right) + G_k s_k - \epsilon_k + \epsilon_{mdl} \]

Meteor. state error
\[ \epsilon_k^x = x_k - x_k^{true} \]

Constituent error
\[ \epsilon_k^c = c_k - c_k^{true} \]

Flux error
\[ \epsilon_k^s = s_k - s_k^{true} \]

Chem error

Flux error
Higher order terms
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 CO₂, 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. (CO₂ is a passive tracer; CH₄, CO use parameterized climate-chemistry with monthly OH)

• Comparing CO₂ simulations to observations reveals model errors due to meteorological processes → leading to feedback on meteorological model
Dealing with model error: variational approach

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

\[ c_{k+1} = T_k(x_k, c_k) + G_k s_k + u_k \]

- Use constituent observations to constrain both fluxes and model errors, \( u \) (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

\[
\begin{align*}
    \mathbf{c}_{k+1}^t &= T_k(x_k^t, \mathbf{c}_k^t) + \mathbf{G}_k s_k^t + \mathbf{c}_k^c \\
    s_{k+1}^t &= \Phi_k s_k^t + \epsilon_k^s \\
    \mathbf{c}_k^{obs} &= H_k(\mathbf{c}_k)
\end{align*}
\]

\[
\begin{align*}
    \mathbf{z}_{k+1}^t &= \mathbf{F}_k \mathbf{z}_k^t + \epsilon_k^z \\
    \mathbf{z}_k &= \begin{bmatrix} \mathbf{c}_k \\ s_k \end{bmatrix}, \epsilon_k^z = \begin{bmatrix} \mathbf{c}_k^c \\ \epsilon_k^s \\ \epsilon_k^s \end{bmatrix}, \mathbf{F}_k = \begin{bmatrix} T_k & \mathbf{G}_k \\ 0 & \Phi_k \end{bmatrix}
\end{align*}
\]

- 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)

Using same sources/sinks, same model, same initial condition, CO$_2$ forecasts are still different due to errors in wind fields.

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.
Coupled global weather and greenhouse gas models

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 CO₂ transport using observed meteorology even with no CO₂ 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

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Predictability error definition used

• Drift of climate cycle from reference cycle:
  • \( E = (\text{CO}_2^{\text{clim}} - \text{CO}_2^{\text{ref}}) \)

• A measure of variability:
  • \( P = \text{Global mean (zonal standard deviation (E))} \)

• Normalize by variability in full state itself (at initial time):
  • \( P_0 = \text{Global mean (zonal standard deviation (CO}_2^{\text{ref}(t_0))} \)

• Define Normalized Predictability error:
  • \( N = \frac{P}{P_0} \)
  • 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

a) CO2

b) air_temperature

c) rel_vorticity

d) divergence
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?
- \( \text{CO}_2 \) surface fluxes
- Land/ocean surface

![Graph](image-url)
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

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If CO$_2$ can be reliably simulated only for large spatial scales, this translates to flux uncertainties which are unaccounted for.
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 \(\text{CO}_2\) state estimates through ensemble\(\rightarrow\) requires a good state estimate constrained by lots of observations
- How to deal with differing assimilation window lengths: 6h – meteorology, \(\text{CO}_2\) 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 $\Delta$CO$_2$ (global mean)

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- 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 CO₂ predictability

2009 CO₂, 1000 - 793 hPa
The flux estimation problem

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

\[ \mathbf{c}_f = T(\mathbf{x}^a, \mathbf{c}^a) + \mathbf{G}s + \epsilon \]

- CO\(_2\) forecast
- Forecast model
- Fluxes
- Model error
- Meteorological analysis
- CO\(_2\) analysis

Time →

past  →  present

observations →

Forecast model

Obs-forecast

Environment and Climate Change Canada

Environnement et Changement climatique Canada
Dealing with model error: Coupled state/flux estimation

- Fixed interval Kalman smoother
- 3-day window
- 48 members
- Flux forecast: persistence
- Temporal and spatial localization is done.
- CO₂ mass not conserved due to analysis increments

Miyazaki (2011, JGR)
Coupled state/flux estimation

- EnVar, GEOS-Chem
- State vector: CO$_2$, $\lambda$
- 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

Reference cycle (GLBref)

Climate IC (GLBclim)

Perturbed cycle (GLB pert)

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Predictability of CO$_2$ in a regional model

Jinwoong Kim (ECCC)

June 2015 monthly mean spectra

Wrong BC
Wrong IC

L01-12 lower troposphere
L13-24 mid troposphere
L25-36 upper troposphere
L37-48 stratosphere
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 CO₂ 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
How does uncertainty in winds affect CO$_2$ spread?

- 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 CO₂ and CH₄ using Reflected Sunlight: The Pioneers

- **SCIAMACHY (2002-2012)** – First sensor to measure O₂, CO₂, and CH₄ 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 high spectral resolution over broad spectral range, yielding CO₂, CH₄, and chlorophyll fluorescence (SIF)

- **OCO-2 (2014 ...)** – First NASA satellite to measure O₂ and CO₂ with high sensitivity, resolution, and coverage
  - High resolution imaging grating spectrometer small (< 3 km²) footprint and rapid sampling ($10^6$ samples/day)

- **TanSat (2016 ...)** - First Chinese GHG satellite
  - Imaging grating spectrometer for O₂ and CO₂ bands and cloud & aerosol imager
  - In-orbit checkout formally complete in August 2017

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Slide from Dave Crisp, JPL
Remote Sensing of CO₂ and CH₄: The Next Generation

- **Feng Yun 3D (2017)** – Chinese GHG satellite on an operational meteorological bus
  - GAS FTS for O₂, CO₂, CH₄, CO, N₂O, H₂O
- **Sentinel 5p (2017)** - Copernicus pre-operational Satellite
  - TROPOMI measures O₂, CH₄ (1%), CO (10%), NO₂, SIF
  - Imaging at 7 km x 7 km resolution, daily global coverage
- **Gaofen 5 (2018)** - 2nd Chinese GHG Satellite
  - Spatial heterodyne spectrometer for O₂, CO₂, and CH₄
- **GOSAT-2 (2018)** – Japanese 2nd generation satellite
  - CO as well as CO₂, CH₄, 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 CO₂ sensor to fly in a low inclination, precessing orbit
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 $X_{CO_2}$, $X_{CH4}$, $X_{CO}$ 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
CO₂ Variations with height

Park Falls: 29 May-10 June, 1996

Olsen and Randerson (2004, JGR)

- Diurnal variations, linked to surface sources and sinks, are strongly attenuated in the free troposphere
- Diurnal variations in column CO₂ 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

Diurnally varying surface fluxes
Inversions using surface network

Peylin et al. (2013)

• Inversion methods differ in:
  – Methodology
  – Observations
    ▪ Sfc: 100 flask + continuous
  – A priori fluxes
  – Transport models

• Interannual variability is similar and due to land

1 5-6
2 7-8
3 9
4 10
15
Spatial information

- 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)