WP1 - COORDINATING EFFORTS ON RECONCILING TOP-DOWN AND BOTTOM-UP ESTIMATES

Co-ordinated by ECMWF

CO2 Human Emissions

CHE-VERIFY Joint General Assembly

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Corrine le Quéré, UEA, UK

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WP Objectives

- Deliver a cross section of remote-sensing data products needed in the data assimilation chain to constrain anthropogenic carbon emissions
- Develop novel techniques to constrain anthropogenic and natural carbon emissions from joint surface and space- based carbon cycle data
- Reconcile top-down and bottom-up carbon dioxide source/sink estimates at multiple levels of integration using a community access platform
- Document current shortcomings and needed developments in space-based monitoring of fossil fuel CO2 emissions

Task 1: Improve the processing chain for data assimilation

- *Objective*
  - Provide a number of key datasets needed in carbon cycle data assimilation systems that estimate natural and anthropogenic CO_2 emissions

- *Progress*
  - Protocols for delivery of satellite data, emission data, observational data were made
  - Protocols for delivery of model output were made (next slide)
  - New U. of Bremen OCO-2 XCO2 satellite data product created under CHE released (example follows)
  - Sun-induced fluorescence datasets (NASA-GOME, KNMI-SIFTER) and XCO2 datasets (NASA OCO-2, GoSAT) made accessible for partners
  - Common bottom-up fossil fuel emission datasets, and observational CO_2 data (ObsPack) created and disseminated
  - One change to Work Plan: New Leicester custom GoSAT and OCO-2 retrieval product (details follow)

Protocol (https://www.che-project.eu/node/142)

CO_2 Human Emissions About News Events Resources Data portal

D1.1 Protocol defining harmonized input and output datasets

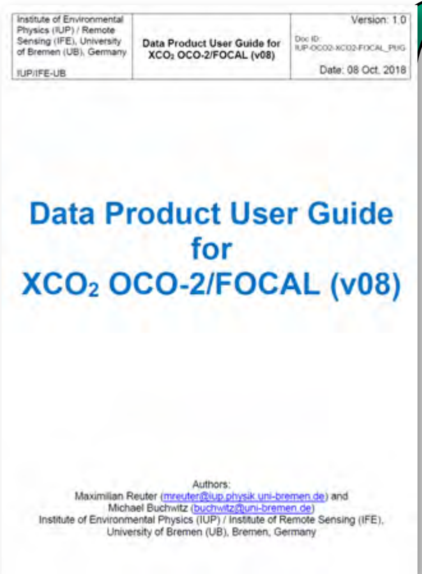
Authors: Liesbeth Florentie (Wageningen University)

Abstract

The current document outlines minimum requirements for input and output datasets as emerging from WP1 of the CO2 Human Emissions (CHE) project. The aim of this protocol consists of harmonizing the different datasets to ensure compatibility and easy accessibility for subsequent integral analyses. Special attention is given to both the set-up and data format of CO2 surface flux inversions, which will be used to assess the effectivity of proposed methodological innovations.

Files: CHE-D1-1-V1-0.pdf

Univ Bremen custom XCO2 retrieval


Institute of Environmental Physics (IUP) / Remote Sensing (IFE), University of Bremen (UB), Germany | Data Product User Guide for XCO_2 OCO-2/FOCAL (v08) | Version: 1.0 | Date: 08 Oct. 2018

IUP/IFE-UB

Data Product User Guide for XCO_2 OCO-2/FOCAL (v08)

Authors:
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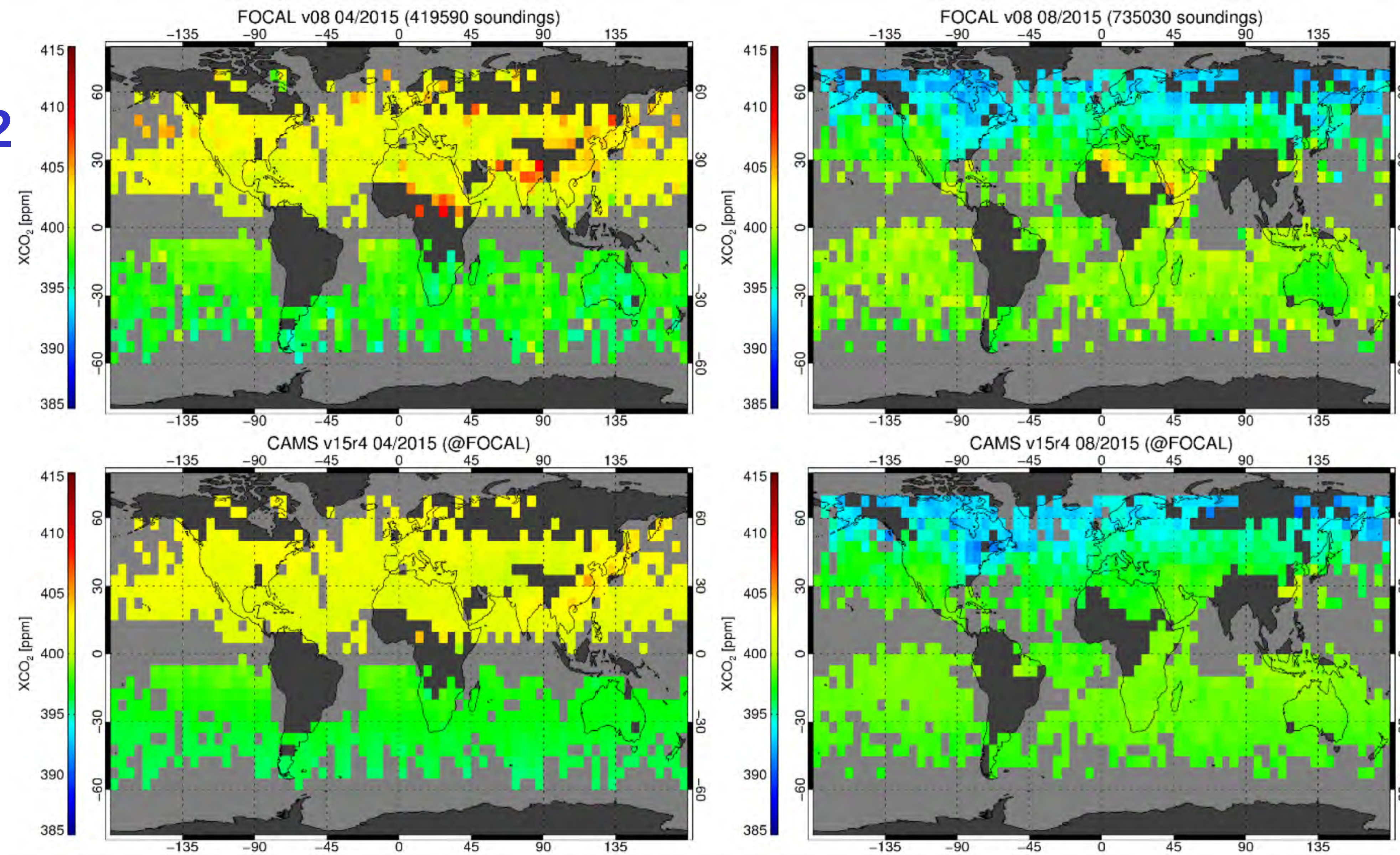
Institute of Environmental Physics (IUP) / Institute of Remote Sensing (IFE), University of Bremen (UB), Bremen, Germany

April 2015 | **August 2015**

OCO-2

CAMS



Data quality via comparison with **TCCON**:

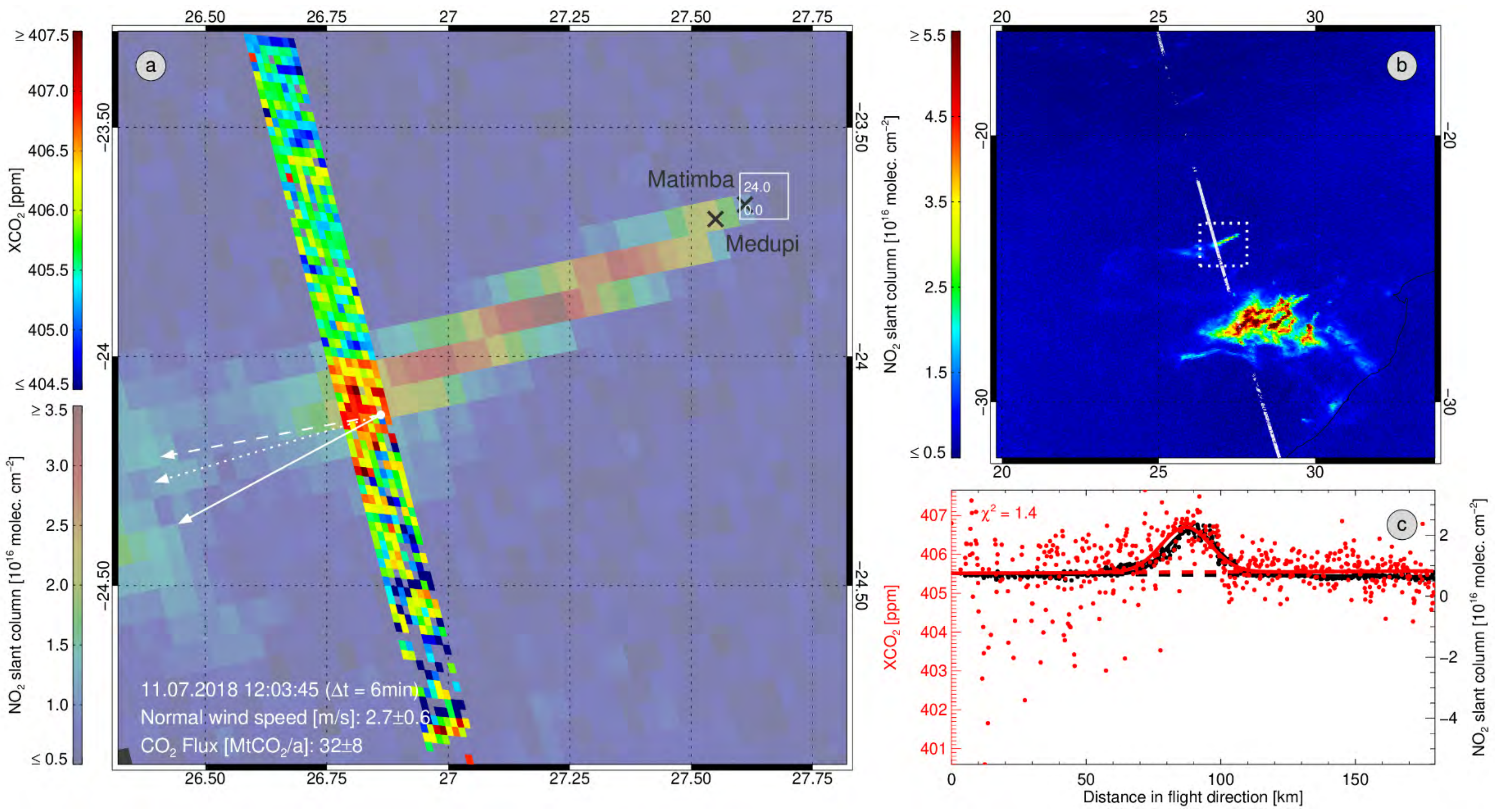
- Systematic (bias): 0.58 ppm; random (scatter): +/- 1.5 ppm (1-sigma)

Use of OCO-2 XCO_2 and S5P XNO2 for anthropogenic emissions (-> link to task 3 in WP3)

Estimation of CO_2 fluxes from localized anthropogenic emission sources using co-located OCO-2 CO_2 and S5P NO_2 observations (TropOMI)

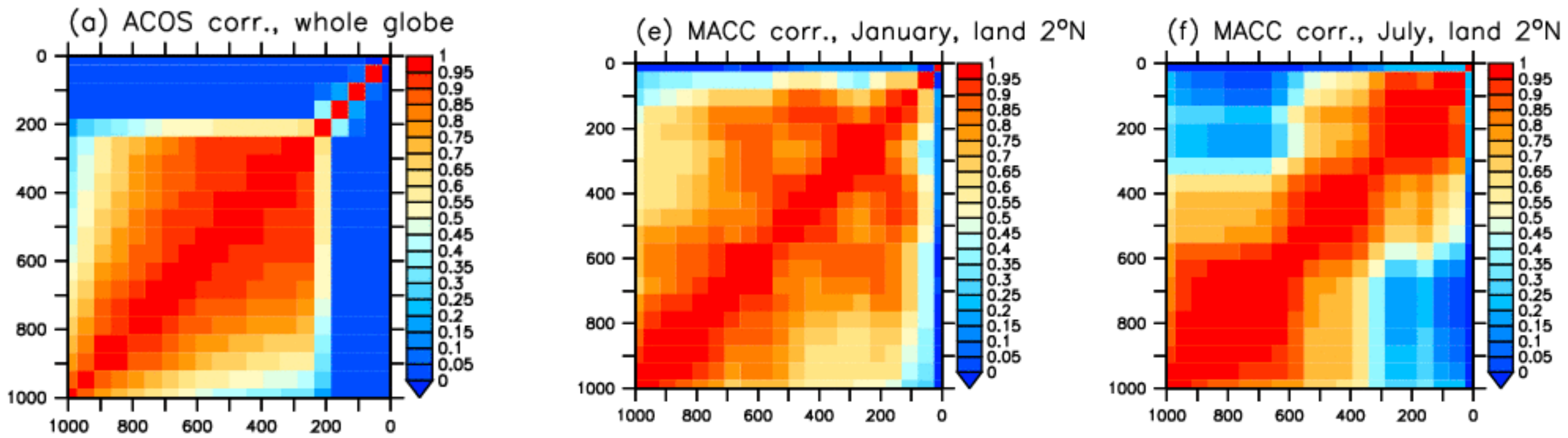
(Reuter et al., ESA ATMOS 2018)

Example: South African power plants Medupi (4.8GW) and Matimba (4.0GW)



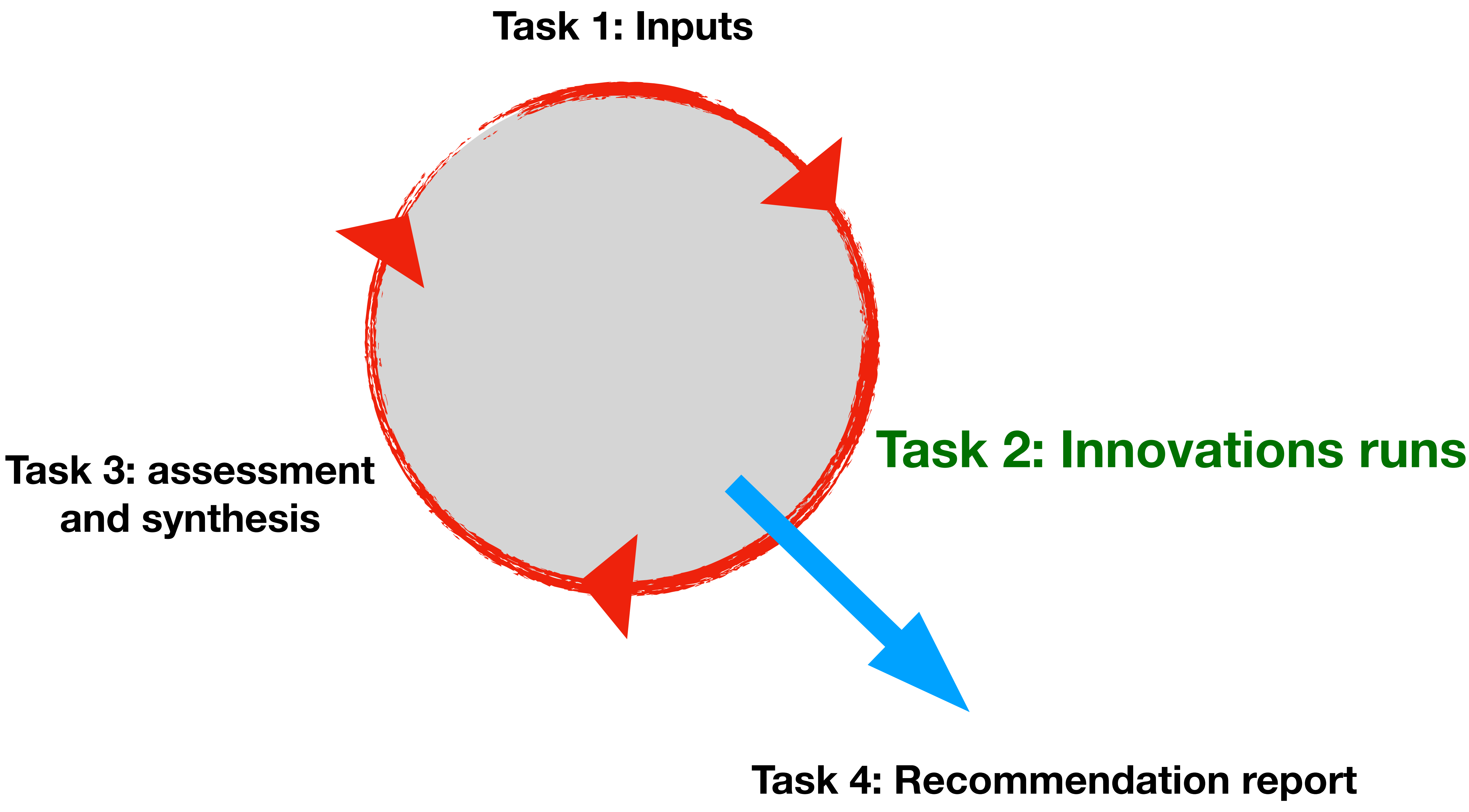
Leicester task: ~~Bias in XCO2 retrievals~~

Correlated errors in XCO2 retrievals



- Change in focus as response to concern of modeling groups
- Goal of this task: Retrieve XCO2 while including the vertical error correlations of underlying unknown fluxes to get consistent representation of inverse modeling system assumptions
- Sounding specific covariance used in retrieval, derived from model covariances representing the MACC/LSCE prior flux uncertainties projected in space and time (F. Chevallier, LSCE)
- Prior flux uncertainty will be propagated using linear analysis to re-generate 1 Year dataset for GOSAT XCO2 based on C3S L2 (mid-2019) and for OCO2 L2 data based on NASA L2 (end-2019)
- Full non-linear CO2 retrievals for 1 Year dataset of GOSAT (early 2020) will also be carried out
- The modified XCO2 datasets will then be used in MACC inverse scheme under Task 2, addressing “grand challenge” of including consistent errors in processing chain.

Task 2: Develop novel data fusion techniques for joint surface and space-based carbon cycle data



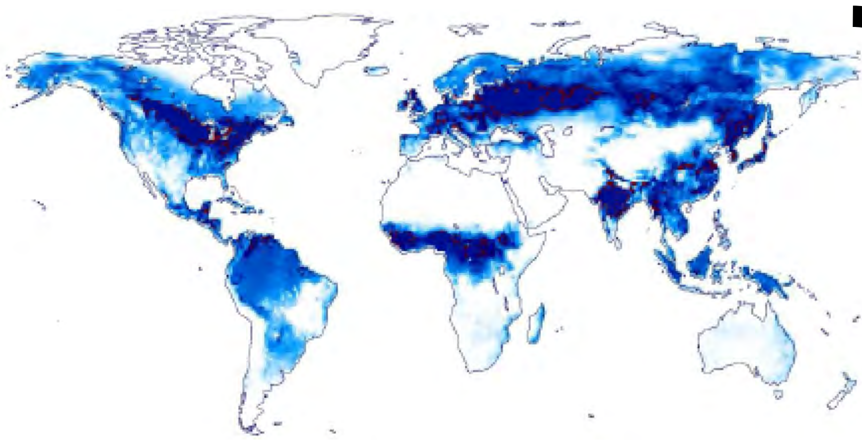
Task 2: Develop novel data fusion techniques for joint surface and space-based carbon cycle data

Progress

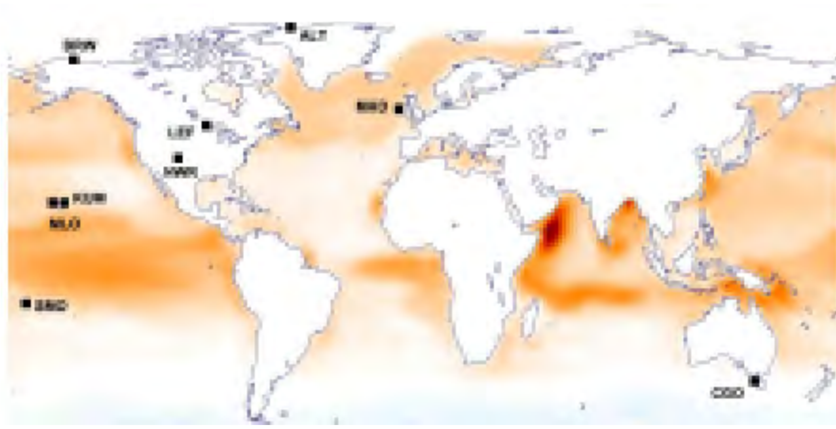
- LSCE and WU made their ‘base simulations’ in the summer of 2018, and fed them to task 3 for benchmarking
- LSCE performed first inversions with NASA OCO-2 XCO2, and is now preparing for joint XCO2 NASA and Bremen FoCAL-OCO2), SIF (NASA and KNMI), and OCS inversions (example follows)
- WU created a new “long-window” inversion in which 0.5x0.5 degree monthly retrieved SIF-anomalies (KNMI-SIFTER and NASA) drive interannual variations in net ecosystem exchange alongside CO_2 surface observations (—> Poster Liesbeth)
- MPI created high-resolution (0.25 degree) satellite inversion system for Europe that can ingest XCO2 and various other satellite products, to be nested in global TM3 runs (example follows)

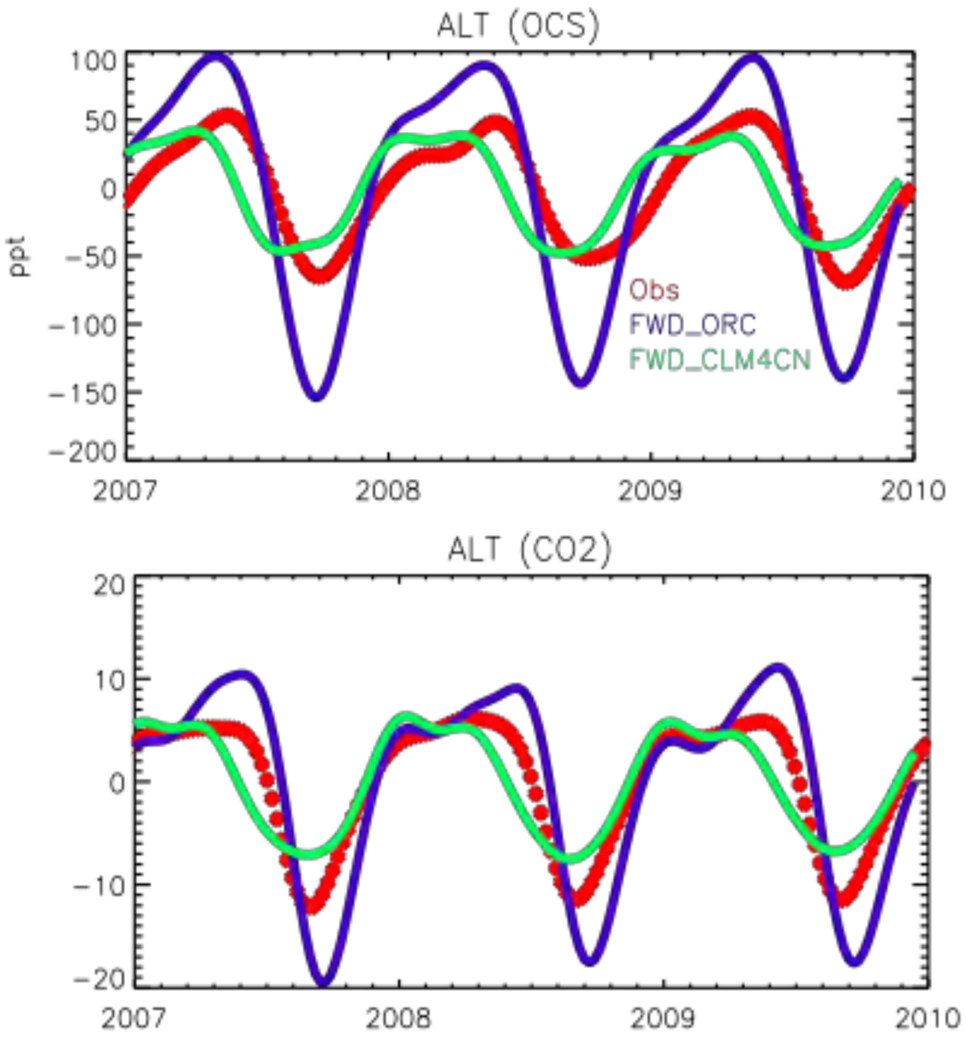
Simulated [OCS] & [CO_2] with LMDz at LSCE: illustration with 2 land carbon models (ORCHIDEE & CLM4CN) and compared with NOAA measurements at station Alert (Canada)

F_{cos_GPP} (ORC-July)



F_{ocean} (July)





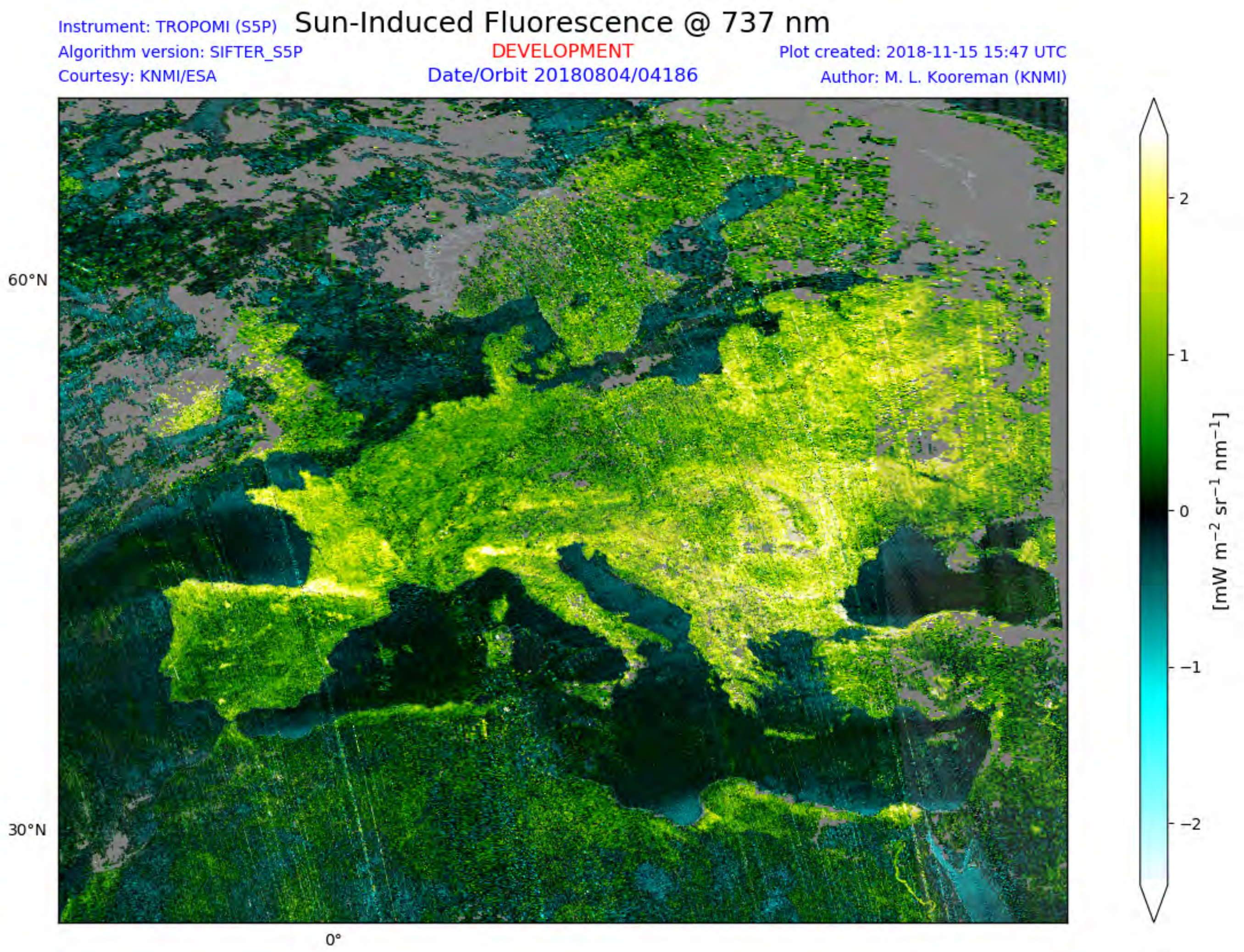
- ORCHIDEE has too large GPP amplitude at high latitudes
- CLM4CN shows an advance of phase for GPP at high latitudes

We expect to constrain the phase and the amplitude of GPP with OCS. Addresses Grand Challenge #3

WU: Parameter optimization in a simple surface flux model

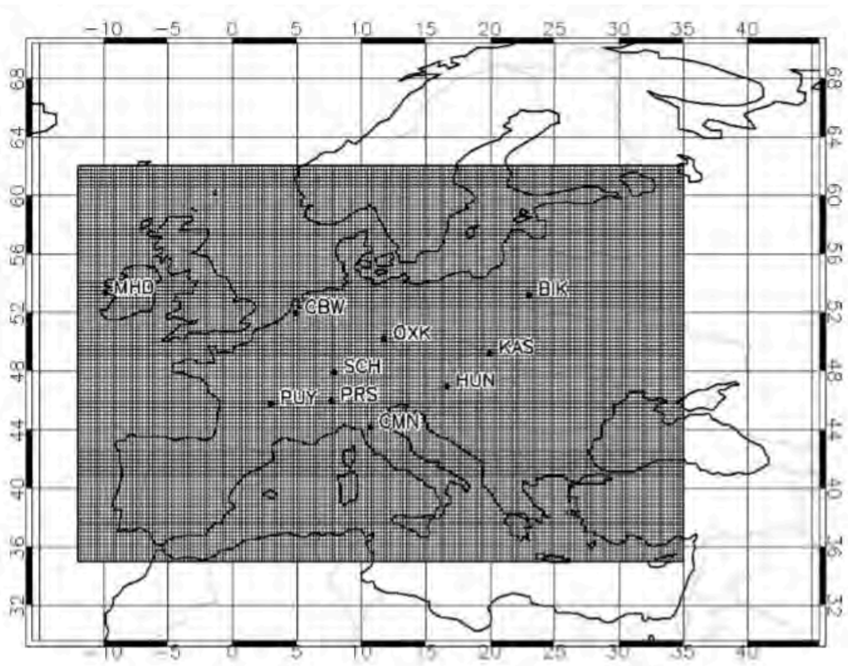
- Rationale:
  - Use satellite data (e.g. SIF, NIR_V) as proxy for anomalies and spatial patterns

See Poster Liesbeth Florentie

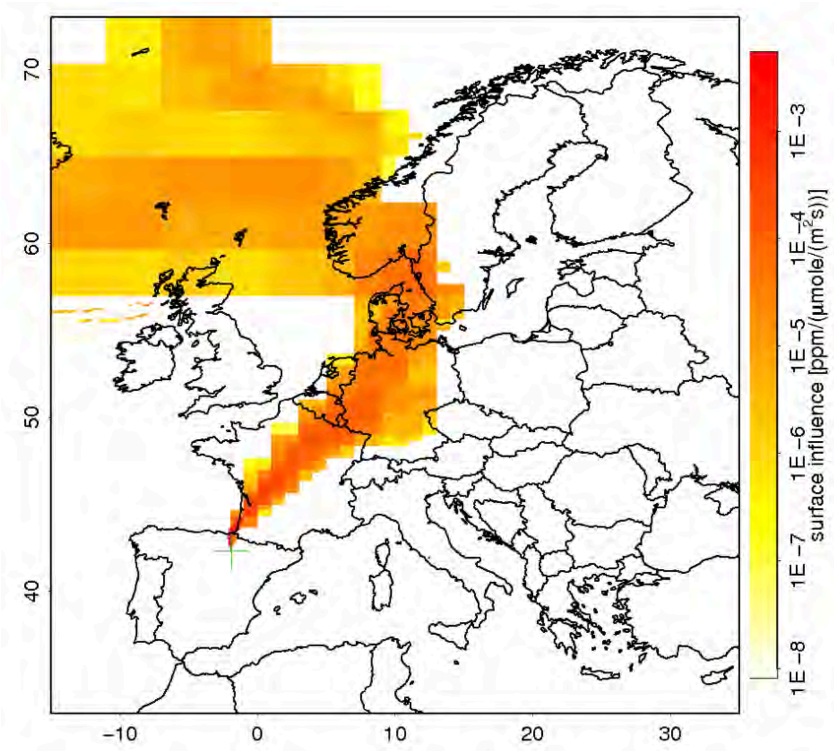


Nested regional inversions (MPI)

- Based on established nested TM3-STILT 2-step inversion
- *Progress*
  - Implementation of Lagrangian column operator in STILT, based in part on X-STILT from Wu et al., 2018
  - Allows for inclusion of satellite measurements in 0.25 degree regionally nested inversions already performed for Europe



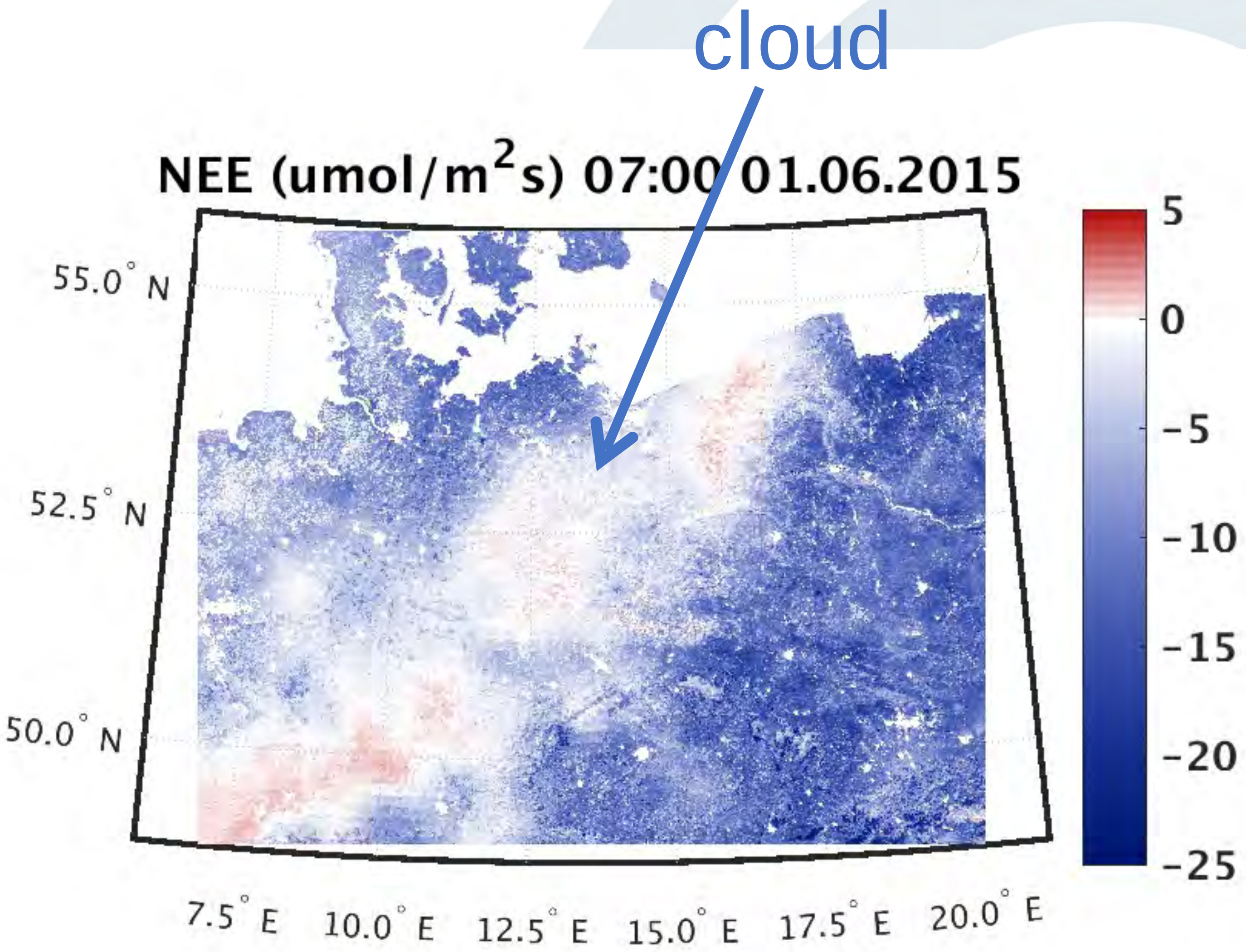
Trusilova et al., 2010



Footprint of a single GOSAT sounding from October 2011

Nested regional inversions (MPI)

- *Plans*
  - To be coupled with high-resolution (cloud-resolving) VPRM prior
  - To be tested for simulation period in 2015
- *Impact*
  - Will test for impact of clear-sky bias in the interpretation of satellite measurements, addressing Grand Challenges #1 and #3



Task 3: Reconcile carbon source/sink estimates from different top-down approaches with each other, and with bottom-up constraints

- *Objectives*
  - Reconcile existing and new results on the global and regional carbon balance
  - Implement a system that allows fast and easy assessment of data assimilation system results on an open-access platform.

- *Progress*
  - Protocol for delivery of model results created and agreed
  - Test with four models (2x CHE, 2x external) done for GCP2018 release
  - Open-source based analysis on ICOS Carbon Portal implemented and used for comparisons
  - Prototype benchmarks based on aircraft CO_2 data, and new one to be developed based on TCCON XCO2 columns

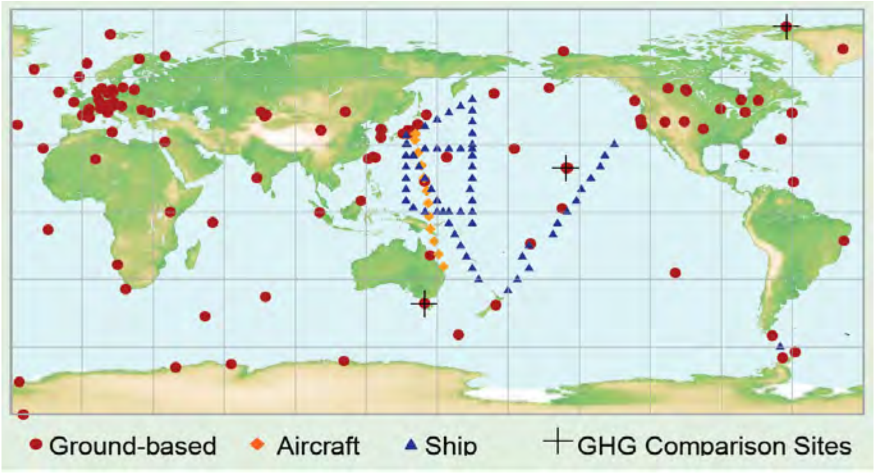
- *Impact*
  - Community engagement in benchmarking inverse runs
  - Contributed to published Global Carbon Balance in 2018
  - Shared platform development with EUROCOM, VERIFY, and CARBAM

Benchmarking inverse systems: Top-down inversions from satellite and surface data

Atmospheric inversions using the surface CO_2 measurement network:

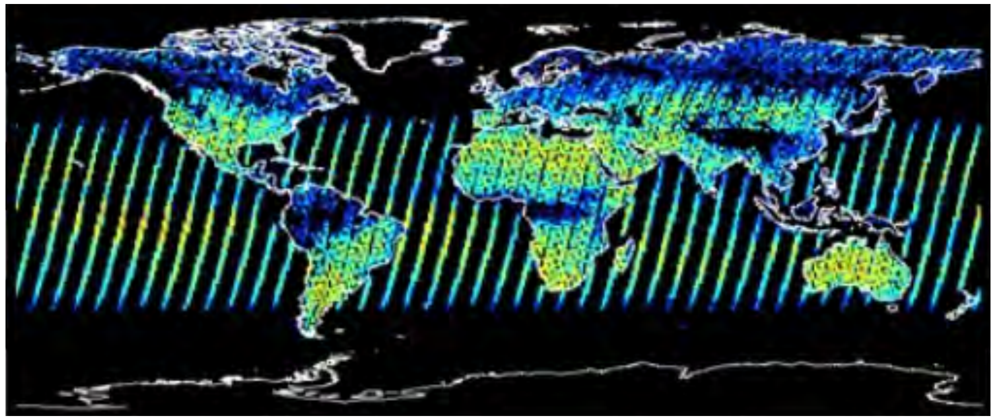
Sparse coverage. CO_2 measurement accuracy <0.2 ppm

1. Copernicus Atmospheric Monitoring Service (LMDZ)
2. Jena CarboScope s76 (TM3)
3. Carbon Tracker (TM5)



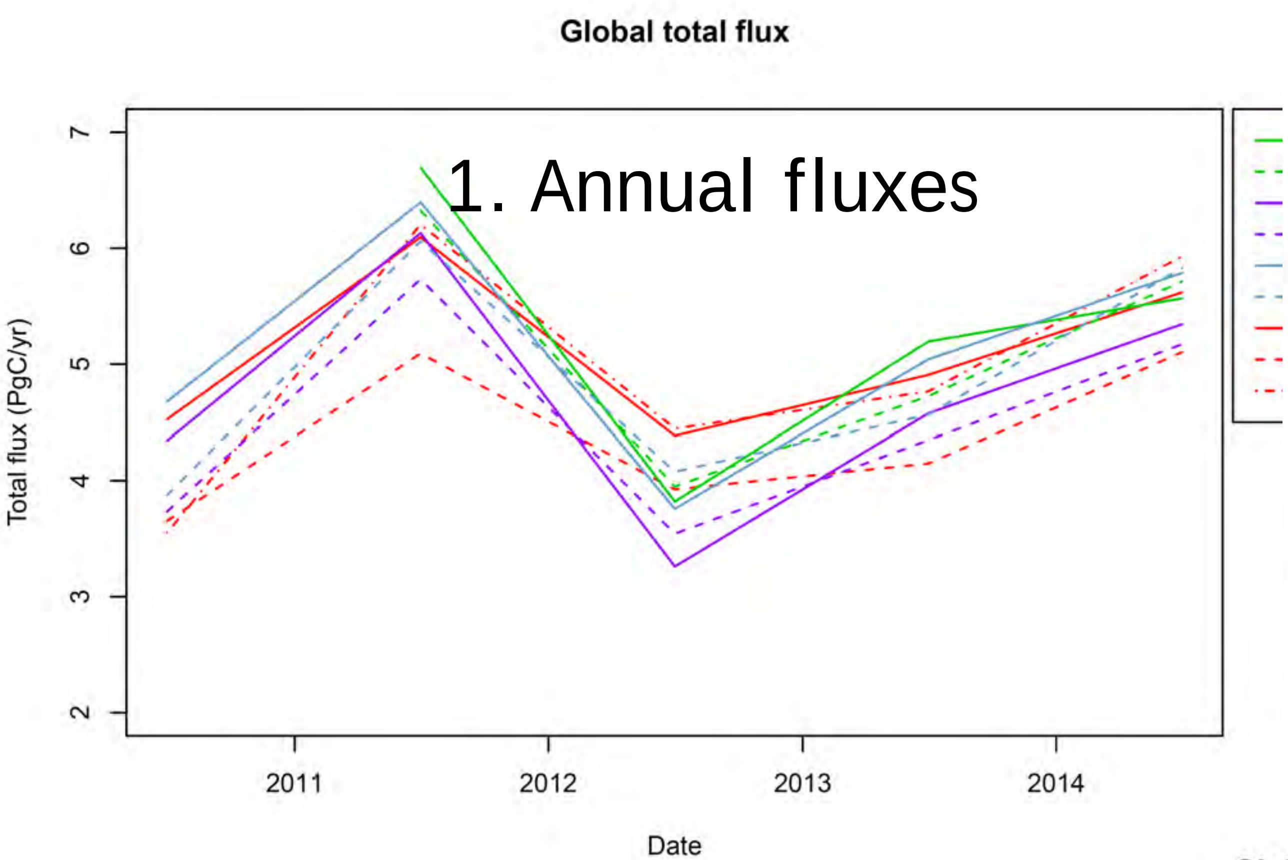
Atmospheric inversions using satellite CO_2 measurements

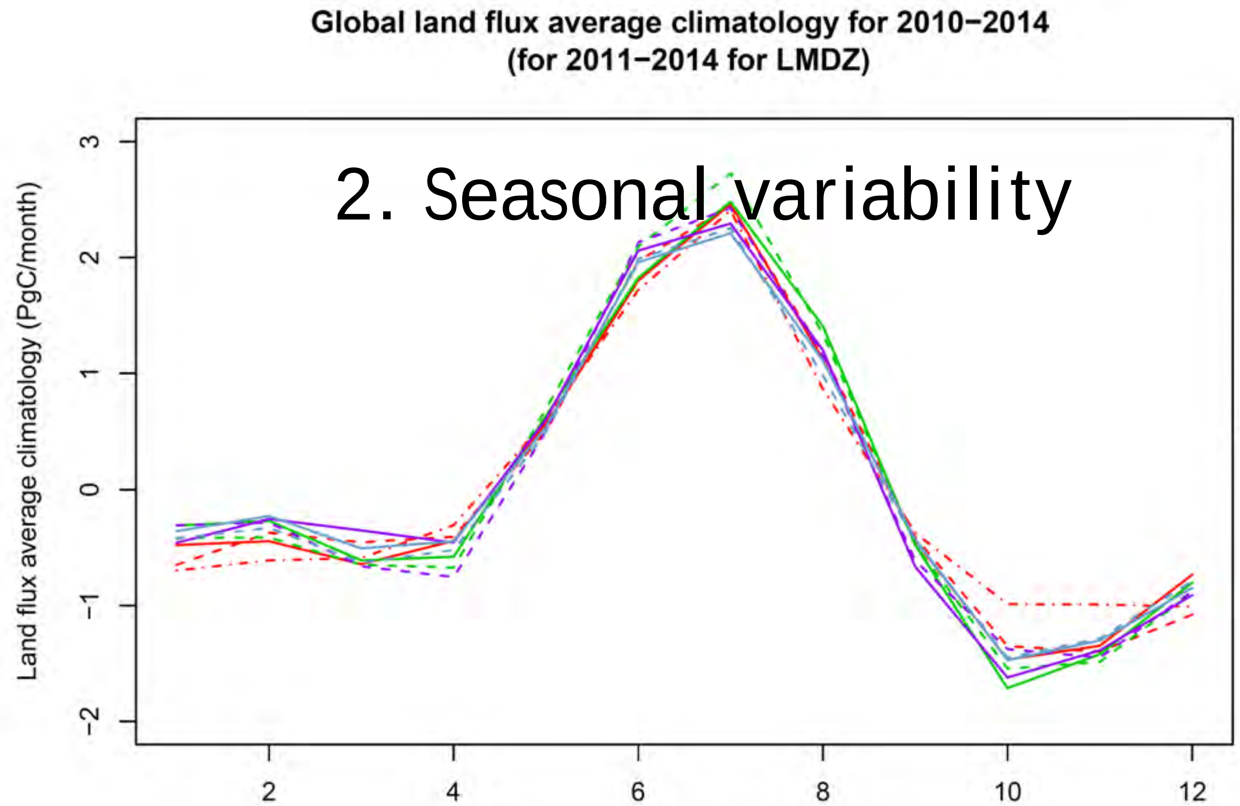
GOSAT: Global (sort of) coverage ~every 3 days, CO_2 measurement accuracy 2-3 ppm

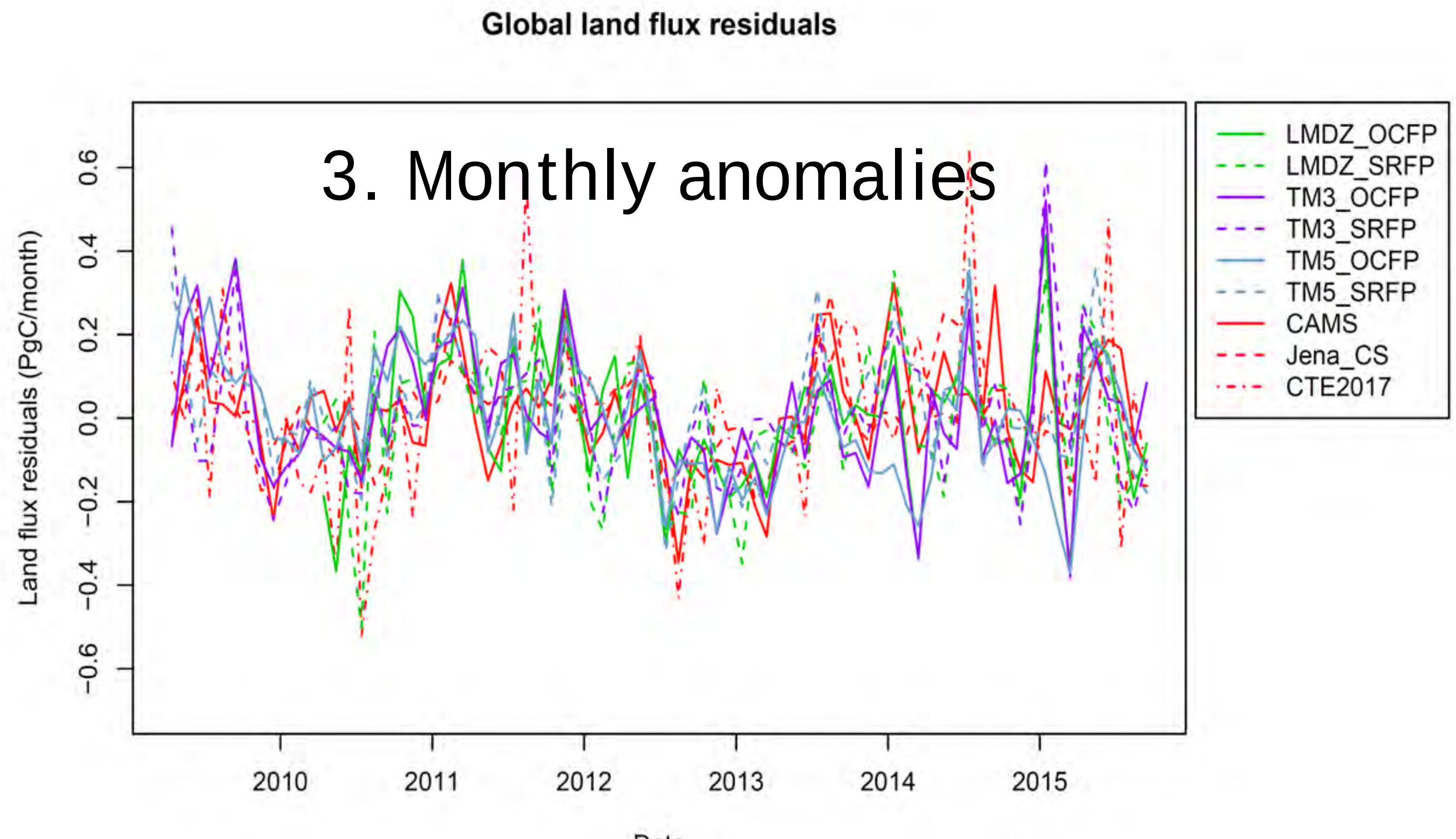


Satellite retrieval algorithm	Provider of satellite data	Transport model	Provider of inversion
OCFP (from GOSAT)	University of Leicester	LMDZ	LSCE
		TM3	MPI-BGC
		TM5	SRON
SRFP (from GOSAT)	SRON/KIT (Netherlands Institute for Space Research/Karlsruhe Institute of Technology)	LMDZ	LSCE
		TM3	MPI-BGC
		TM5	SRON

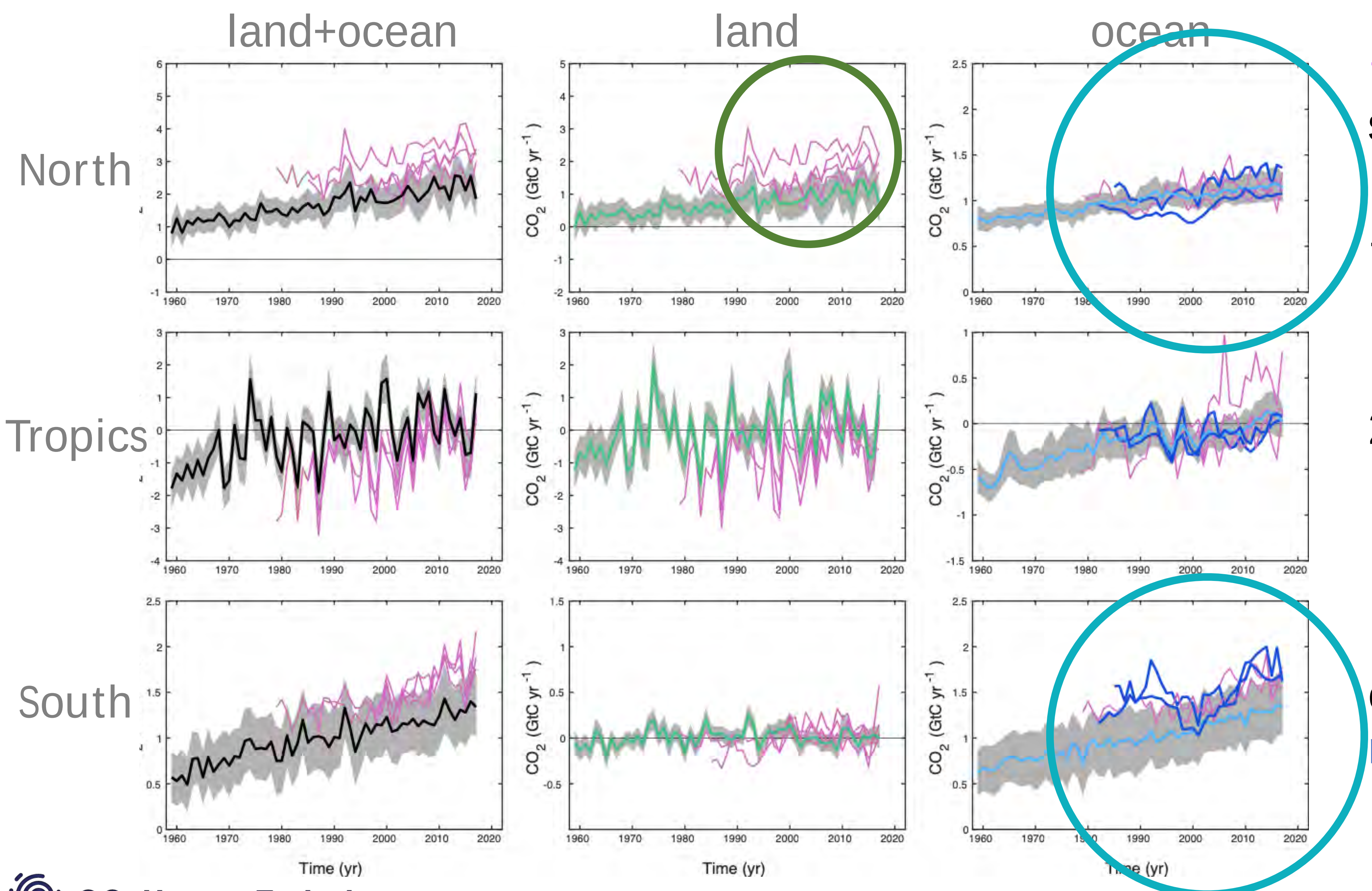
Benchmarking inverse systems:
Top-down inversions from satellite and surface data







Comparison of top-down inversion based on surface data and bottom-up process models



top-down inversions suggest:

1) a larger CO_2 sink over land in the North

2) larger decadal variability in the extra-tropical oceans

compared to process models

CO₂ Human Emissions

VERIFY

Le Quéré et al. ESSD 2018

jupyter make_gcp_plots_2018 Last Checkpoint: a few seconds ago (autosaved)

Control Panel | Logout

File | Edit | View | Insert | Cell | Kernel | Help | Trusted | Python 2

Code

In [3]:
```
%pylab inline
```

Populating the interactive namespace from numpy and matplotlib

In [4]:
```
import numpy as np
import datetime as dt
import pandas as pd
import numpy as np
import csv
import matplotlib.pyplot as plt
import matplotlib.lines as lines

import PySCRIP as scrip
from PySCRIP.config import PySCRIPConfig
import netCDF4 as cdf
from matplotlib import gridspec
matplotlib.rcParams.update({'font.size':25, 'lines.linewidth':2.5,'axes.grid':True, 'grid.color':'grey', 'grid.line
```

Read CAMS

In [5]:
```
# def read_CAMS(filename):
filename_CAMS = 'v17r1_GCPbud.txt'
filename_CAMS2 = 'CAMS_v17r1_allmonths.nc'
f_cams = open(filename_CAMS, 'r')
```

Plot fluxes

In [84]:
```
labels=['CAMS','CarboScope','CTE','MIROC']
```

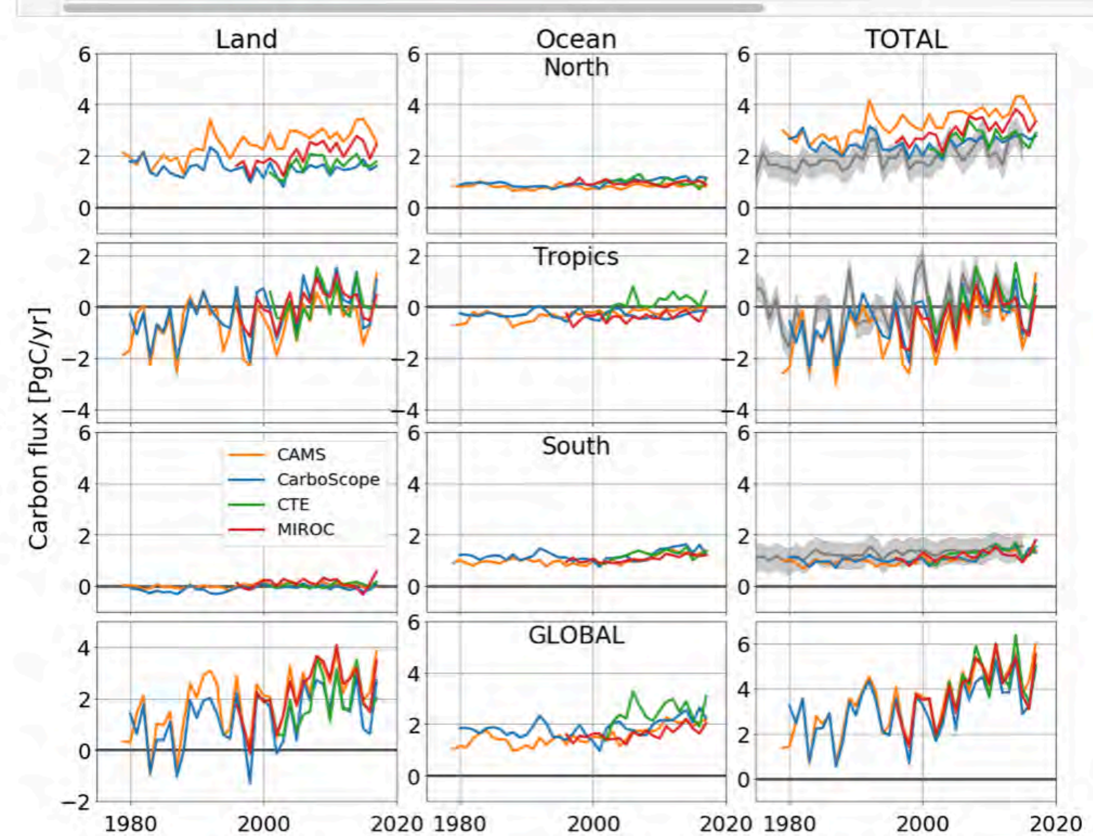
In [85]:
```
for r in [df_CAMS_NTS,df_Jena_NTS,df_CTE_NTS,df_MIROC_NTS]:
    r.index = pd.to_datetime(r.index)
```

In [86]:
```
df_CAMS_NTS=df_CAMS_NTS.loc[df_CAMS_NTS.index<dt.datetime(2018,1,1,0,0,0)]
df_Jena_NTS=df_Jena_NTS.loc[(df_Jena_NTS.index>=dt.datetime(1976,1,1,0,0,0))&(df_Jena_NTS.index<dt.datetime(2018,1,
df_CTE_NTS = df_CTE_NTS.loc[(df_CTE_NTS.index>=dt.datetime(2001,1,1,0,0,0))&(df_CTE_NTS.index<dt.datetime(2018,1,1,
df_MIROC_NTS = df_MIROC_NTS.loc[(df_MIROC_NTS.index>=dt.datetime(1996,1,1,0,0,0))&(df_MIROC_NTS.index<dt.datetime(2
```

In [87]:
```
df_CAMS_NTS_yr=df_CAMS_NTS.resample('A',label='left',loffset='1d').mean()
df_Jena_NTS_yr=df_Jena_NTS.resample('A',label='left',loffset='1d').mean()
df_CTE_NTS_yr=df_CTE_NTS.resample('A',label='left',loffset='1d').mean()
df_MIROC_NTS_yr=df_MIROC_NTS.resample('A',label='left',loffset='1d').mean()
```

In [88]:
```
#Plot NTS total fluxes as in paper
#df=pd.read_csv('/opt/data/modeledData/NTS_plot2.csv')
df=pd.read_csv('NTS_plot_2016.csv')
df.index = [dt.datetime(i,1,1) for i in df['Time'][:]]

f, ([(ax1,ax5,ax9), (ax2,ax6,ax10), (ax3,ax7,ax11), (ax4,ax8,ax12)]) = plt.subplots(4,3, sharex=True, figsize=(20,1

f.subplots_adjust(hspace=0.05,wspace=0.1)

f.add_subplot(111, frameon=False)
# hide tick and tick label of the big axes
plt.tick_params(labelcolor='none', top='off', bottom='off', left='off', right='off')
plt.grid(False)
plt.ylabel('Carbon flux [PgC/yr]',fontsize=28)

## Col 1: Land
#North
#ax1.plot(df['Time'],df['Models_N'],label='GCP',c='C7',linewidth=5)
ax1.plot(df_CAMS_NTS_yr.index.year,df_CAMS_NTS_yr['CAMS_N_land'],c='C1',linewidth=3,label=labels[0])
ax1.plot(df_Jena_NTS_yr.index.year,df_Jena_NTS_yr['Jena_N_land'],c='C0',linewidth=3,label=labels[1])
ax1.plot(df_CTE_NTS_yr.index.year,df_CTE_NTS_yr['CTE_N_land'],c='C2',linewidth=3,label=labels[2])
ax1.plot(df_MIROC_NTS_yr.index.year,-df_MIROC_NTS_yr['MIROC_N_land'],c='C3',linewidth=3,label=labels[3])
ax1.plot([1975,2020],[0,0],c='black',zorder=0)
ax1.set_ylim(-1,6)
ax1.set_title('Land')
```

```
ax12.plot([1975,2020],[0,0],c='black',zorder=0)
ax12.set_ylim(-1,7)
ax12.set_xlim(1975,2020)
ax12.xaxis.set_major_formatter(plt.FormatStrFormatter('%i'))
ax12.tick_params(axis='x', pad=12)


f.savefig('Figures/GCP_fig8_split_2018',dpi=200)
```



Task 3 impact and plans

- Benchmarking in Task 3 is becoming the standard approach for Global Carbon Project, EUROCOM, and CHE
- New metrics are actively developed
- Next target: recent key events like 2018 drought, 2015/2016 El Nino
- Online analysis platform to expand to new users and projects

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THANK YOU

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