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Vertical Distribution of Arctic Methane from Ground-based FTS Measurements

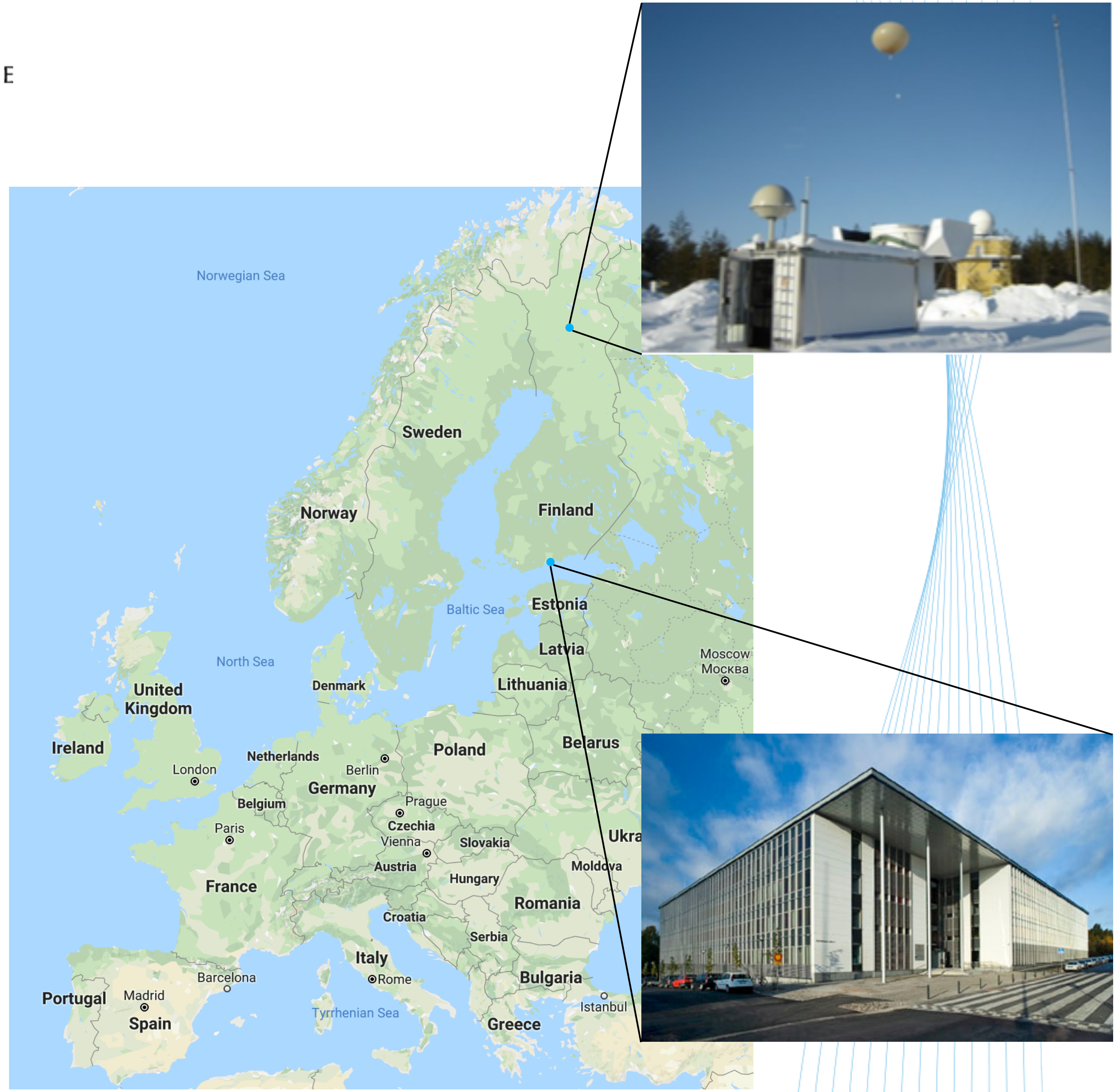
Otto Lamminpää, T. Karppinen, S. Tukiainen, M. Laine, J. Tamminen

14th IWGGMS, Toronto
May 8th 2018

Introduction

Finnish Meteorological Institute
-Sodankylä & Helsinki

Greenhouse Gases and Satellite Methods group



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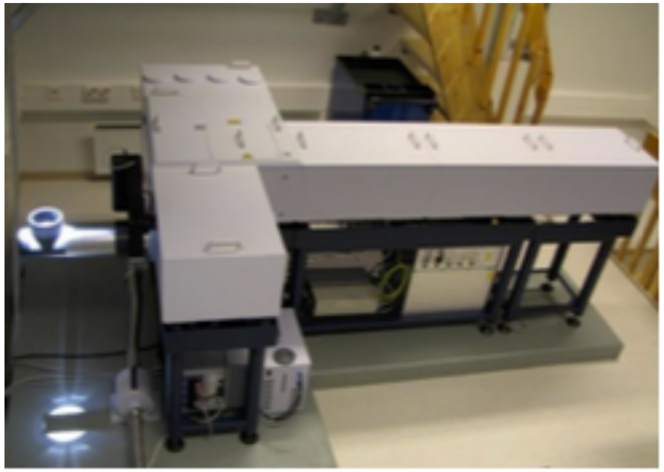
Introduction: Sodankylä Arctic Research Centre

- Fourier transform infrared spectrometer (FTS): measurement of absorption spectra, part of TCCON network. Our focus: measured **CH_4 [1]**
- AirCore balloon sounding: collects gas samples for up to 30km, used as ”ground truth” to validate the retrievals **[2]**



FTIR-spectrometer

AirCore balloon sounding

Introduction: FTS measurement

FTS measurement is modeled with Beer-Lambert law:

$$I(\lambda) = I_0(\lambda) \exp\left(-\sum_i^N \int_l \sigma_i(l) x_i(l) dl\right) (a\lambda^2 + b\lambda + c) + \text{offset}$$

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where for each trace gas *i:*

$I(\lambda)$ is the intensity of measured light at given wavelength

σ_i are the absorption coefficients

x_i are the unknown trace gas densities

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The inverse problem

Consider the non-linear *inverse problem*

$$y = F(x) + \varepsilon$$

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Statistical approach:

- view all parameters as random variables
- use Bayes' Formula to find the posterior distribution of the unknown x:

$$\pi(x|y) \propto \pi_{\varepsilon}(y|x)\pi_{pr}(x)$$

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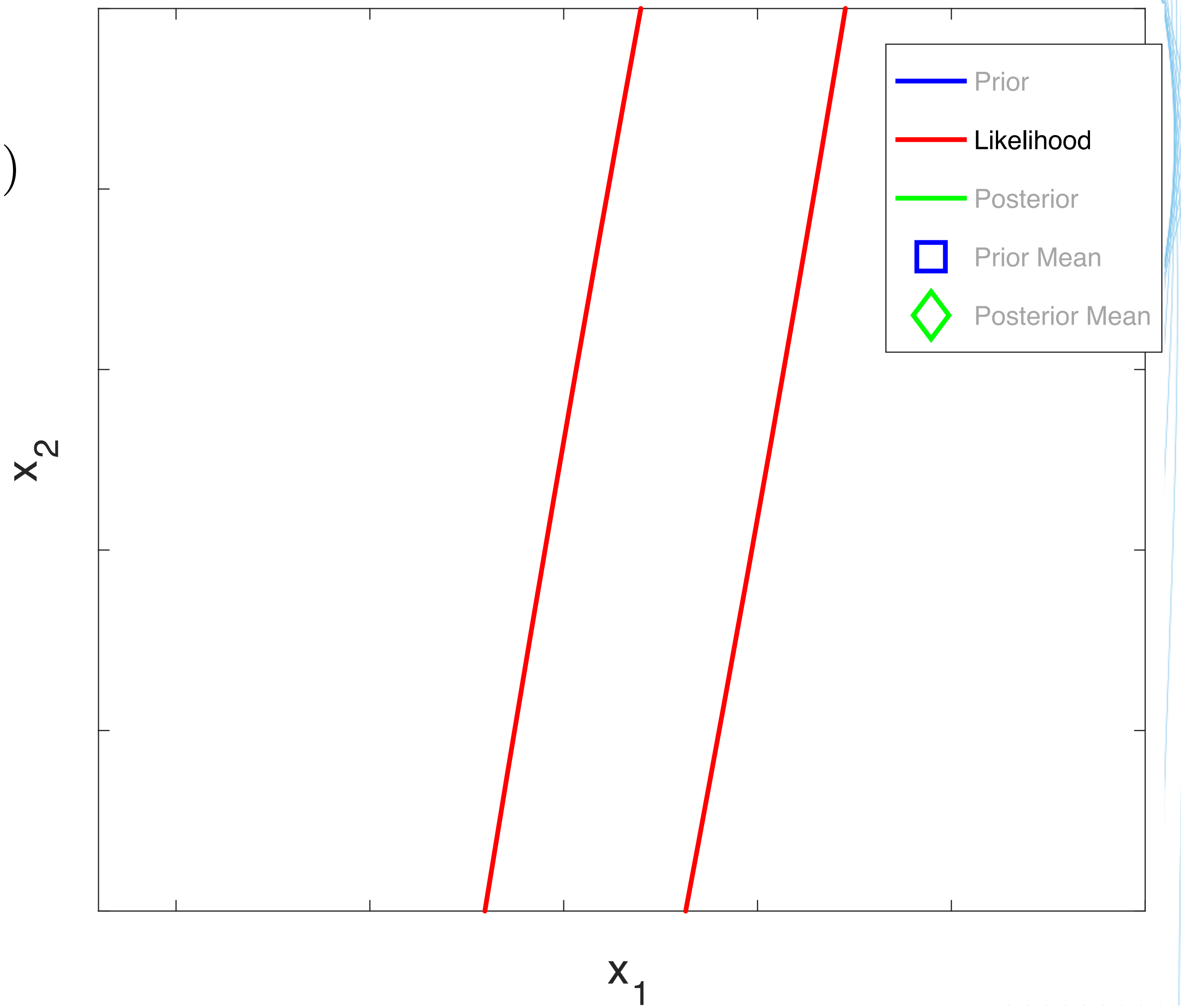
Assume: Gaussian prior and likelihood:

$$x_{pr} \sim \mathcal{N}(x_o, L_x^T L_x), \quad \varepsilon \sim \mathcal{N}(0, L_{\varepsilon}^T L_{\varepsilon})$$

2D Example Posterior

$$\pi_\varepsilon(y|x)$$

$$\varepsilon \sim \mathcal{N}(0, L_\varepsilon^T L_\varepsilon)$$



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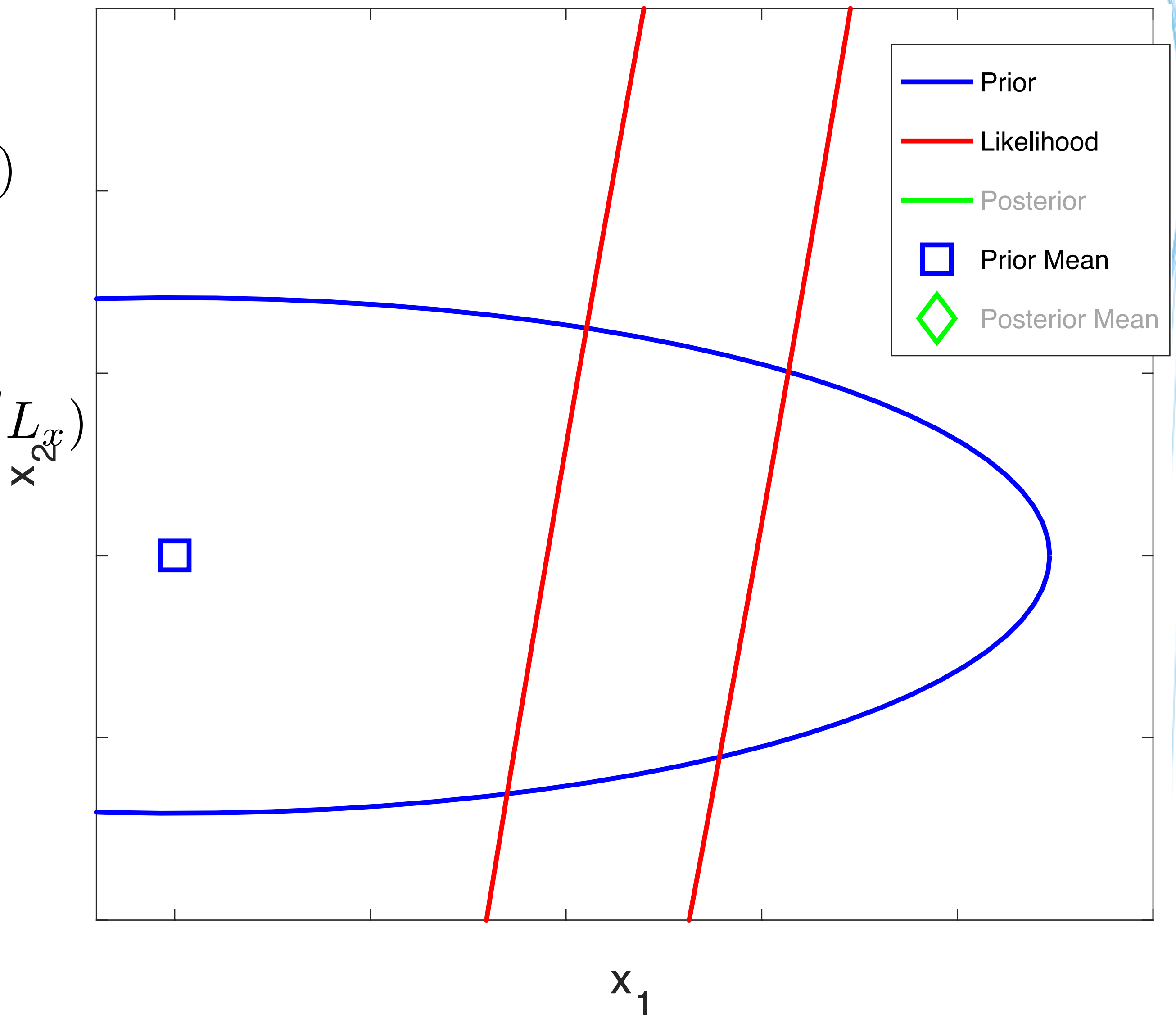

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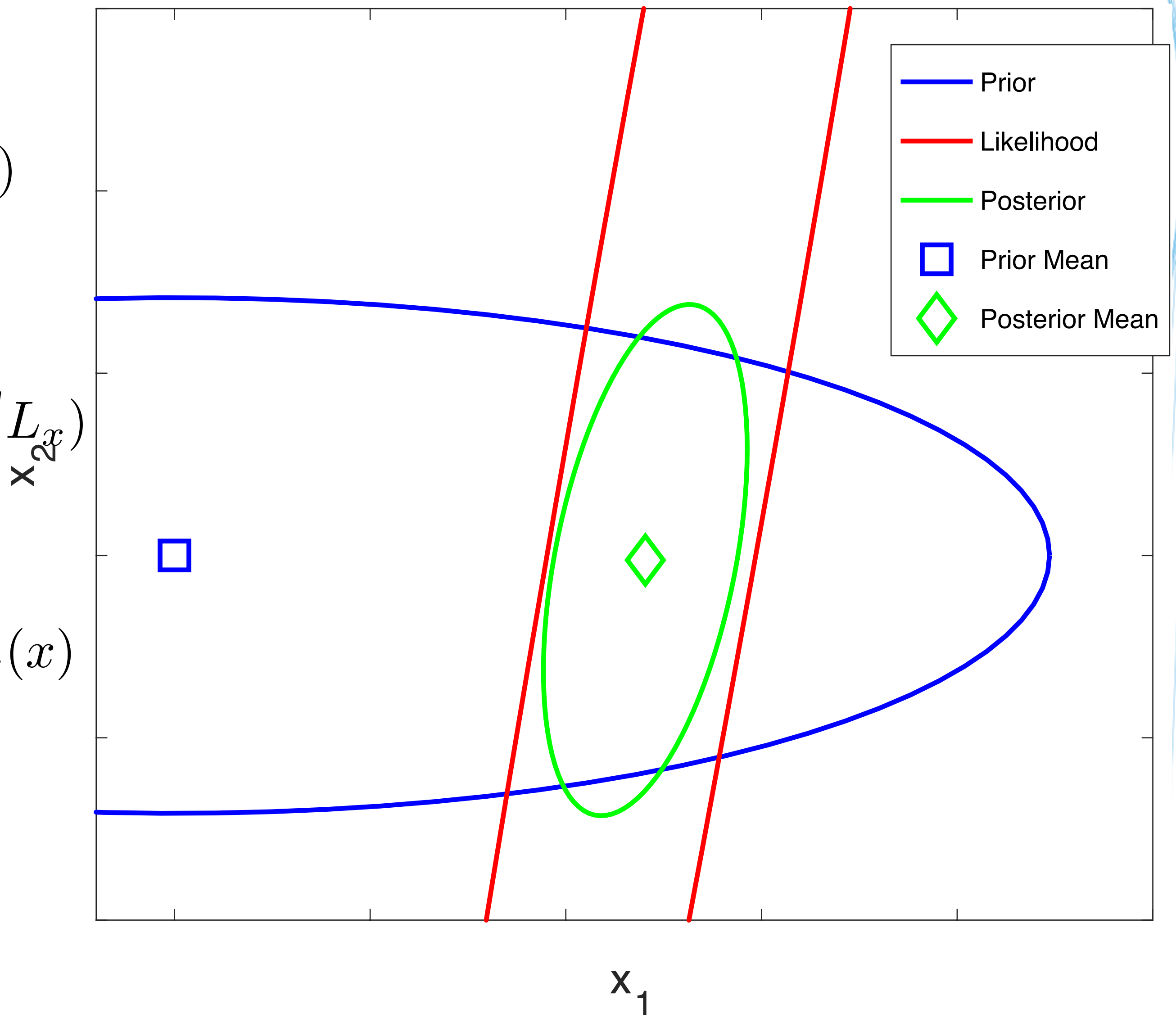

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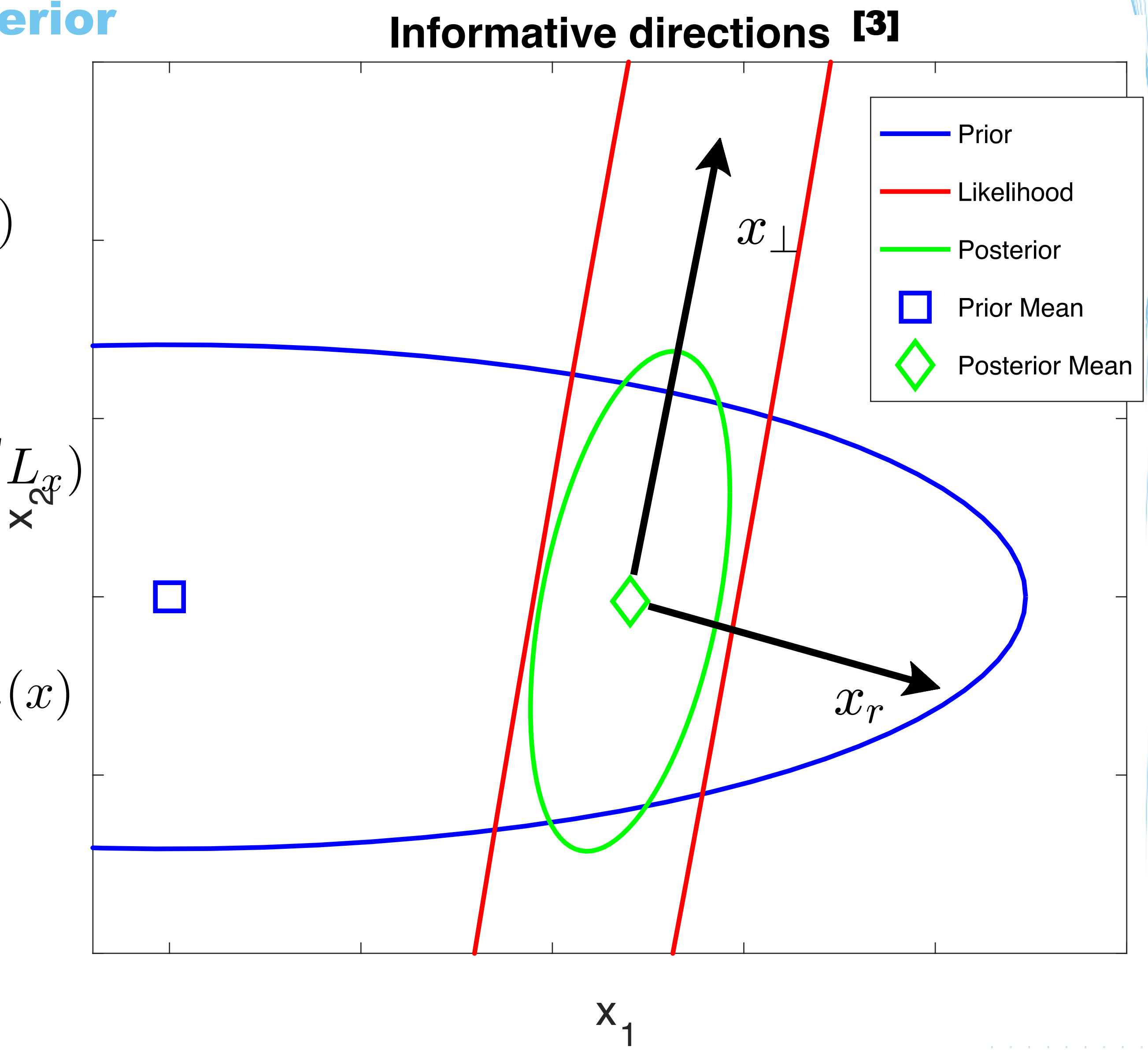

Likelihood-Informed (LIS) Dimension Reduction

Following T. Cui & al. **[4]** we use SVD $\widetilde{J}\widetilde{J}^T = U \Lambda V^T$ and define matrices

$$\Phi_r = L_x V_{1:r}, \quad \Phi_\perp = L_x V_{r+1:N},$$

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The approximate posterior can now be written as

$$\widetilde{\pi}(x|y) \propto \pi(y|\Phi_r x_r)\pi_r(x_r)\pi_\perp(x_\perp)$$

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Profile retrieval

- Solution by Optimal Estimation (OE): Maximum A Posteriori estimate by

$$x_{MAP} = \arg\min_{x \in \mathbb{R}^n} \left\{ \|y - F(x)\|_{\varepsilon}^2 + \|x - x_0\|_{pr}^2 \right\}$$

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- Uncertainty Quantification using Adaptive Markov Chain Monte Carlo (MCMC) **[5]**, significant computational gains with LIS **[6]**

SWIRLAB

Freely available MATLAB toolbox by Simo Tukiainen (FMI) **[7]**

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- Radiative transfer forward model for FTS retrieval
- Effects from scattering and aerosols assumed negligible
- Absorption coefficients calculated using HITRAN2012
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- Retrieval using LIS dimension reduction: OE & MCMC

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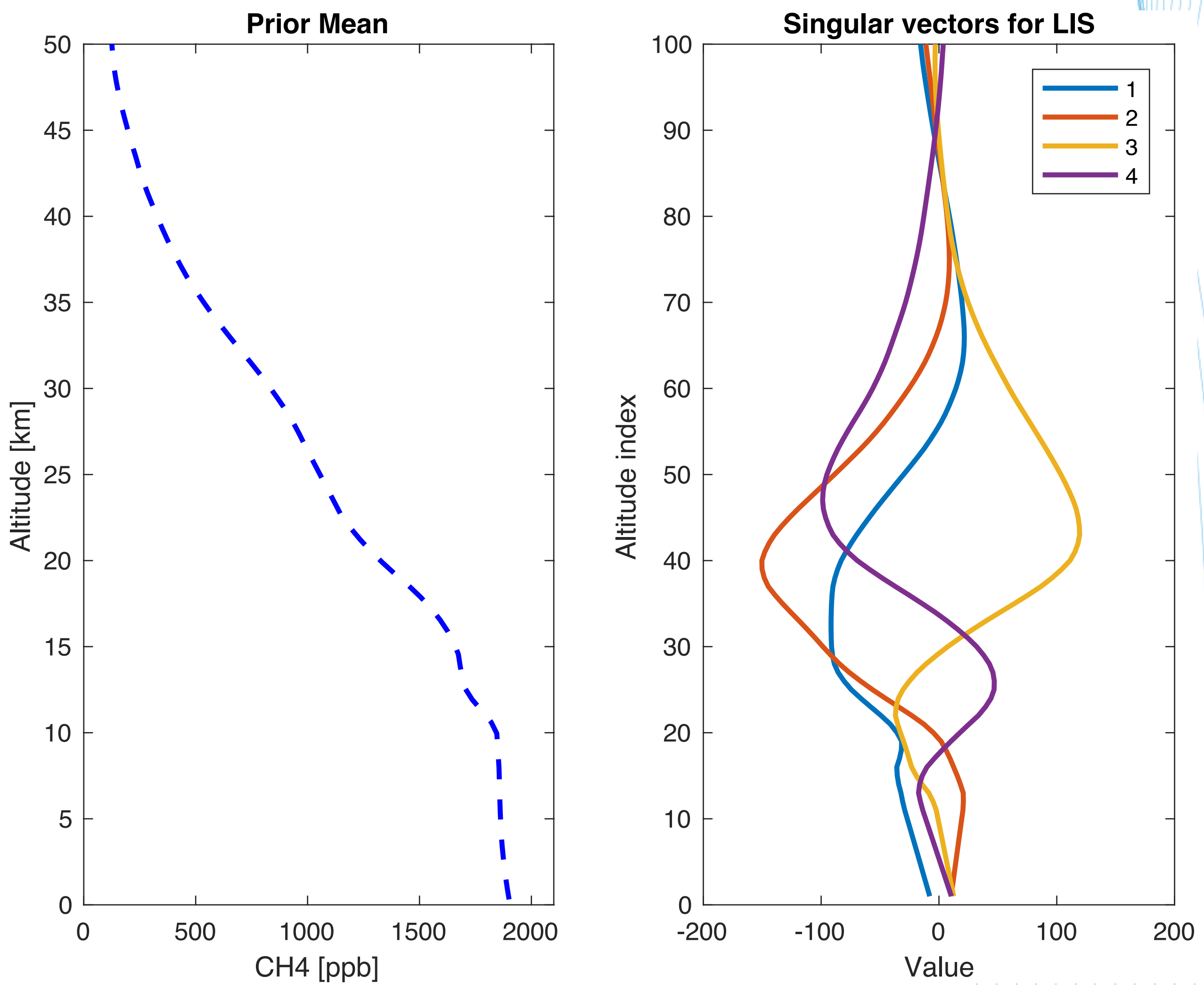
SWIRLAB profile retrieval

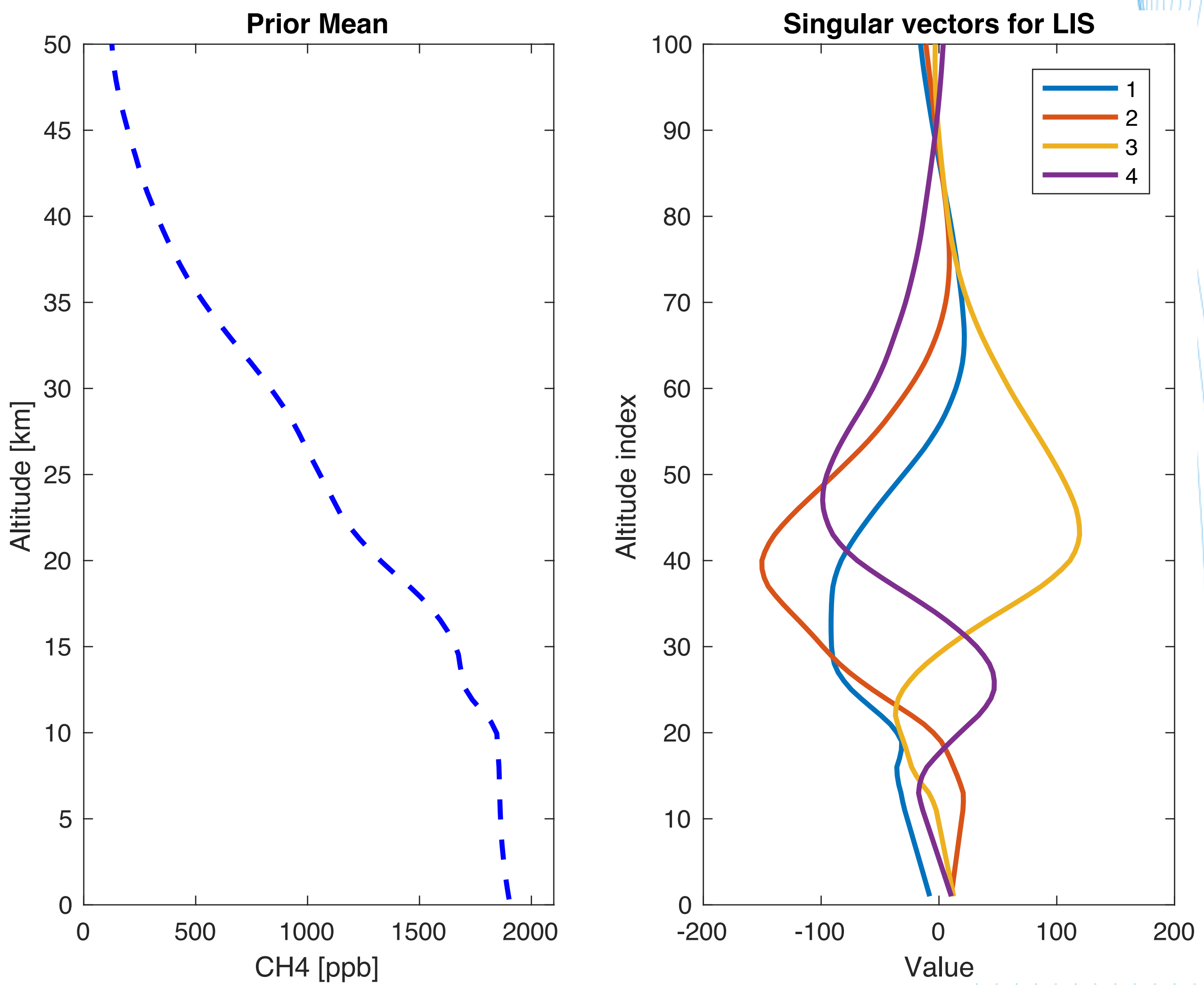
- Optimal Estimation based fast retrieval algorithm for the FTS problem



SWIRLAB profile retrieval

- Optimal Estimation based fast retrieval algorithm for the FTS problem

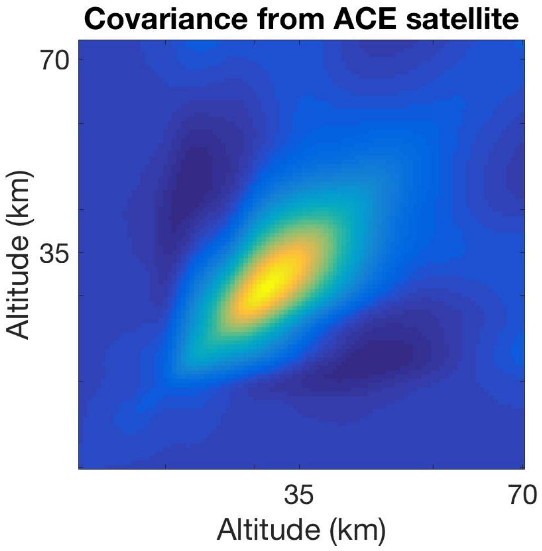
- Motivation: currently, operational retrieval only has 1 degree of freedom: scaling the prior mean

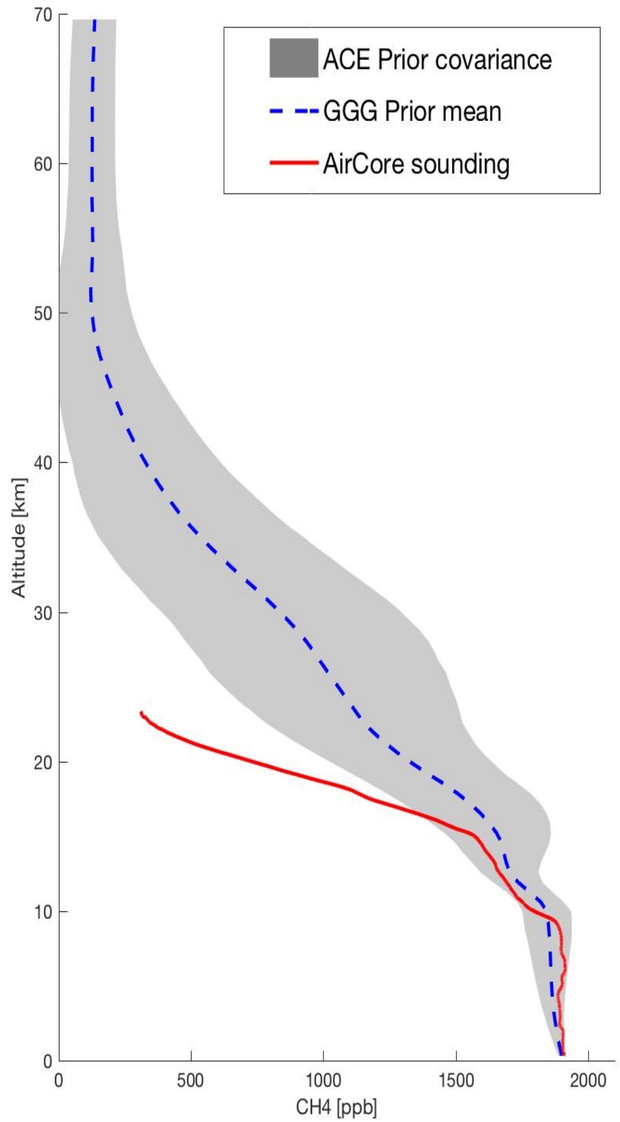


SWIRLAB Prior

Multivariate Gaussian:

<u>Covariance:</u> derived from an ensemble of ACE-FTS satellite measurements.





SWIRLAB Prior

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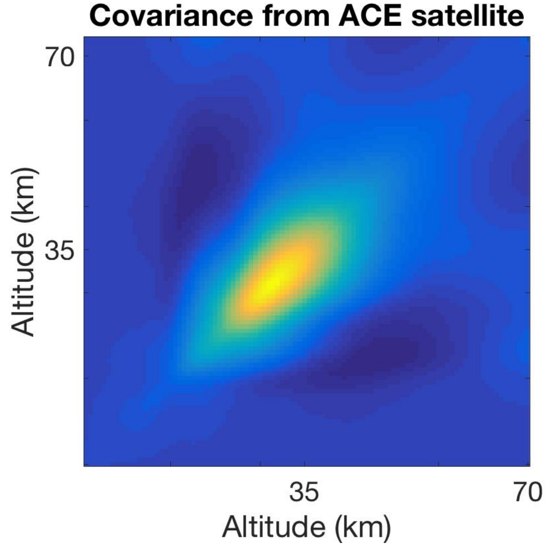
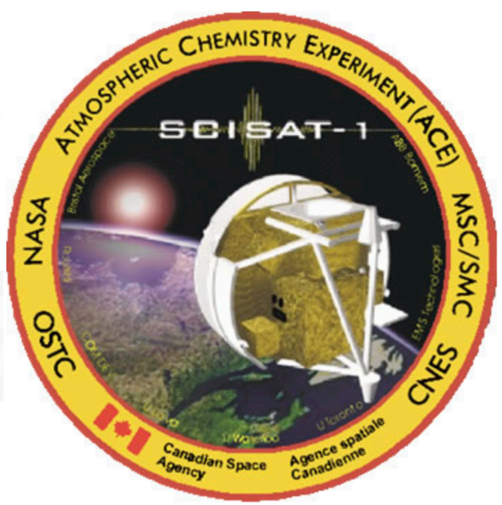
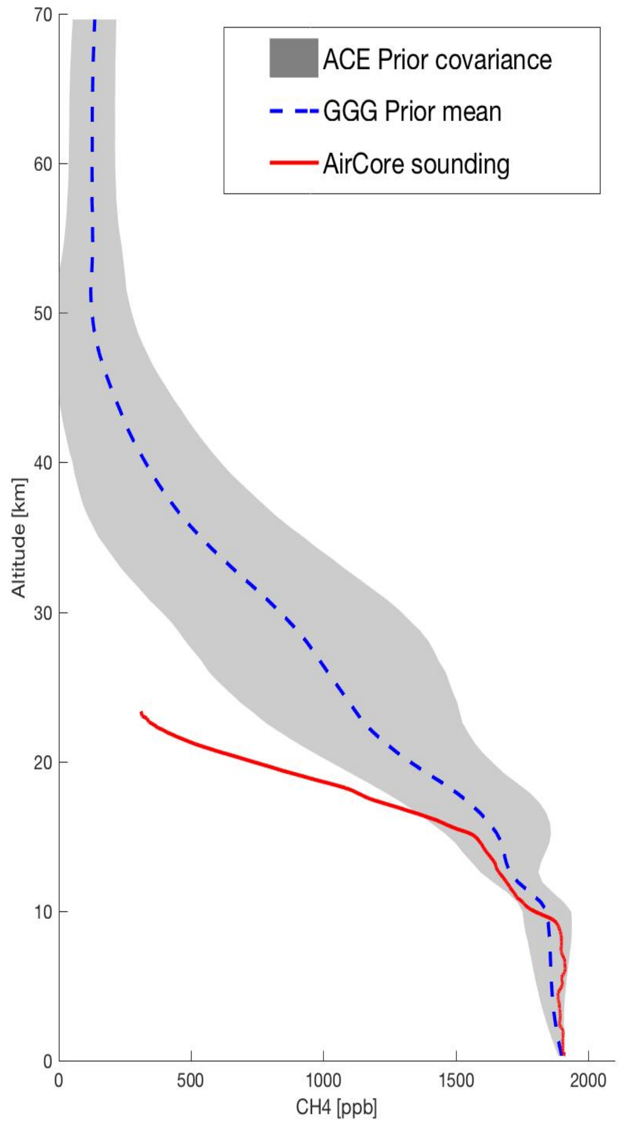
<u>Covariance:</u> derived from an ensemble of ACE-FTS satellite measurements.

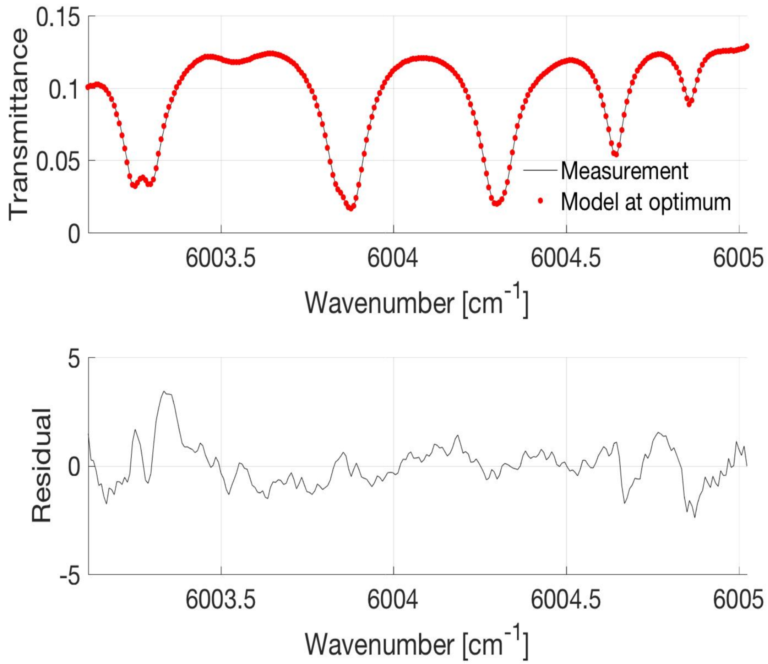
<u>Mean:</u>
- Lower part from GGG2014
- Upper part from ACE-FTS

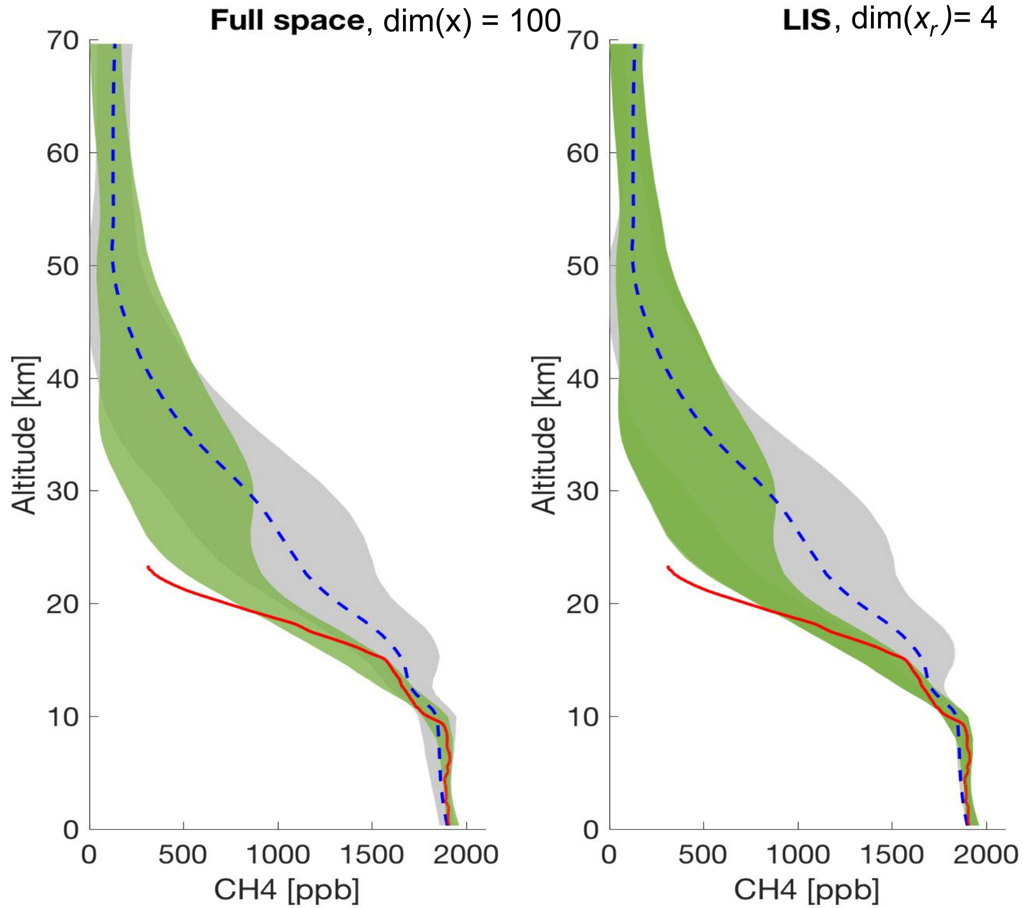






MCMC results





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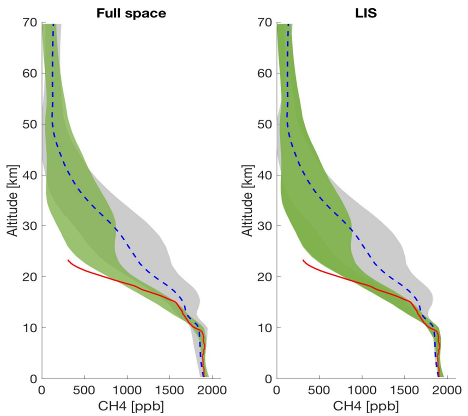
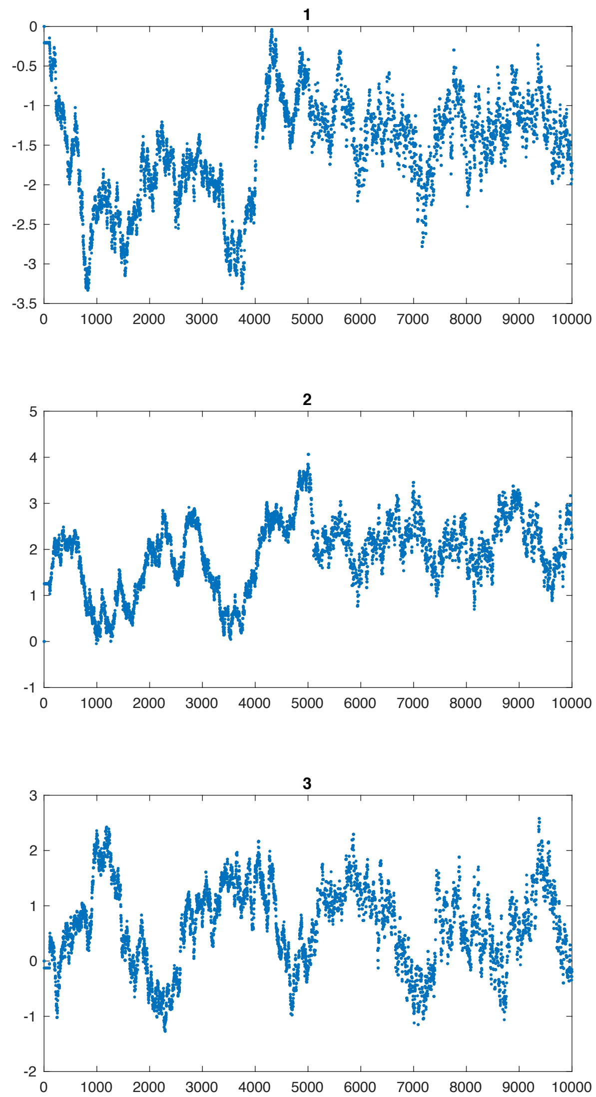
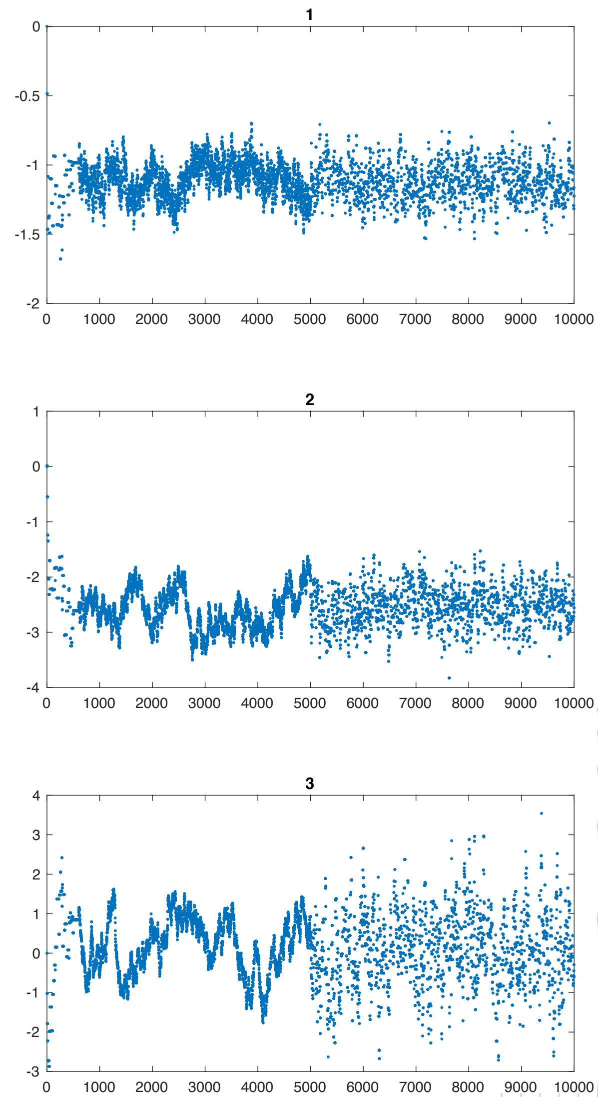


$$\mathbb{V}(\text{full}) = 1,56$$

$$\mathbb{V}(\text{LIS}) = 19,01$$



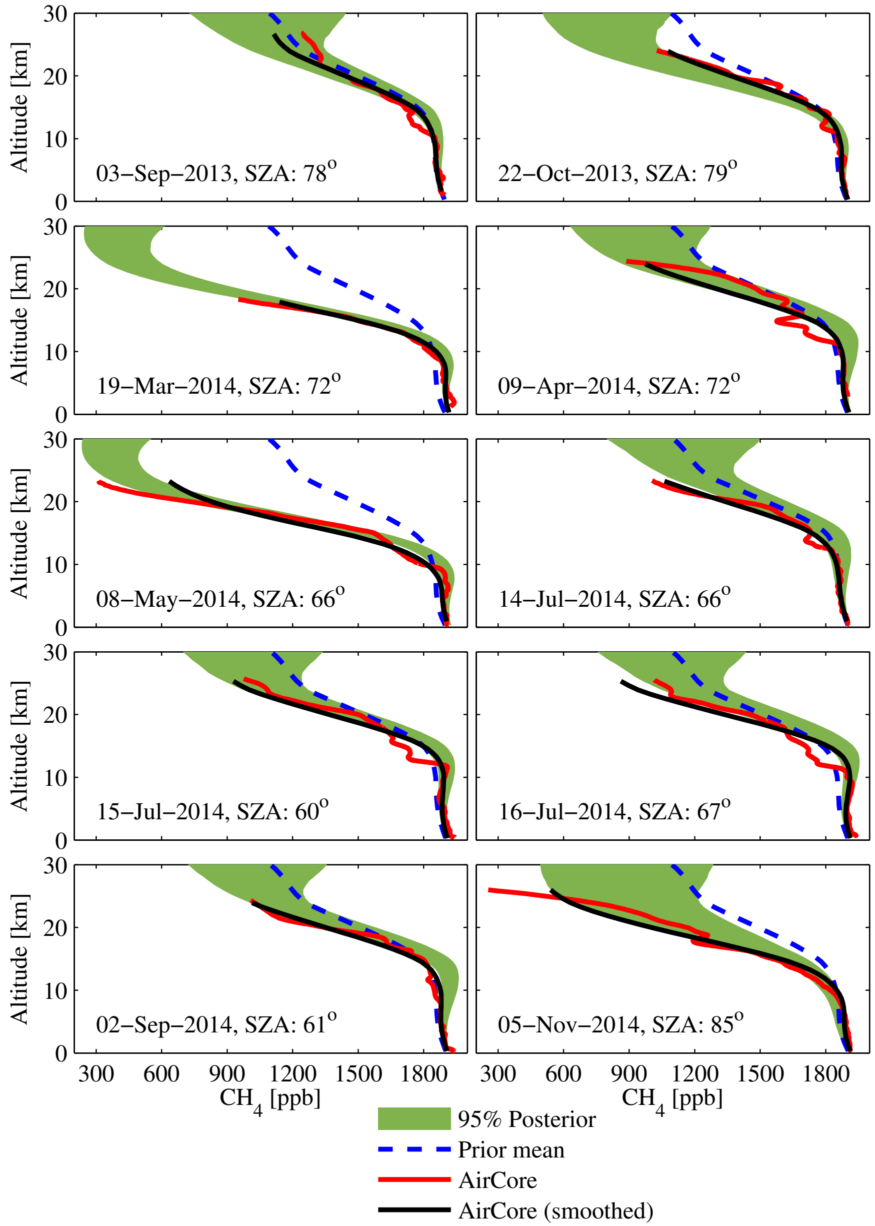
Full space, dim = 100



LIS, dim = 4

MCMC results

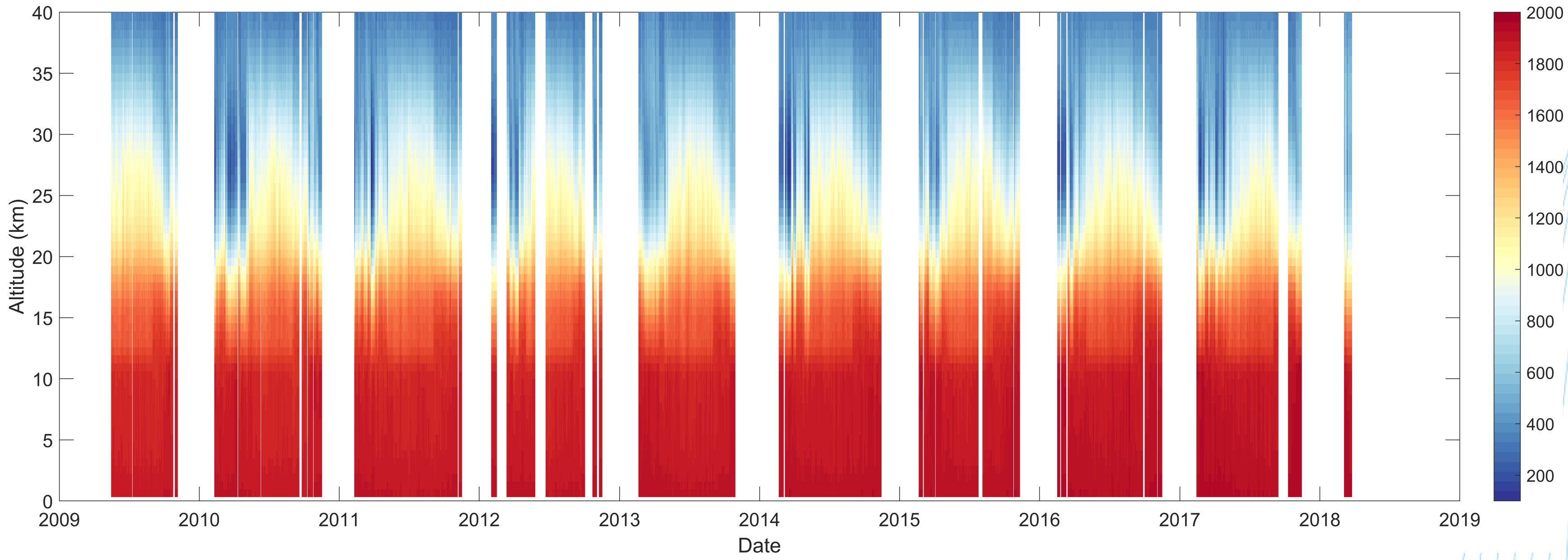
Retrievals for several measurements:



Retrieval of time series: 2009-2017

Preliminary results: vertical information on CH_4

- allows time series analysis on different altitudes



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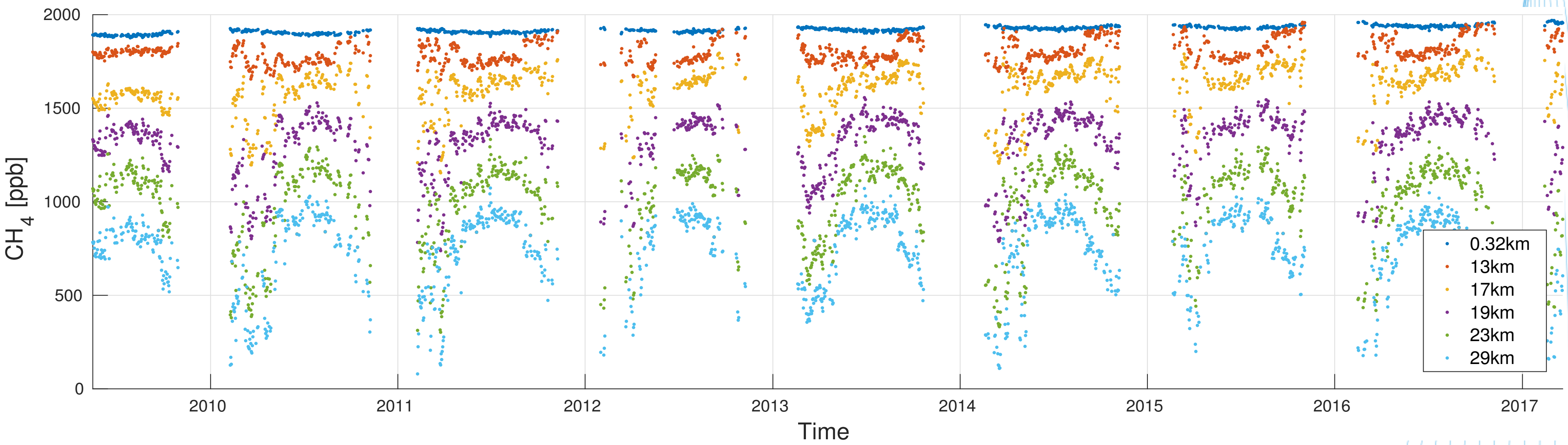

Dynamic Linear Model (DLM)

Smooth regression tool for time series analysis, MATLAB toolbox by Marko Laine **[8]**

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- Hierarchial statistical model for uncertainties in data, process and parameters

$$y_t = F_t x_t + v_t \qquad v_t \sim N(0, V_t)$$
$$x_t = G_t x_{t-1} + w_t \quad w_t \sim N(0, W_t)$$

y_t : observations
x_t : hidden model states
F_t : observation operator
G_t: model operator
v_t : observation uncertainty
w_t: model uncertainty

- Can be used to extract trend, seasonal component etc.

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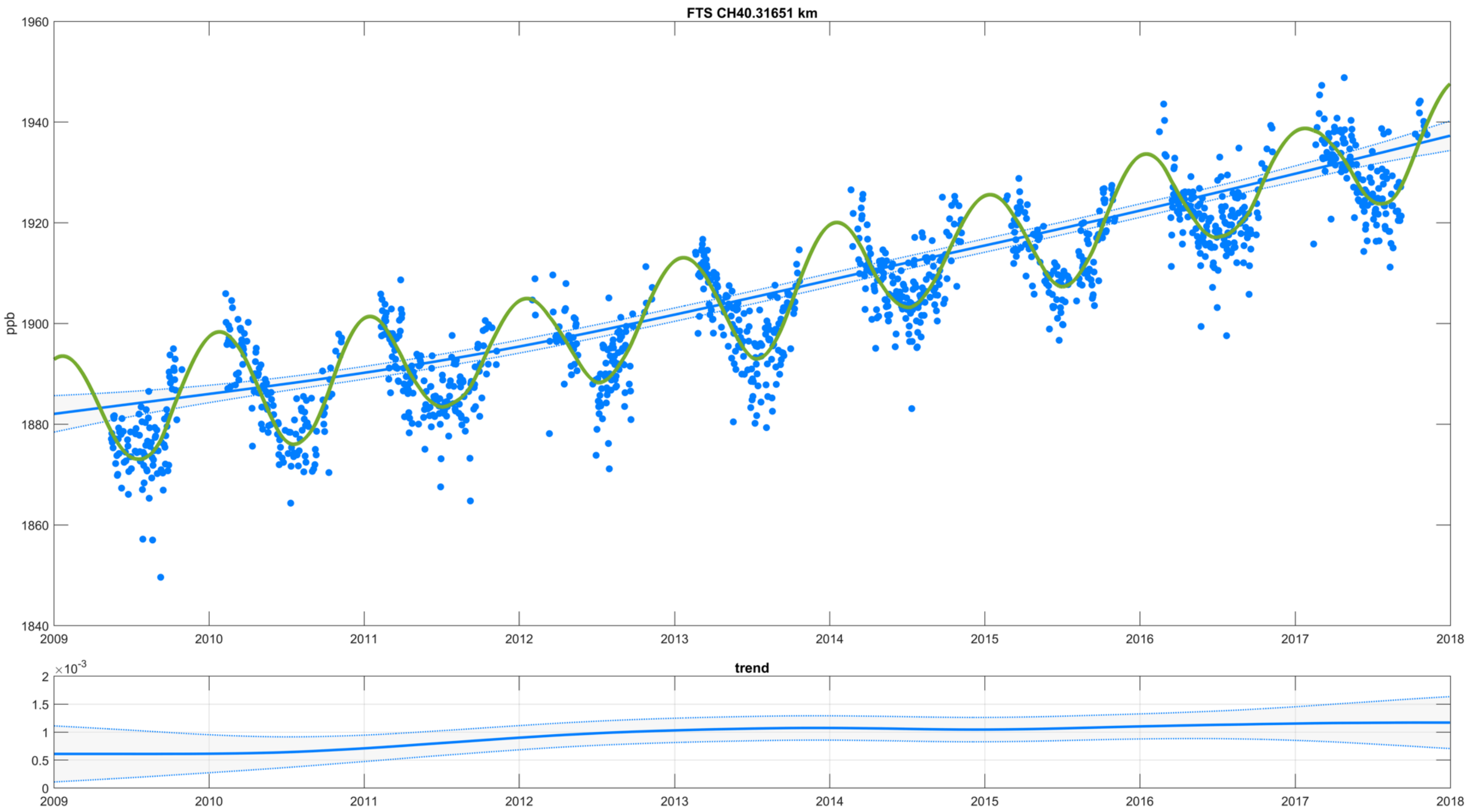
DLM fit: FTS (0.3km)



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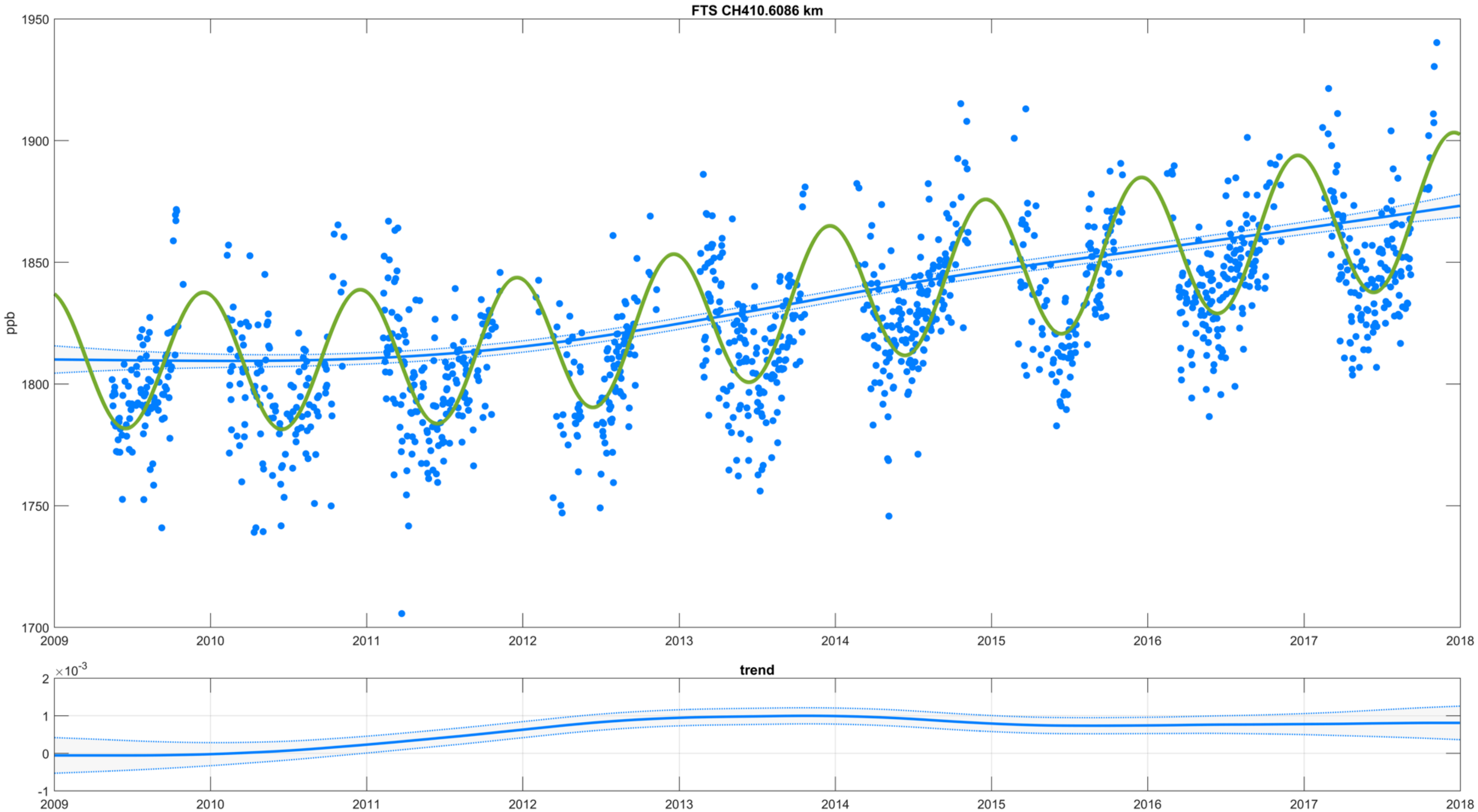
DLM fit: FTS (10km)



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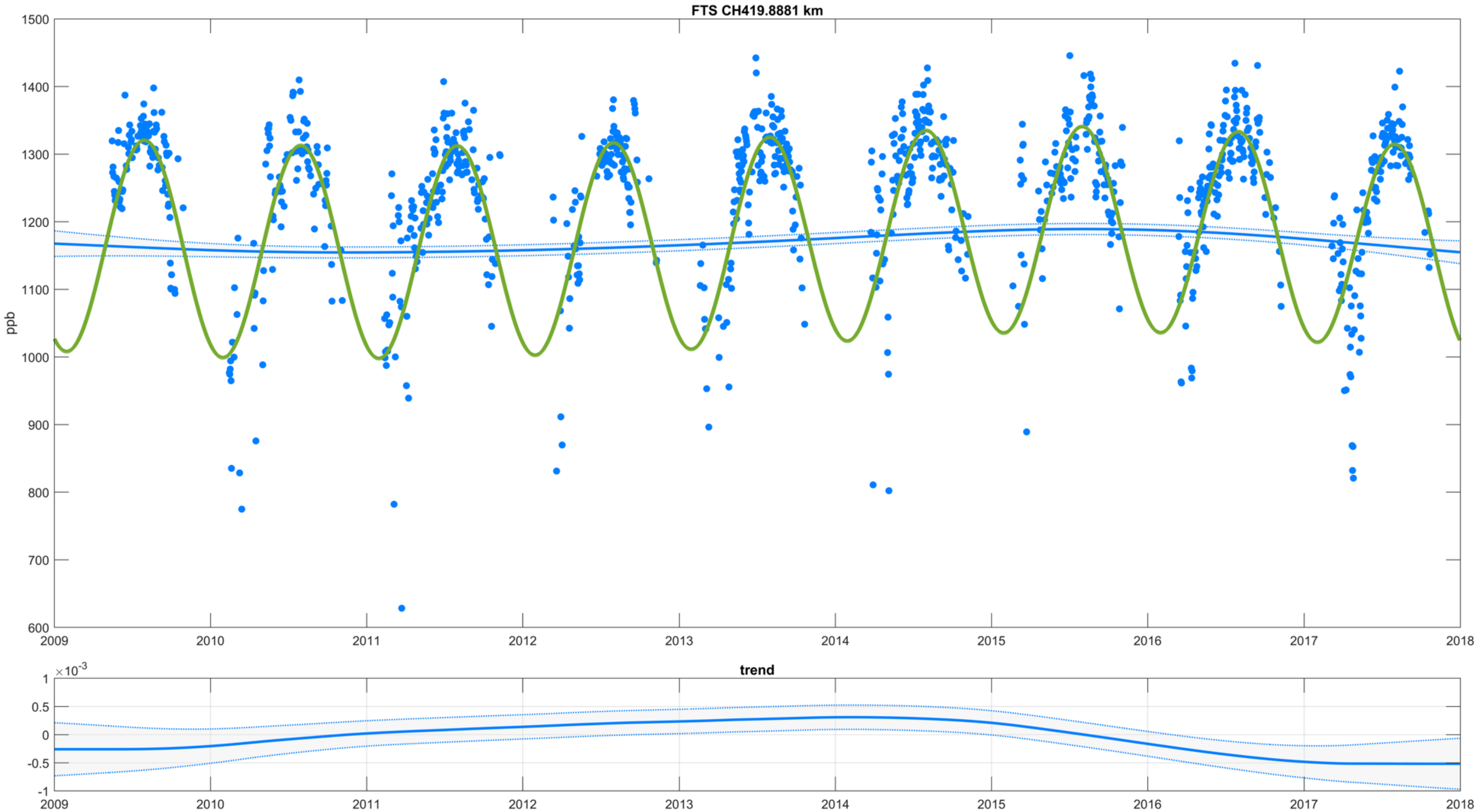
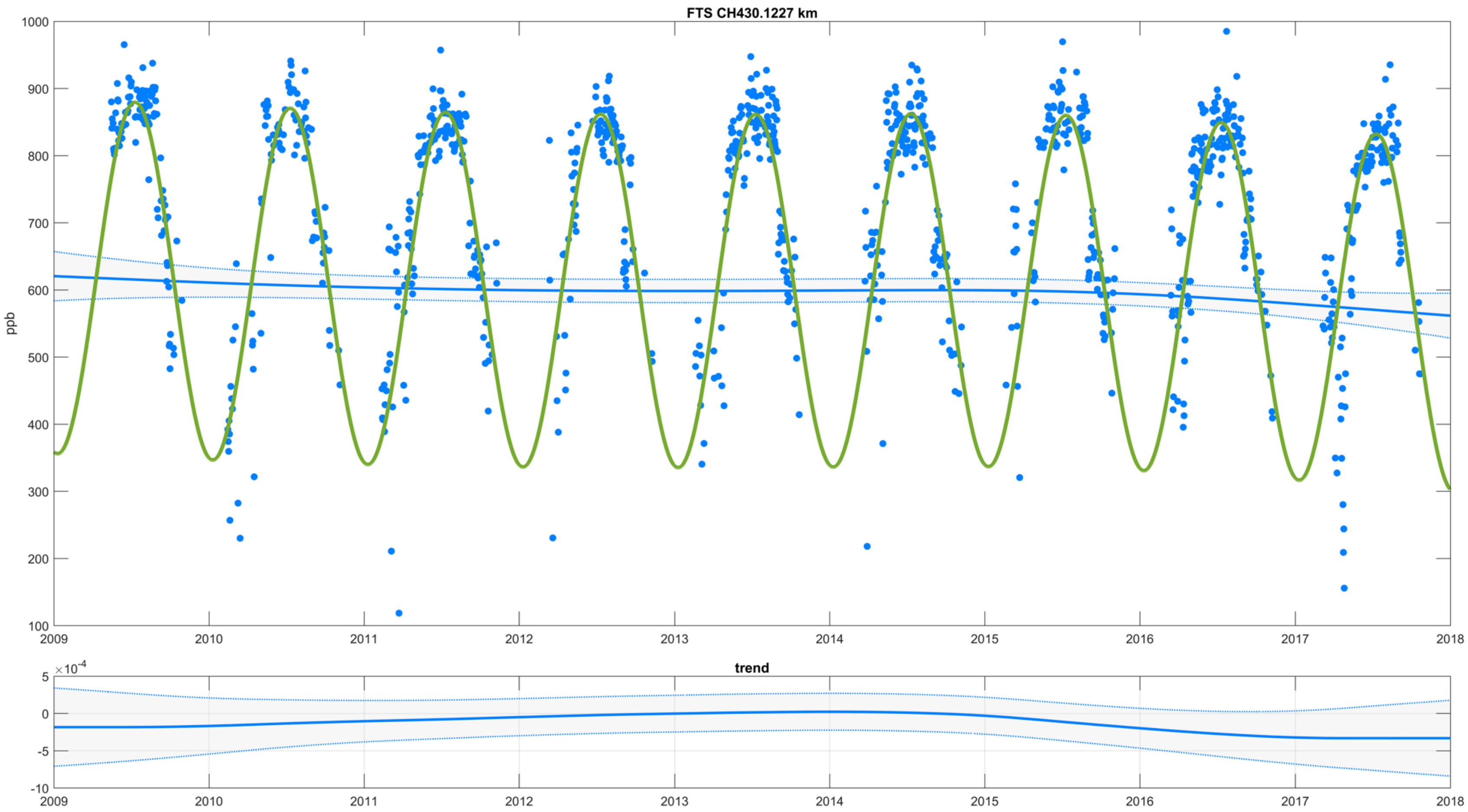
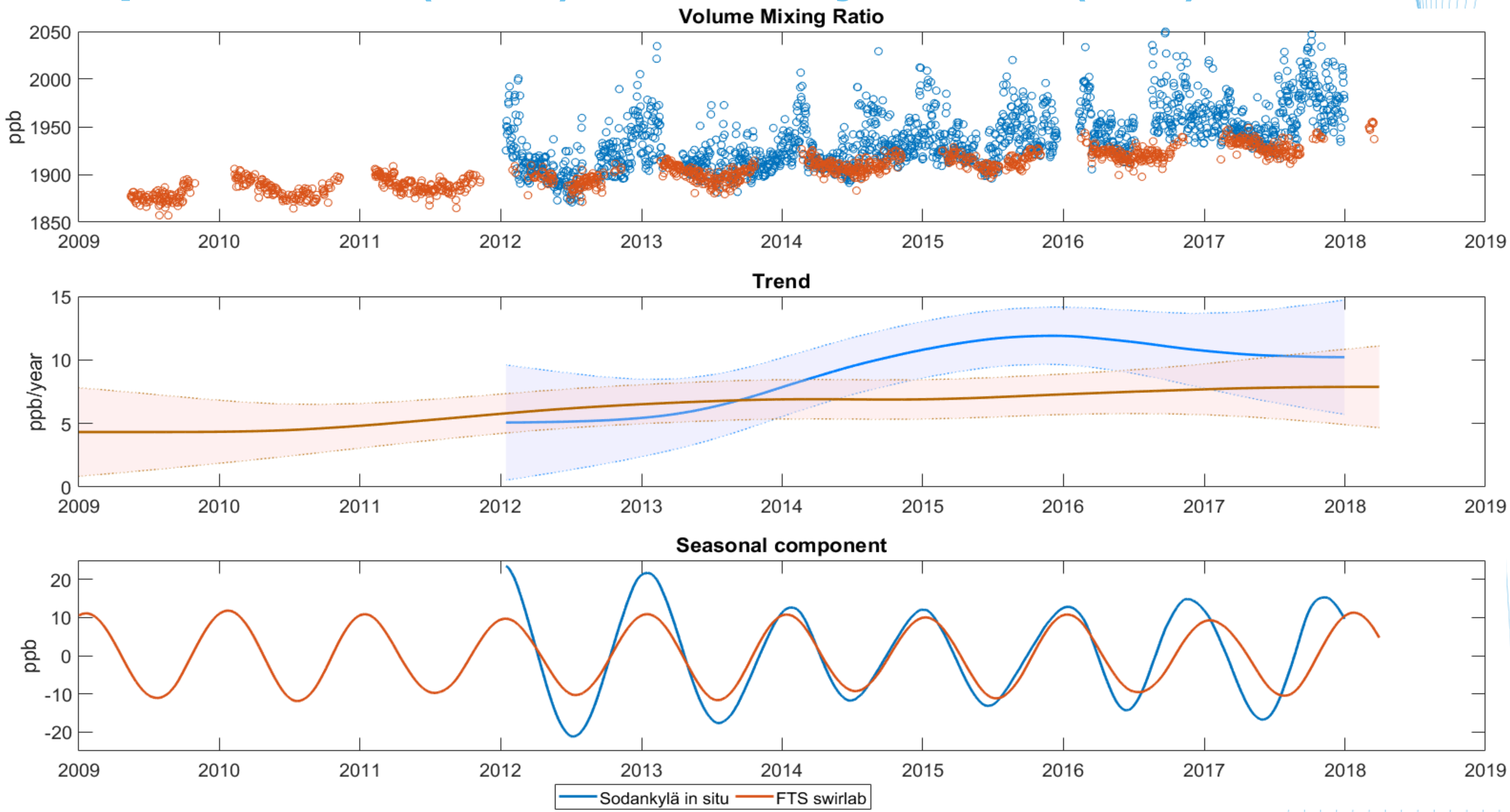
DLM fit: FTS (20km)



DLM fit: FTS (30km)



Comparison: FTS (300m) vs. Sodankylä in situ (50m)



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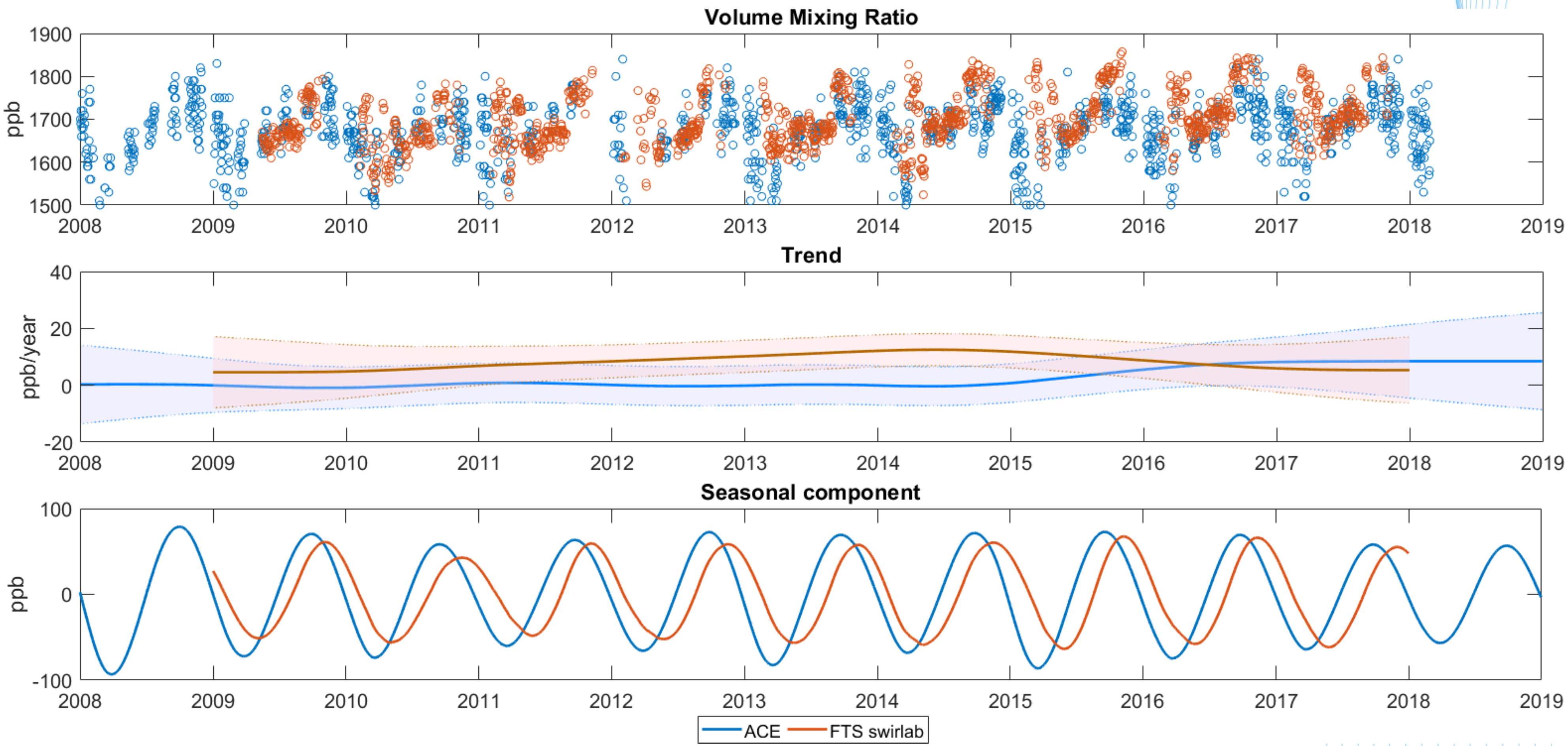
Comparison: FTS vs ACE (13.5km)



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[2] Karion, A., Sweeney, C., Tans, P., Newberger, T.: AirCore: An Innovative Atmospheric Sampling System. Journal of Atmospheric and Oceanic Technology 27(11), 1839–1853 (2010). DOI 10.1175/2010JTECHA1448.1

[3] Rodgers C.D., \emph{Inverse Methods for Atmospheric Sounding: Theory and Practice}, World Scientific Publishing Co. Pte. Ltd., 2000.

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[5] Haario, H., Saksman, E., Tamminen, J.: An adaptive Metropolis algorithm. Bernoulli 7(2), 223–242 (2001). DOI 10.2307/3318737

[6] O. Lamminpää, M .Laine, S. Tukiainen, J. Tamminen: Likelihood informed dimension reduction for inverse problems in remote sensing of atmospheric constituent profiles https://arxiv.org/abs/1709.02611v1

[7] SWIRLAB: https://github.com/tukiains/swirlab

[8] DLM: http://helios.fmi.fi/~lainema/dlm/

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Thank you!

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