

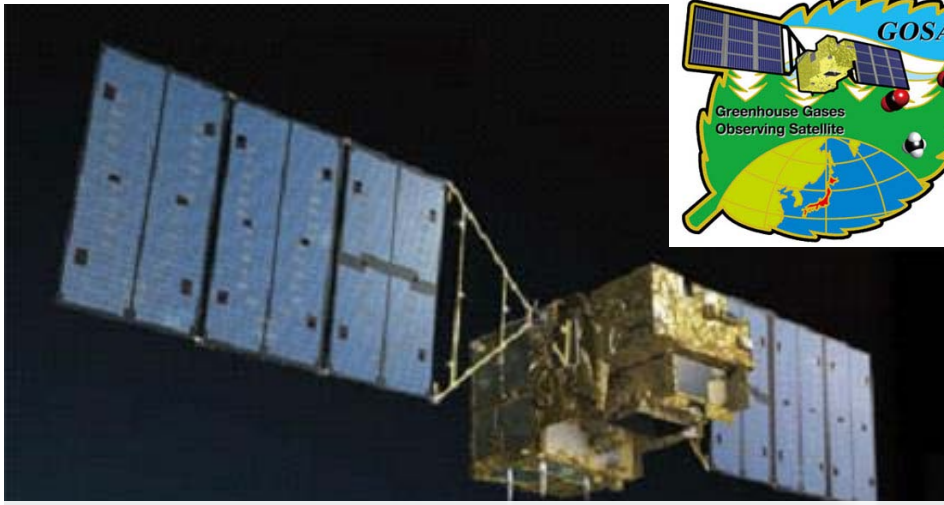
# CO2 fluxes estimated with satellite, aircraft, and surface observations using an ensemble- based 4D data assimilation system

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*submitted to JGR-Atmosphere*

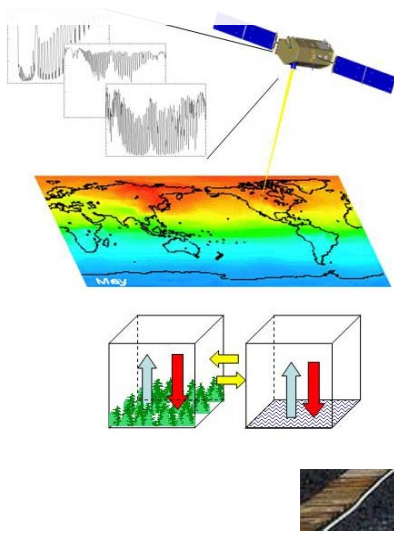




Activities of CONTRAIL project in the first 3 years.

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 Y. Abe<sup>3</sup>, T. Endo<sup>3</sup>, T. Honda<sup>3</sup>, N. Kondo<sup>4</sup>, M. Sakai<sup>5</sup>,  
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 K. Ishijima<sup>7</sup>, T. Umezawa<sup>10</sup>, C. Crevoisier<sup>11</sup>, O. Uchino<sup>1</sup>  
1. NIES, 2. MPI, 3. JAL, 4. JAMCO, 5. FAO, 6. COSPAR, Tokyo, 7. JAMSTEC, 8. MPI/IMA, 9. AIST,

**This study discusses a method to efficiently utilize various observations to estimate surface CO<sub>2</sub> flux estimations, and investigate the relative importance of different platform observation data (satellite, aircraft, and surface observations).**



**Various type data sets are available for CO<sub>2</sub> !!!**

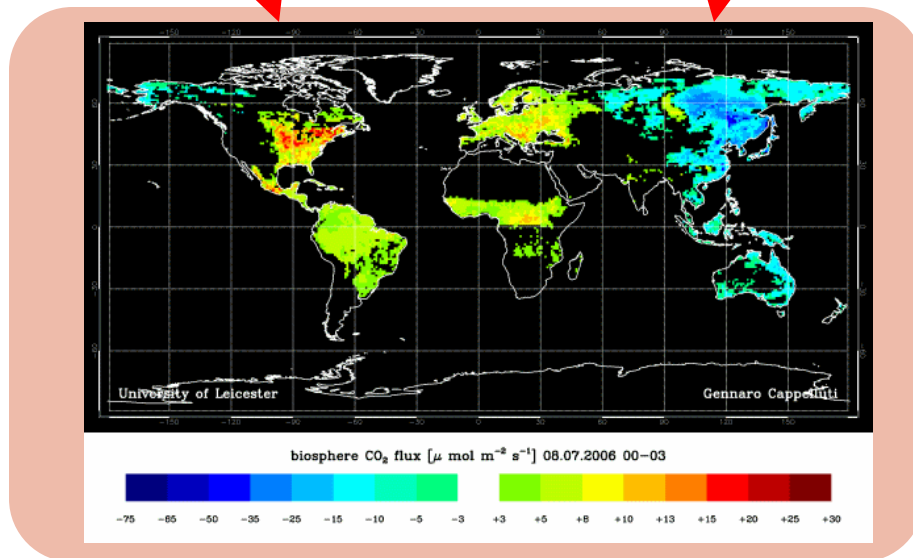


**Transport model**



**CO2 observations**

*Data assimilation*



**CO2 flux & concentration**



# 4D data assimilation system for carbon cycle

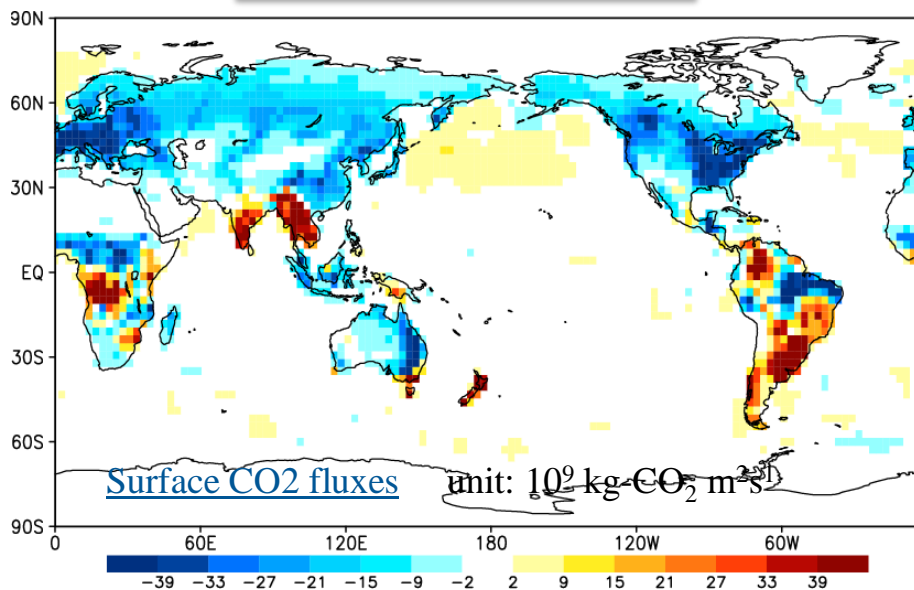
- *Forecast model:*

FRCGC transport model coupled to CCSR/NIES AGCM @ T42L32  
(transport = grid-scale + parameterized convection and diffusion)

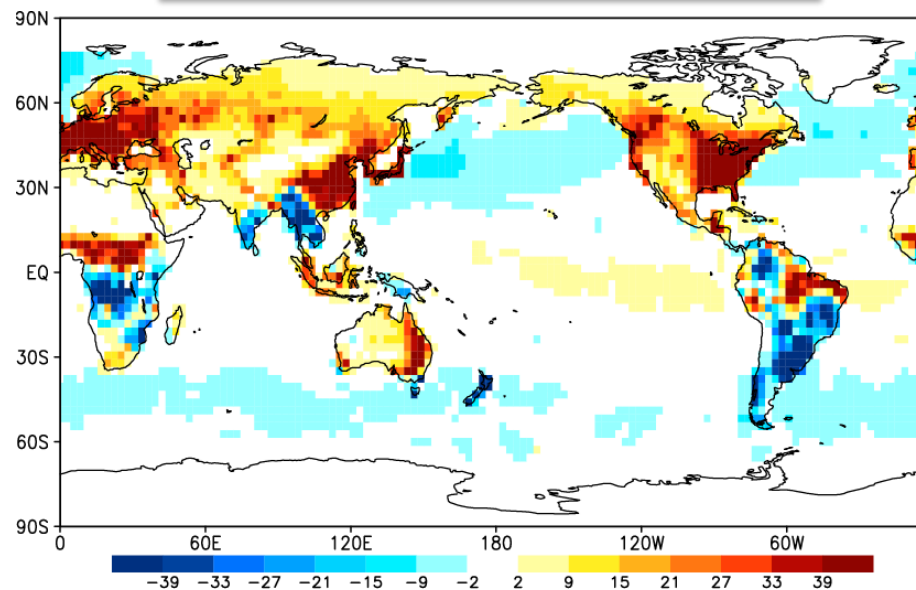
- *Data assimilation:*

Local ensemble transform Kalman filter (LETKF) with state augmentation technique

A priori error



True flux (Nov.-Dec)



The ensemble spread for CO2 flux is initialized such that the standard deviation is equal to the initial error

# Local ensemble transform Kalman filter (Hunt et al. 2007)

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The LETKF is one of the ensemble square root filters in which the observations are assimilated to update only the ensemble mean by

$$\bar{\mathbf{x}}^a = \bar{\mathbf{x}}^f + \mathbf{K}[\mathbf{y}^o - H(\bar{\mathbf{x}}^f)], \quad \mathbf{K} = \mathbf{X}^f \tilde{\mathbf{P}}^a (\mathbf{H}\mathbf{X}^f)^T \mathbf{R}^{-1}$$

The ensemble perturbations are updated by transforming the background perturbations through a transform matrix  $\mathbf{T}$

$$\mathbf{X}^a = \mathbf{X}^f \mathbf{T}, \quad \mathbf{T} = [(\mathbf{K} - \mathbf{1})\tilde{\mathbf{P}}^a]^{1/2},$$

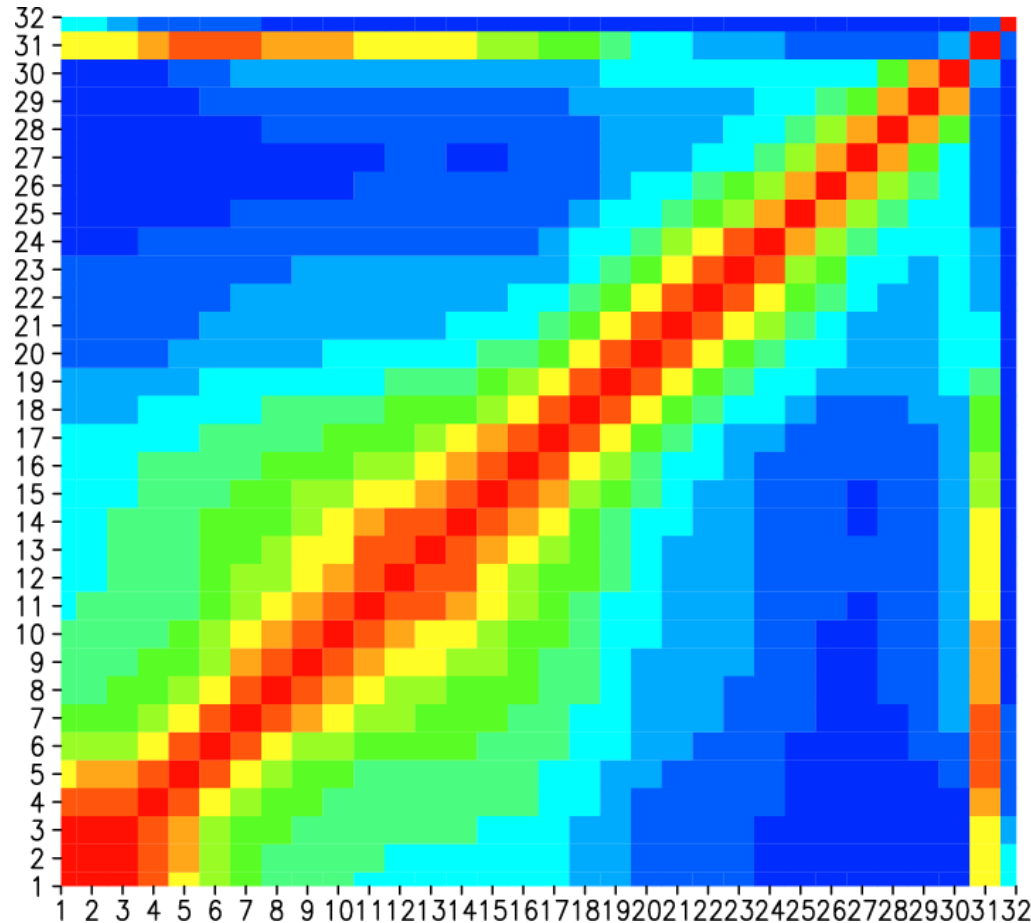
The analysis error covariance in ensemble space is given by

$$\tilde{\mathbf{P}}^a = [(\mathbf{K} - \mathbf{1})\mathbf{I} + (\mathbf{H}\mathbf{X}^f)^T \mathbf{R}^{-1} (\mathbf{H}\mathbf{X}^f)]^{-1},$$

*The LETKF performs the analysis in ensemble space (rather than in model or obs space), which greatly reduces the computational cost.*

# Simultaneous estimation of state and parameter

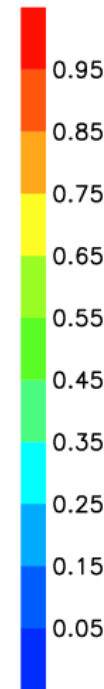
Background covariance structure



1-30: CO2 conc. at each model level,  
31:CO2 column, 32:surface flux

New state vector

$$z = \begin{pmatrix} x \\ flux \end{pmatrix}$$



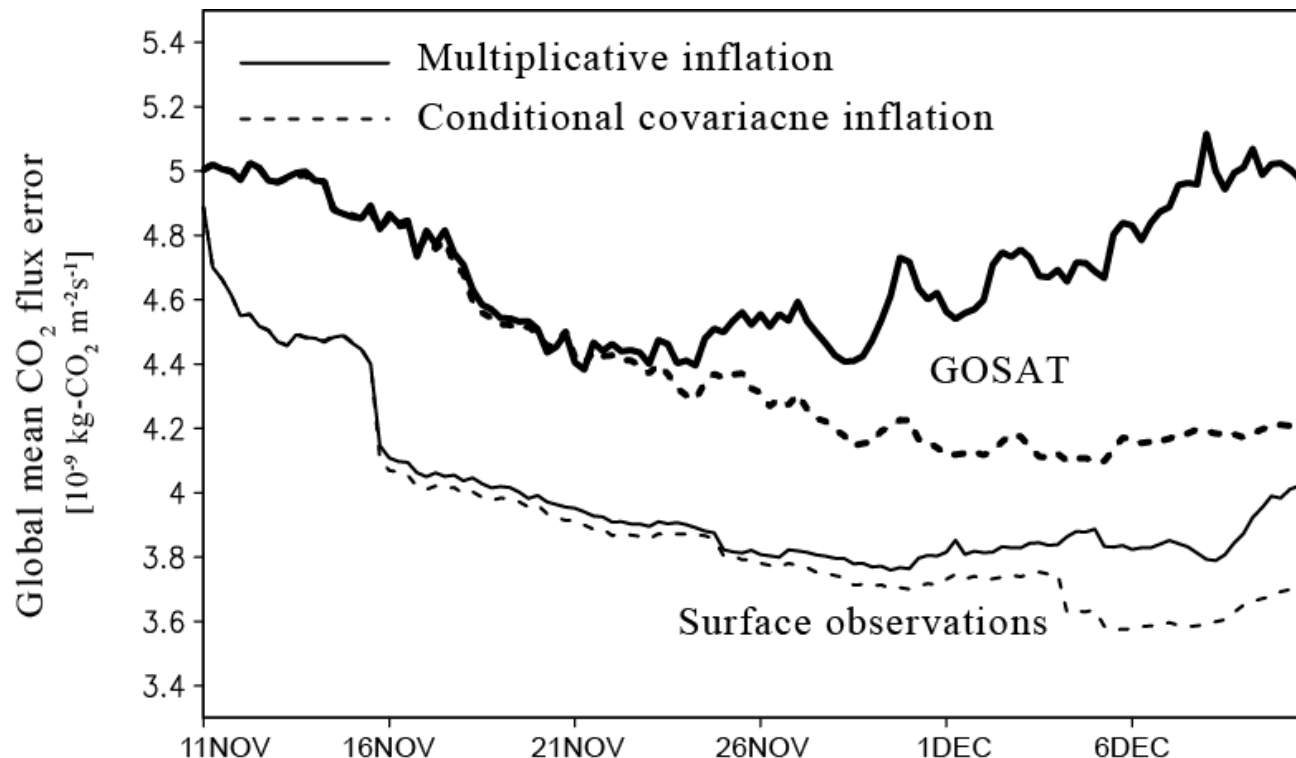
The state vector augmentation method has been applied to simultaneously estimate the **model state (met. & CO2 conc.)** and the **uncertain model parameter (surface CO2 flux)**.

# Covariance inflation technique

*Covariance inflation technique is used to avoid filter divergence caused by progressive underestimation of the model error covariance magnitude.*

- Multiplicative inflation (Anderson and Anderson, 1999)
- Additive inflation (Whitaker et al., 2008)
- Conditional covariance inflation (e.g., Aksoy et al., 2006)

The analyzed standard deviation is inflated back to a minimum or maximum predefined value

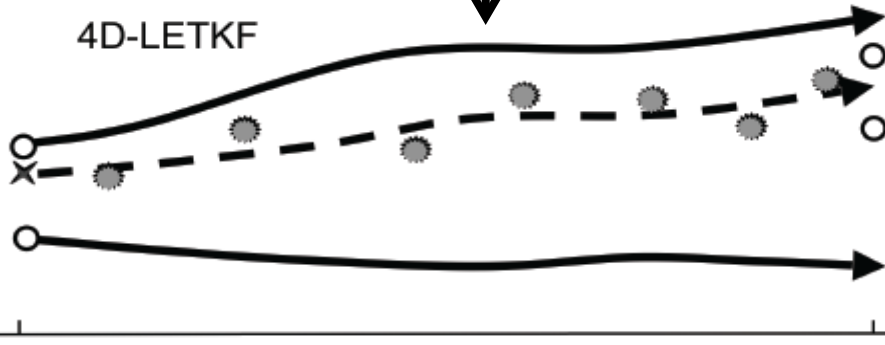


# 4D-LETKF vs. 3D-LETKF

Analysis time



4D-LETKF



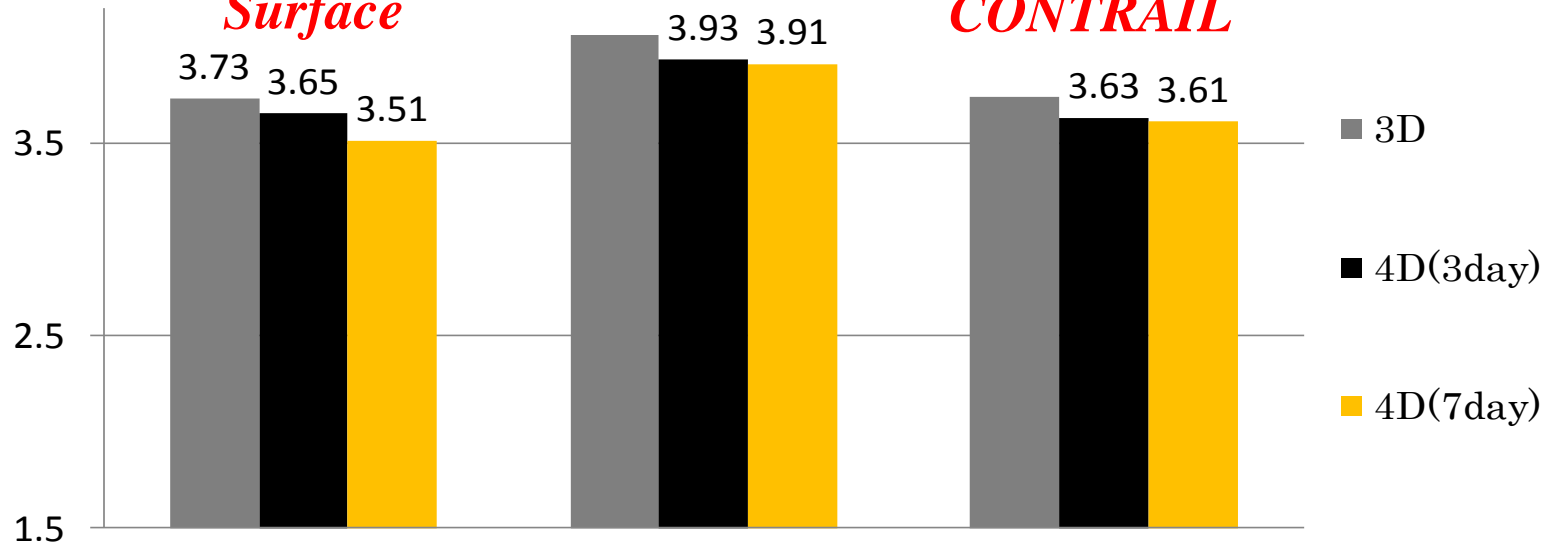
A 4D EnKF data assimilation system uses a trajectory that best fits all the observations in a data assimilation window. It provides an analysis in terms of the weights of the ensemble forecast members at the analysis time.

*GOSAT*

*Surface*

*CONTRAIL*

CO<sub>2</sub> flux RMSE





# 4D-LETKF vs. 3D-LETKF

Data	3D	4D (3-day)	4D (7-day)
Surface (h=600 km)	3.94	3.94	3.81
Surface (h=900 km)	3.66	3.65	3.53
Surface (h=1200 km)	3.70	3.61	3.46
GOSAT (h=600 km)	4.51	4.43	4.38
GOSAT (h=900 km)	4.36	4.13	4.64
GOSAT (h=1200 km)	4.17	3.78	4.54
CONTRAIL (h=600 km)	4.04	4.04	4.89
CONTRAIL (h=900 km)	3.88	3.85	3.69
CONTRAIL (h=1200 km)	3.68	3.56	5.43

**When a long assimilation window (i.e., a 7-day window) or a long localization length (i.e., 1200 km) is used, the surface flux analysis suffers from large (both temporal and spatial) spurious correlations and is degraded**

# Observation system simulation experiments (OSSEs)

## Continuous and flask surface observations

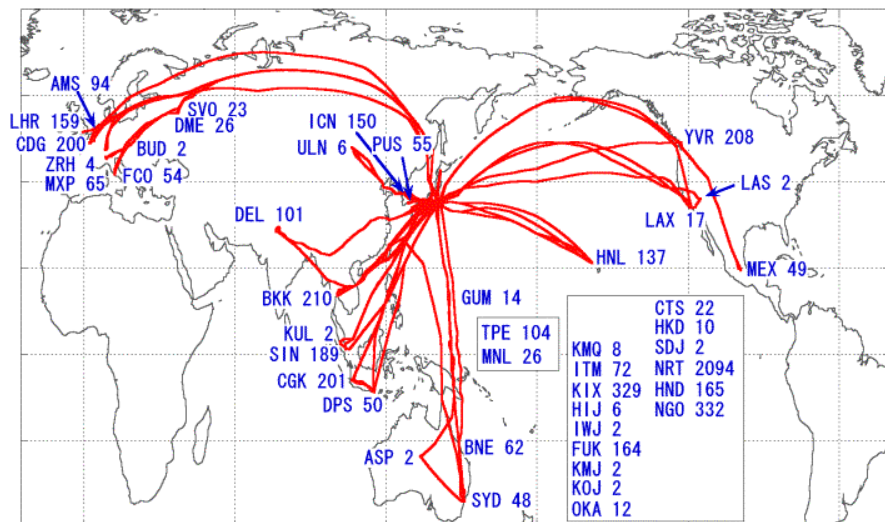
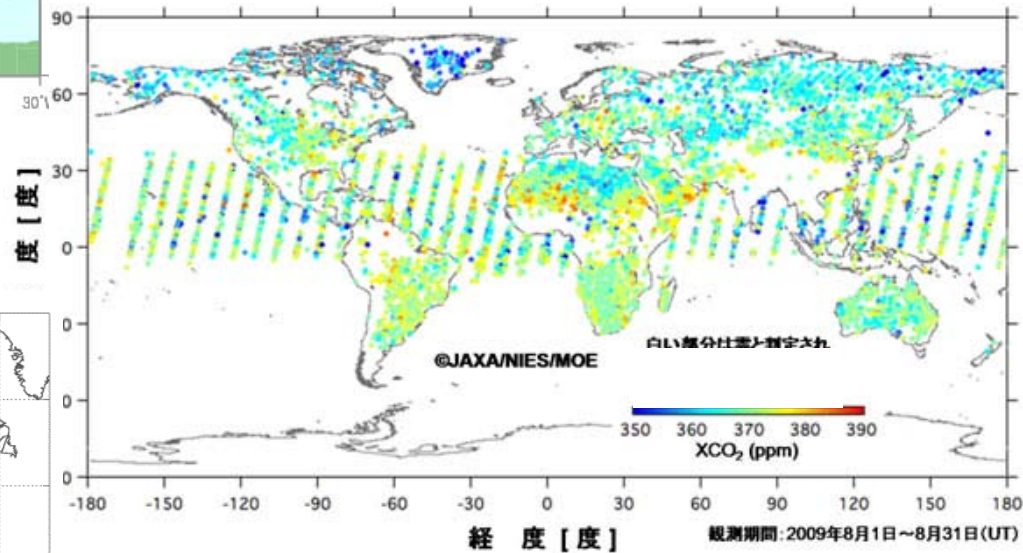
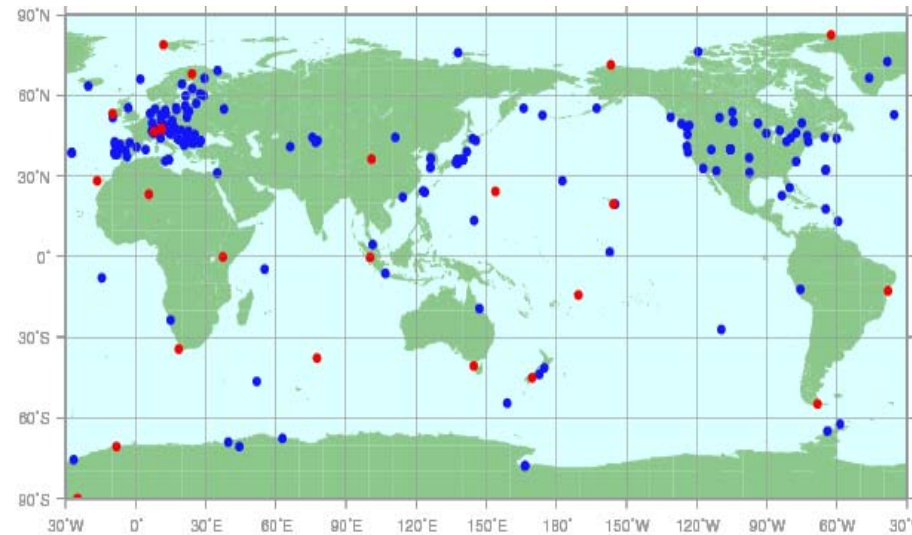
Density: low

Error: small

## GOSAT observations

Density: high

Error: relatively large



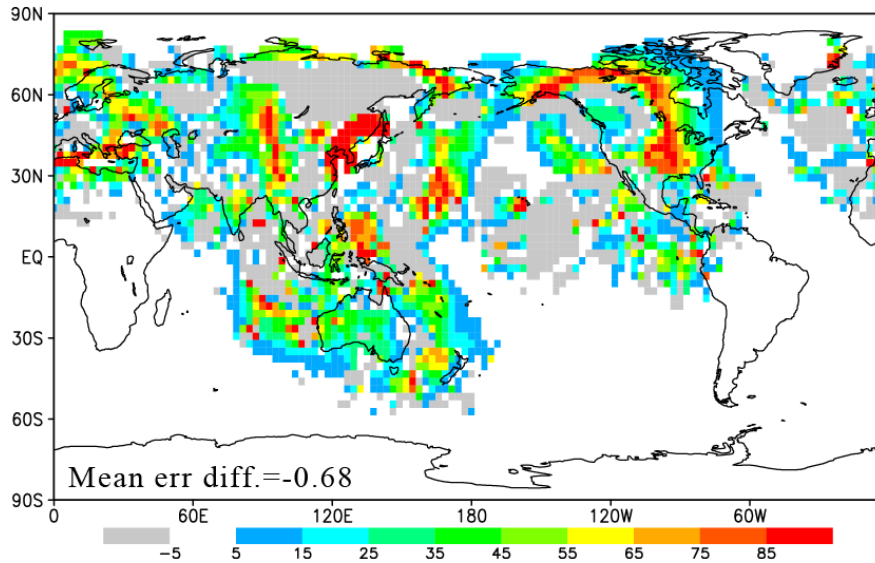
## CONTRAIL aircraft observations

Density: high (+vertical profile)

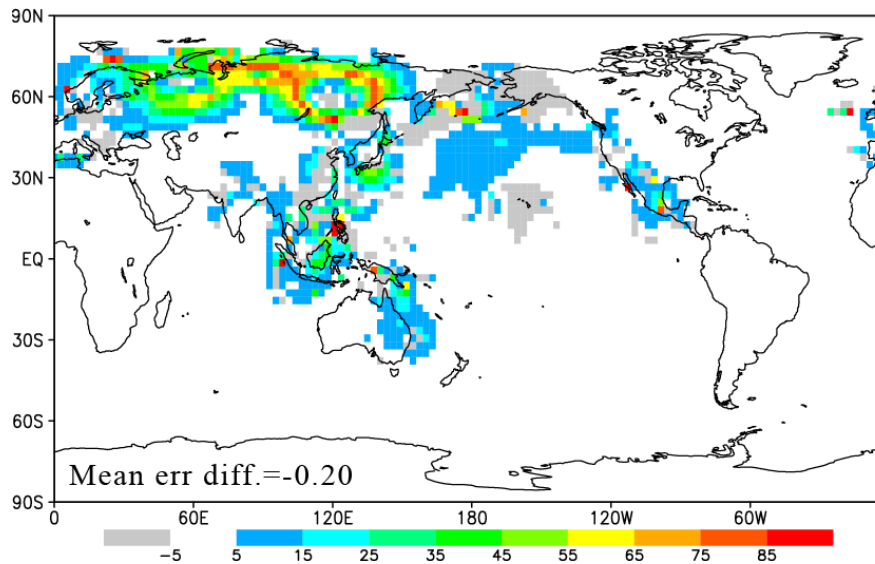
Error: small

# Localization: CONTRAIL data assimilation

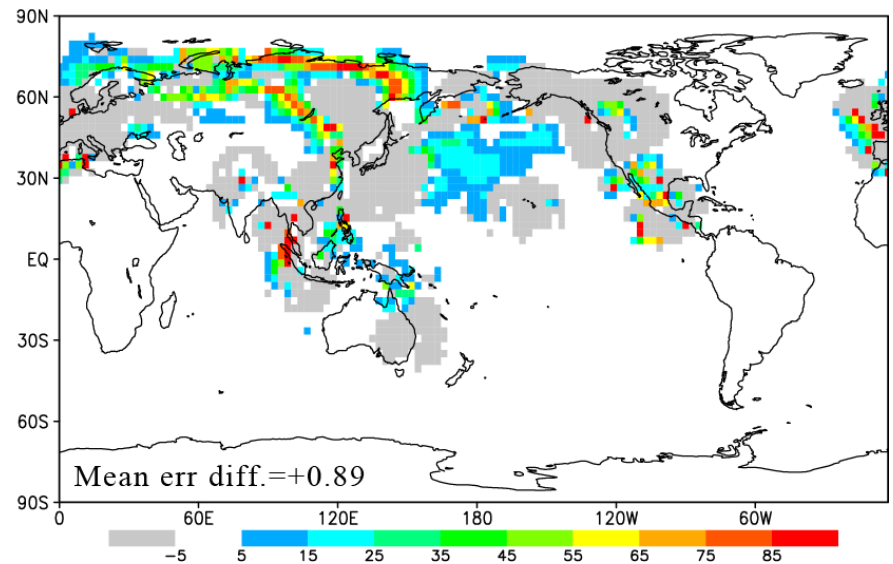
(a) CONTRAIL h=1200-600 km 3D



(b) CONTRAIL p-top=250-500 hPa 3D

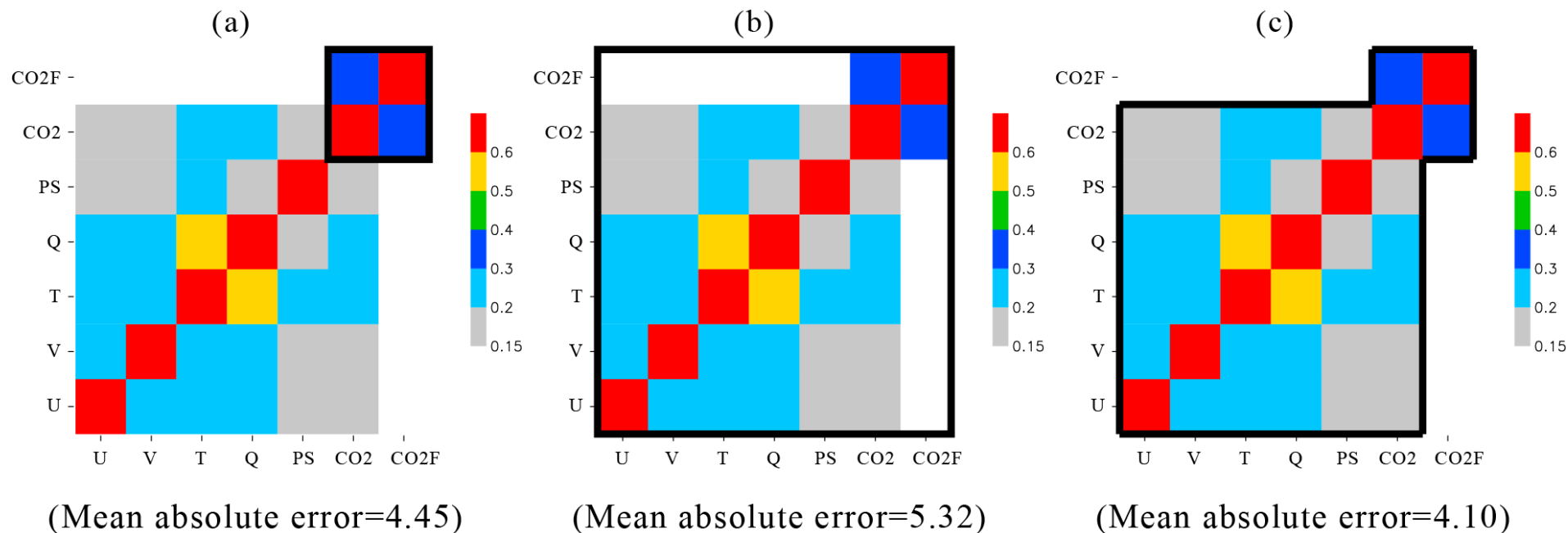


(c) CONTRAIL p-top=100-500 hPa 3D



The increase in the vertical localization length allows an increased use of the upper tropospheric data in surface flux estimates, reducing the surface flux analysis error. # In contrast, because of significant spurious correlations between variations in surface fluxes and lower stratospheric concentrations, the increase of the vertical localization length to  $\ln P=1$  has an adverse impact.

# Design of the state vector: coupling data assimilation



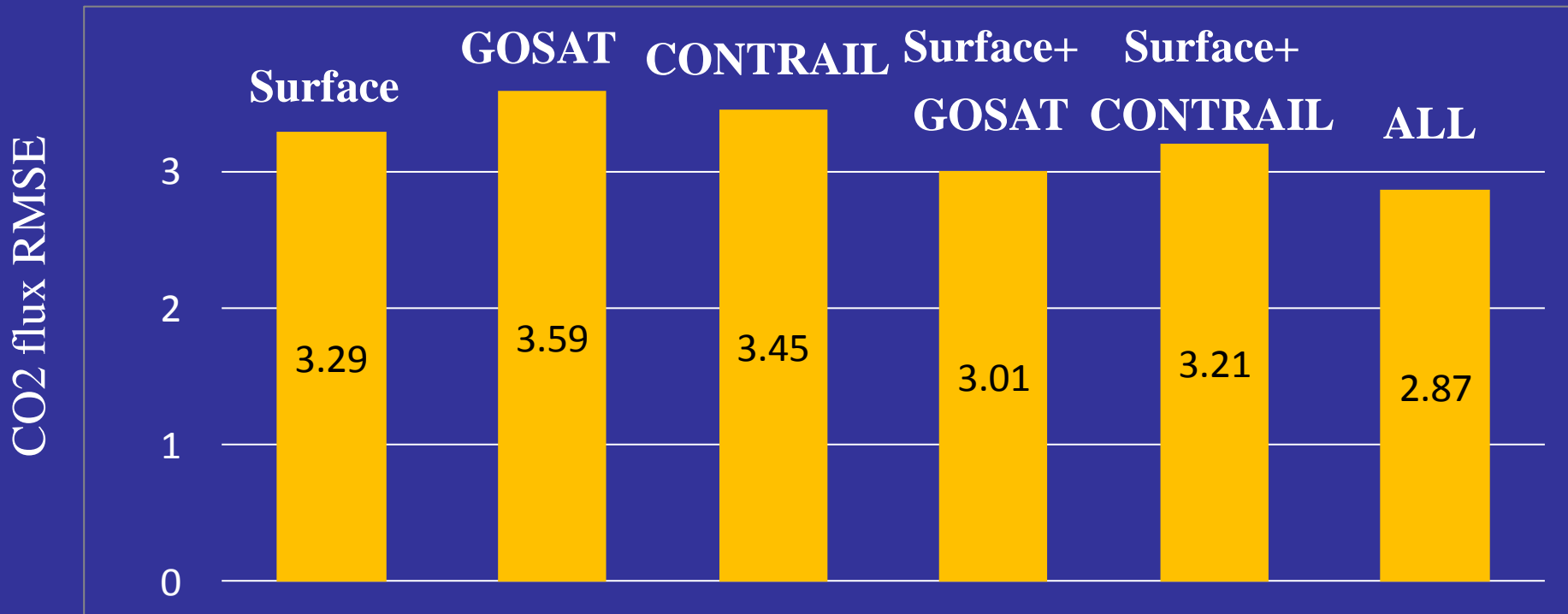
## Background error covariance structure @ bottom level

Although meteorological data assimilation can provide more constraints on the flux estimation, spurious correlations among meteorological variables and CO2 flux significantly degraded the flux analysis in (b). By considering variable localization, it's possible to stabilize and improve the CO2 flux analysis in (c)

# Relative importance of different platform data

## Optimal data assimilation system

- State augmentation method for parameter (i.e., surface flux estimations)
  - Localization:  $h=1200$  km,  $\log P=0.75$  hPa
    - Conditional covariance inflation
  - Weight-interpolated column data assimilation
  - 4D data assimilation with 3-day window

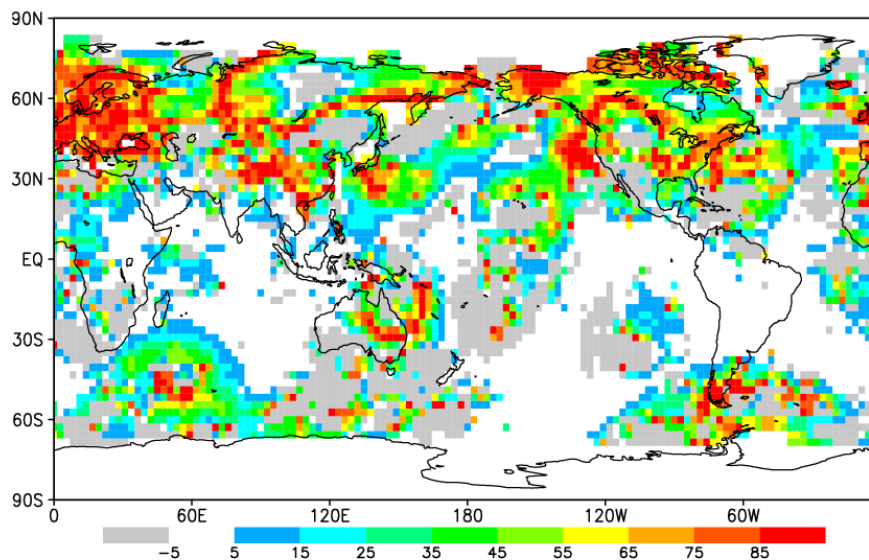


**Initial RMSE = 5.4, Global mean absolute flux = 6.2**

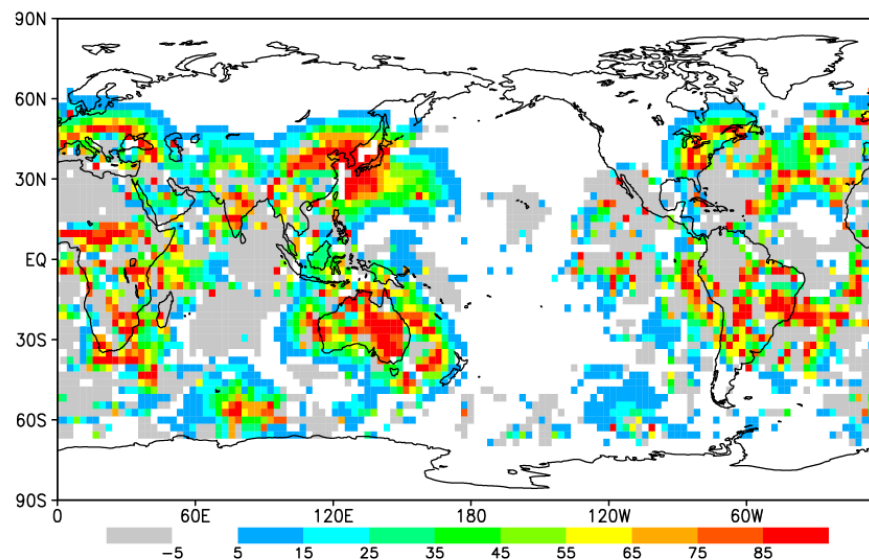


# Surface flux error reduction rate [%]

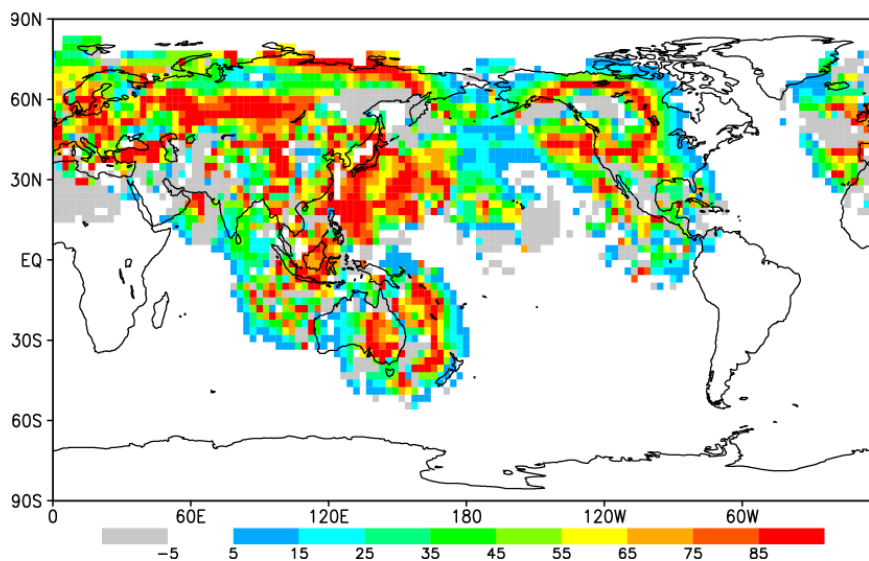
(a) Surface network



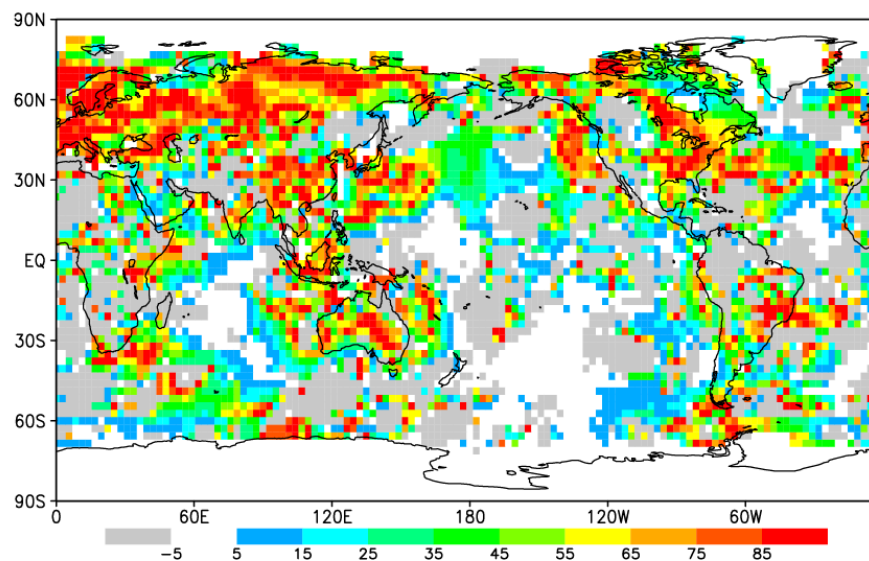
(b) GOSAT



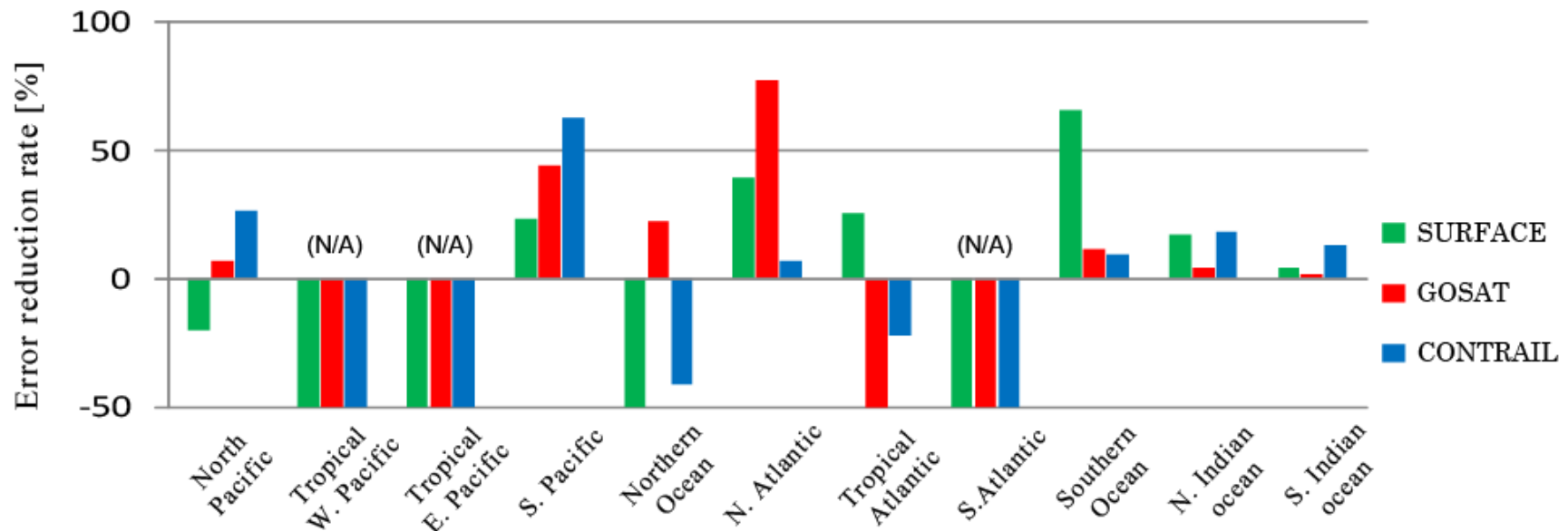
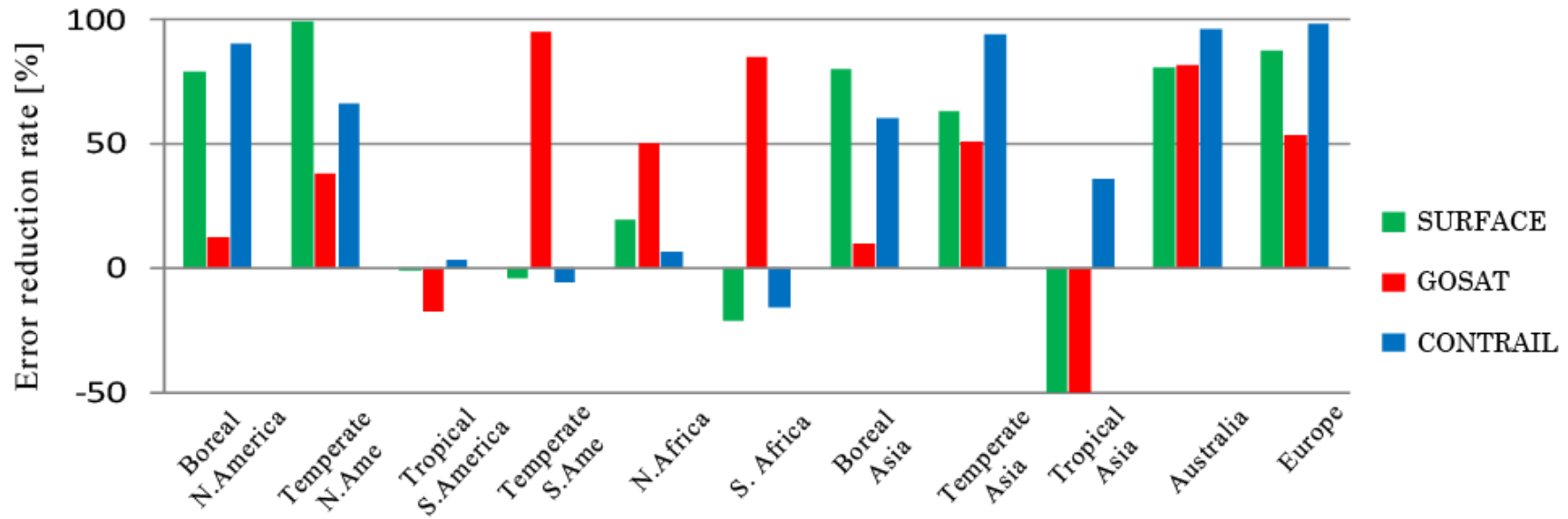
(c) CONTRAIL



(d) All

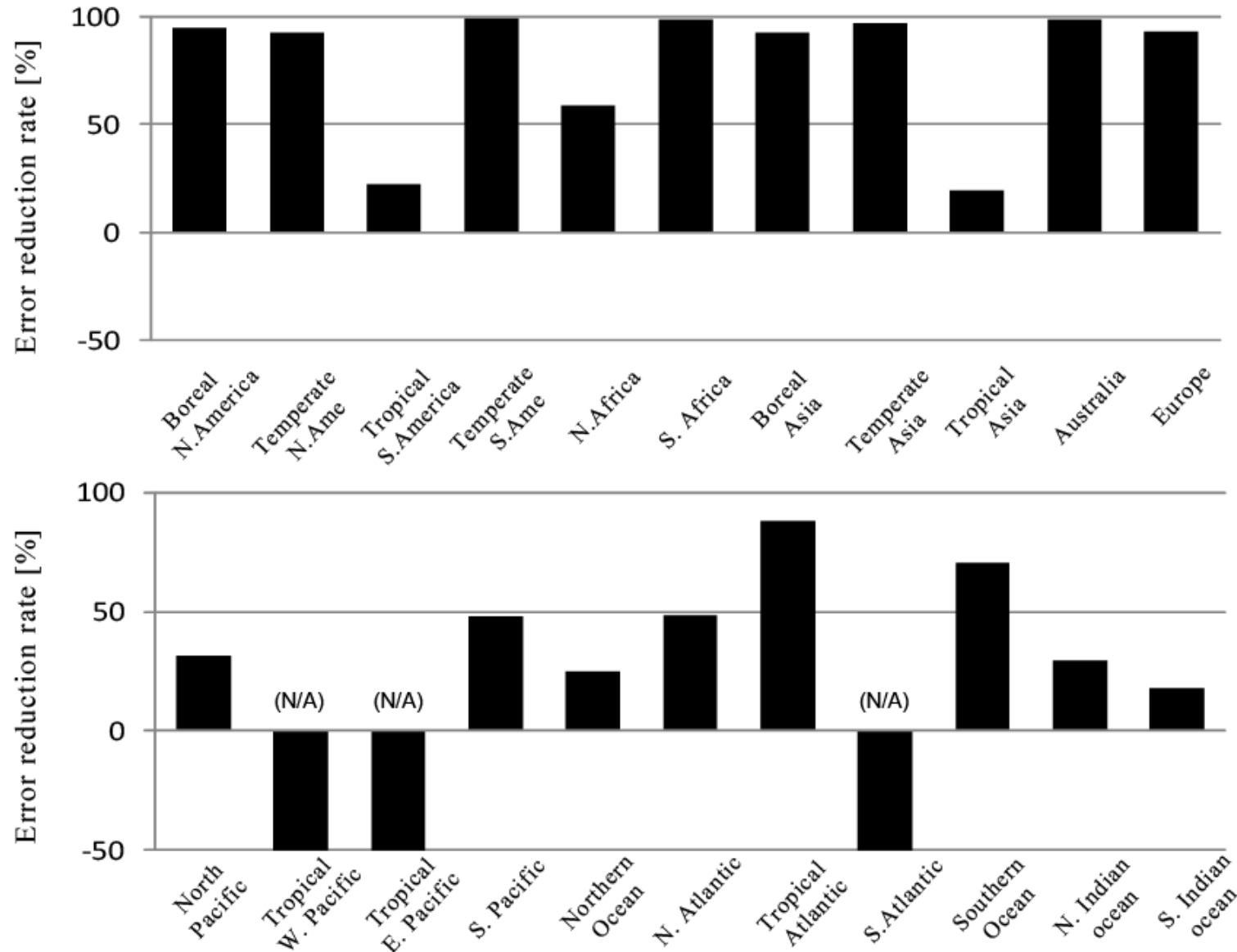


# Surface flux error reduction rate [%]



**GOSAT XCO<sub>2</sub> and CONTRAIL vertical profile data provide strong additional constraints on the surface flux estimation.**

# Surface flux error reduction rate [%]



**By combining all the platform datasets, the data assimilation system significantly improved the global estimation of the surface CO<sub>2</sub> fluxes by compensating for the unobserved areas.**

# Conclusions

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**The potential impacts of various types of CO<sub>2</sub> concentration data obtained from surface, satellite (by the GOSAT project), and aircraft (by the CONTRAIL project) measurements on the estimation of surface CO<sub>2</sub> fluxes have been investigated using an EnKF DA system.**

- Conventional surface network data contributes to largest error reductions.**
- GOSAT gives large flux error reduction over south-America and Africa.**
- The impacts of CONTRAIL data are large over Europe, Australia, trop.-temp. Asia, and North America, where many vertical profiles data exist.**
- By combining information obtained from all the data sets, the data assimilation system significantly improves the flux estimation globally.**
- The simultaneous data assimilation system for all types of data is expected to improve our knowledge of the carbon cycle.***