Estimation of Surface Carbon Fluxes with Data Assimilation

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  - Vertical localization of column mixed observations – (3)
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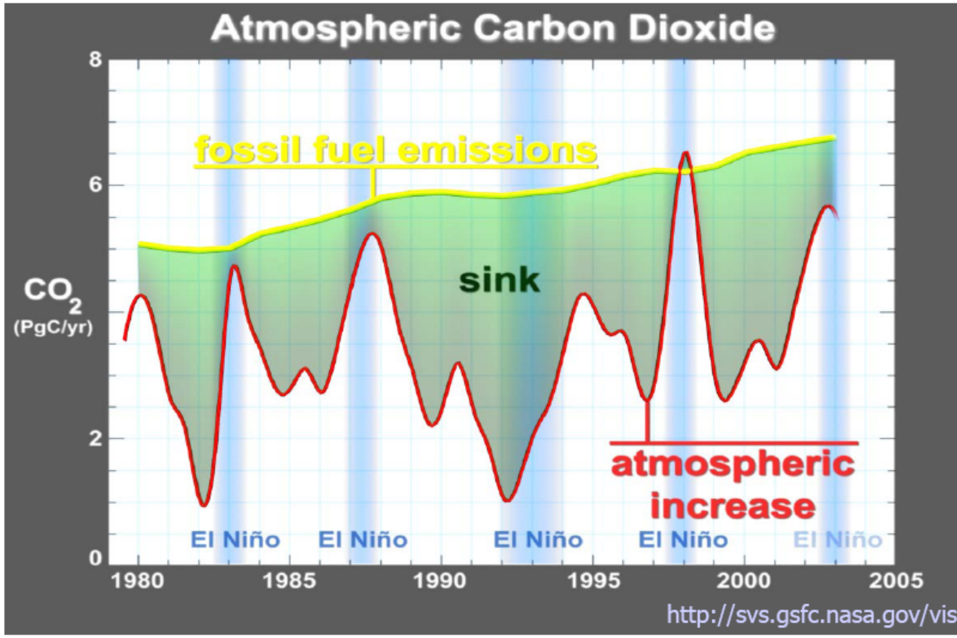
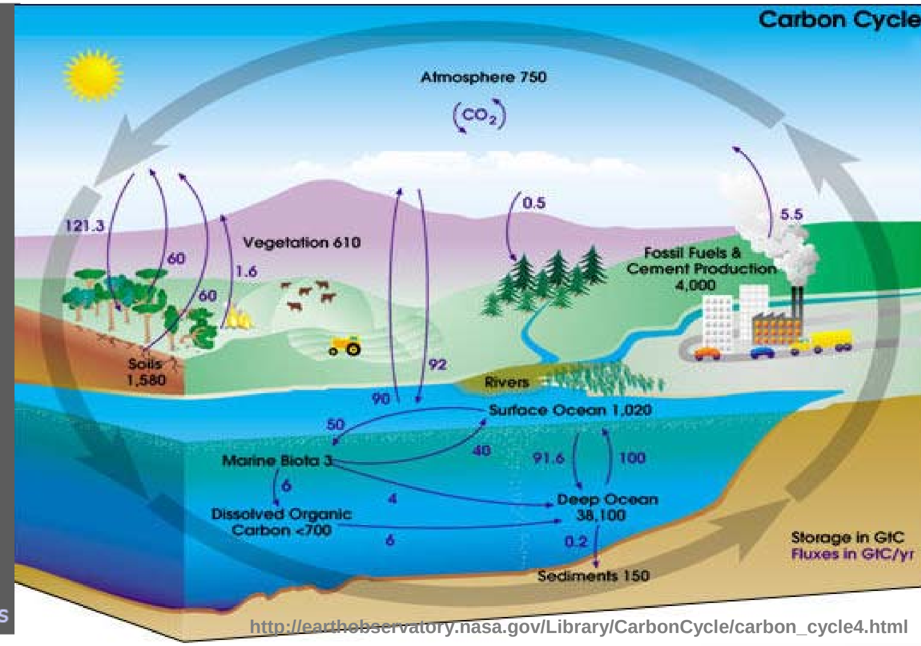
- Summary of Carbon Cycle Data Assimilation Experiments
- Application to moisture/heat flux estimations
- Future Plans

Introduction





- Substantial increase of atmospheric CO_2 caused by human activities
- About half of anthropogenic CO_2 emission has sunk into land and ocean
  - The capacity of the land and ocean CO_2 uptake varies substantially with time and space, and is strongly dependent on climate anomalies (e.g. El Nino-drought and fire, changes in balance between plant growth and death, etc)

Introduction

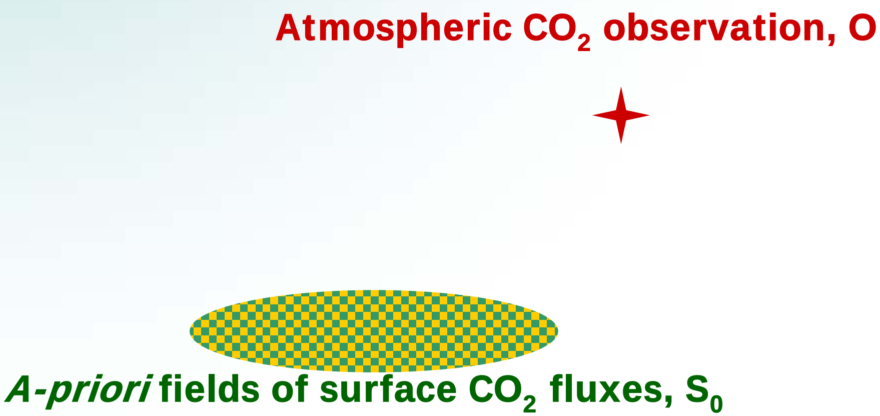
- In order to understand the carbon cycle and its impact on climate change, we need to quantify the temporal and spatial **CO_2 sources and sinks** at the Earth's surface
- **Difficulties**:
  - Lack of the spatial coverage of direct carbon flux measurements
  - Lack of the sophistication of numerical models of the carbon cycle

  ➔ Atmospheric CO_2 mixing ratio measurements are used for estimating surface CO_2 fluxes: "top-down approach"

Inversion Problem: top-down approach

- Inversion modeling (e.g. Gurney et al., 2004; Rodenbeck et al., 2003)
  - in-situ & flask atmospheric CO_2 observations
  - Sub-continental and sub-seasonal scales
  - Inverse of transport model: difficult and ill-posed
  - Computationally impractical for high-density data
- Data Assimilation (DA) (e.g. Peters et al., 2007; Baker et al., 2010; Feng et al., 2009)
  - Satellite CO_2 observations in addition to in-situ & flask data
  - Model-grid scale and weekly estimates (e.g. Carbon Tracker)

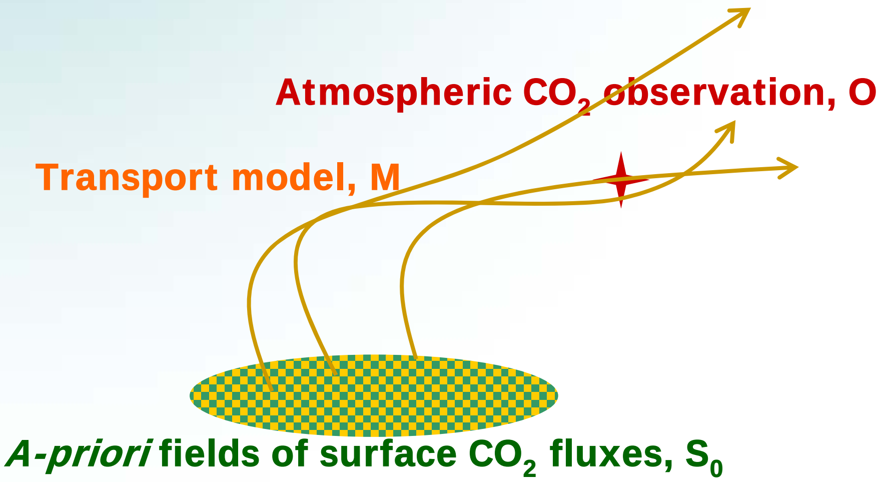
Inversion Problem: Issues



➔ **Require a prior estimate of surface CO_2 flux fields**

- A prior estimate of surface CO_2 fluxes
  - It should be pre-calculated by independent observations or another model simulation
- Transport errors (for several weeks window)
  - It is one of critical factors to degrade the flux estimation (e.g. Stephens et al.; 2007; Miyazaki, 2009; Liu et al., 2011)

Inversion Problem: Issues



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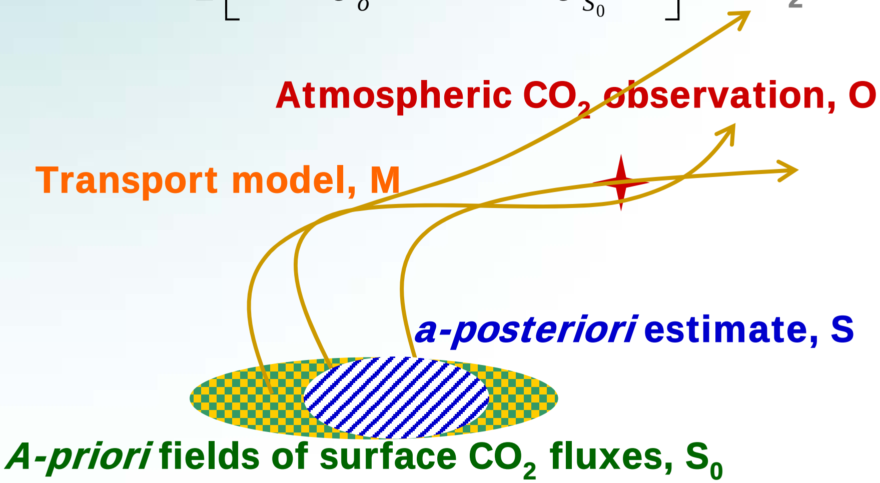
Inversion Problem: Issues

$$J = \frac{1}{2}\left[\frac{\{\mathbf{M}(S)-O\}^2}{\sigma_o^2} + \frac{(S-S_0)^2}{\sigma_{S_0}^2}\right]$$

Minimizing the difference between the simulated CO_2 concentration and the observed CO_2, prior errors of CO_2 variables



➔ Require **a prior estimate of surface CO_2 flux fields**
➔ Don't account for the **transport errors** explicitly

- A prior estimate of surface CO_2 fluxes
  - It should be pre-calculated by independent observations or another model simulation
- Transport errors (for several weeks window)
  - It is one of critical factors to degrade the flux estimation (e.g. Stephens et al.; 2007; Miyazaki, 2009; Liu et al., 2011)

Objectives of our study

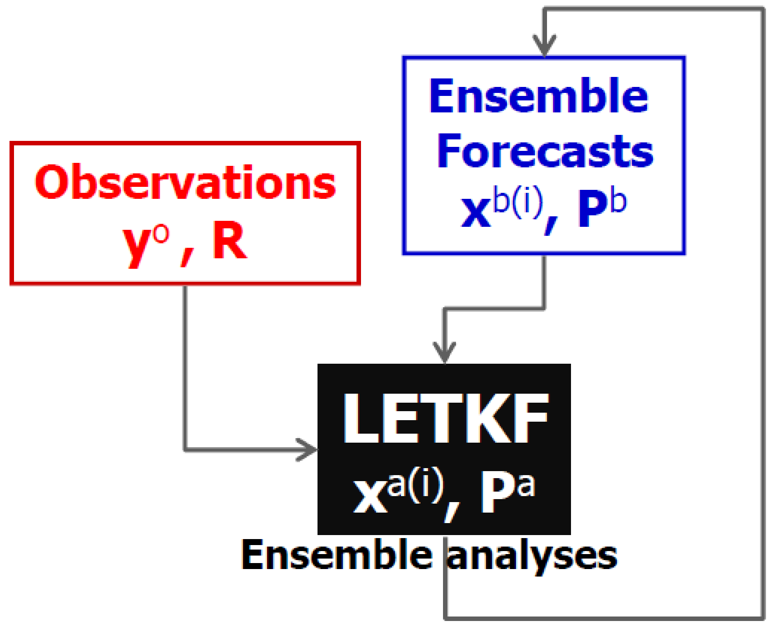
- Explore the feasibility of **estimating surface CO_2 fluxes at the model-grid scale** by assimilating atmospheric variables (U, V, T, q, Ps) and atmospheric CO_2 *simultaneously*
  - Consider transport errors in analyzing CO_2 variables
  - No *a-priori* information for CO_2

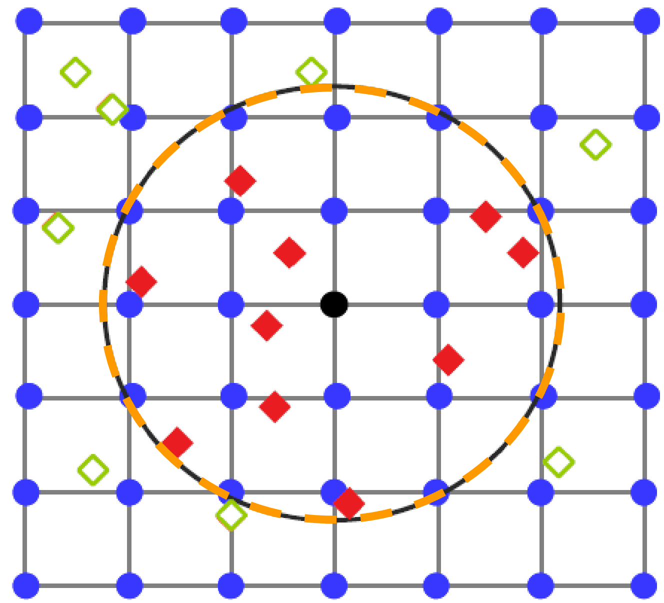
"Carbon Data Assimilation with a Coupled Ensemble Kalman Filter"
Supported by Climate Change Prediction Program in Department of Energy

Simulation mode (SPEEDY)
Develop new methodologies
University of Maryland
Prof. Eugenia Kalnay

Realistic System (CAM/CLM)
Assimilating real observation of GOSAT & AIRS
UC Berkeley
Prof. Inez Fung

Local Ensemble Transform Kalman Filter
(Hunt et al., 2007)





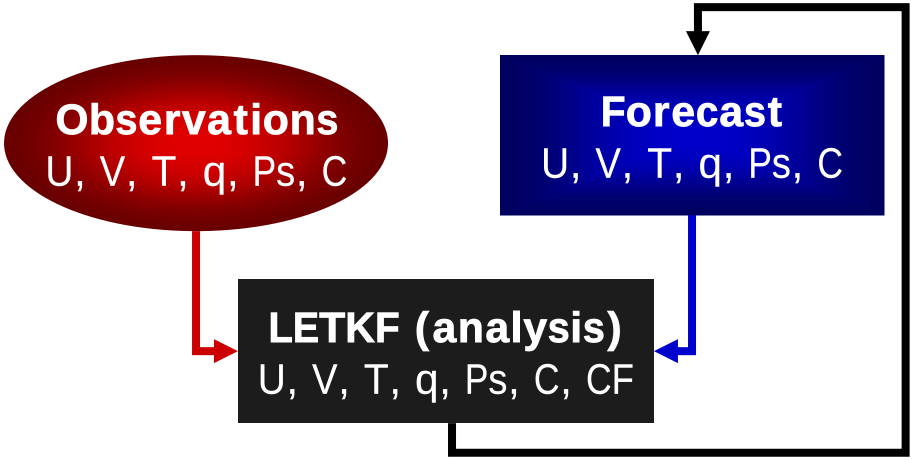
- **Analysis**=(1-**K**)***background** + **K*****obs**
  - **K** (Kalman gain) is determined by the error statistics of ensemble forecast (background) and observations
  - EnKF provides background and **analysis** uncertainty estimation in every analysis step (P^b, $\mathbf{P^a}$)
  - LETKF assimilates the observations locally

UMD-Berkeley LETKF-C System

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

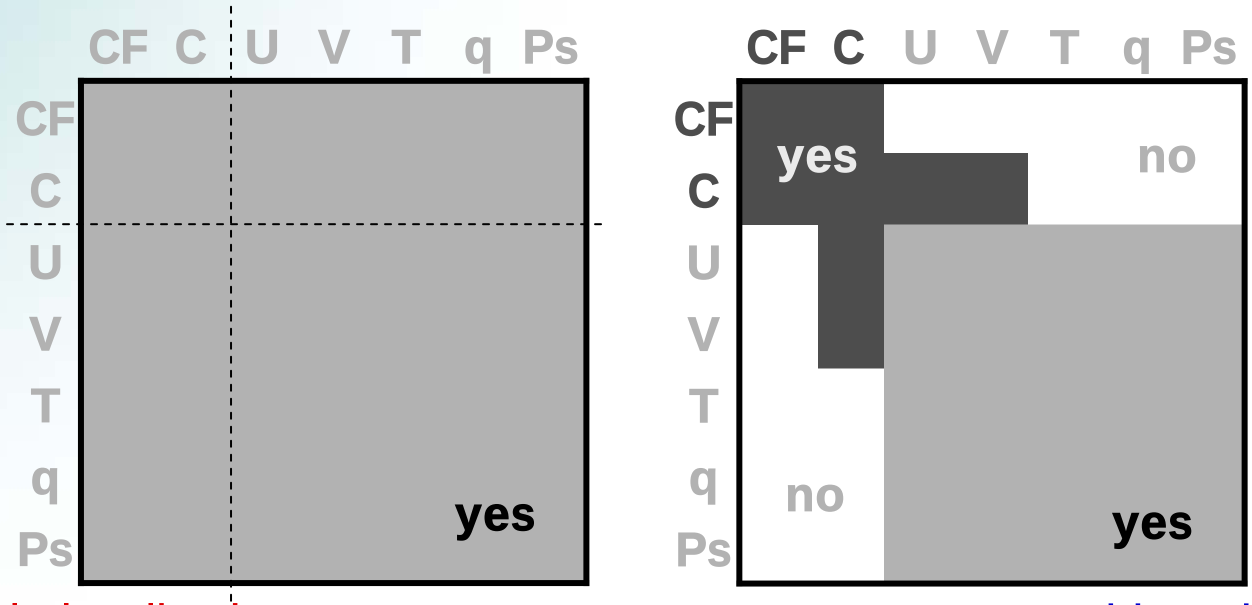
$\mathbf{X}$: model state vector (U, V, T, q, Ps, C)

$\mathbf{CF}$: 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



without variable localization Background error covariance matrix with variable localization

- 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

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

(Kang et al., 2011, JGR)

Observing System Simulation Experiments (OSSEs)

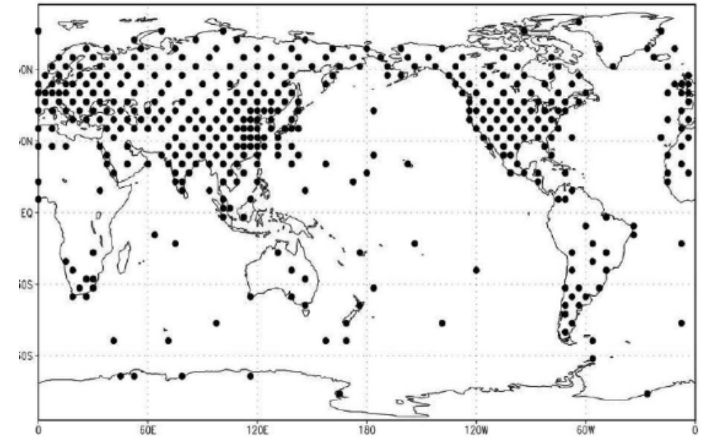
- We assume that *we know the true state!*
  - True state (nature run) is generated by a simulation of the model
  - Observations are simulated from the true state
  - Forecast starts from perturbed/random initial guess
  - ➔ *See if our new data assimilation techniques or new datasets improve the analysis compared with the truth*
- Test of three data assimilation techniques
  - Localization of variables – (1)
  - Advanced inflation methods – (2)
  - Vertical localization of column mixed CO_2 data – (3)
- Test of impact of CO_2 observations on surface CO_2 flux estimation
  - in-situ & flasks, GOSAT (OCO-2) and AIRS – (4)

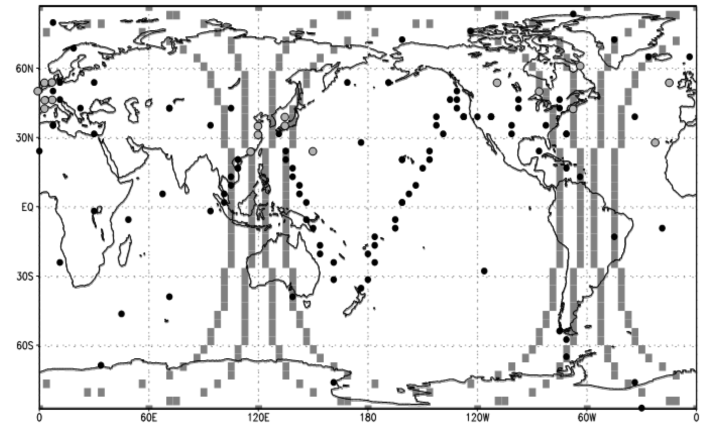
OSSEs – (1)

- **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)
- Forecast model
  - SPEEDY-C with persistence forecast of surface CO_2 fluxes (CF)
    - **CF is updated only by the data assimilation**
  - Initial condition: random (no a-priori information)
    - Ensemble mean of initial CF is close to zero

Simulated Observations – (1)

- Meteorological variables (U, V, T, q, Ps)
  - Rawinsonde
    - Every six 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 squares
- No direct measurement of surface CO_2 fluxes

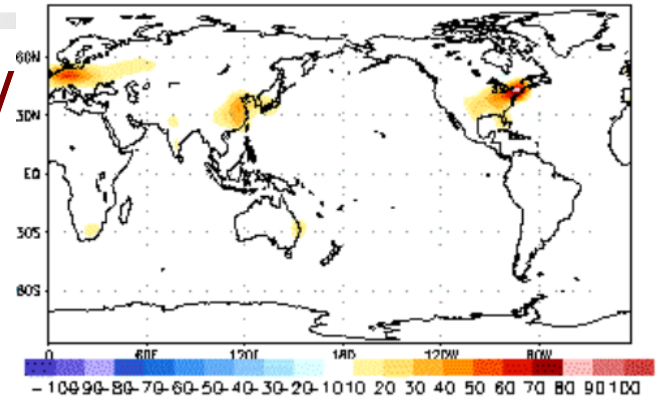


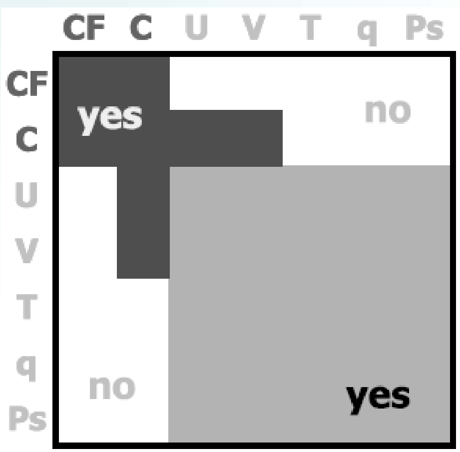


Results: Impact of variable localization

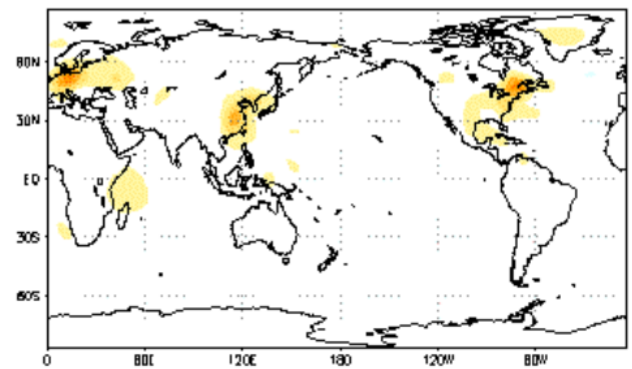
- The experiments *only with a fossil fuel emission*
  - Variable localization significantly reduce sampling errors

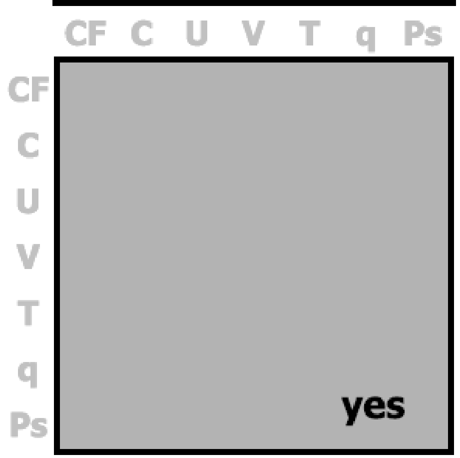
True CO_2 fluxes ➔





Analysis of CO_2 fluxes
with variable localization
➔





Analysis of CO_2 fluxes
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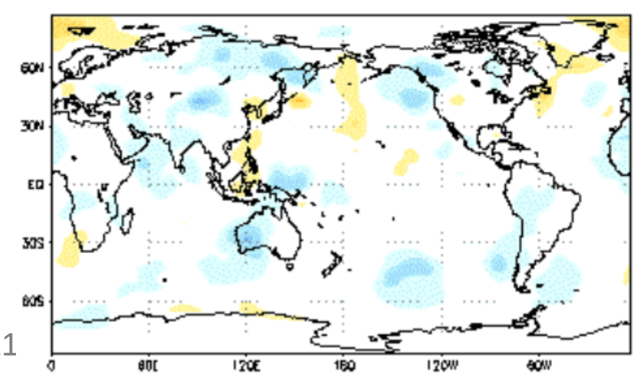


Nature with “evolving” CF

In order to estimate surface CO_2 fluxes evolving in time, we need more advanced data assimilation techniques.

✓ Advanced inflation methods

✓ Vertical localization of column mixing CO_2 data

(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 of background uncertainty 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!*

Experiments for inflation methods

- Fixed multiplicative inflation **(FixedM)**
  - Standard method
  - Fixed multiplicative inflation parameter (α) in time and space

- FixedM + Additive inflation **(FixedM + Addi)**
  - Add perturbations to analysis of CO_2 variables

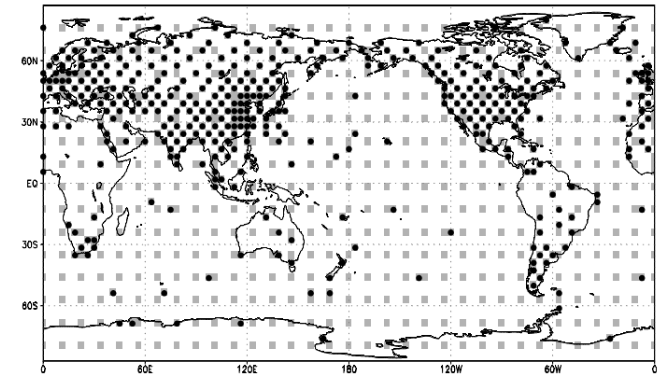
- Adaptive multiplicative inflation + Additive inflation **(AdaptM + Addi)**
  - Estimates multiplicative inflation parameter at each grid point at every analysis step adaptively (Miyoshi, 2011)

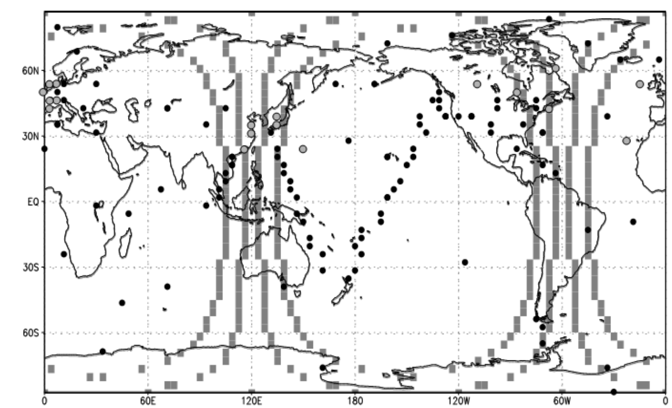
OSSEs – (2) & (3)

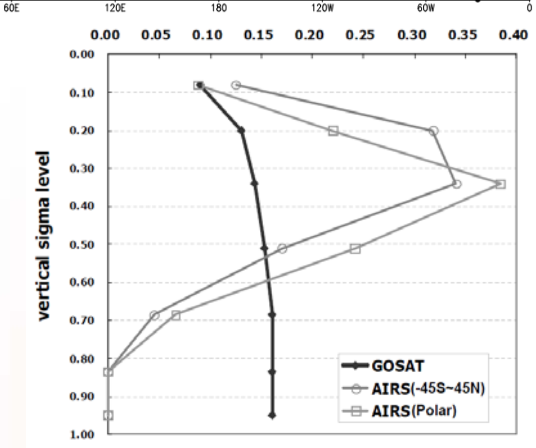
- **Nature run**: assumed true state in the experiments
  - SPEEDY-C: the modified version of SPEEDY (Molteni, 2003)
    - AGCM with a tracer gas of atmospheric CO_2 (C)
    - Spectral model with T30L7
    - Prognostic variables: U, V, T, q, Ps, C
    - No diurnal cycle
  - **“True” CO_2 fluxes** (true 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 – (2) & (3)

- 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

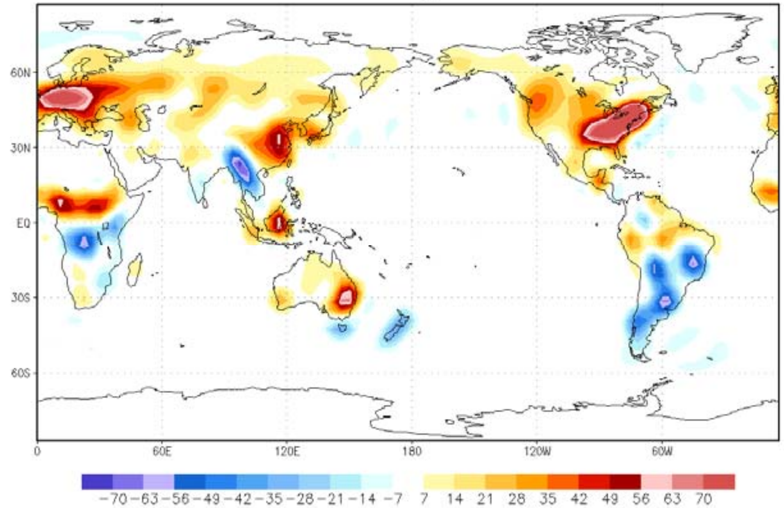




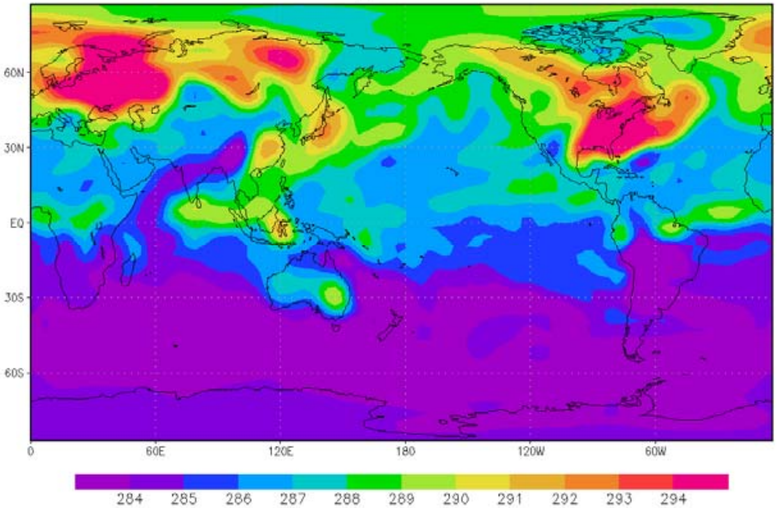


Initial Conditions for Carbon Variables

True CO_2 fluxes @ initial time

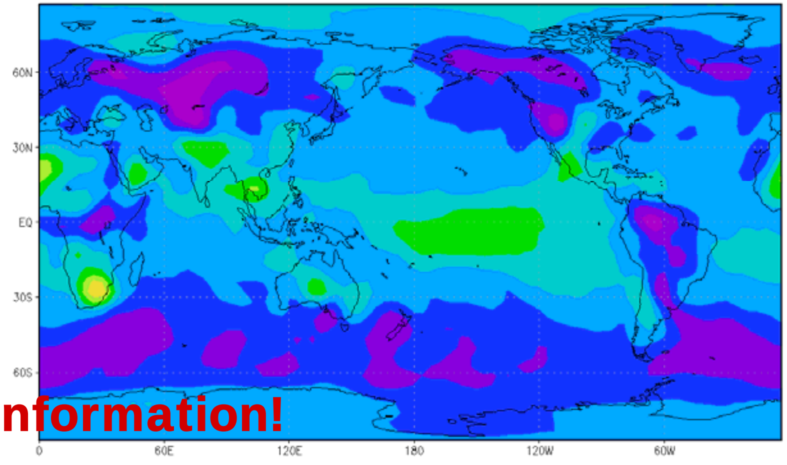


True atmospheric CO_2 near surface @ initial time



Initial condition of surface CO_2 fluxes

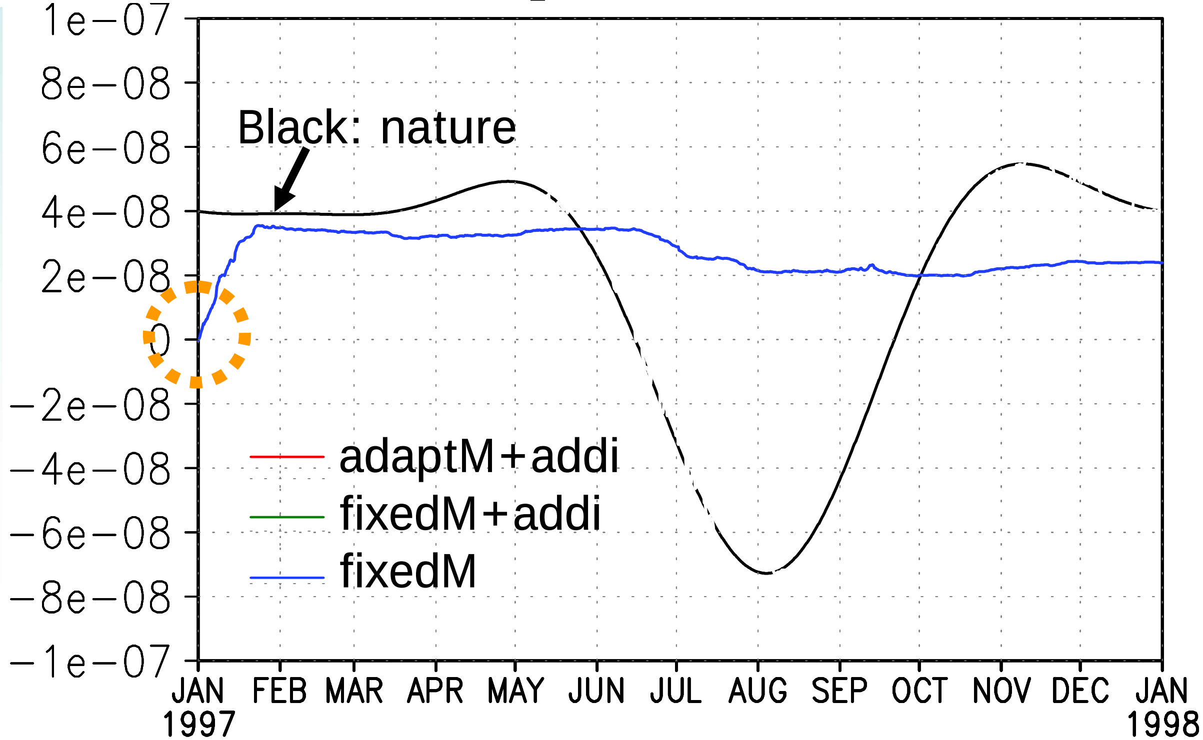
Initial condition of atmospheric CO_2 near surface



No *a-priori* information!

Results: Impact of the inflation methods

Time series of surface CO_2 fluxes over East of North America



- Fixed multiplicative inflation fails to estimate seasonal changes of CO_2 fluxes due to a serious underestimation of background uncertainty.

Results: Impact of the inflation methods

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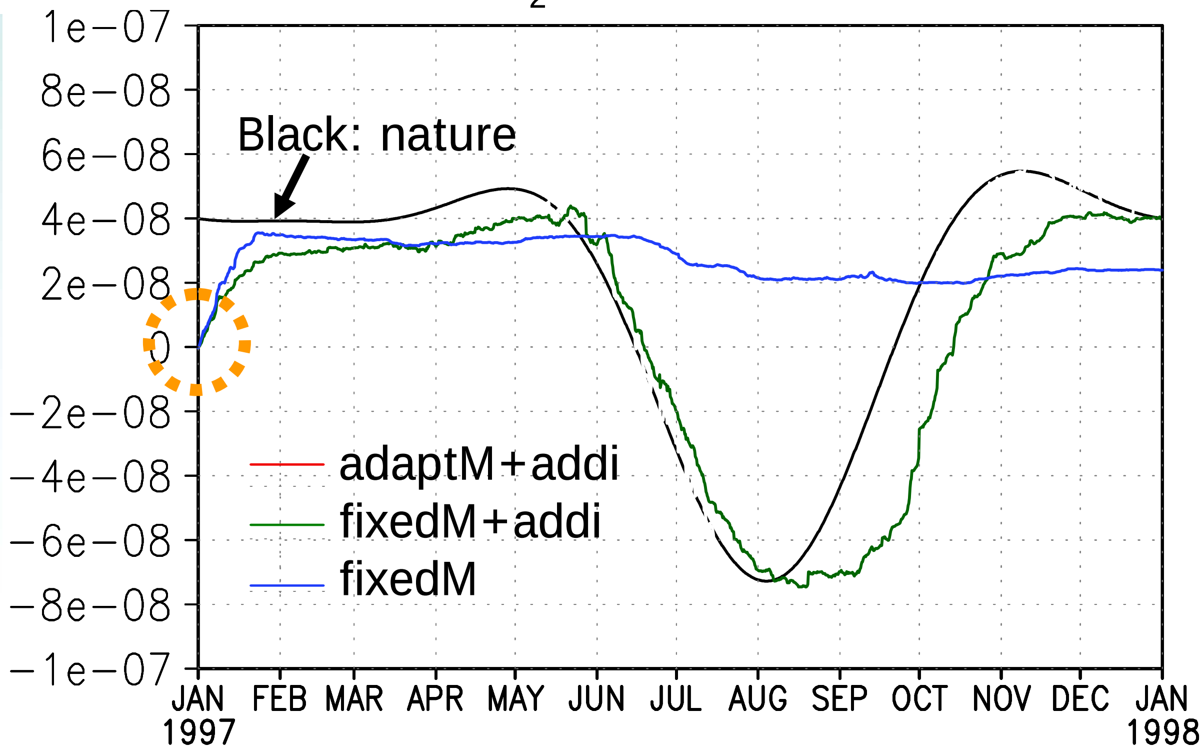

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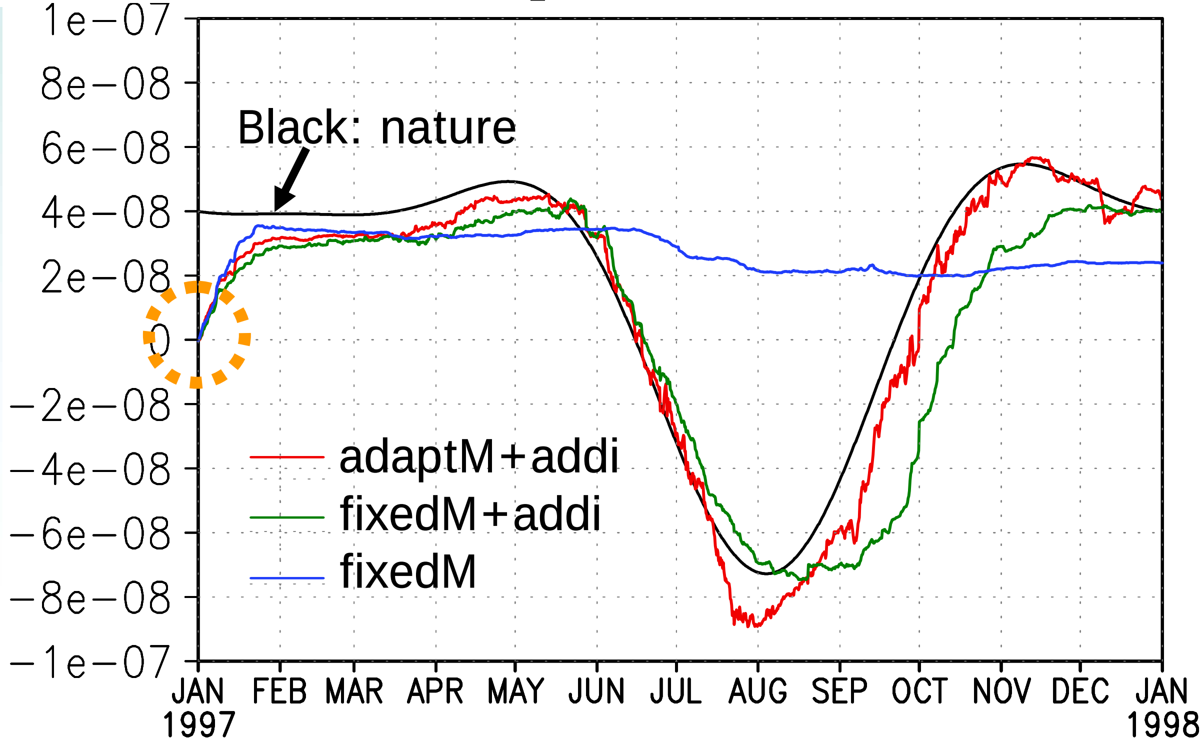
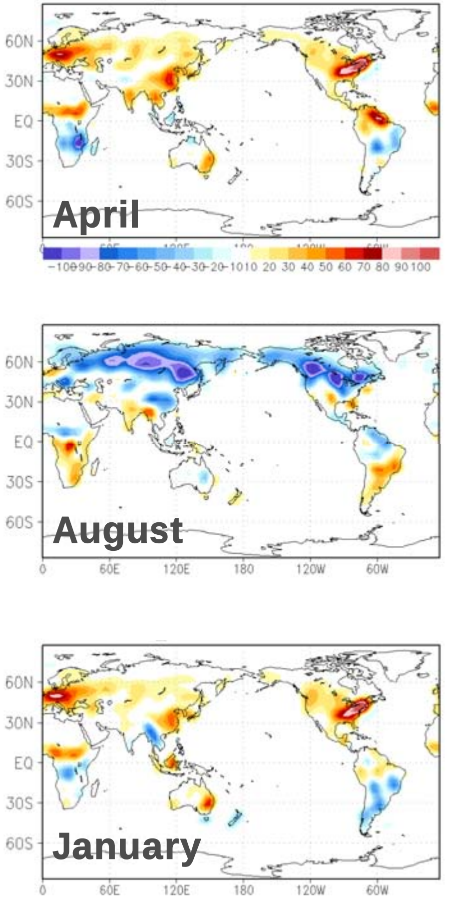


- Fixed multiplicative inflation fails to estimate seasonal changes of CO_2 fluxes due to a serious underestimation of background uncertainty.
- Additive inflation and adaptive inflation improve the representation of background uncertainty significantly so that the analysis maintains the quality till the end of one-year data assimilation

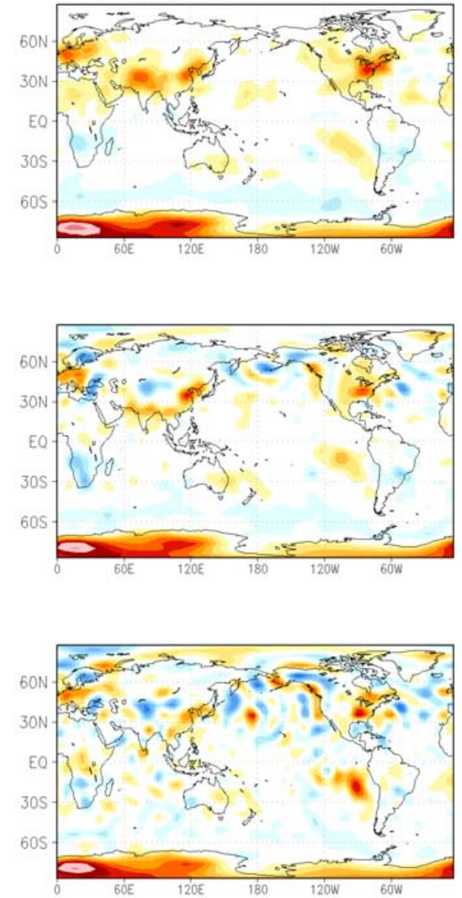
Results: Impact of the inflation methods

- Global maps of surface CO_2 fluxes in different seasons

A: True fluxes



D: FixedM



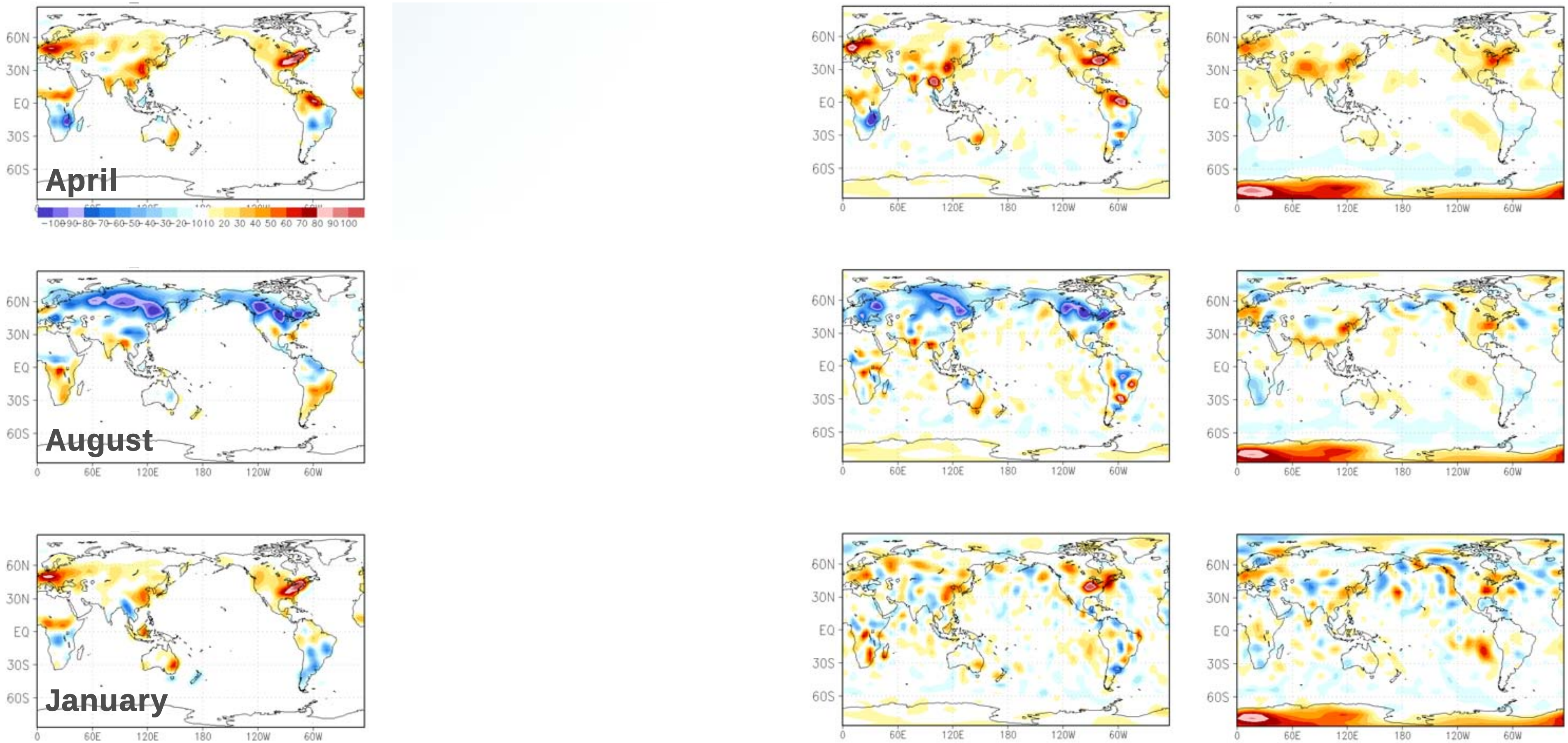
Results: Impact of the inflation methods

- Global maps of surface CO_2 fluxes in different seasons

A: True fluxes

C: FixedM+Addi

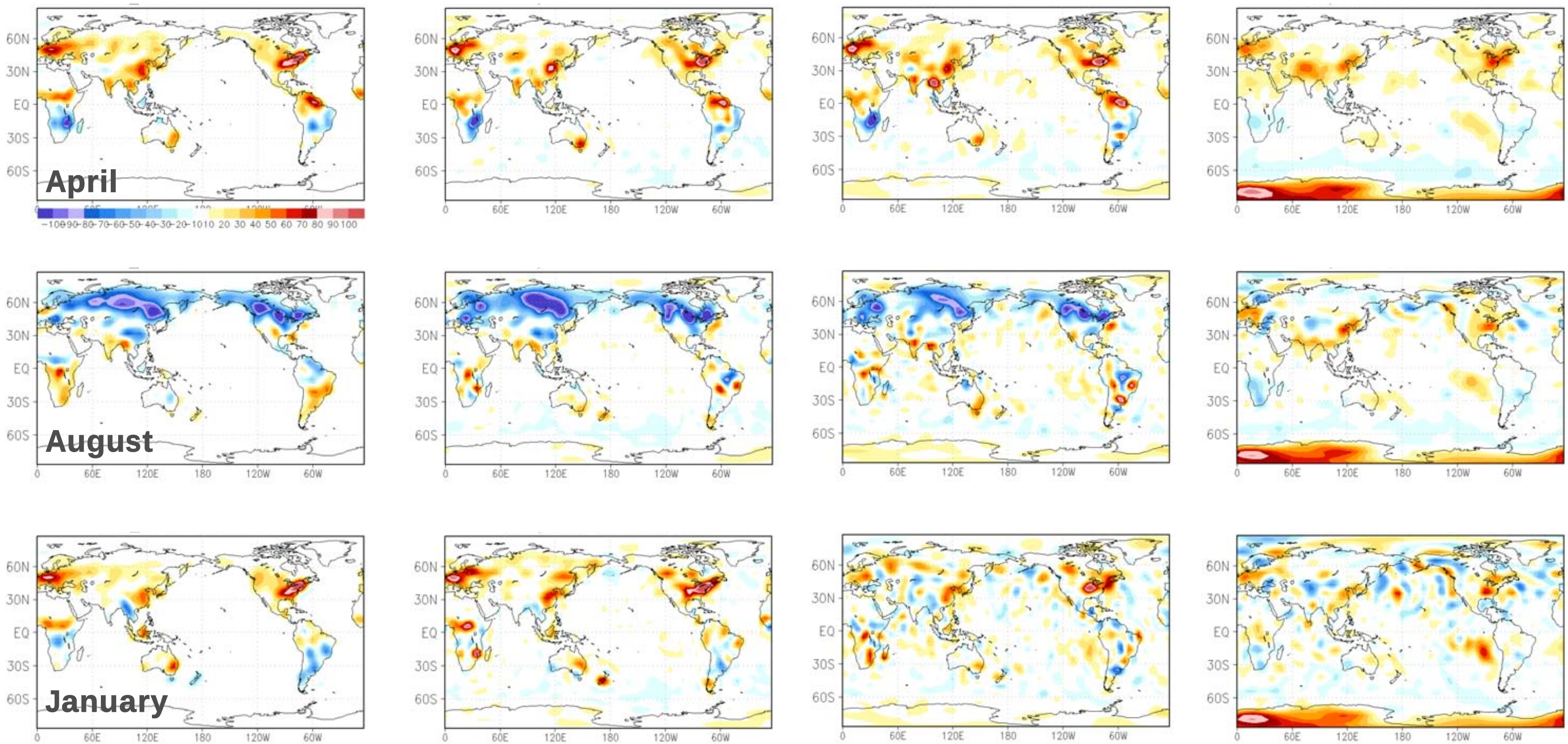
D: FixedM



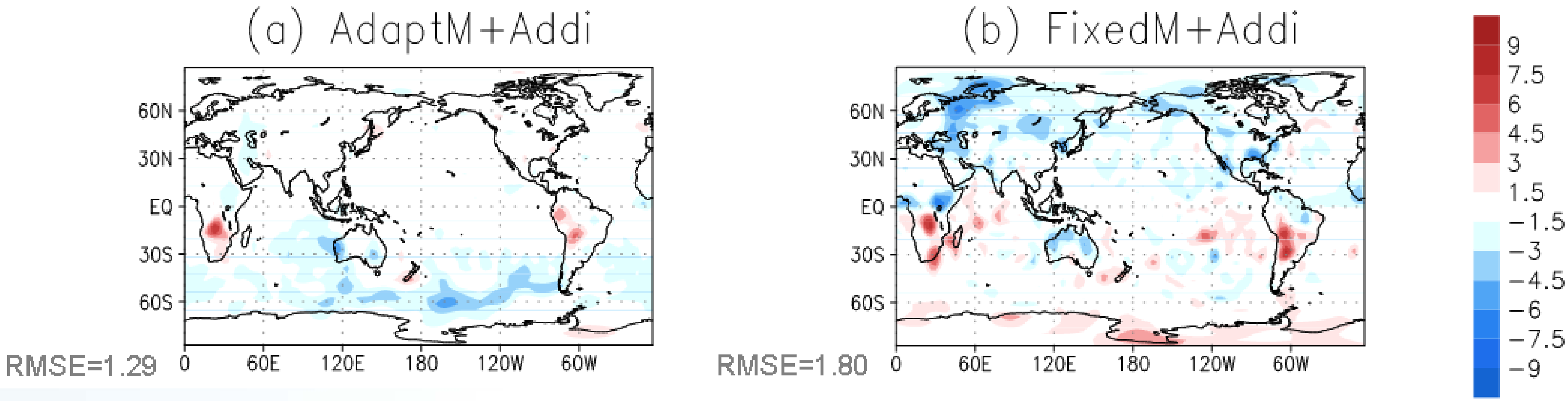
Results: Impact of the inflation methods

- Global maps of surface CO_2 fluxes in different seasons

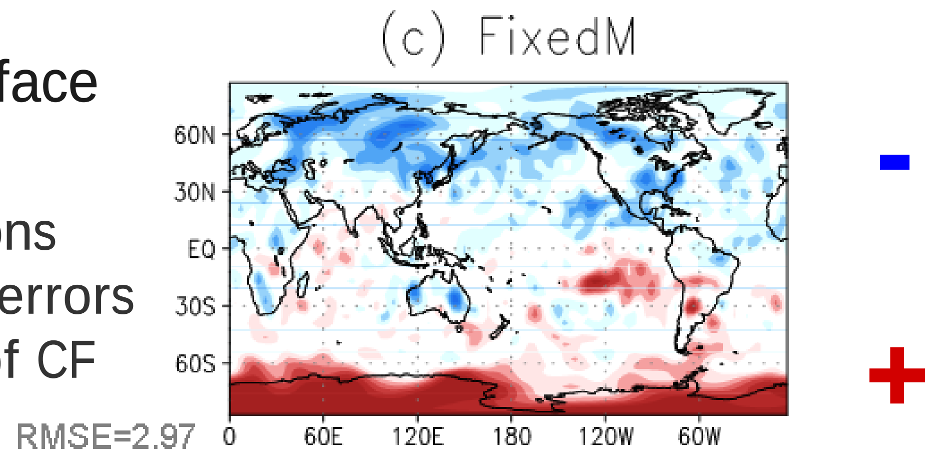
A: True fluxes | B: AdaptM+Addi | C: FixedM+Addi | D: FixedM



Impact of the inflation methods on errors



- Analysis errors of atmospheric CO_2 near the surface at the end of one-year DA
  - Adaptive and additive inflations reduce the atmospheric CO_2 errors caused by the imperfection of CF forecast

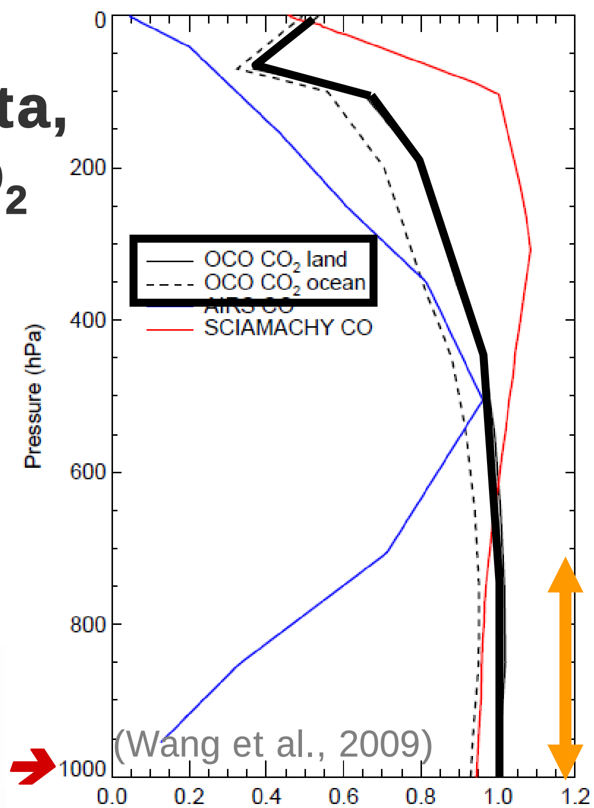


(3) Vertical Localization

- **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

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

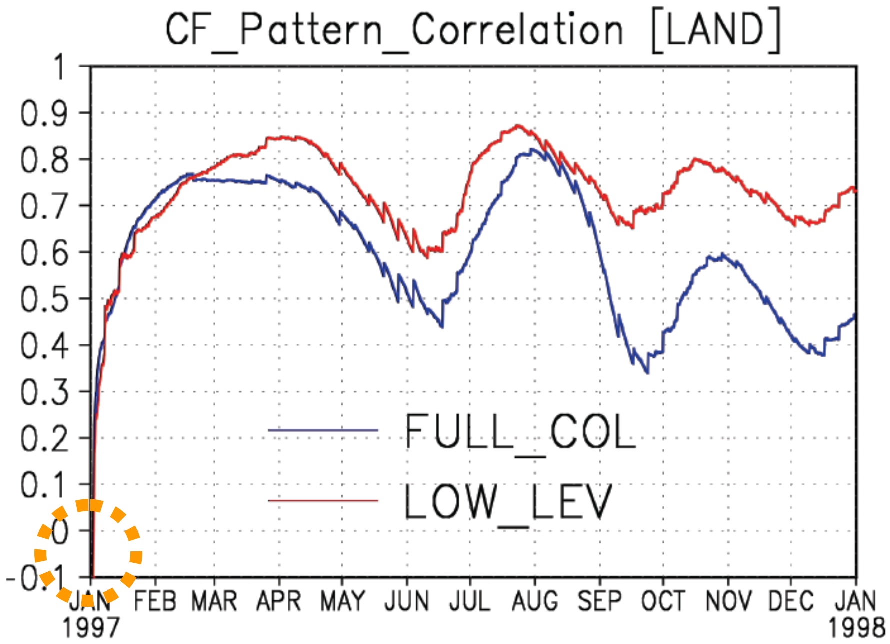
    – Calculating innovation based on the averaging kernel

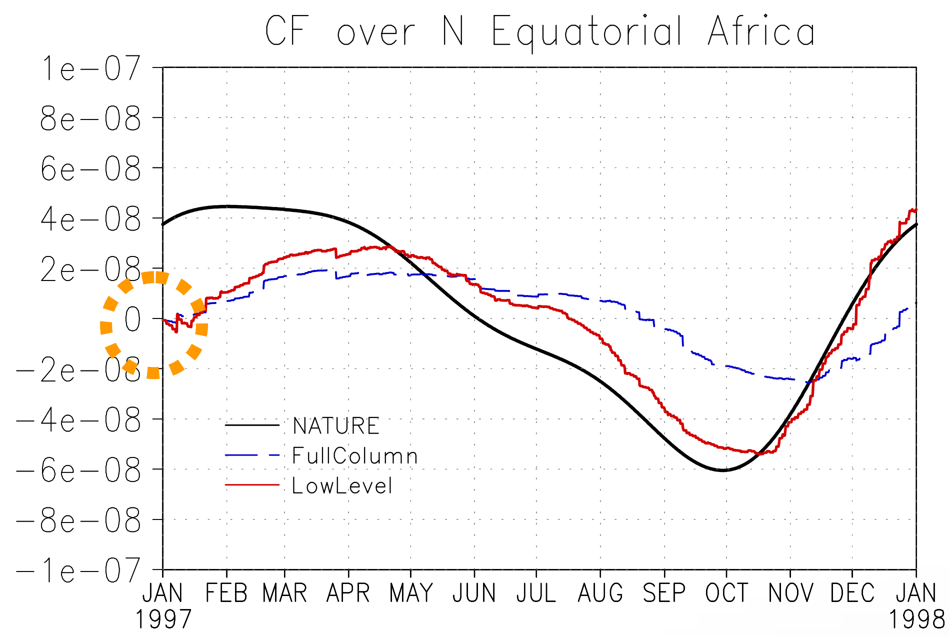


(Kang et al., in prep.)

Forcing is at the surface ➔

Results: Impact of vertical localization

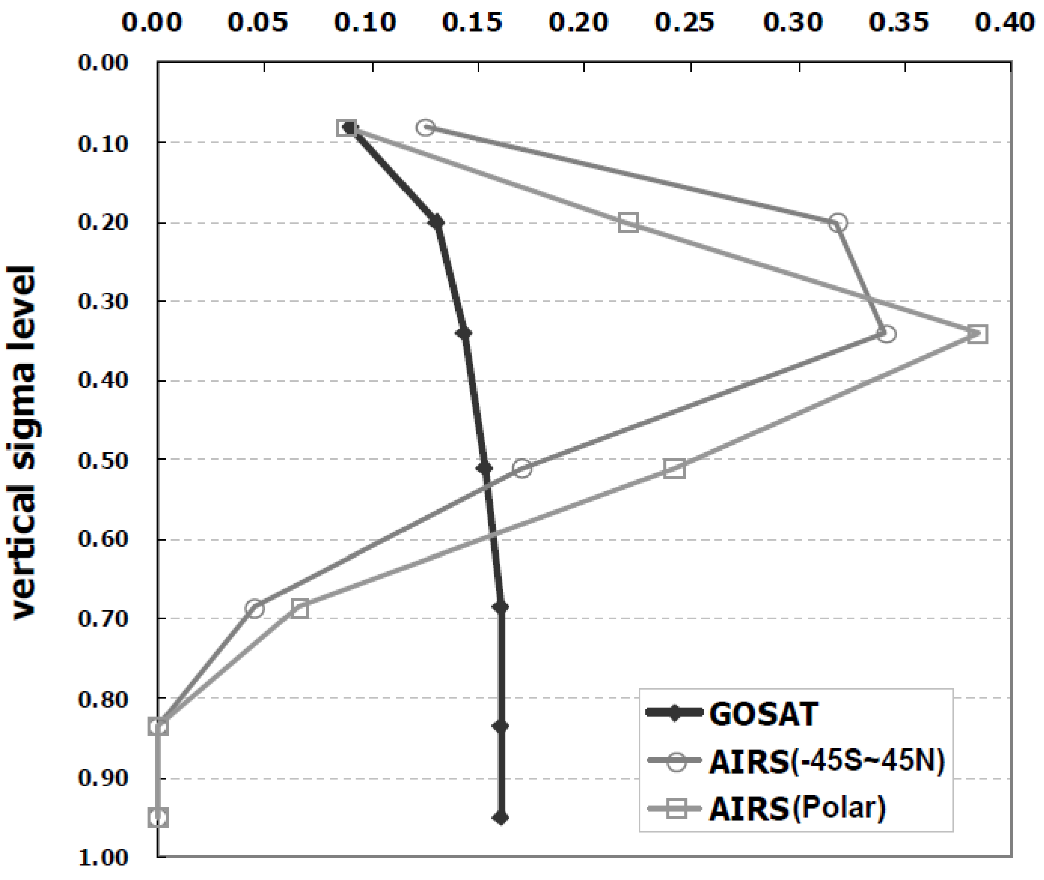




- This method improves analysis of CF mainly over where there are few observations and where there is strong variability of CF
  - We need a careful localization on column mixing CO_2 observations

(4) Observation Impact on errors

- Impact of CO_2 observations on surface CO_2 flux estimation
  - SFC: in-situ & flask data
  - SFC + AIRS
  - SFC + GOSAT
  - SFC + GOSAT + AIRS



(4) Observation Impact on errors

- Impact of CO_2 observations on surface CO_2 flux estimation
  - SFC: in-situ & flask data
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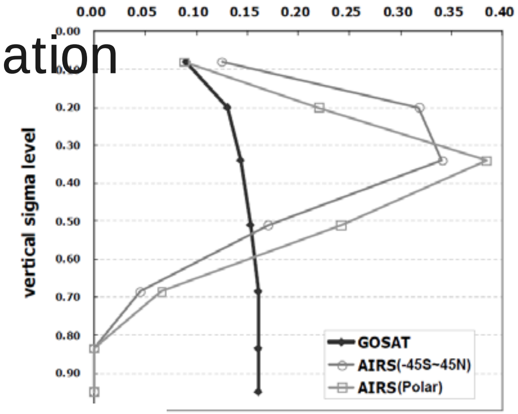
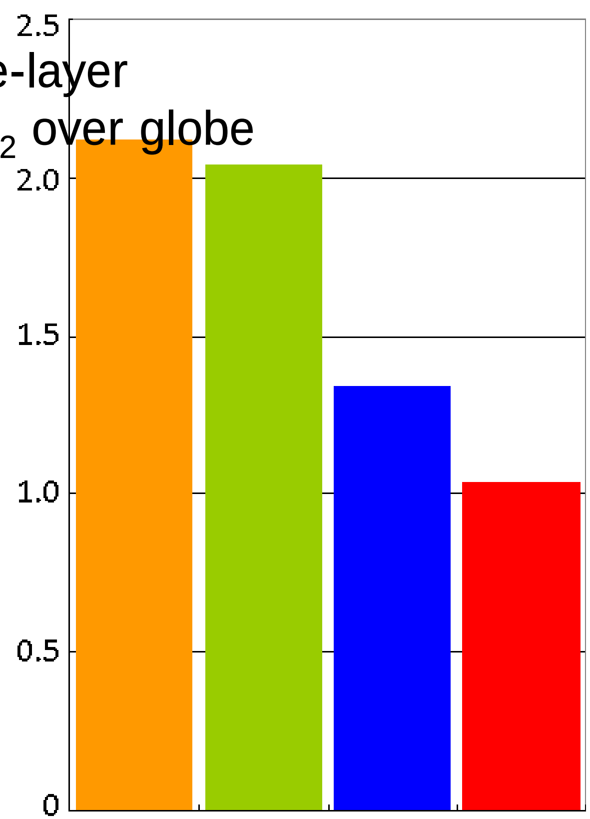
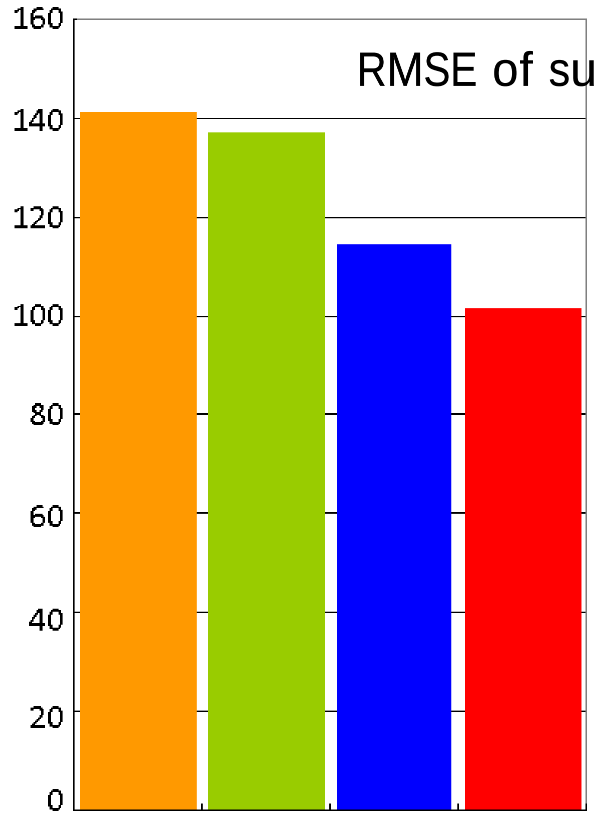
  - SFC + GOSAT + AIRS



RMSE of surface-layer atmospheric CO_2 over globe (ppmv)



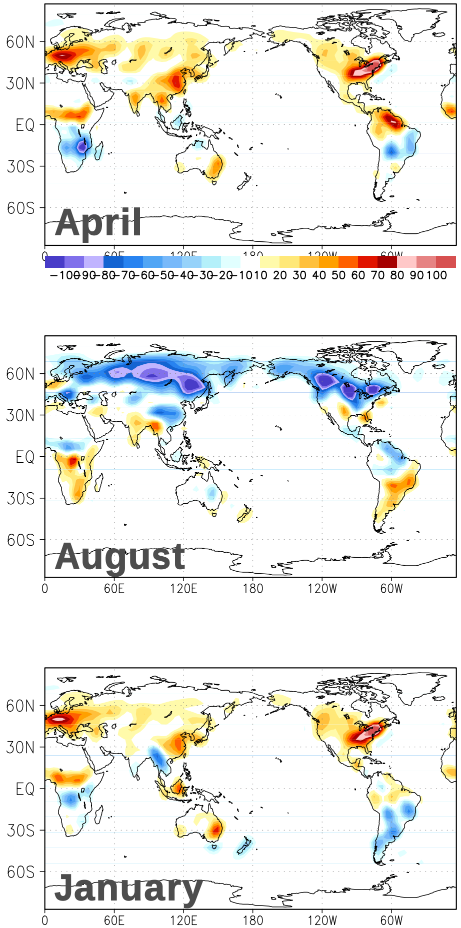


RMSE of surface CO_2 fluxes over globe ($gC/m^2/yr$)

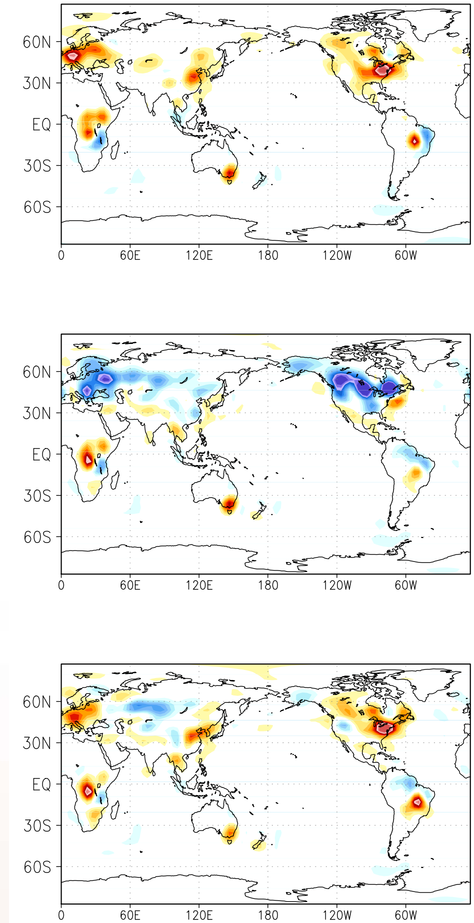
Results: Observation Impacts

- Global maps of surface CO_2 fluxes in different seasons

A: True fluxes



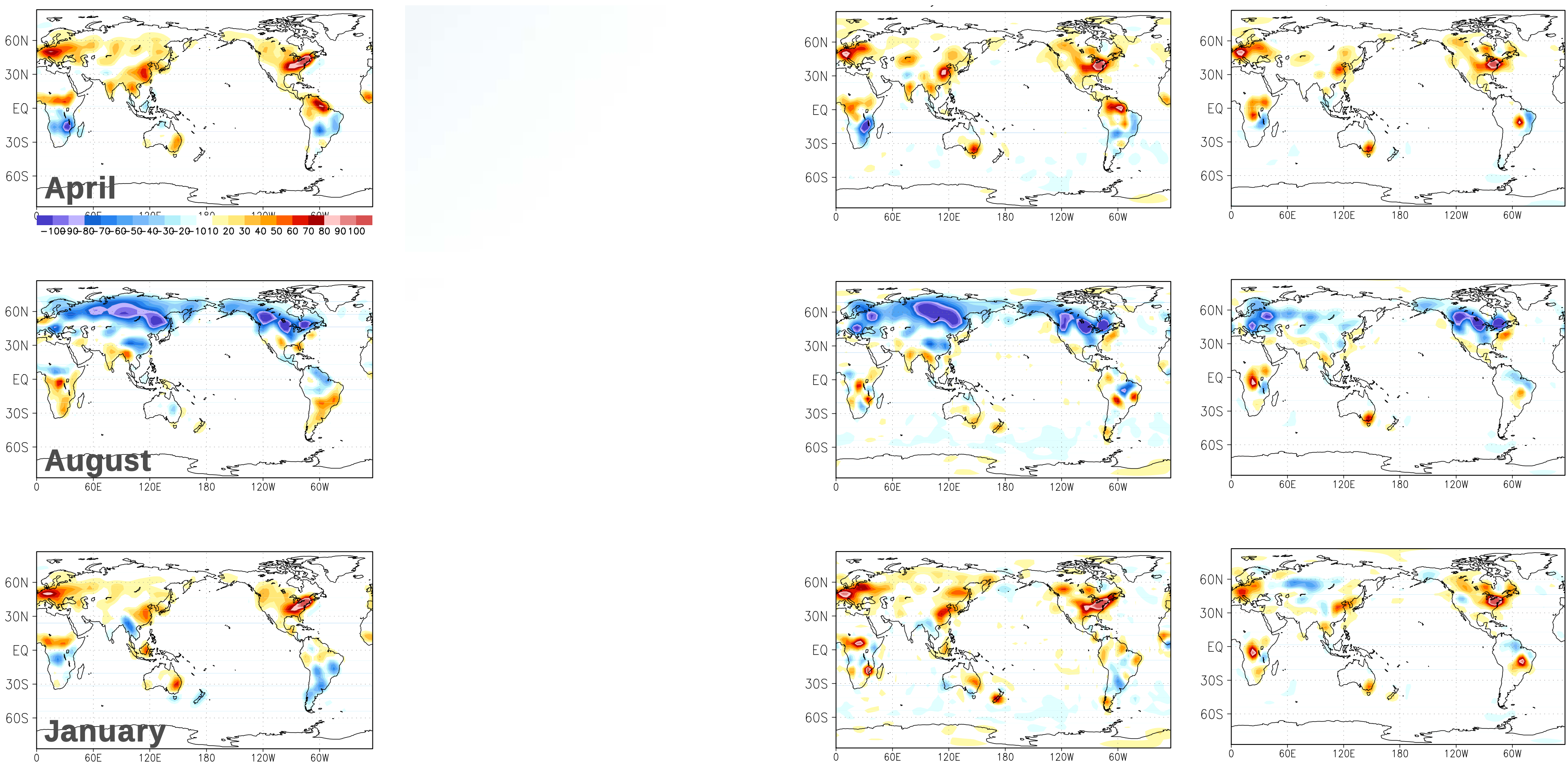
D: SFC



Results: Observation Impacts

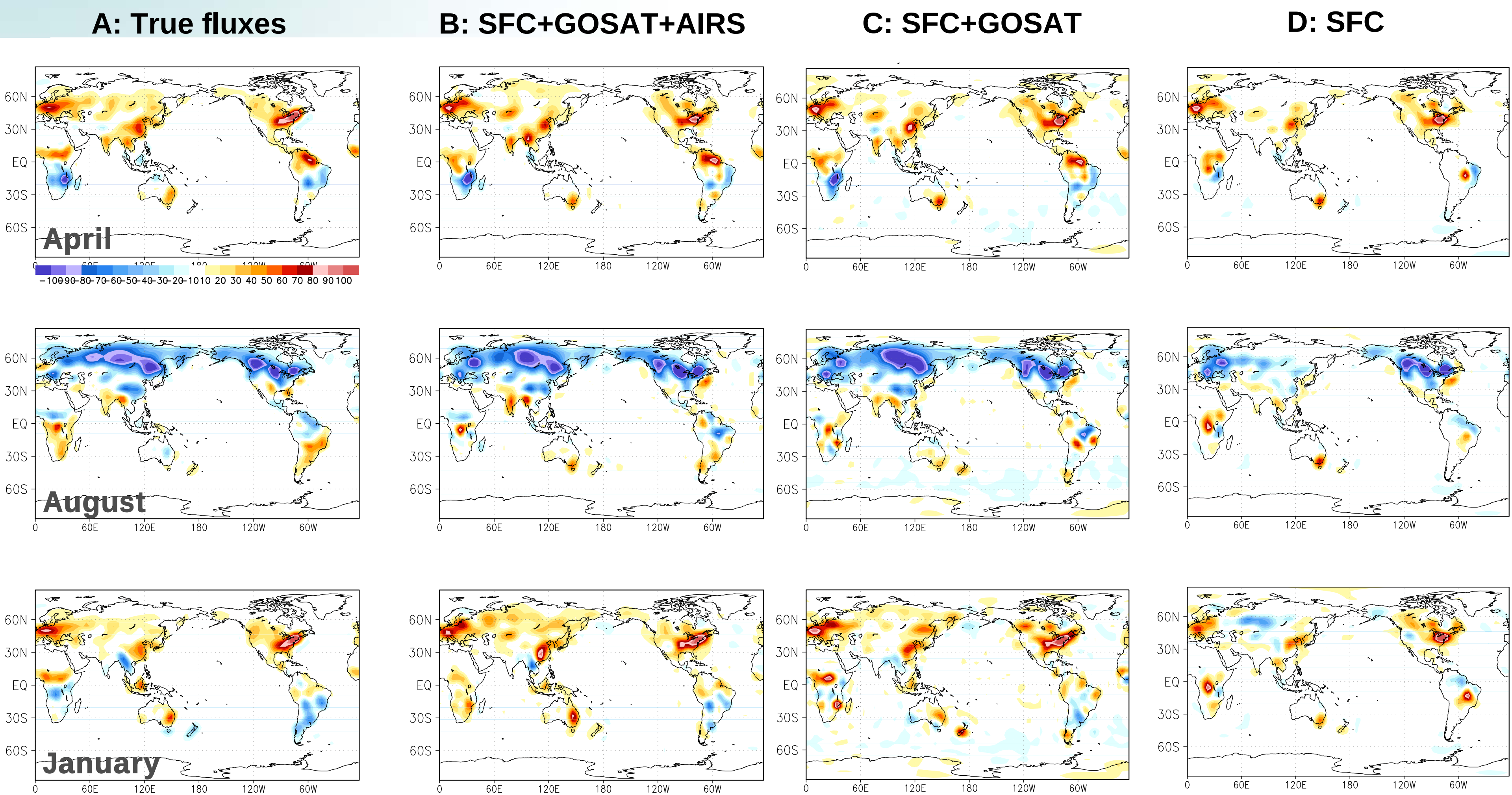
- Global maps of surface CO_2 fluxes in different seasons

A: True fluxes **C: SFC+GOSAT** **D: SFC**



Results: Observation Impacts

- Global maps of surface CO_2 fluxes in different seasons



Summary of Carbon Cycle DA

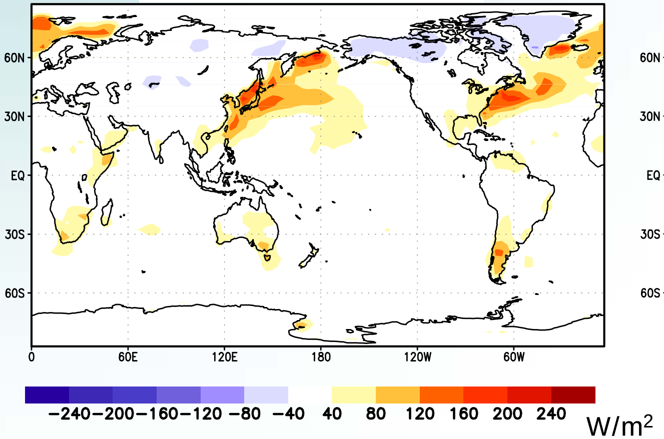
- We succeed in estimating surface CO_2 fluxes with the advanced LETKF-C system, even without *a-priori* information (OSSEs)
  - Localization of variables
    - reduces sampling errors from the correlation between the variables which are not physically correlated
  - Advanced inflation methods
    - represents background uncertainty well
  - Vertical localization of column mixing CO_2 data
    - better estimate surface CO_2 flux changes rather than updating full column of CO_2
- Dedicated CO_2 monitoring satellite (GOSAT) contributes to the surface CO_2 flux estimation significantly
- AIRS CO_2 retrievals help CO_2 flux estimation due to better analysis of atmospheric CO_2 circulation

How about heat/moisture fluxes?

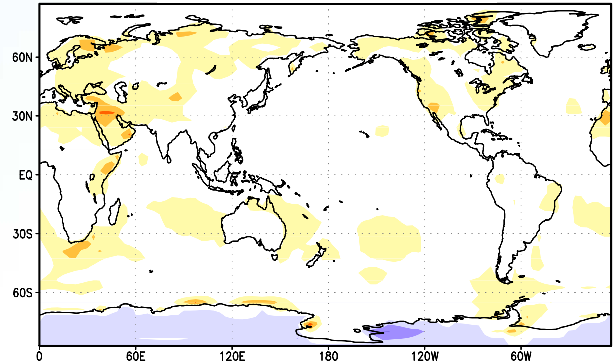
- Can we estimate **surface moisture/heat fluxes** by assimilating atmospheric moisture/temperature observations? *We can use the same methodology!*
- OSSEs
  - Nature: SPEEDY
  - Forecast model: SPEEDY with **persistence forecast of Sensible/Latent heat fluxes (SHF/LHF)**
  - Observations: conventional 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*)

Result: Analysis of SHF

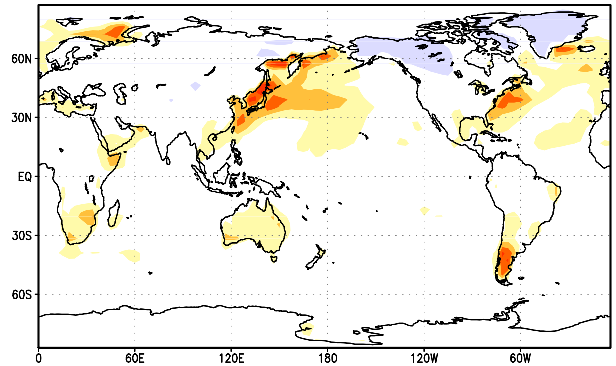
True SHF in FEB



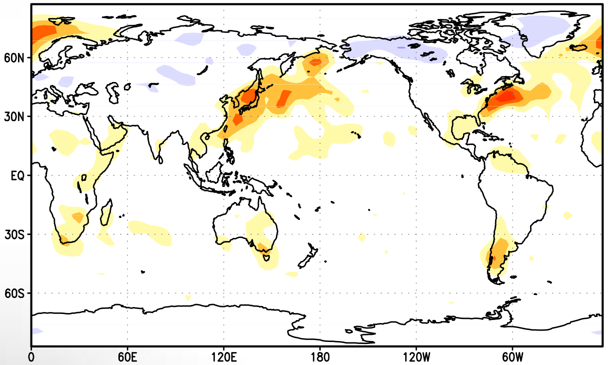
True SHF in JUL



True SHF in DEC



Analysis of SHF in FEB



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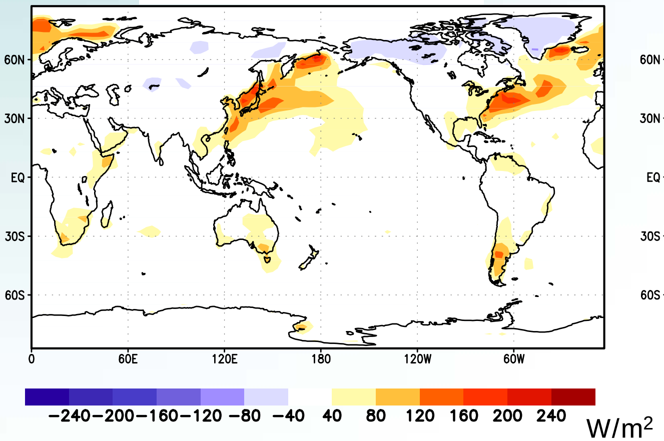
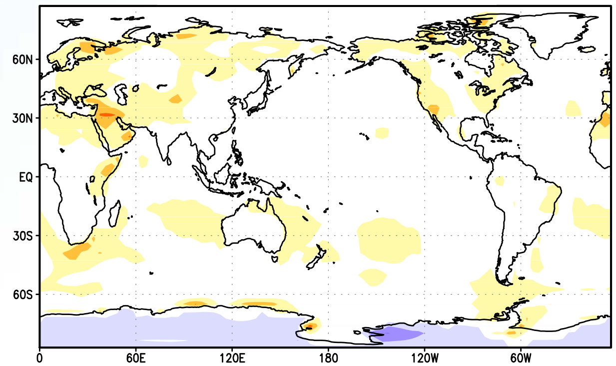


True SHF in JUL



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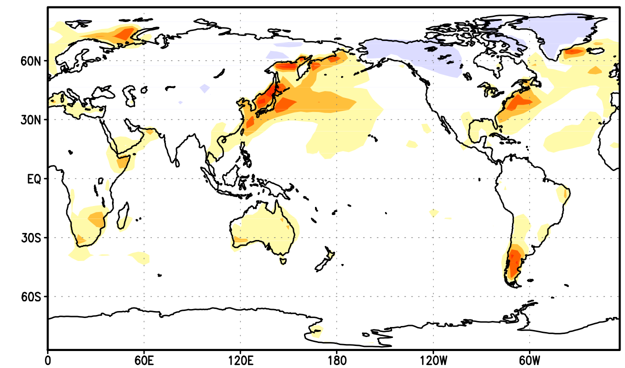

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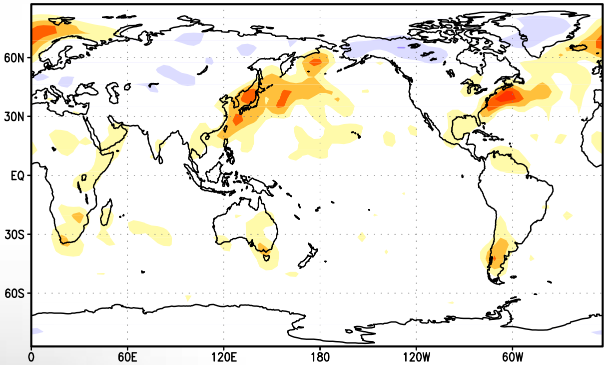

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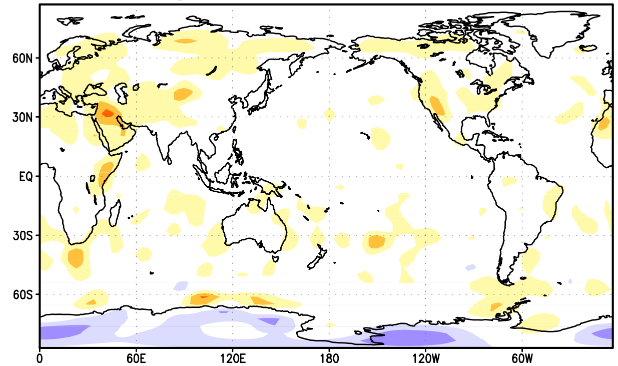

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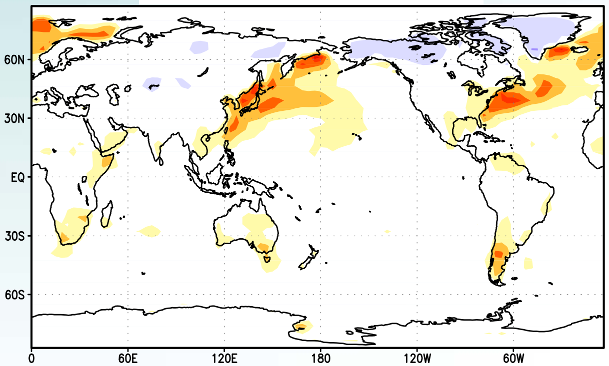

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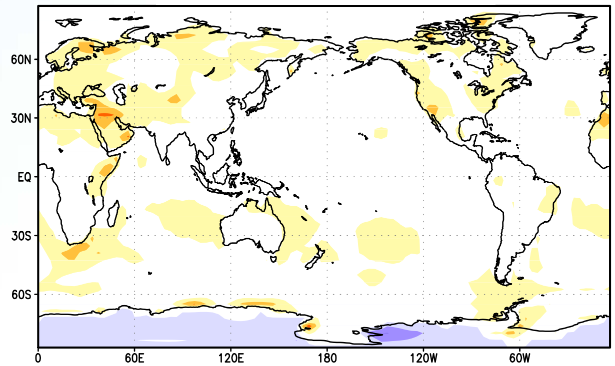

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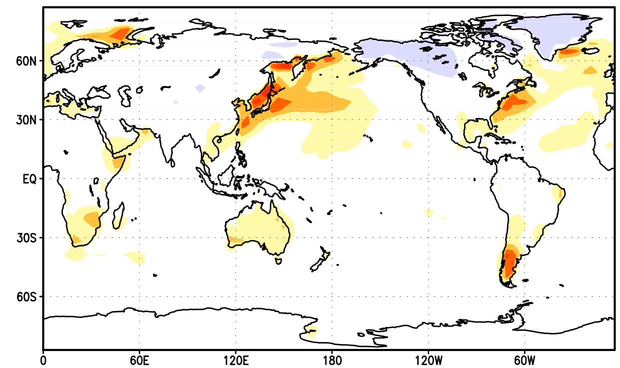
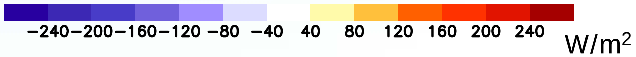
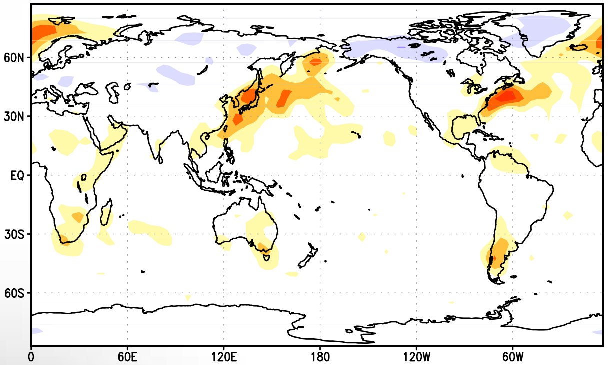




Analysis of SHF in FEB



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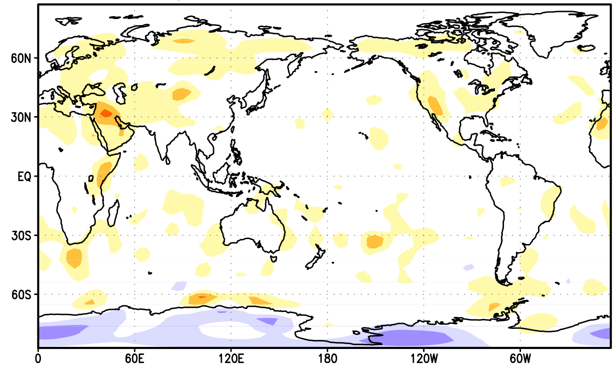
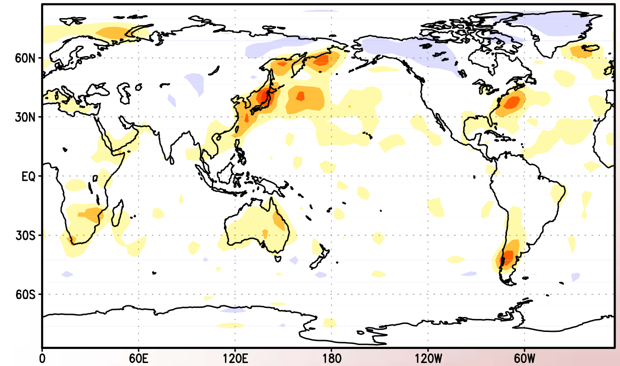
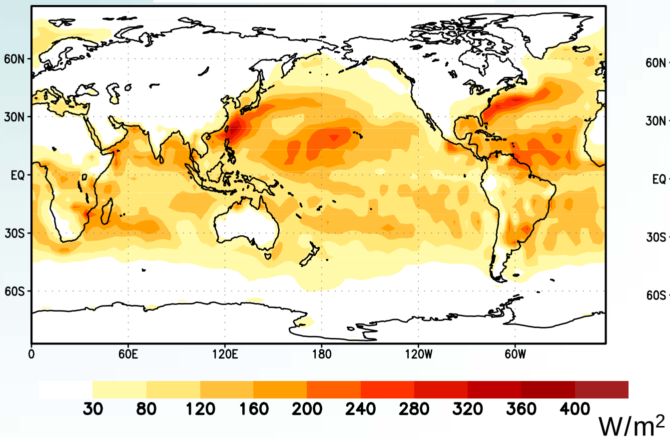


Analysis of SHF in DEC

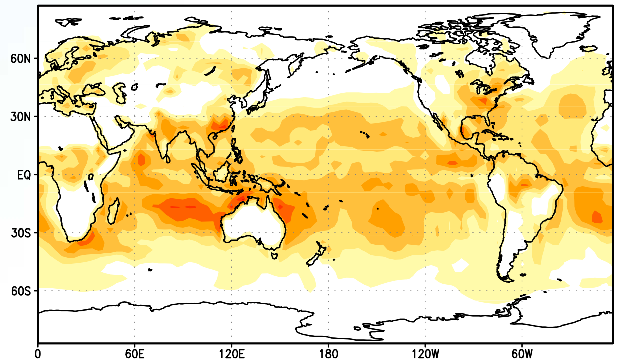


Result: Analysis of LHF

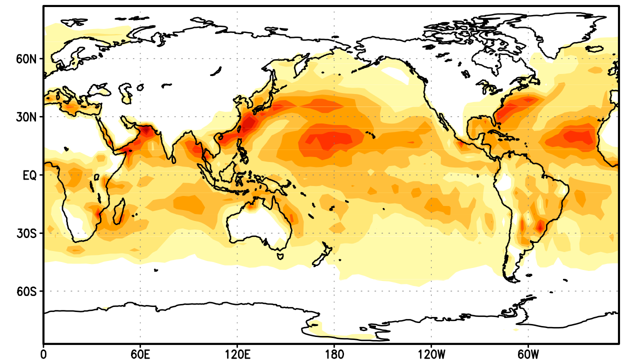
True LHF in FEB



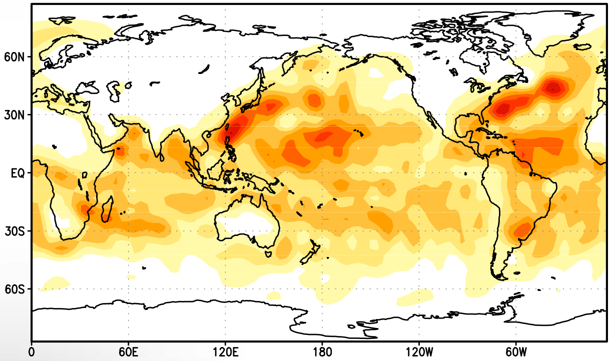
True LHF in JUL



True LHF in DEC



Analysis of LHF in FEB



Result: Analysis of LHF

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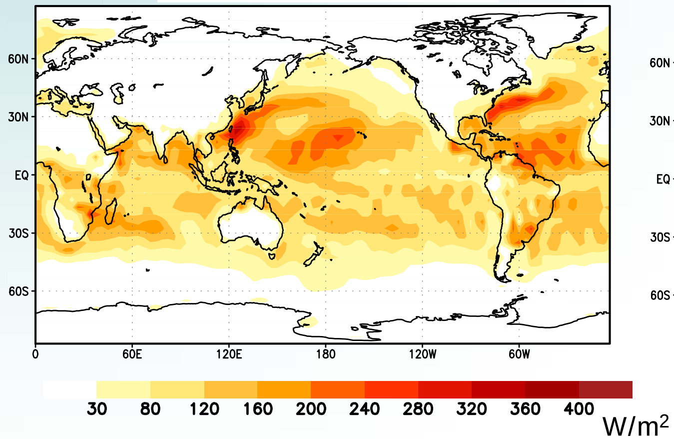

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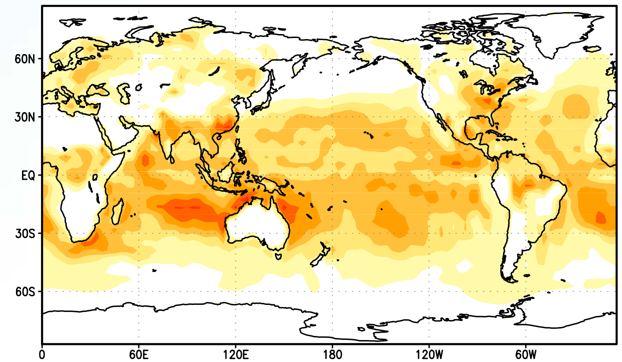

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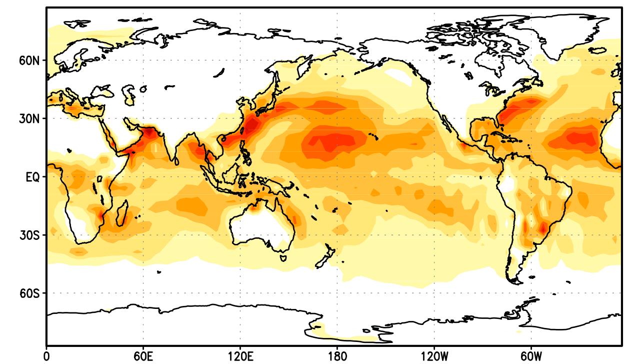

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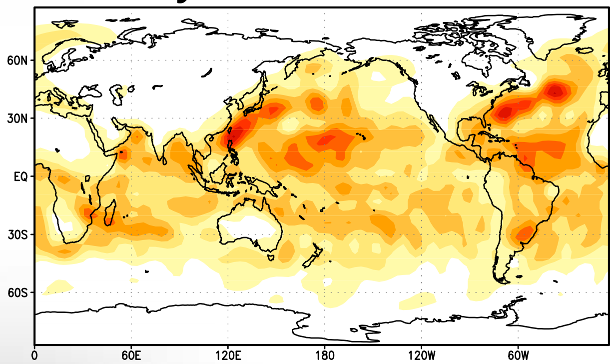

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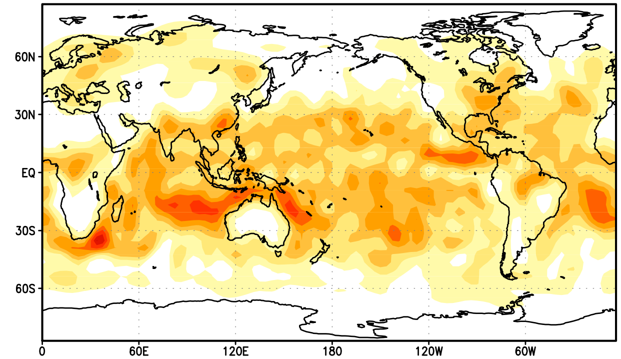

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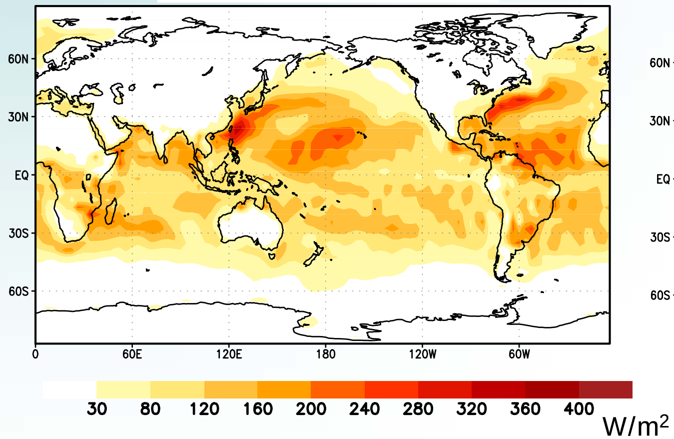
True LHF in FEB



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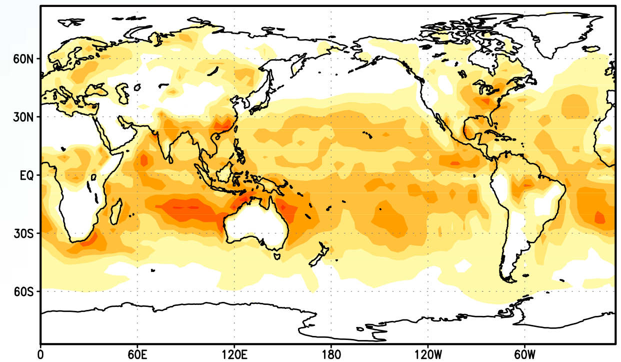

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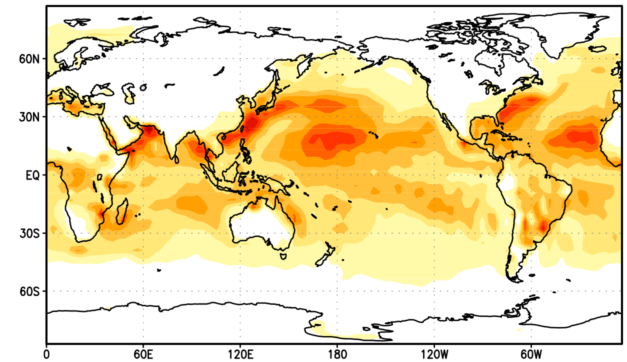

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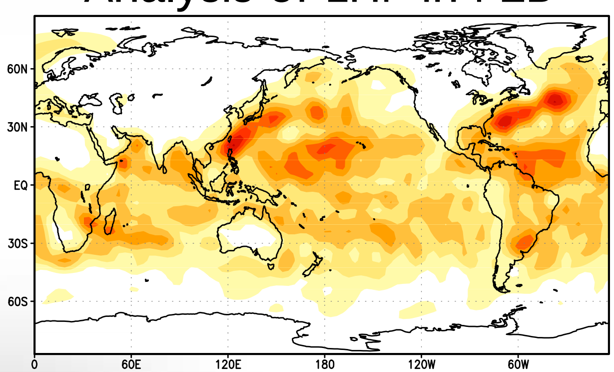

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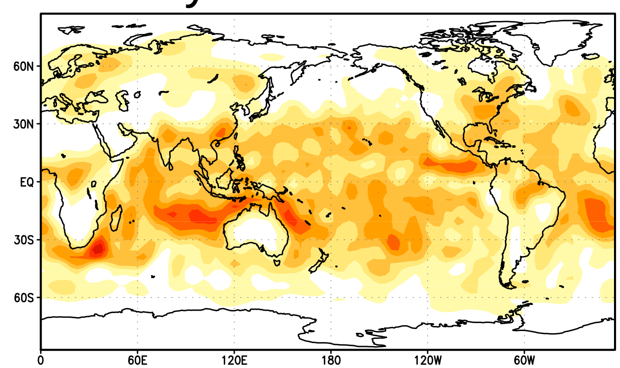
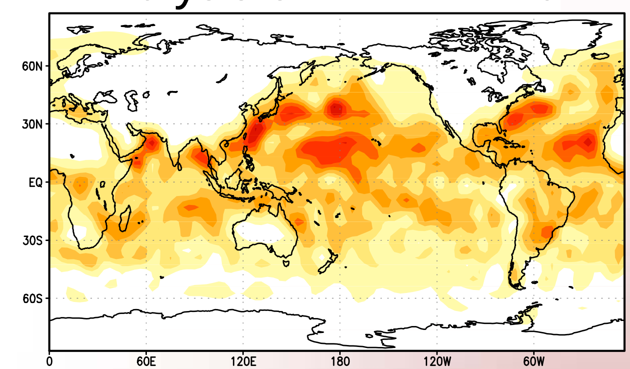
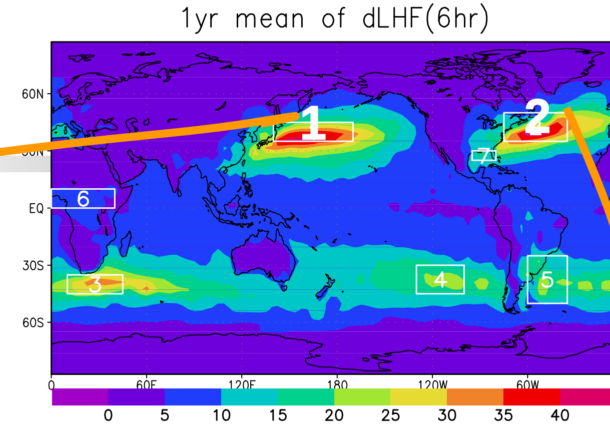


Analysis of LHF in DEC

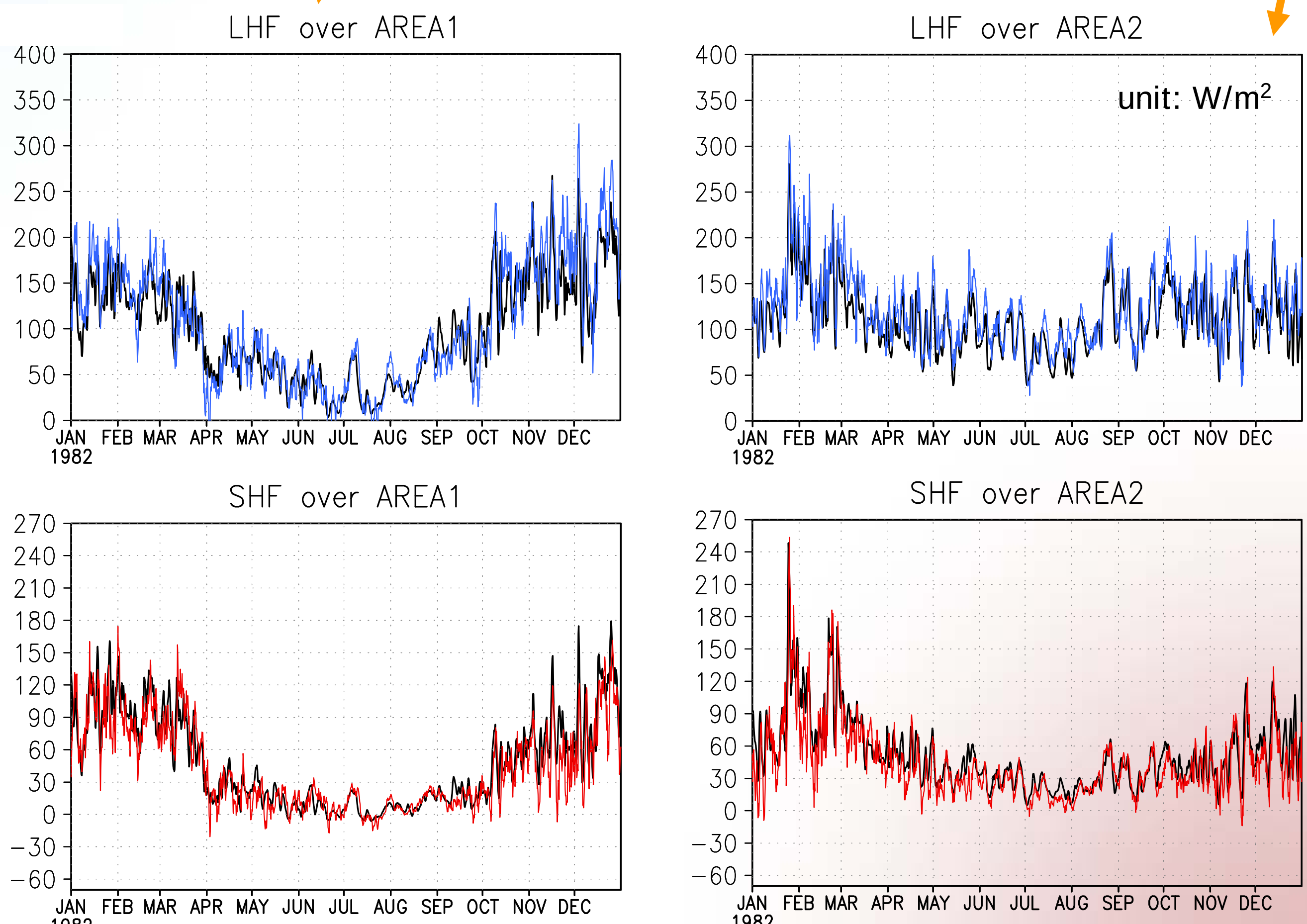


Time series of LHF / SHF

- Black: nature
- Color: analysis of LHF (blue)/SHF(red)



Recall that LHF & SHF are updated only by the data assimilation here!



Promising results from the estimation of “evolving parameters” with data assimilation

Future Plans

- More CO_2 datasets
  - HIAPER Pole to Pole Observations (HIPPO) data (Wofsy, 2011)
  - Orbiting Carbon Observatory (OCO-2) data
- The advanced LETKF + CAM3.5 or CAM5 model with **real** observations
  - On-going project
- Imperfect model experiments for both CO_2 fluxes and SHF/LHF
  - Impact of model error on flux estimation
  - Bias estimation and correction

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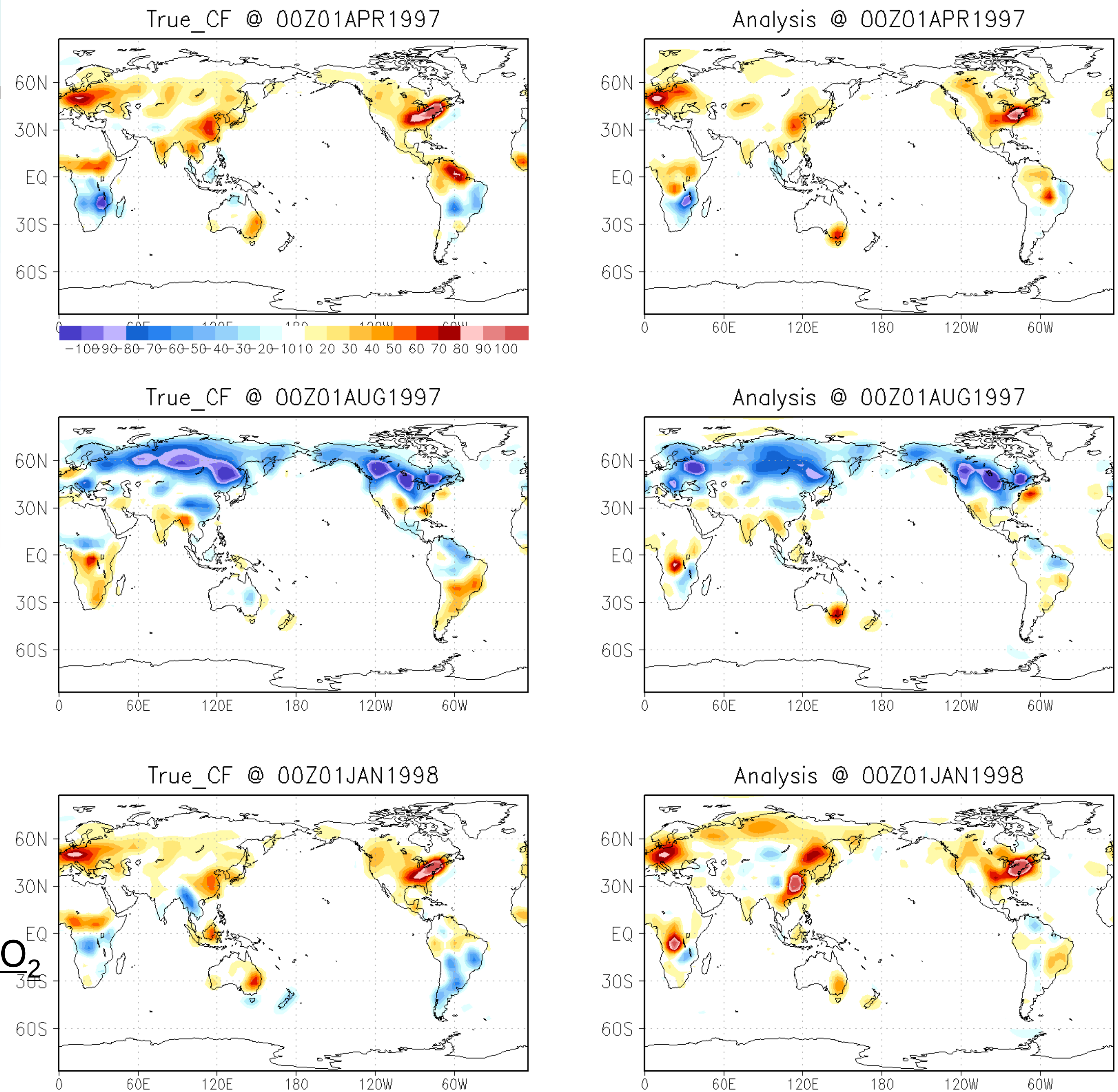
The End

Thank you for your attention!



<u>Observation error of CO_2</u>
3.0 ppmv for GOSAT
2.0 ppmv for AIRS

LETKF with SHF/LHF

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

: model state vector (U, V, T, q, Ps)

: sensible & latent heat fluxes (SHF, LHF)

- No *a-priori* information➔