Greenhouse gas observations from space: Why and how?

Michael Buchwitz
Institute of Environmental Physics (IUP)

www.iup.uni-bremen.de
Overview Talks 1 - 3

Greenhouse gas observations from space

1. Why and how?

2. Results from ESA‘s GHG-CCI project

3. Proposed future mission CarbonSat
Greenhouse gas observations from space: Why and how?

• Why ?
  • … including at least a little bit of the most relevant background information …

• How ?
  • From satellite radiances -> atmospheric GHG concentrations -> GHG surface fluxes (sources & sinks)
Greenhouse gas observations from space

Why?
Large and increasing human influences

We are living in a new geological epoch (TBC), the „Anthropocene“ (Crutzen, 2000)

A complex system with many positive and negative feedback cycles.
Greenhouse Effect

1370 W/m²

"Solar constant"

[Diagram showing the Earth’s global energy budget with various fluxes and energy balances, including:

- Reflected Solar Radiation: 101.9 W m⁻²
- Incoming Solar Radiation: 341.3 W m⁻²
- Outgoing Longwave Radiation: 238.5 W m⁻²
- Traffic:
  - 100 W/m²
  - 340 W/m²
  - 240 W/m²

References:


http://www.bis.gov.uk/go-science/climatescience/greenhouse-effect
Climate Change: Observations

Mean temperature increase (1880-2012): 0.85 [0.65 to 1.06] °C

Source: IPCC 2013, AR5, Approved "Summary for Policy Makers"
Radiative Forcing

Source: IPCC 2013, AR5, Approved "Summary for Policy Makers"

2.3 W/m² [1.1-3.3] corresponds to observed 0.85 °C [0.65-1.06]
Solar energy input and long-wave outgoing radiation

Solar Input:

- Solar radiation
- Wavelength in $10^{-6}$ meter = $\mu$m
  - $0.5 \times 10^{-6}$ meter = 500 nm
  - $15 \times 10^{-6}$ meter = 15 $\mu$m

Heat Output:

- Radiation emitted by Earth
- Absorptivity
  - Nitrogen ($N_2$)
  - Oxygen and ozone ($O_2$ and $O_3$)
  - Carbon dioxide ($CO_2$)
  - Water vapor ($H_2O$)
  - Total Atmosphere

Wavelength in $10^{-6}$ meter = $\mu$m
Doubling CO$_2$: Radiative transfer simulations

Rule of thumb (neglecting feedbacks): $\Delta F = 5.3 \ln(\text{CO}_2\text{-ratio}=2) = 3.7 \rightarrow 3.7/3 = \sim 1.2 \text{ K} = \Delta T$
Climate sensitivity: Temperature change for doubling CO₂:

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**CO₂ x2**

Ts = 15°C

Houghton, 2004

**CO₂ x2**

Ts = 15°C

Ts = 15°C

Ts = 15+(1.5-4.5) °C

(AR5 likely range equilibrium clim. sensit.)

Doubling?: Pre-industrial = 280 ppm x2 -> 560 ppm

400 ppm reached in May 2013 (= maximum of seasonal cycle, not yearly average)

„2 degree goal“: ~450 ppm should not be exceeded
(Controversial !?: e.g. Hansen argues for < 350 ppm)
Earth’s breathing

Atmospheric CO₂ 2002 -2008

For 1959–2011, the terrestrial carbon sink was estimated from the residual of the other budget terms:

\[ S_{\text{LAND}} = E_{\text{FF}} + E_{\text{LUC}} - (G_{\text{ATM}} + S_{\text{OCEAN}}) \]
NOAA/Scripps CO$_2$ Time series

The more accurate and the longer the observational time series, the more we can learn from analyzing the observations …
Observed Emissions and Emissions Scenarios

Emissions are on track for 3.2–5.4°C “likely” increase in temperature above pre-industrial. Large and sustained mitigation is required to keep below 2°C.

Linear interpolation is used between individual data points.

Source: Peters et al. 2012a; CDIAC Data; Global Carbon Project 2013
Why bother? Just a few degrees more!

-4°C

Ice & snow

Copyright © 2005 Pearson Prentice Hall, Inc.

Medieval warm period (Vikings in Greenland with cattle & sheep, etc.)
CO₂ emissions -> Temperature change

Emitted until 2011: 
531 (446-616) GtC

IPCC 2013, AR5
„Summary for Policy Makers“

Future: Large uncertainty, e.g., response of terrestrial biosphere to changing climate?
Houghton, Biologist, 2002:

“Strangely, the difference between the net terrestrial sink and the emissions from land-use change suggests that there is a residual terrestrial sink, not well understood, that locked away as much as 3.0 PgC/yr during the last two decades. ... The exact magnitude, location and cause of this residual terrestrial sink are uncertain, ...”
Natural CO$_2$ fluxes from in-situ (mostly surface) obs.

Towards robust regional estimates of CO$_2$ sources and sinks using atmospheric transport models

Gurney et al., Nature, 2002

Observations:
Very accurate but sparse

Information content sources & sinks (excluding fossil fluxes):
Large regions only (continents, ocean basins)
Large uncertainties (often +/- 100%)

A priori land

Inversions:
\(\times\) Mean flux
\(\bigcirc\) Within model uncertainty

Left / right: different inversions
Natural CO$_2$ fluxes from space?:
• Yes! If …

Precision < 2.5 ppm for monthly 8°x10°

The utility of remotely sensed CO$_2$ concentration data in surface source inversions

P. J. Rayner
Cooperative Research Centre for Southern Hemisphere Meteorology and CSIRO Atmospheric Research, Aspendale, Victoria, Australia

D. M. O’Brien
CSIRO Atmospheric Research, Aspendale, Victoria, Australia

Abstract. This paper aims to establish the required precision for column-integrated CO$_2$ concentration data to be useful in constraining surface sources. We use the method of synthesis inversion and compare the uncertainties in regional sources calculated from a moderate-sized surface network and either global or oceanic coverage of column-integrated pseudodata. With a simple measure of total uncertainty, we require precision of monthly averaged column data better than 2.5 ppmv on a 8° × 10° footprint for comparable performance with the existing surface network. If coverage is only oceanic we require 1.5 ppmv precision. We recommend more detailed studies on the feasibility of obtaining such observations from current and future satellite instruments.

Correction to “The utility of remotely sensed CO$_2$ concentration data in surface source inversions”
Uncertainty reduction using satellite data - II

Prior uncertainty

Fig. 1. Prior uncertainty of weekly fluxes in g C m\(^{-2}\) d\(^{-1}\). The white lines show the borders of the 200 regions for which the surface fluxes are retrieved.

Altitude sensitivity

Hungershöfer et al., 2010

Weekly mean error reduction
Methane

- Natural gas
- Coal mining
- Wetlands
- Rice
- Wastewater
- Landfills
- Termites
- Ruminants
- Energy
- Hydrates
Methane

- Second most important anthropogenic GHG (directly after CO$_2$)
- Many anthropogenic and natural sources; large uncertainties

Kirschke et al., 2013
How will sources and sinks behave in a changing climate?

**CO$_2$ and CH$_4$ sources and sinks: !! ??**

How strong are the various **sources** and **sinks**?

How much is emitted where, when and by what?

Are the reported emissions correct?

How much CO$_2$ is absorbed by land and oceans? Where and when?

How will today's CO$_2$ sinks behave in a changing climate?

How will today's CH$_4$ sources (e.g., wetlands) behave in a changing climate?

Will sinks turn into sources?

Will sources be amplified?

How will sources and sinks behave in a changing climate?
CO$_2$ and CH$_4$ are the two most important anthropogenic greenhouse gases and increasing concentrations result in global warming.

Reliable climate prediction requires a good understanding of the natural and anthropogenic (surface) sources and sinks of CO$_2$ and CH$_4$.

Important questions are, for example:

- Where are they?
- How strong are they?
- How do they respond to a changing climate?

A better understanding requires appropriate global observations and (inverse) modelling.

ECV GHG (GCOS-154*):

“Retrievals of greenhouse gases, such as CO$_2$ and CH$_4$, of sufficient quality to estimate regional sources and sinks.”

*) „SYSTEMATIC OBSERVATION REQUIREMENTS FOR SATELLITE-BASED DATA PRODUCTS FOR CLIMATE“
Why?

- The greenhouse gases (GHGs) carbon dioxide (CO$_2$) and methane (CH$_4$) are „Essential Climate Variables“ (ECVs)
- Increasing atmospheric concentrations result in global warming
- Reliable prediction of the future climate of our planet requires a good understanding of their (variable) natural and anthropogenic sources and sinks
- Our understanding has large gaps and global satellite data help to improve our understanding, i.e., they help reducing uncertainties on GHG sources and sinks (#)

(#{See Talk 2: GHG-CCI results}}
Greenhouse gas observations from space

How?
Viewing Geometries

Satellite Observation Geometries

Nadir
- SCIAMACHY, AIRS, IASI, TES, GOSAT, OCO-2, CarbonSat, A-SCOPE, MERLIN, ASCENDS, …

Limb
- SCIAMACHY, MIPAS, …

Occultation
- SCIAMACHY, ACE-FTS, …

Most relevant for GHG source / sink application
Measurement Techniques

Passive
- Solar
  - SCIAMACHY, GOSAT, OCO-2, CarbonSat, …
- Thermal
  - TOVS, IMG, AIRS, IASI, TES, MIPAS, …

Active
- Laser
  - A-SCOPE, MERLIN, ASCENDS, …

Most relevant for GHG source / sink application
Reflected solar (NIR/SWIR) vs thermal (TIR)

Thermal emission

NIR absorption

Sensitive to mid/upper troposphere

Sensitive (also) to near-surface GHG concentration variations

Important to get source/sink info

Figure 7. Representative vertical averaging kernels for column CO$_2$ soundings using NIR absorption of reflected sunlight in the 1.61 µm CO$_2$ band (blue) and thermal IR emission near 14.3 µm (red). TIR soundings are less sensitive to near-surface CO$_2$ because of the small surface–atmosphere temperature contrast (Crisp et al., 2004; Chahine et al., 2005).
Note:

In the following I will focus on

- **nadir** observations in the
- **solar** spectral region using
- **passive** satellite observations
Global satellite observations

Global information on near-surface CO₂ & CH₄

SCIAMACHY/ENVISAT

TANSO/GOSAT

Upper layer CO₂ & CH₄

IASI, MIPAS, SCIA/occ, AIRS, ACE-FTS, ...

Global observations

Calibrated radiances

Calibration (L 0-1)

Retrieval (L 1-2)

Atmospheric GHG distributions

Reference observations

Validation

Improved information on GHG sources & sinks

Inverse modelling (L 2-4)
SCIAMACHY Scanning Imaging Absorption Spectrometer for Atmospheric CHartographY

SCIAMACHY on ENVISAT

**sciamachy** /ˈsʌɪəməki/ n. (also **skiamachy** /ˈskəməki/) formal 1 fighting with shadows. 2 imaginary or futile combat. [Greek *skiamakhia* (as SCIAMOGRAPHY, -makhia ‘fighting’)]

Nadir mode:
Swath width: 960 km
XCO₂ & XCH₄ from 1.6 & 0.76 μm bands
Horizontal resolution: 30 x 60 km²
Tropospheric data products from SCIAMACHY/nadir

<table>
<thead>
<tr>
<th>NO2</th>
<th>SO2</th>
<th>CO</th>
<th>H2O</th>
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<td><img src="image3" alt="CO Image" /></td>
<td><img src="image4" alt="H2O Image" /></td>
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<th>HCHO</th>
<th>BrO</th>
<th>CO2</th>
<th>CH4</th>
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<td><img src="image7" alt="CO2 Image" /></td>
<td><img src="image8" alt="CH4 Image" /></td>
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<th>IO</th>
<th>Aerosols</th>
<th>Clouds</th>
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<td><img src="image10" alt="IO Image" /></td>
<td><img src="image11" alt="Aerosols Image" /></td>
<td><img src="image12" alt="Clouds Image" /></td>
</tr>
</tbody>
</table>

... and more.
Greenhouse gases via SCIAMACHY/ENVISAT

Carbon Dioxide SCIAMACHY/BESD 2006-2011

Methane SCIAMACHY/WFMD 2003-2005
XCO₂ = \text{CO}_2 \text{ column} / \text{Air column}

XCO₂ := \text{CO}_2 \text{ column-averaged dry air mixing ratio (mole fraction)}

Buchwitz et al., ACP, 2005

\pm 10\%\hspace{2cm} \pm 1.5\%
\[ X_{\text{CO}_2} \] Counting molecules …

\[ X_{\text{CO}_2} = \frac{\text{CO}_2\text{-Column}}{\text{Air-Column}} \]

Buchwitz et al., 2008

\[ X_{\text{CO}_2} := \text{CO}_2\text{ column-averaged dry air mixing ratio (mole fraction)} \]
Measurement principle - I
Measurement principle - II
Light path issues

Atmospheric Propagation Effects

scattering & reflection from clouds
scattering in clouds
transmission through clouds
scattering & reflection by surface

absorption
scattering
Aerosol
Clouds
Molecules

absorption by surface

From: SCIAMACHY – Monitoring the changing Earth's atmosphere
SCIAMACHY nadir spectrum

Buchwitz, 2000; Schneising et al., 2008, 2009
Radiative Transfer

Change of radiance \( I, \, dl \), along path \( ds \) due to sources \((+\epsilon S)\) and/or losses \((-\epsilon I)\).

e.g., plane-parallel RTE

\[
\frac{dI}{ds} = \epsilon (S - I)
\]

\[
\mu \frac{dI(z, \mu, \phi)}{dz} = -\epsilon(z) I(z, \mu, \phi) \]

\[
+ \frac{\beta(z)}{4\pi} \int_{0}^{2\pi} \int_{-1}^{1} p(z, \mu, \mu', \phi, \phi') I(z, \mu', \phi') d\mu' d\phi.
\]
SCIA: IUP-UB retrieval algorithms

WFM-DOAS (WFMD)

- $\text{XCO}_2$ & $\text{XCH}_4$
- Focus on speed and data volume
- Tabulated RT
- Least squares fitting
- References:
  - Buchwitz et al., 2000, 2005
  - Heymann et al., 2012
  - Schneising et al., 2011, 2012, 2013

Details see ATBDs at http://www.esa-ghg-cci.org/

BESD

- $\text{XCO}_2$
- Focus on accuracy and precision
- Online RT
- Optimal estimation
- References:
  - Reuter et al., 2010, 2011
Measured radiation -> CO$_2$ emissions

Inversion-Models

„Retrieval“

„Inversion“

Forward-Models

Radiative-Transfer-Model

Transport-Chemistry-Model

Measured Radiation

Atmospheric CO$_2$ or CH$_4$

CO$_2$ or CH$_4$ Emissions

A

B

C
Inversion?

- **Different methods**
  - (Nearly all are) Based on „adjusting“ model parameters until model data „optimally“ agree with the observations
  - Requires sufficiently accurate and fast forward models
  - Often based on „Bayesian Inference“ or „Optimal Estimation“

**Thomas Bayes** [beɪz] (~1701 - 1761).
- English statistician, philosopher and Presbyterian minister.
- **Bayes‘ Theorem**: he suggested using this theorem to update beliefs considering new knowledge.

\[
P(X|Y) = \frac{P(Y|X)P(X)}{P(Y)}
\]

- \(P(X = \text{atmos.COO}_2 | Y = \text{radiation})\)
- \(P(X = \text{CO}_2 \text{ emission} | Y = \text{atmos.COO}_2)\)

To be minimized cost function (Optimal Estimation (Rodgers, 2000)):

\[
C(x) = (y^0 - y^m(x))^T S_y^{-1} (y^0 - y^m(x)) + (x - x_a)^T S_x^{-1} (x - x_a)
\]
$P(Y) = \sum_i P(Y|X_i) \times P(X_i)$

$$P(X = x_i | Y = y_j) = \frac{P(Y = y_j | X = x_i)P(X = x_i)}{\sum_i P(Y = y_j | X = x_i)P(X = x_i)}$$
Does God exist?

GOD AND REV. BAYES

Bayes' theorem (Thomas Bayes, d. 1761) provides a means for directly calculating the probability for a statement being true based on the available evidence. In a 2003 book *The Probability of God* (New York: Three Rivers Press), Stephen Unwin attempted to calculate the probability that God exists. Unwin's result: 67%. Physicist Larry Ford (private communication) has examined Unwin's calculation and made his own estimate using the same formula. Ford's result: $10^{-17}$. In what follows I present Ford's nicely concise analysis, slightly modified.

http://www.colorado.edu/philosophy/vstenger/Briefs/Bayes.pdf
Bayesian inference: Example: Monty Hall problem

A priori probabilities to win the car:
p(C=i):

<table>
<thead>
<tr>
<th>Door</th>
<th>p(C=1)</th>
<th>p(C=2)</th>
<th>p(C=3)</th>
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<tbody>
<tr>
<td>1</td>
<td>1/3</td>
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<td>1/3</td>
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<td>3</td>
<td></td>
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<td>1/3</td>
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3 closed doors
1 car
2 goats

Choose one of the doors.
If you pick the right one, the car is yours.

What is the probability to win the car?
Bayesian inference: Example: Monty Hall problem

1

2

3

\[ p(C=1) = \]
\[ p(\text{stay}) = \frac{1}{3} \]
Bayesian inference: Example: Monty Hall problem

$p(C=1) = p(\text{stay}) = 1/3$

I will now open one of the two remaining doors
Bayesian inference: Example: Monty Hall problem

1

2

3

p(C=1) = p(stay) = 1/3

Stay or switch?

p(C=2) = p(switch) = ???

Stay or switch?
Bayesian inference: Example: Monty Hall problem

\[ p(C=1) = p(\text{stay}) = \frac{1}{3} \]

\[ p(C=2 \mid \text{???}) = \]
Bayesian inference: Example: Monty Hall problem

What is the probability that the car is behind door 2 (C=2) given that door 3 (D=3) has been opended?

\[
p(C=2 | D=3) = \frac{p(D=3 | C=2) \times p(C=2)}{p(D=3 | C=1) \times p(C=1) + p(D=3 | C=2) \times p(C=2) + p(D=3 | C=3) \times p(C=3)}
\]

\[
p(C=1) = p(\text{stay}) = \frac{1}{3}
\]

Probability that door 3 has been opended (D=3) given that the car is behind door 2 (C=2)
Bayesian inference: Example: Monty Hall problem

\[ p(C=1) = \frac{1}{3} \]
\[ p(\text{stay}) = \frac{1}{3} \]
\[ p(\text{switch}) = \frac{2}{3} \]

So you better switch as this doubles your chance to win the car.

Except if you want a goat …
Retrieval: Optimal Estimation (Rodgers, 2000)

High-resolution radiance

\[ I_{\lambda}^{\text{mono}}(x) \overset{\text{def}}{=} \pi L_{\lambda}(x)/F_{\lambda} \]

Radiance @ instrument resolution

\[ < I_{\lambda}^{\text{mono}}(x) >_{\lambda} \overset{\text{def}}{=} I(x) \overset{\text{def}}{=} \pi < L_{\lambda}(x) > / < F_{\lambda} > \]

Linearized model:

\[ \ln(I(x)) \approx \ln(I(x_a)) + \frac{\partial}{\partial x} \ln(I(x))|_{x=x_a} (x-x_a) \]

\[ y^{\text{mod}}(x) = y_a + K(x-x_a) \]

\[ y_a \overset{\text{def}}{=} y^{\text{mod}}(x_a) \]

Jacobian matrix \( K \):

rel./abs.

\[ K_{ij} \overset{\text{def}}{=} \frac{\partial y_i}{\partial x_j} = \frac{\partial \ln(I(x_j))}{\partial x_j} \approx \frac{\Delta I/I}{\Delta x_j} \rightarrow \Delta \hat{x}_j = x_j - x_{aj} \]

rel./rel.

\[ K_{ij} \overset{\text{def}}{=} \frac{\partial y_i}{\partial \ln(x_j)} = \frac{\partial \ln(I(x_j))}{\partial \ln(x_j)} \approx \frac{\Delta I/I}{\Delta x_j/x_j} \rightarrow \Delta \hat{x}_j = (x_j - x_{aj})/x_{aj} \]

Cost function:

\[ C(x) = (y - y^{\text{mod}}(x))^T S_y^{-1}(y - y^{\text{mod}}(x)) + (x - x_a)^T S_{xa}^{-1}(x - x_a) \]

Solution: Linear problem

\[ \hat{x} = x_a + G_y (y - y_a) \]

\[ G_y = \frac{d\hat{x}}{dy} = \hat{S} x K^T S_y^{-1} \]

\[ \hat{S}_x = \frac{d\hat{x}}{dy} = (K^T S_y^{-1} K + S_{xa}^{-1})^{-1} \]

Non-linear problem

\[ x_{i+1} = x_i + \hat{S}_x [K_i^T S_y^{-1} (y - y^{\text{mod}}(x_i)) - S_{xa}^{-1}(x_i - x_a)] \]
CarbonSat: BESD/C algorithm

**Measured spectra:**
radiance & solar irradiance (L1 product)

**Auxiliary data:**
e.g., interpolated met. data

**Absorption line parameters / cross-sections / coefficient tables**

**Other Auxiliary data:**
e.g., surface topography

**Pre-screening**

**XCO₂ & XCH₄ retrieval**

**Quality filtering**

**Bias correction**

**Product file generation**

**Level 2 product**

Via pre-processing:
- Surface albedo
- VCF / SIF @ 755 nm
- Cirrus Optical Depth (COD)

**Construct a priori state vector xₐ and covariance matrix**

**Forward model**
y = F(x,b)

**Inverse model:**
Minimize C(x, xₐ, ...)

**XCO₂ & XCH₄ calculation, error analysis**
SCIAMACHY / BESD: Example fit

RMS: 8.74e−01%

RMS: 6.44e−01%

Reuter et al., JGR 2011
Jacobian matrix (K): Example

CarbonSat BESD/C Jacobian Matrix

Columns of K

State vector index [-]

NIR 0 500 1000 1500 2000 SWIR-1 SWIR-2

Spectral index [-]

Wavelength

Details: Buchwitz et al., AMT, 2013
Jacobian matrix (K): Example

CarbonSat BESD/C Jacobian Matrix

Columns of K

State vector index [-]

Wavelength

Details: Buchwitz et al., AMT, 2013
Jacobian matrix (K): Example

Details: Buchwitz et al., AMT, 2013
Jacobian matrix (K): Example

CarbonSat BESD/C Jacobian Matrix

Columns of K

State vector index [-]

Wavelength

Spectral index [-]

Zoom into Water Vapor Jacobian

Details: Buchwitz et al., AMT, 2013
Jacobian matrix (K): Example

Details: Buchwitz et al., AMT, 2013

Columns of K

State vector index [-]

Wavelength

CarbonSat BESD/C Jacobian Matrix

Zoom into Albedo NIR Jacobian

Spectral index [-]

NIR

0

10

20

30

0

500

1000

1500

2000

SWR-1

SWR-2

Wavelength

SWR-1

SWR-2

Details: Buchwitz et al., AMT, 2013
One could say much more ...

Retrieval algorithms:

• DOAS (WFM-DOAS, IMAP-DOAS, ...), ...

• Full Physics (FP) versus Proxy (PR), ...

Modelling & inverse modelling:

• ...

Other topics:

• ...
Satellite XCO\textsubscript{2} retrieval algorithms …

From „First ever“ to „recent“

Buchwitz et al., 2000
JOURNAL OF GEOPHYSICAL RESEARCH, VOL. 105, NO. D12, PAGES 15,231–15,245, JUNE 27, 2000
WFMD
A near-infrared optimized DOAS method for the fast global retrieval of atmospheric CH\textsubscript{4}, CO, CO\textsubscript{2}, H\textsubscript{2}O, and N\textsubscript{2}O total column amounts from SCIAMACHY
Envisat-1 nadir radiance
Michael Buchwitz, Vladimir V. Rozanov, and John P. Burrows
Institut für Fernerkundung, Universität Bremen, Bremen, Germany

Bovensmann et al., 2010
Remote sensing technique for global monitoring of power plant CO\textsubscript{2} emissions from space and related applications
E. Bovensmann, M. Buchwitz, J. P. Burrows, M. Reuter, J. Kipfer, K. Guderian, O. Schneising, J. Herman
Remote Sensing Group, Institute for Environmental Physics, University of Bremen, D-28359 Bremen, Germany

Reuter et al., 2010, 2011
A method for improved SCIAMACHY CO\textsubscript{2} retrieval in the presence of optically thin clouds
M. Reuter, M. Buchwitz, O. Schneising, J. Herman, R. Buchwitz, and J. P. Burrows
University of Bremen, Institute of Environmental Physics, PO. Box 200368, 28334 Bremen, Germany

Oschepkov et al., 2008
PPDF-based method to account for atmospheric light scattering in observations of carbon dioxide from SCIAMACHY
J. Schneising, V. Tokev, D. Stamm, and L. Oeschger
Laboratory for Climate and Environmental Physics, University of Bern, Bern 3032, Switzerland

Butz et al., 2011
Remote-C
Towards accurate CO\textsubscript{2} and CH\textsubscript{4} observations from GOSAT
Geophysical Laboratory, NASA, Washington, DC 20019, USA

Buchwitz et al., 2013
WFMD
Remote-C
Carbon Monitoring Satellite (CarbonSat): assessment of atmospheric CO\textsubscript{2} and CH\textsubscript{4} retrieval errors by error parameterization

O’Dell et al., 2012
ACOS
The ACOS CO\textsubscript{2} retrieval algorithm – Part 1: Description and validation against synthetic observations

WFMD
Remote-C
Terrestrial carbon sink observed from space: variation of growth rates and seasonal cycle amplitudes in response to interannual surface temperature variability
O. Schneising, M. Reuter, M. Buchwitz, J. Herman, and J. P. Burrows
Institute of Environmental Physics, University of Bremen, D-28359 Bremen, Germany

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Atmospheric methane and carbon dioxide from SCIAMACHY satellite data: initial comparison with chemistry and transport models

M. Buchwitz¹, R. de Beek², J. P. Burrows¹, H. Bovensmann¹, T. Warnke², J. Notholt², J. F. Meinhardt², A. P. He­ods², F. Bergamaschi¹, S. Körner¹, M. Reimann¹, and A. Uehle²

From „First ever“ to „recent“
Many thanks for your attention!