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Estimation of Surface Fluxes of Carbon, Heat, Moisture and Momentum from Atmospheric Data Assimilation

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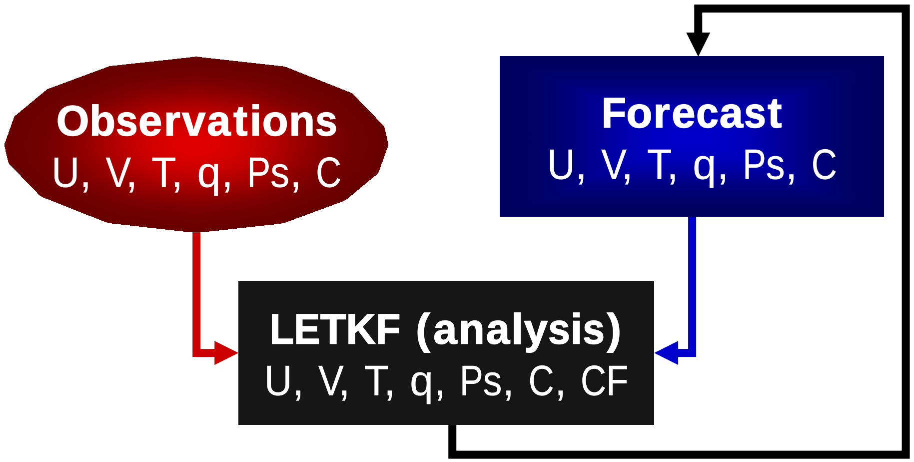
Objectives

- Explore the feasibility of **estimating surface fluxes at the model-grid scale by assimilating atmospheric variables (U, V, T, q, Ps) and the flux variables simultaneously**
  - Consider multivariate error covariance in analyzing the flux variables
  - No *a-priori* information for the fluxes

UMD-Berkeley LETKF-C System

$$\mathbf{X}^b = \begin{bmatrix} \mathbf{X} \\ \mathbf{CF} \end{bmatrix}$$

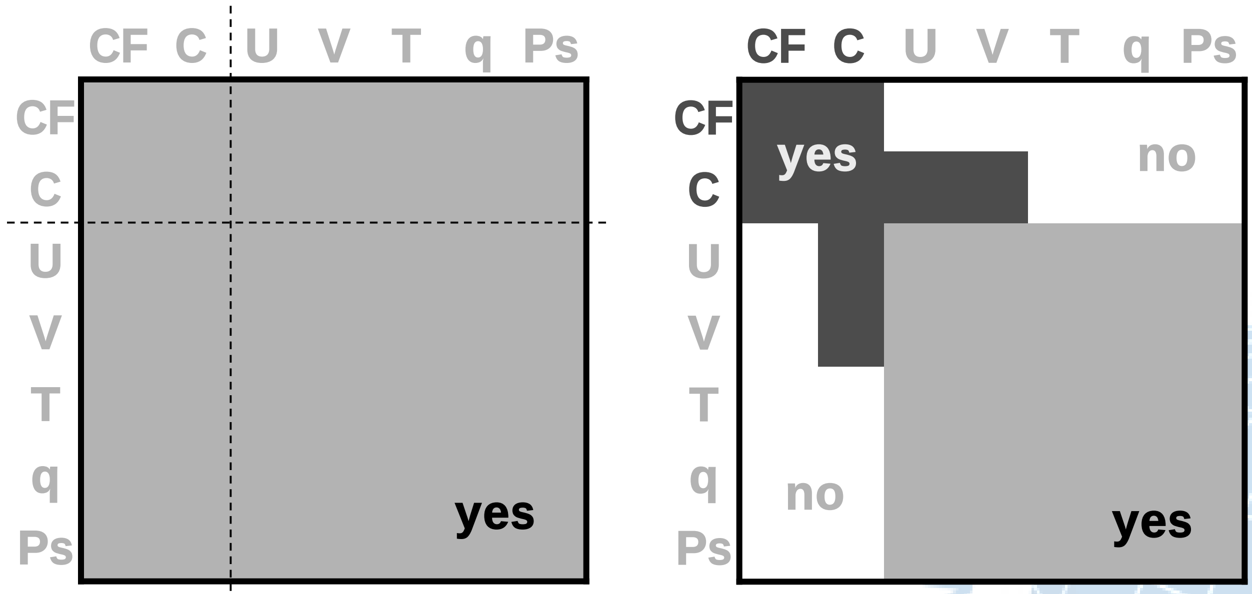
- $\mathbf{X}$: model state vector (U, V, T, q, Ps, C)
- $\mathbf{CF}$: surface CO_2 flux



- **Parameter estimation: state vector augmentation**
  - Append **CF** (surface CO_2 fluxes)
  - Update **CF** as part of the data assimilation process
- **Simultaneous analysis of carbon and meteorological variables**
  - **Multivariate** analysis with **a localization of the variables** (Kang et al., 2011)
  - Update all variables at every six hours

(1) Localization of Variables

- **If variables in the state vector are not physically correlated each other, error covariance between those variables can introduce a sampling error into the analysis system**



without variable localization Background error covariance matrix with variable localization

➔ **Zeroing out the background error covariance between those variables improves the result of the analysis**

(Kang et al., 2011, JGR)

(2) Inflation Methods

- Background uncertainty tends to be underestimated with a limited ensemble size due to the imperfection of the model and nonlinearity of the system.
  - Underestimation is more serious over the observation-rich area.

  ➔ EnKF needs "**inflation**"

Multiplicative inflation	**Additive inflation**
Multiply (1.0+α) to the background variance	Add perturbations to the background/analysis state

- The choice of **inflation parameter**
  - α for the multiplicative inflation
  - Scaling factor for the additive perturbation in additive inflation

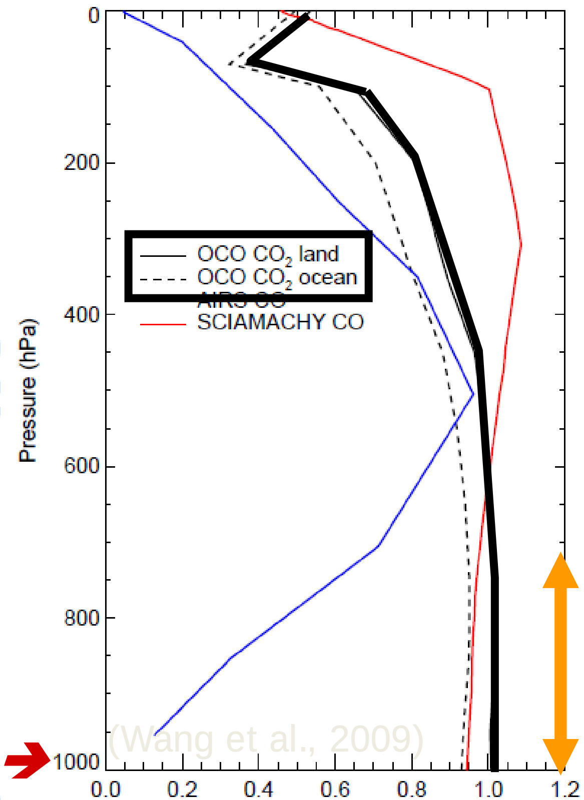
  ➔ ***Manual tuning**: very expensive or often infeasible!*
- **Adaptive multiplicative inflation**
  - Estimates multiplicative inflation parameter at each grid point at every analysis step adaptively (Anderson, 2009; Miyoshi, 2012)

(3) Vertical Localization

- **Vertical localization** of column mixing CO_2 observation from remote sensing (e.g. GOSAT, OCO-2)
  - Averaging kernel is nearly uniform in the vertical, although the forcing term (our ultimate estimate) is at the surface
  - We have **localized the column CO_2 data, updating only lower atmospheric CO_2** rather than a full column of CO_2

$$\mathbf{y}_i^b = h(\mathbf{x}_{i,k}^b) = \sum_{k=1}^{nlev} a_k S(\mathbf{x}_{i,k}^b)$$

    - Calculating innovation based on the averaging kernel



Forcing is at the surface ➔

(Kang et al., 2012)

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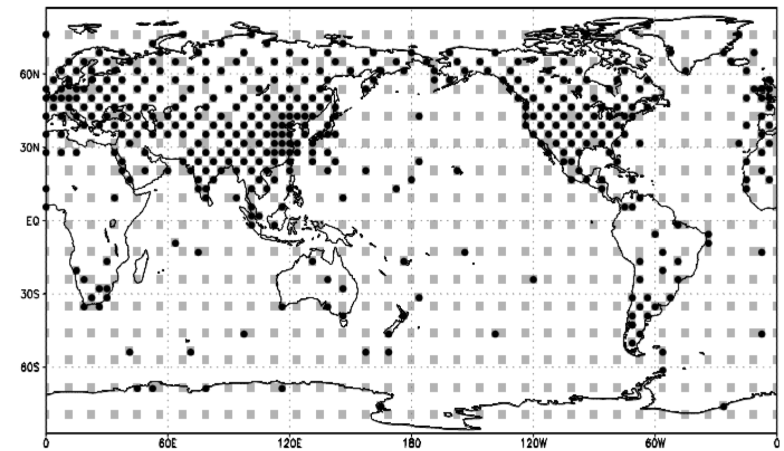
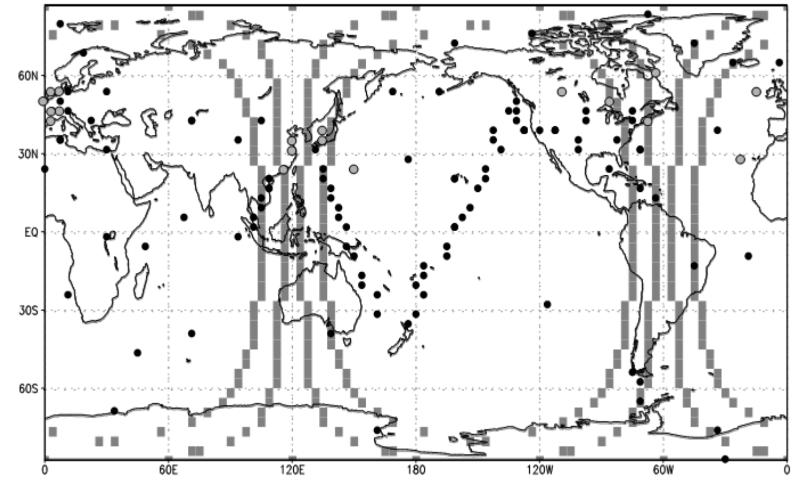
Observing System Simulation Experiments

- **Nature run: assumed true state in the experiments**
  - SPEEDY-C: the modified version of SPEEDY (Molteni, 2003)
    - AGCM with a tracer gas of atmospheric CO_2 (C)
    - Spectral model with T30L7
    - Prognostic variables: U, V, T, q, Ps, C
    - No diurnal cycle
  - **"True" CO_2 fluxes** (true CF)
    - A constant fossil fuel emission (Andres et al., 1996)
    - CASA terrestrial CO_2 fluxes (Gurney et al., 2004)
    - Oceanic CO_2 fluxes (Takahashi et al., 2002)
- **Forecast model**
  - SPEEDY-C with persistence forecast of surface CO_2 fluxes (CF)
    - **CF is updated only by the data assimilation**

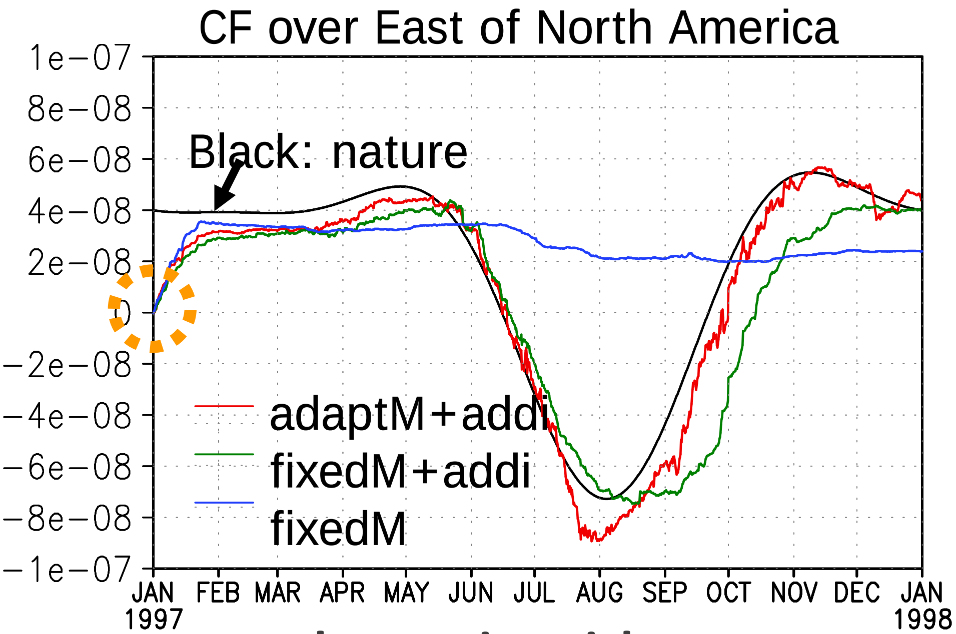
Simulated Observations

- **Meteorological variables (U, V, T, q, Ps)**
  - Conventional data
    - U, V, T, q: black dots (every 12 hours)
    - Ps: gray boxes (every 6 hours)
- **Atmospheric CO_2 concentrations**
  - in-situ & flask observations
    - Weekly records: black dots (107)
    - Hourly records: gray dots (18)
  - Satellite data from GOSAT
    - GOSAT provides column mixed CO_2 information which has a sensitivity near the surface: gray boxes
- **No direct measurement of surface CO_2 fluxes**

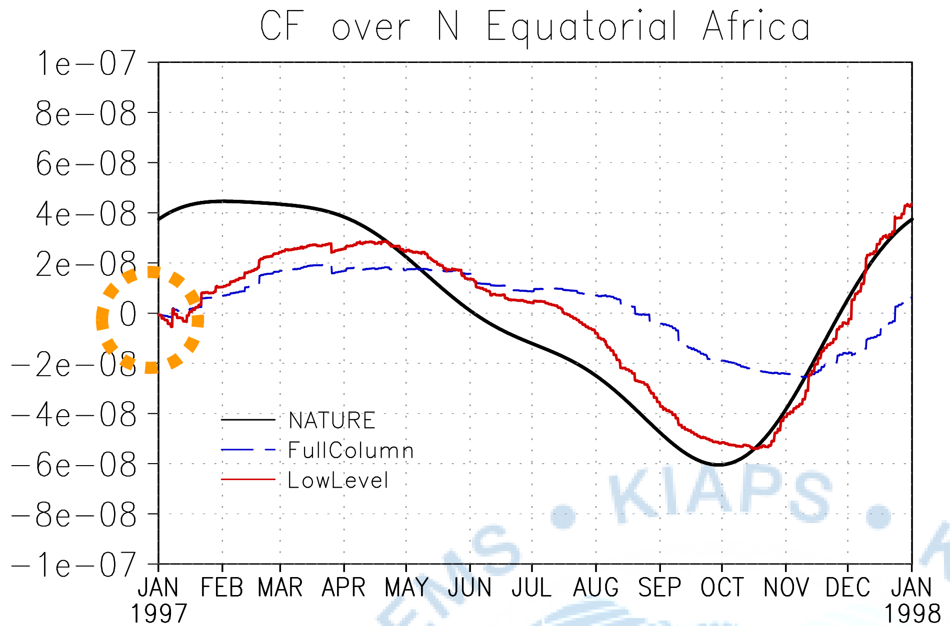




Results: time series of surface CO_2 fluxes



< observation-rich area >



< observation-poor area >

- Advanced inflation methods prevent ensemble from collapsing over observation rich area
  - Additive & adaptive multiplicative inflations help analysis estimate seasonal change of CF.
- Vertical localization improve the CF estimation over area where satellite data are dominant

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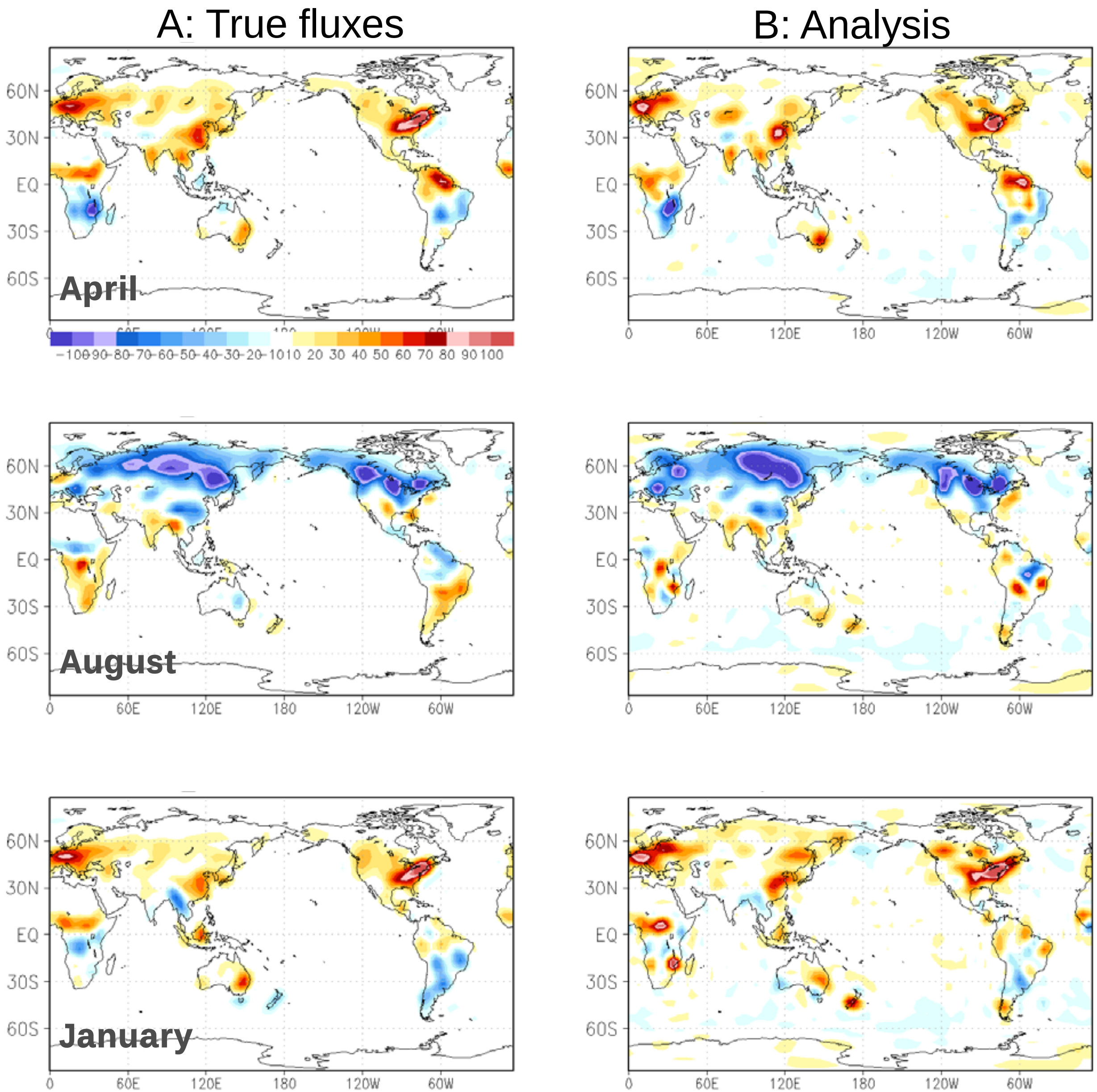
Results: surface CO_2 fluxes in different seasons



Due to the following techniques:

1) Localization of variables *(Kang et al. 2011)*
2) Advanced inflation methods (adaptive multiplicative inflation + additive inflation)
3) Vertical localization of column mixing CO_2 data *(Kang et al. 2012)*

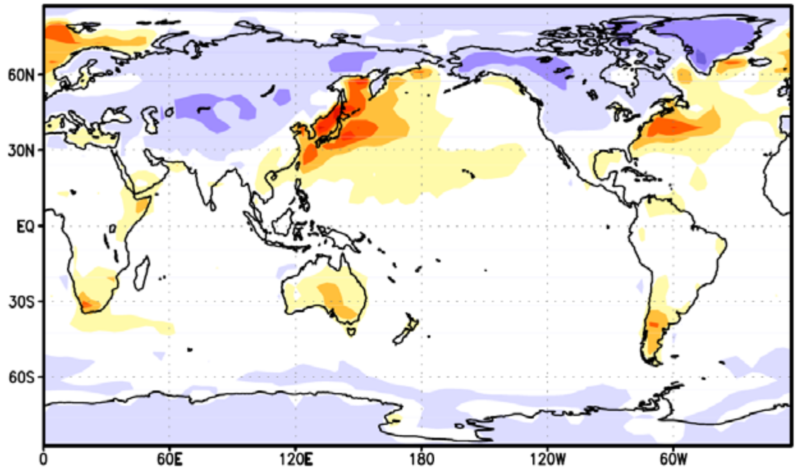
we has estimated surface CO_2 fluxes evolving in time successfully!

How about heat/moisture fluxes?

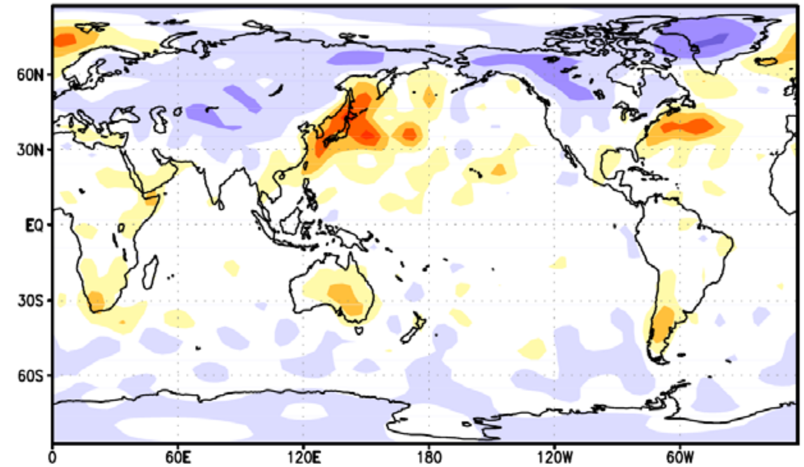
- **Can we estimate surface moisture/heat fluxes by assimilating atmospheric moisture/temperature observations?** ***We can use the same methodology!***
- **OSSEs**
  - Nature: SPEEDY (perfect model)
  - Forecast model: SPEEDY with **persistence forecast of Sensible/Latent heat fluxes (SHF/LHF)**
  - Simulated observations: conventional observations of (U, V, T, q, Ps) and **AIRS retrievals** of (T, q)
  - Analysis: U, V, T, q, Ps + **SHF** **&** **LHF**
- **Fully multivariate data assimilation**
- **Adaptive multiplicative inflation + additive inflation**
- **Initial conditions: random (*no a-priori information*)**

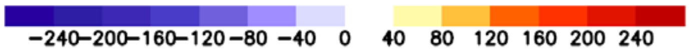
Results: SHF & LHF (perfect model of WSTR)

True SHF @ end of JAN



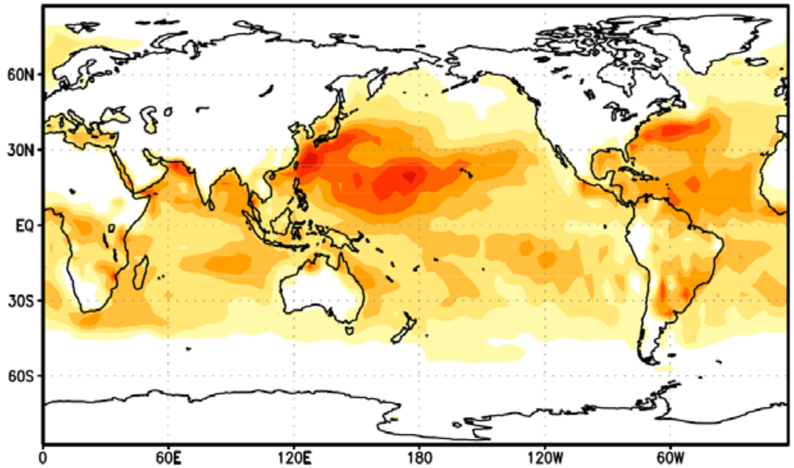
SHF analysis @ end of JAN



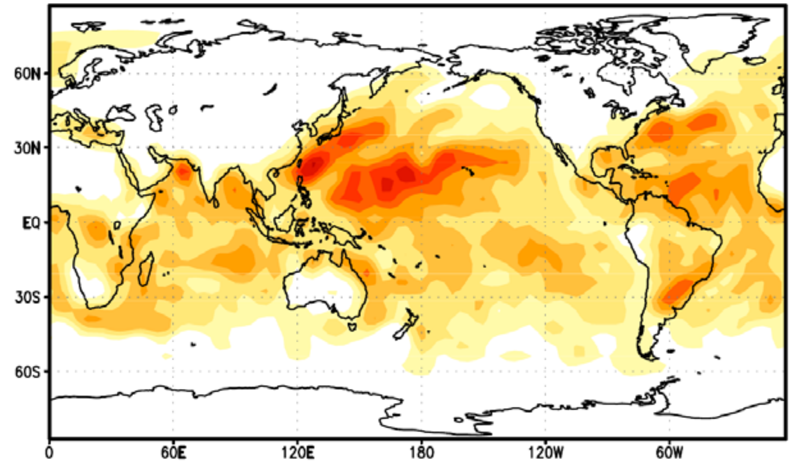


Estimations converge to the true state just after one month!

True LHF @ end of JAN



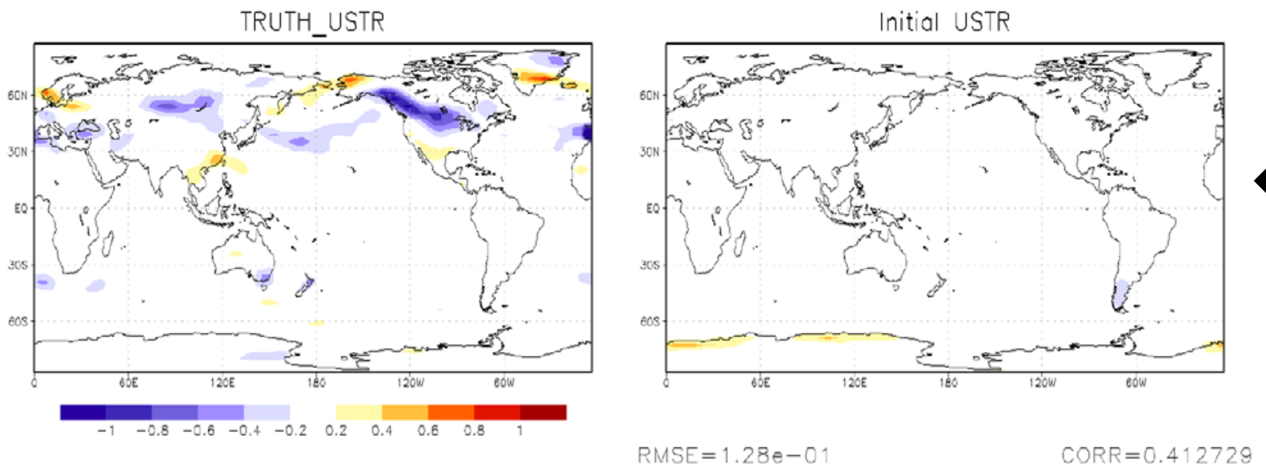
LHF analysis @ end of JAN



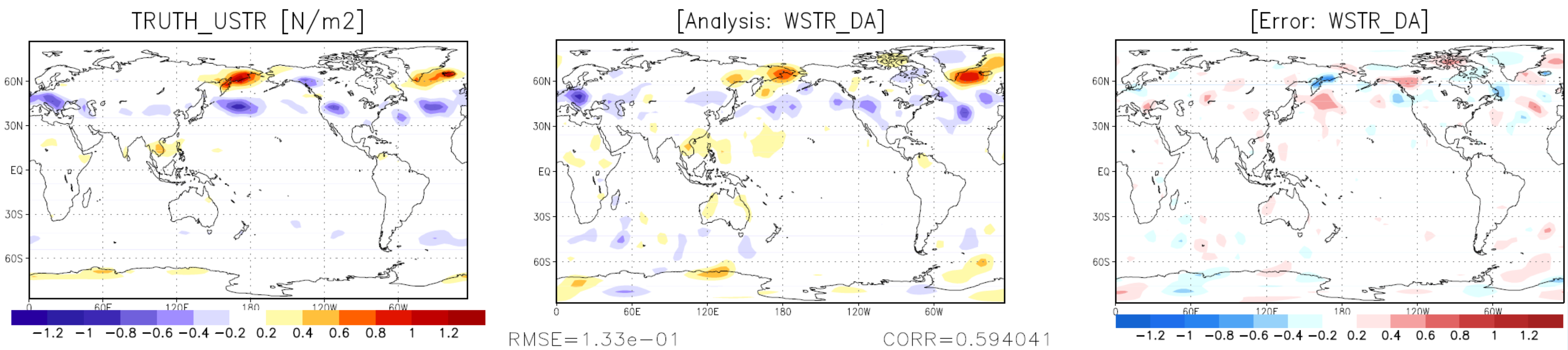
Can we also estimate wind stress?

- **OSSEs**
  - Nature: SPEEDY
  - Forecast model: SPEEDY with **persistence forecast of Sensible/Latent heat fluxes (SHF/LHF) and wind stress (USTR, VSTR) [ALL_FLUXES]**
  - Simulated observations: conventional observations of (U, V, T, q, Ps), AIRS retrievals of (T, q), and **ASCAT ocean surface wind observations**
    - **Observation error of ASCAT: 3.5m/s (not as good as AIRS data)**
    - ASCAT covers the global ocean every 12 hours, but little overlapped with AIRS data distribution
  - Analysis: U, V, T, q, Ps + **SHF, LHF, USTR, VSTR**
- **Fully multivariate data assimilation**
- **Initial conditions: random (*no a-priori information*)**

Result: USTR from [ALL_FLUXES]



🡐 Initial condition includes no a-priori information of USTR



🡑 After one month of DA, USTR estimation converges to the true USTR

Impact of imperfect WSTR on LHF analysis

True USTR

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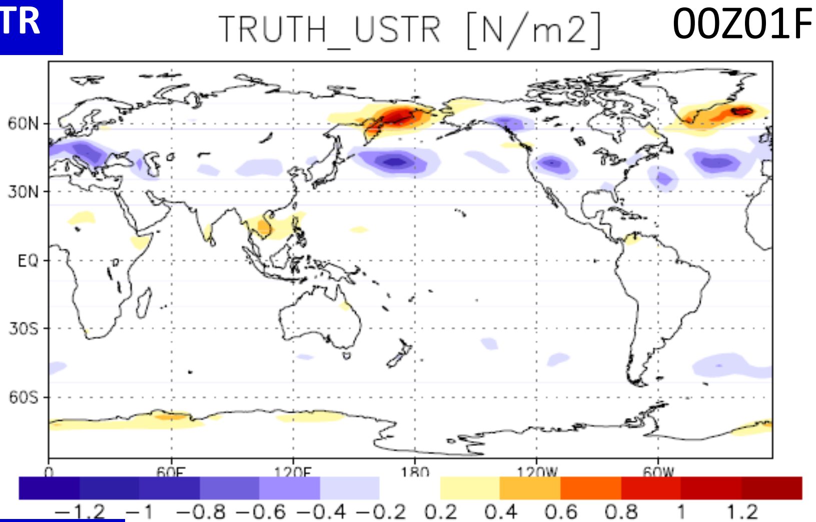
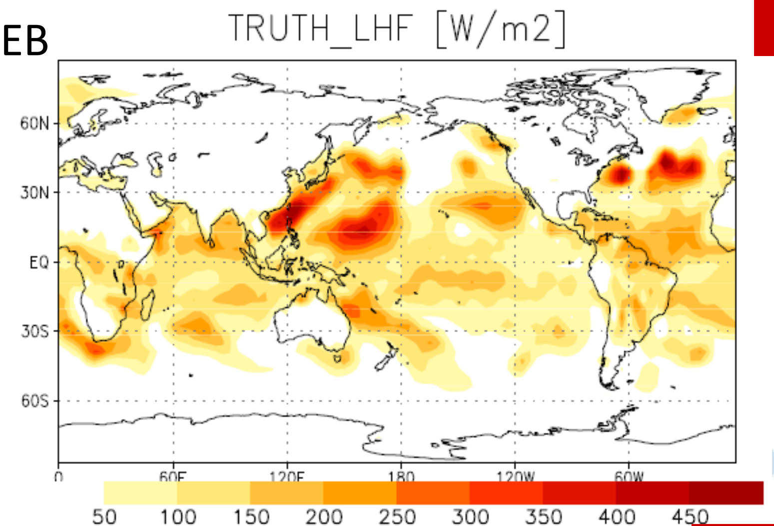
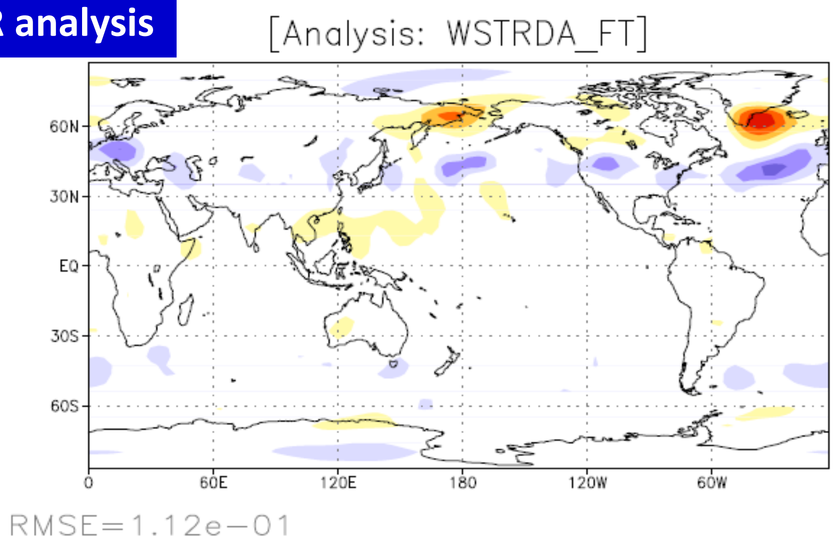
True LHF

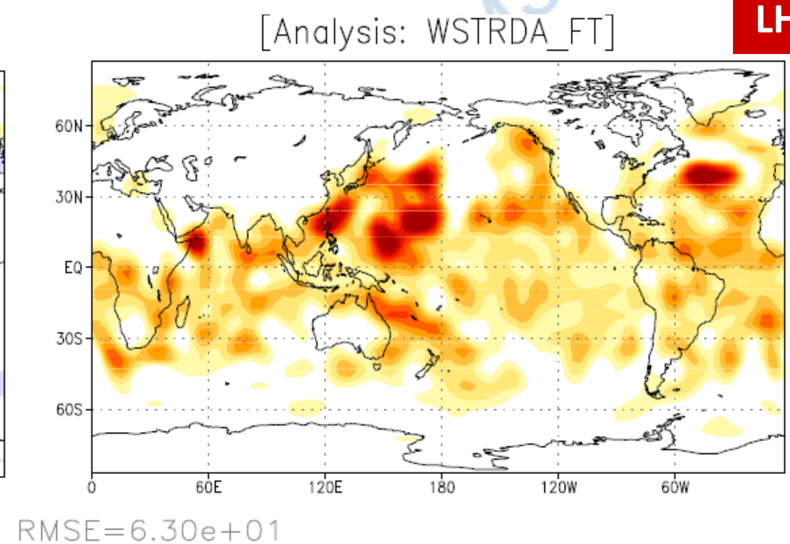




USTR analysis

LHF analysis





Summary and Discussion

- **We succeed in estimating surface CO_2 fluxes with the advanced LETKF-C system, even without *a-priori* information (OSSEs)**
- **With the same methodology, we could estimate surface heat/moisture fluxes!**

  ➔ After a short spin-up period (~a week), estimation of SHF and LHF converges very well, under the perfect model of WSTR
- **We attempt to estimate wind stress (WSTR) within LETKF (without computing it from a physical parameterization of the perfect model) in addition to SHF/LHF estimation**
  - The analysis system still needs further improvement to avoid a negative feedback among WSTR, SHF, LHF, and other prognostic variables due to the imperfect WSTR.
  - Addition of ASCAT data gives fairly good estimation of WSTR