

Quantifying the Benefit of an Active CO₂ Mission Concept in a Carbon Cycle Data Assimilation System

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Problem statement

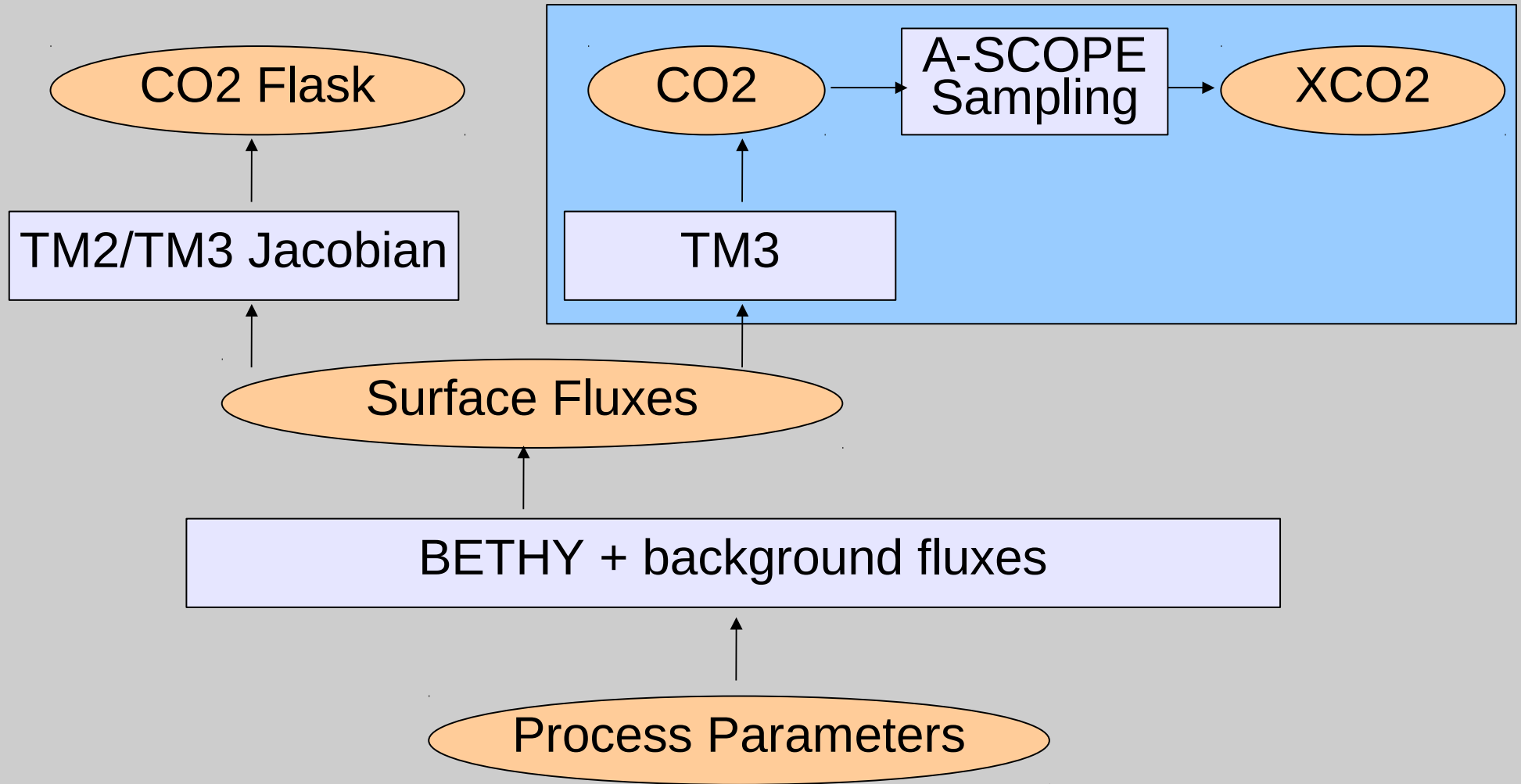
Question:

What is the benefit of XCO₂ from an active LIDAR as quantified by the posterior uncertainty for surface fluxes in a CCDAS?

Uncertainty in a terrestrial model simulation:

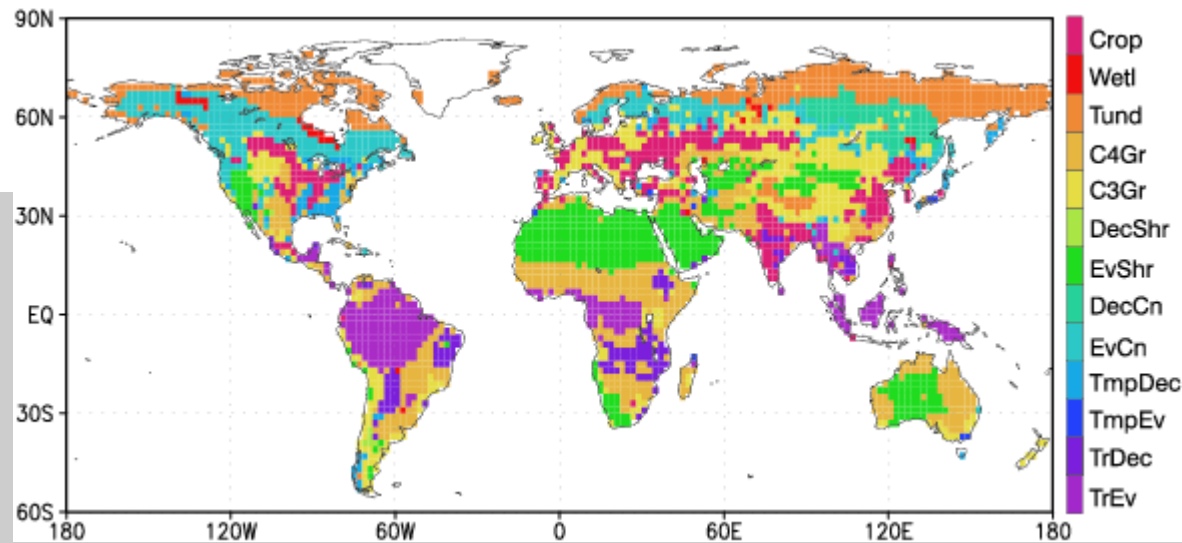
- Driving data
- Relevant processes and their implementation (structural)
- Process parameters (parametric)
- Initial state

CCDAS

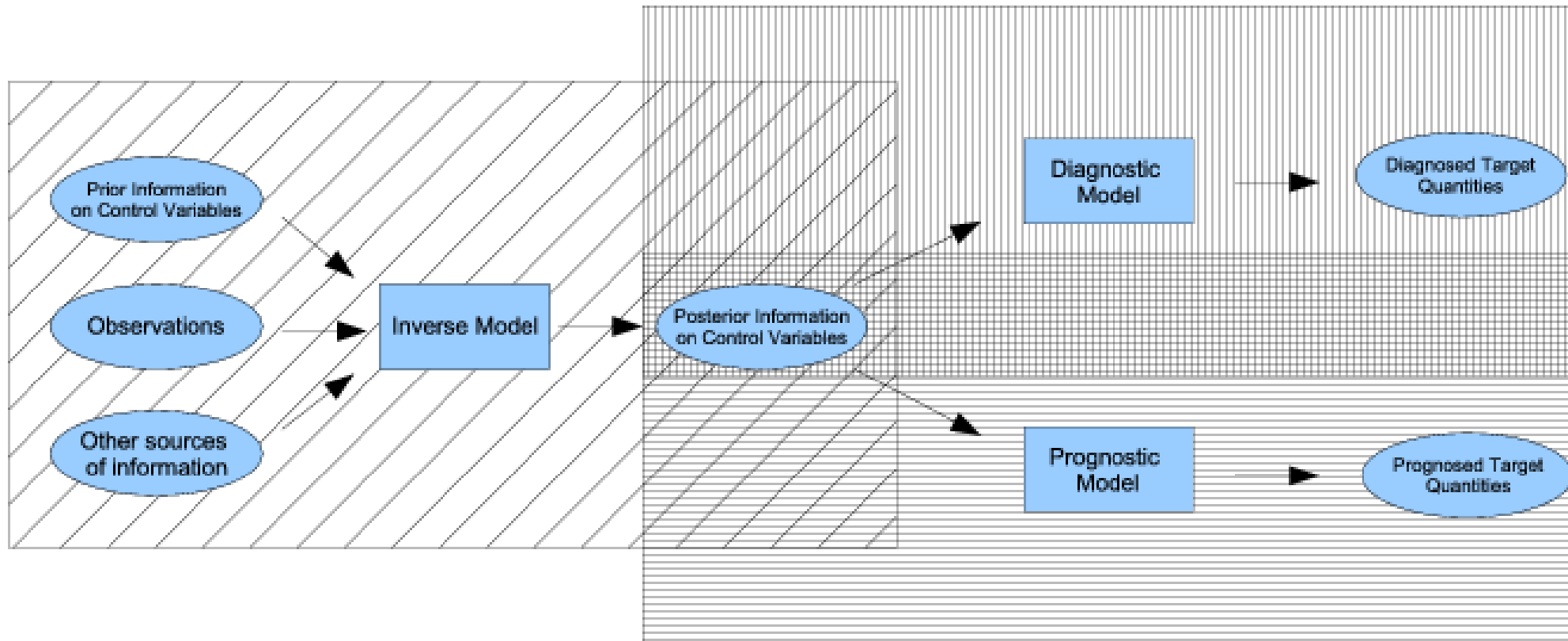


BETHY setup

- 2 by 2 degrees, global
- 13 Plant Functional Types
- 57 Process Parameters (Initial Conditions)
 - 3 PFT specific
 - 17 not PFT specific
 - 1 atmospheric
- Parameter values taken from Scholze et al. (2007)
- Prior parameter uncertainties taken from Scholze et al. (2007), in the order of 25%



CCDAS scheme



Rayner et al. (2005); Scholze et al. (2007)

Uncertainty calculation in 2 steps

Inverse step:

$$J(x) = \frac{1}{2} (x - x_{pr})^T C_{pr}^{-1} (x - x_{pr}) + \frac{1}{2} \sum_{i=1,nd} \left(\frac{M_i(x) - d_i}{\sigma_{d_i}} \right)^2$$

$$\frac{d^2 J(x)}{dx^2} = C_{pr}^{-1} + \sum_{i=1,nd} \frac{1}{\sigma_{d_i}^2} \frac{d^2}{dx^2} (M_i(x) - d_i)^2$$

- Hessian independent of x for linear model
- For synthetic data use $d = M(x)$.
- Decomposes nicely, can precompute model contribution

uncertainty
in observations
AND model

$$C_{po} \approx \frac{d^2 J(x_{po})}{dx^2}^{-1}$$

Propagation step:

$$\sigma_y^2 \approx \frac{dy(x_{po})}{dx} C_{po} \frac{dy(x_{po})}{dx}^T \approx \frac{dy(x_{po})}{dx} \frac{d^2 J(x_{po})}{dx^2}^{-1} \frac{dy(x_{po})}{dx}^T$$

- x : Parameters
- x_{pr} : Priors
- C_{pr} : Uncertainties
- $M(x)$: Model
- d : Observations
- C_d : Their uncertainties
- σ_{d_i} : Uncorrelated!
- $J(x)$: Cost function
- $\frac{d^2 J(x)}{dx^2}$: Hessian
- x_{po} : Posterior parameters
- C_{po} : Posterior uncertainties
- $y(x)$: Target quantity
- σ_y : Its uncertainty

All derivative code
generated from model code
by automatic differentiation
tool TAF

Data Uncertainty

$$C(d) = C(d_{\text{obs}}) + C(d_{\text{rep}}) + C(d_{\text{mod}})$$

$$\sigma_{\text{rep}}^2 = \frac{\sigma_{\text{het}}^2}{n}$$

For default setup (monthly sampling, 1.6 micron) in ppm:

- $\sigma_{\text{obs}} = 0.5$ (land)/1.5 (ocean)
- $n = 30$, $\sigma_{\text{het}} = 3$
- $\sigma_{\text{mod}} = 0.5$
- all uncorrelated

Setup

Target quantities:

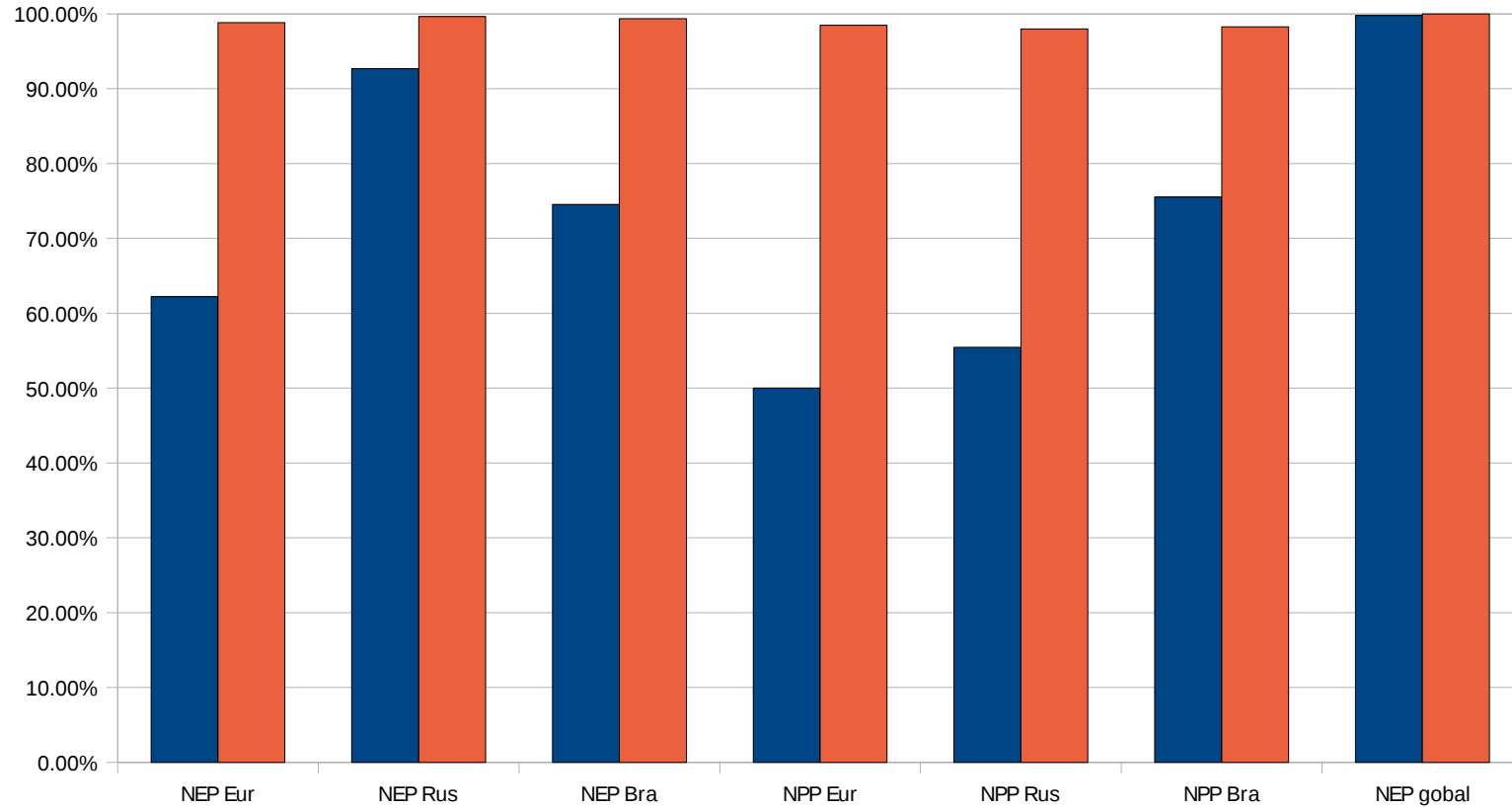
- NEP
- NPP
- regionally integrated
- averaged over 20 years

Assimilation window:

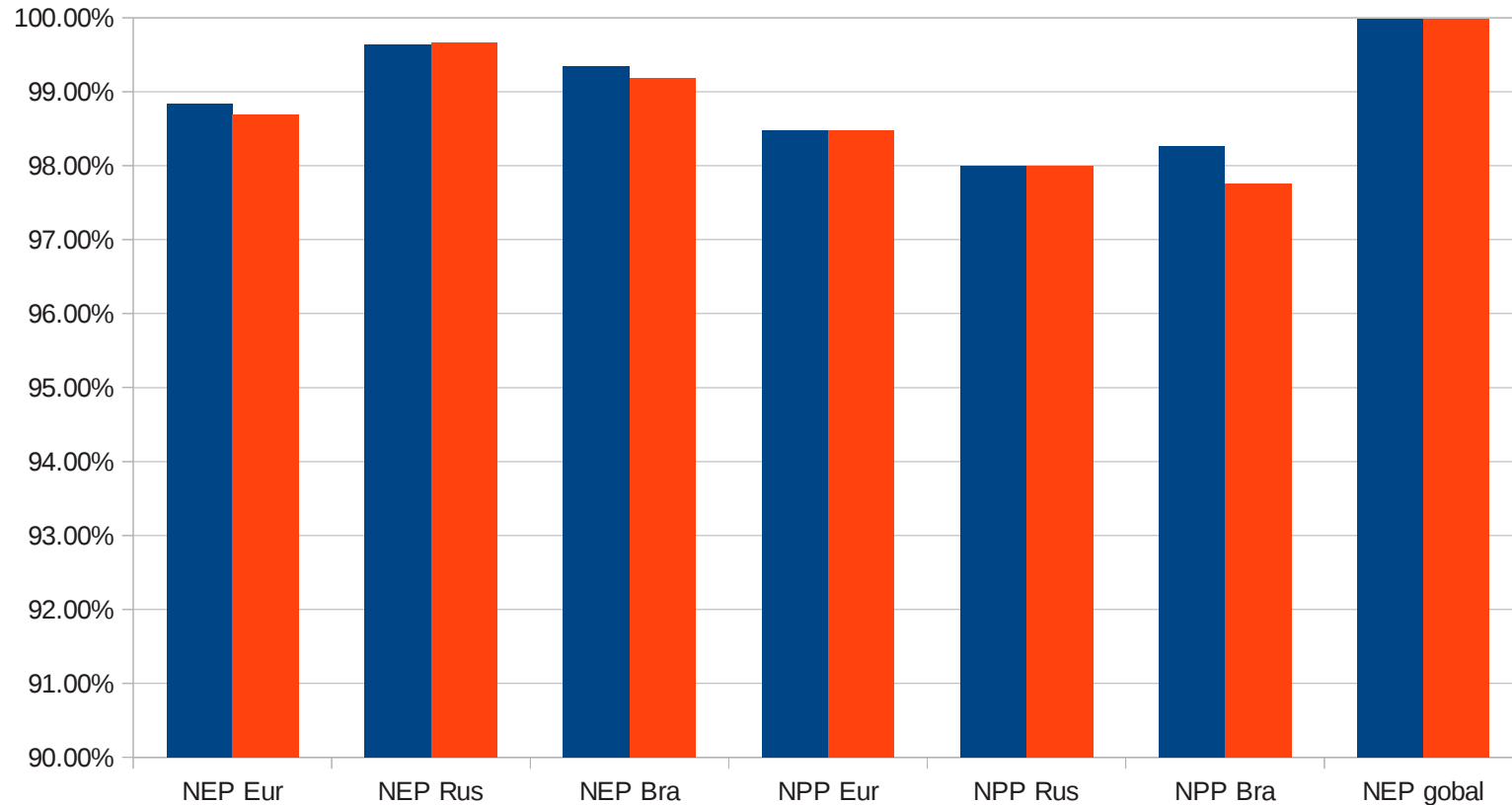
- A-SCOPE: 1 years
- Flask: 20 years

Flask assessment with 41 GLOBALVIEW sites taken from Scholze et al. (2007)

A-SCOPE + flask (red) vs flask (blue)



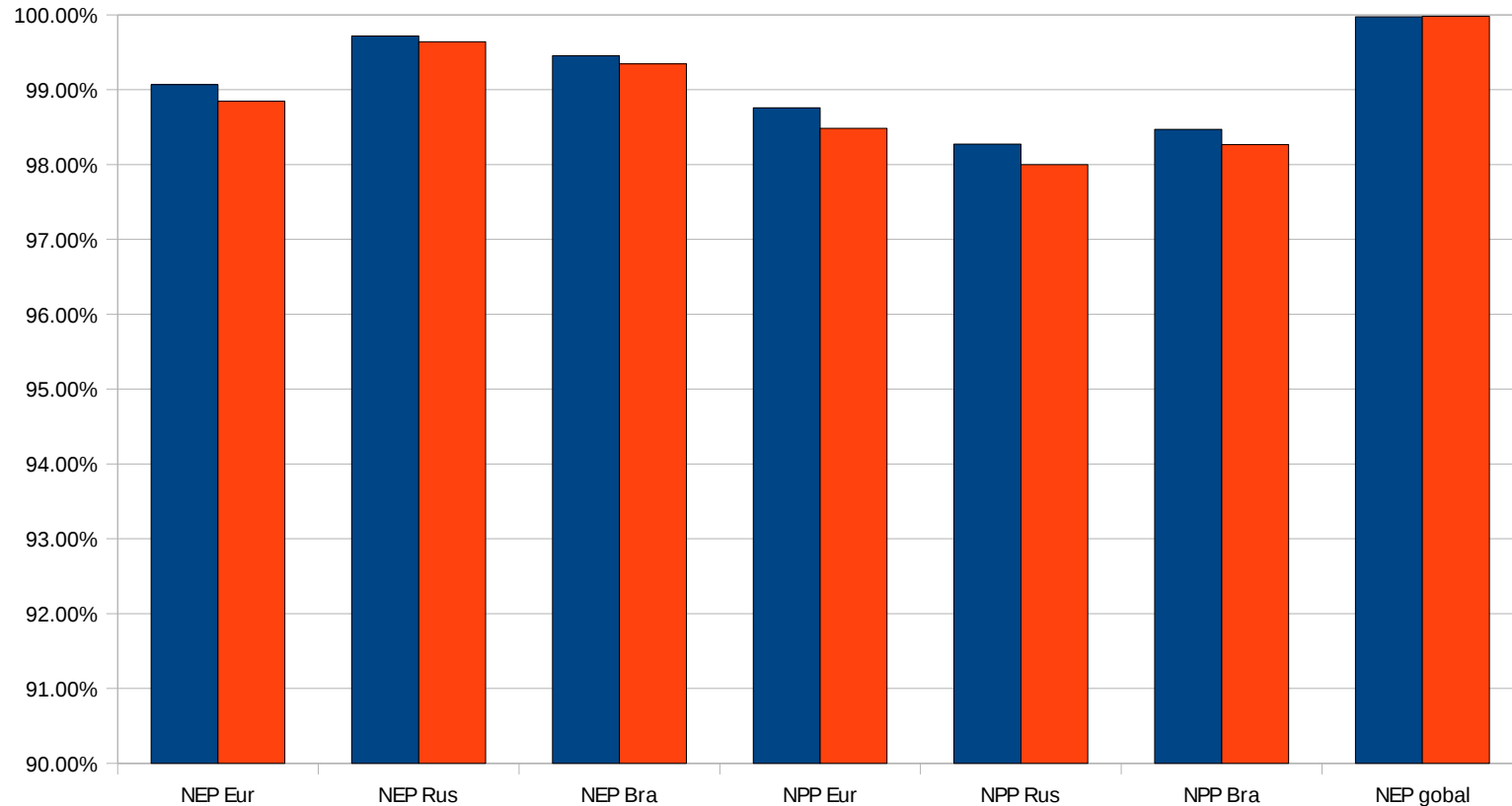
A-SCOPE + GLOBALVIEW monthly (red) vs inst. sampling (blue)



inst. sampling: $3\sigma_{\text{mod}}$

A-SCOPE + GLOBALVIEW

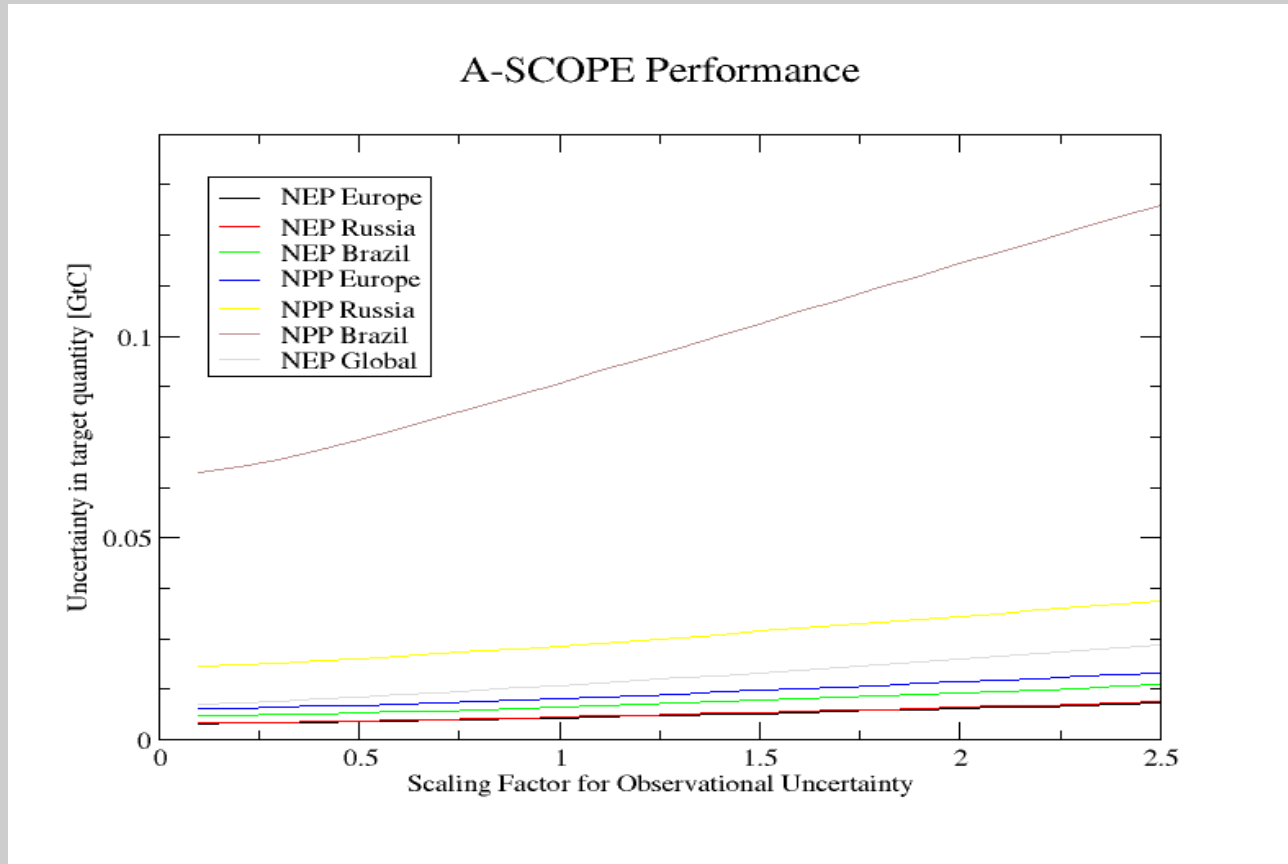
1.6 micron (red) vs 2.0 micron (blue)



2.0 micron: $2\sigma_{\text{obs}}$

A-SCOPE + GLOBALVIEW

Impact of observational uncertainty



$$\sigma(y_{mod})=0$$

$$\sigma(y)^2 = \mathbf{D}(\mathbf{N}) \left(\frac{1}{k\sigma_{obs}^2 + \sigma_{rep}^2 + \sigma_{mod}^2} H_A + H_0 \right)^{-1} \mathbf{D}(\mathbf{N})^T + \sigma^2(y_{mod})$$

Conclusions

- Evaluated A-SCOPE performance for calibration of a terrestrial biosphere model
- Assumed uncorrelated data uncertainty
- A-SCOPE performs better than ground-based flask sampling network
- Better performance regardless of weighting function and sampling in the model
- Holds for a range of observational uncertainties
- CCDAS approach shows potential for higher level RS products: carbon stocks and fluxes (beyond net and beyond assimilation period)