DEPARTMENT OF
ATMOSPHERIC &
OCEANIC SCIENCE

Assimilation of Humidity Observations with Local Ensemble Transform Kalman Filter

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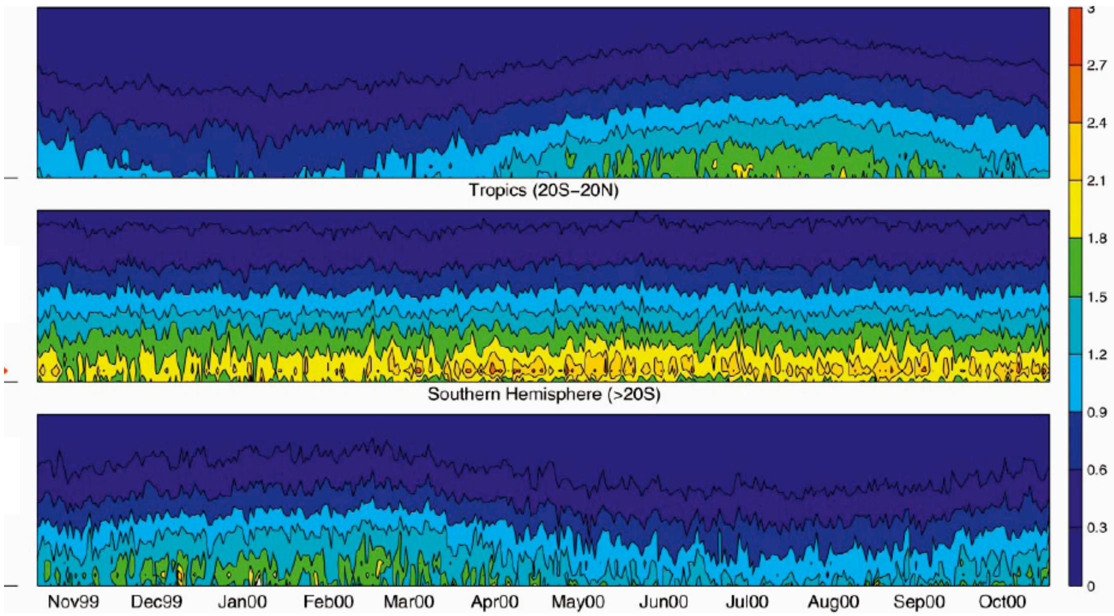
Error characteristics of specific humidity

RMS statistics of Obs minus background (over a year)

NH

Tropics

SH



Dee and DaSilva, 2003

Daily RMS statistics of rawinsonde observed-minus-background mixing ratio residuals during the period 1 Nov 1999—31 Oct 2000, produced by fvDAS.

- The error has spatial and time dependence.
- The error changes abruptly over vertical levels.
- Humidity has close relationship with other dynamical variables physically. However, operationally, the humidity is still assimilated univariately.

Motivation for assimilating humidity with LETKF

- Forecast step

$$\mathbf{x}_t^f = m\mathbf{x}_{t-1}^a$$

$$\mathbf{P}_i \approx \frac{1}{k-1}\sum_{i=1}^{K}(x_i^f - \overline{x^f})(x_i^f - \overline{x^f})^T = \frac{1}{k-1}\mathbf{X}^f \bullet \mathbf{X}^{fT}$$

- ➢ Forecast error covariance is updated every analysis cycle.
- ➢ It automatically couples all the variables together

- Analysis step

$$\mathbf{x}_i^a = \mathbf{x}_i^f + \mathbf{K}_i(\mathbf{y}_i^o - h(\mathbf{x}_i^f))$$

$$\mathbf{K} = \mathbf{X}^f \tilde{\mathbf{P}}^a (\mathbf{HX}^f)^T \mathbf{R}^{-1}$$

$$\tilde{\mathbf{P}}^a = \left[(k-1)\mathbf{I}_{\mathbf{kxk}} + \left(\mathbf{HX}^f\right)^{\mathbf{T}} \mathbf{R}^{-1}\mathbf{HX}^f\right]^{-1}$$

$$\mathbf{X}^a = \mathbf{X}^f (\tilde{\mathbf{P}}^a)^{1/2}$$

- ➢ The analysis step can couple all the variables together automatically.

So far, humidity observations assimilation in EnKF is still in preliminary state. (Houtekamer et al., 2005).

Questions we want to address:

What is impact of assimilating specific humidity? and what is impact of interactions between humidity and other dynamical variables during data assimilation in a perfect model scenario?

Experimental Design

- SPEEDY model (Molteni, 2003, Miyoshi, 2005)
  - An Atmospheric General Circulation Model (AGCM) with simplified physical parameterization process.
  - Dynamical variables include winds, temperature, specific humidity and surface pressure.

- Data assimilation scheme
  - Local Ensemble Transform Kalman Filter (LETKF, Hunt et al., 2006)

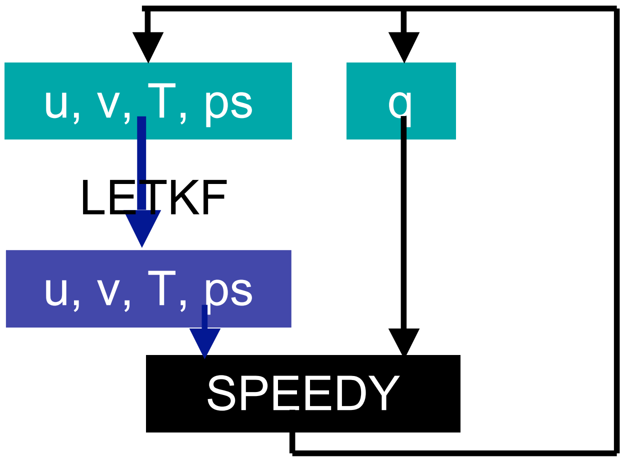
Experimental Design (continued)

- Observations
  - Assume perfect model scenario, in which observations are the truth (long time integration) plus random perturbations.

- Two observation networks:
  - All the dynamical variables observed over 25% grid points
  - → What is the impact of humidity assimilation in the case of dense observation coverage for all dynamical variables?
  - Zonal wind, meridional wind and surface pressure at rawinsonde locations, while temperature and specific humidity are 25% coverage.
  - → What is the impact of humidity assimilation with sparse wind observations but dense humidity observations?

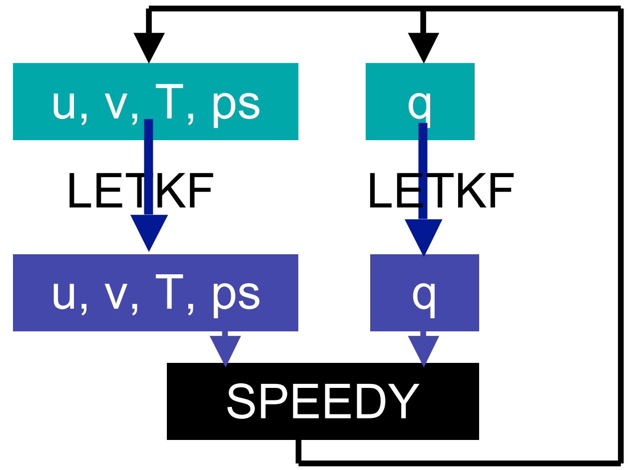
Experimental design

noq



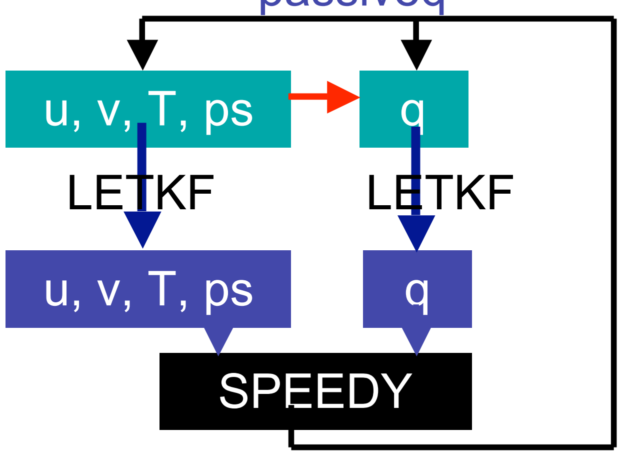
q is copied from background

uniq



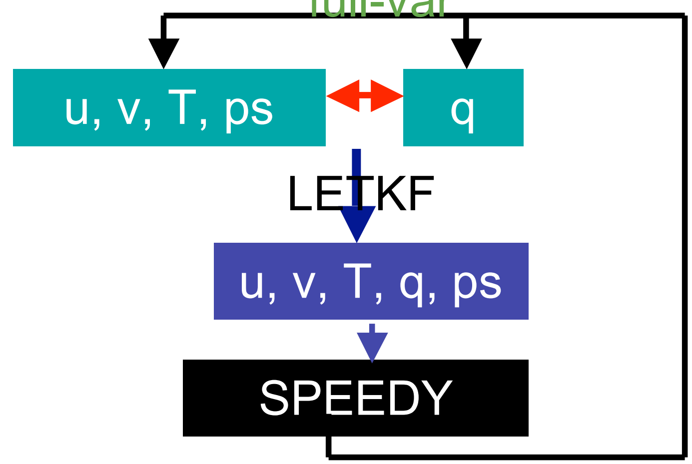
q is updated by itself (univariately).

passiveq



q is updated by the other variables, but it does not affect the other variables.

full-var

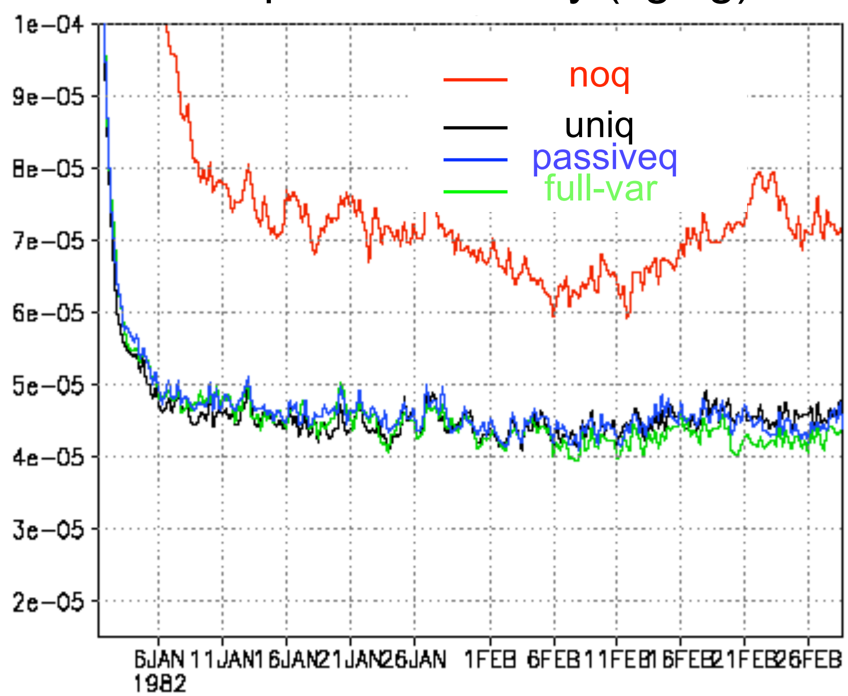


All the variables are coupled together.

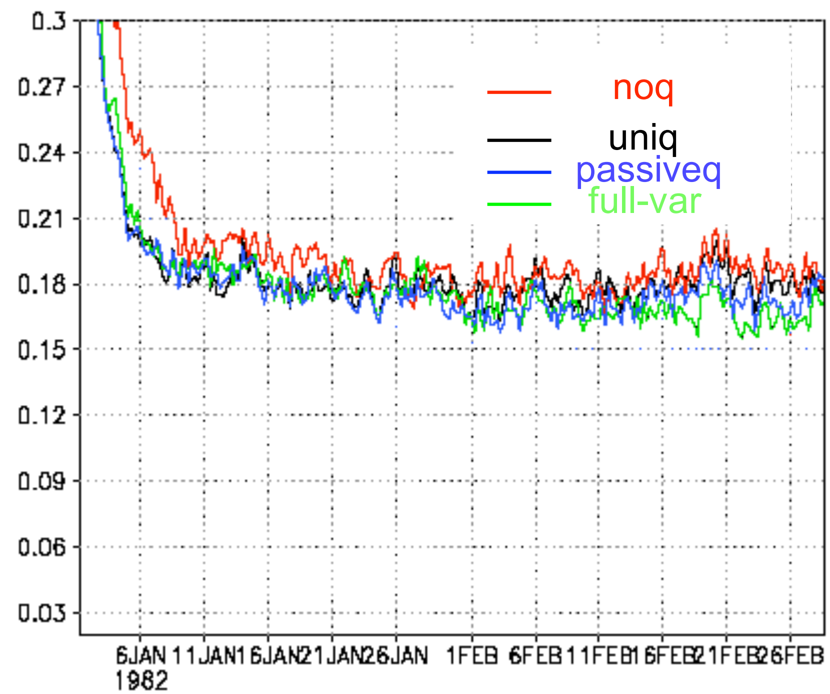
RMS error of dense observation coverage for all dynamical variables

850hPa global average

Specific humidity (kg/kg)



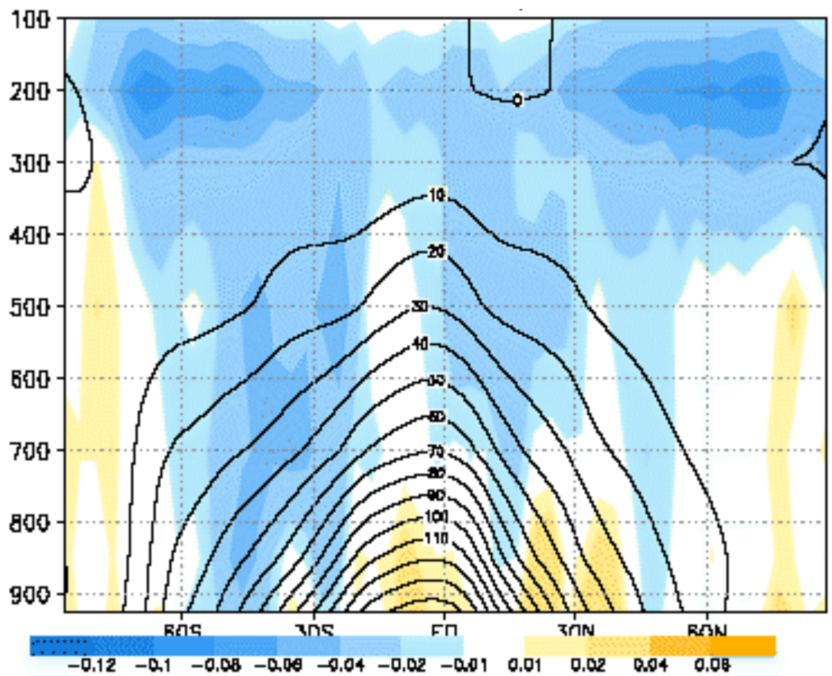
Zonal wind (m/s)



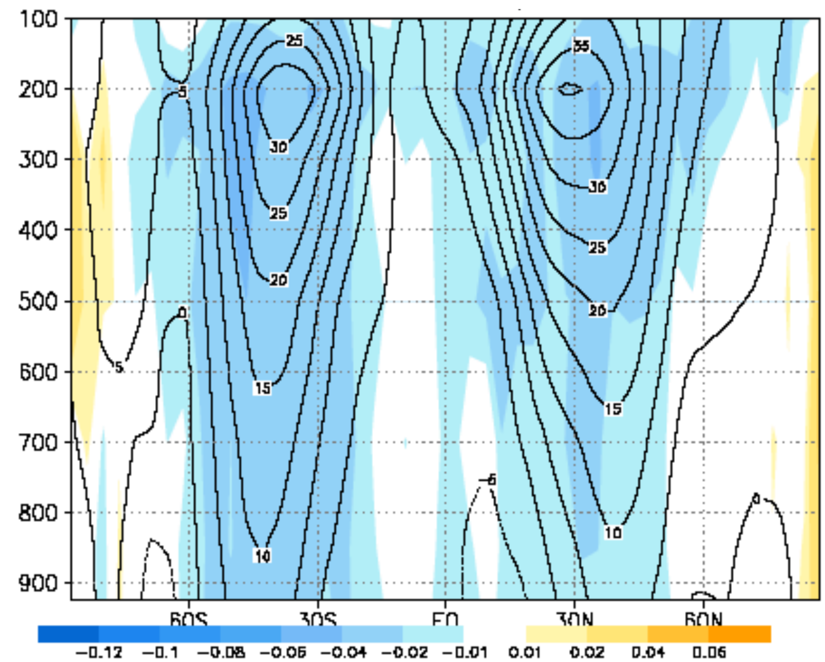
- The assimilation of specific humidity (**uniq**, **passiveq**, **full-var**) improves the specific humidity analysis.
- **Full-var** experiment shows advantage over other experiments after long spin-up time for both specific humidity and zonal wind.

Vertical RMS error difference between full-var and **uniq** experiment

Specific humidity (10^{-4}kg/kg)



Zonal wind (m/s)

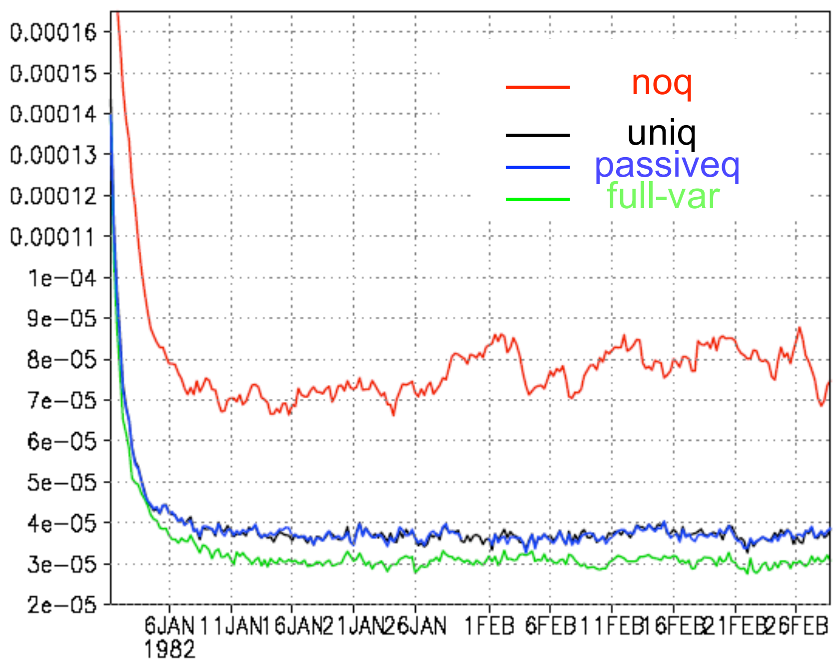


- Compared with **uniq** experiment, the improvement of specific humidity in **full-var** experiment concentrates over tropopause and middle latitudes.
- Compared with **uniq** experiment, **full-var** improves wind analysis by using humidity observations during data assimilation, mainly over large wind areas.

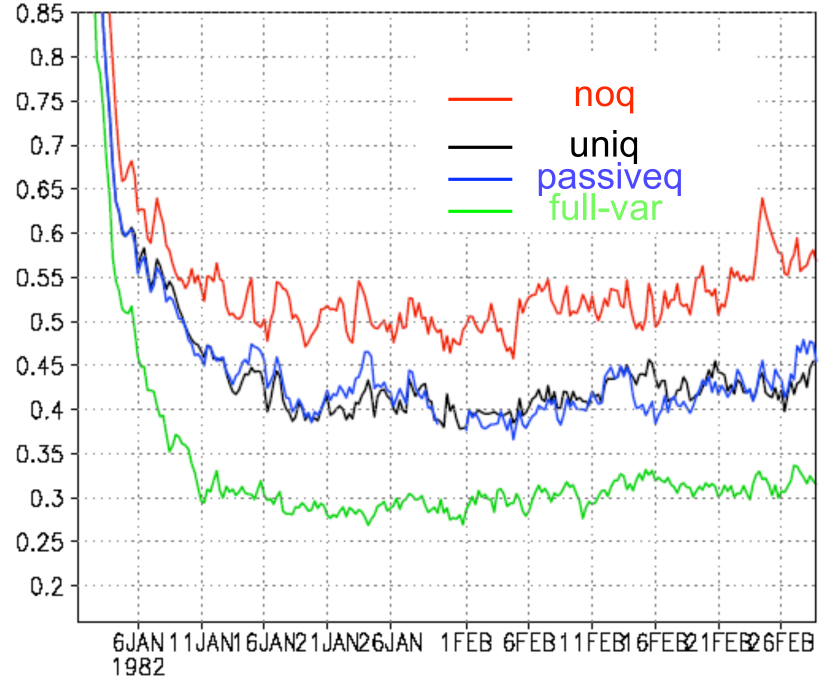
RMS error for winds at rawinsonde locations, temperature and humidity are 25% coverage

850hPa global average

Specific humidity (kg/kg)

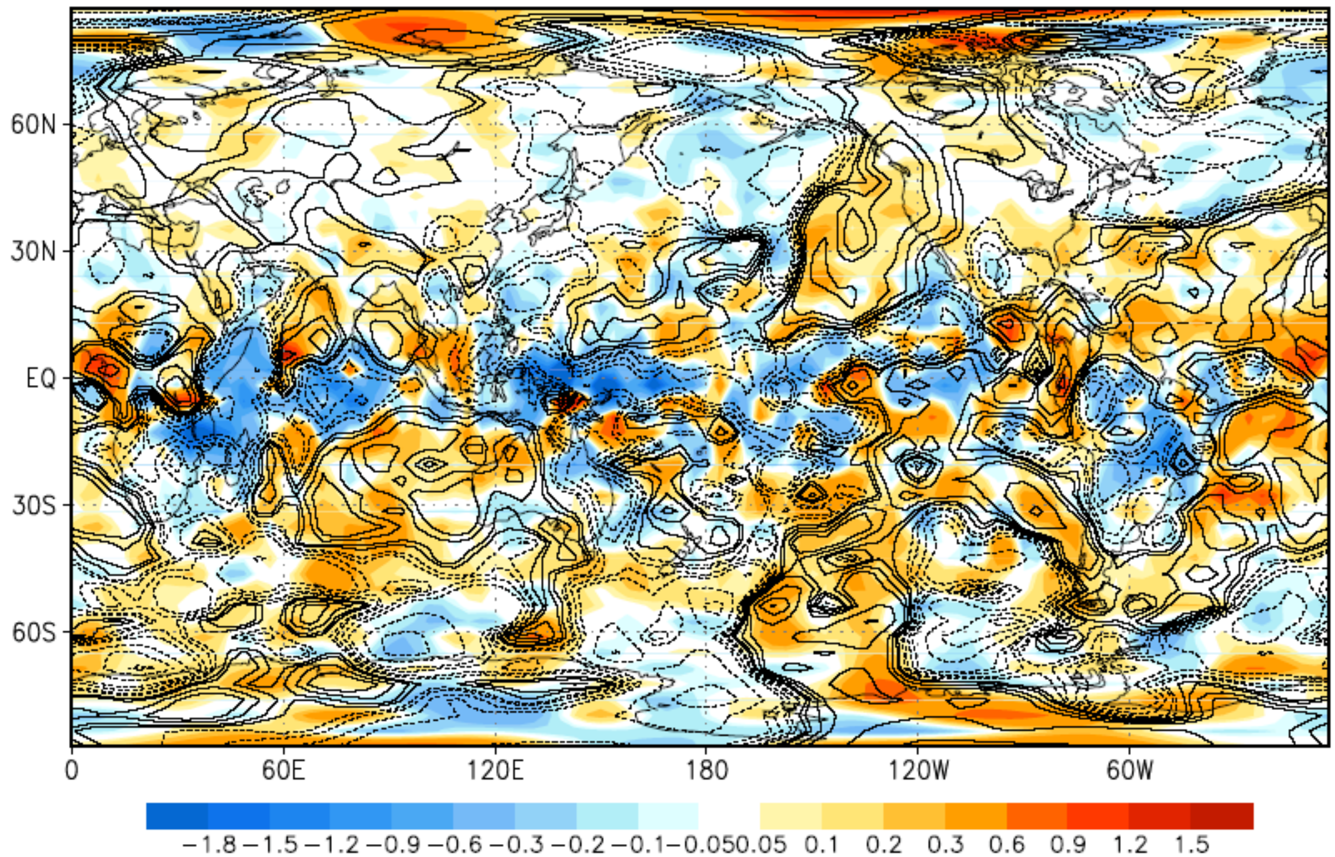


Zonal wind (m/s)



- The assimilation of specific humidity (**uniq, passiveq, full-var**) improves the specific humidity analysis accuracy, with full-var experiment the best result.
- With sparser wind observations, humidity has much more significant impact on winds.
- **Uniq** and **passiveq** improve wind analysis through forecast, but **full-var** experiment improves wind analysis not only through forecast, but also through data assimilation.

Covariance between specific humidity and zonal wind used in LETKF (contour; Unit: m/s ·kg/kg ·1e-5) and true covariance calculated from truth (shaded; Unit: m/s ·kg/kg ·1e-5)



The covariance between humidity and wind used in LETKF reflect the ideal covariance between humidity and winds.

Conclusion and future plan

- LETKF shows the ability to couple specific humidity with other dynamical variables during data assimilation in this perfect model scenario, and get best result compared with other experimental setups (noq, uniq, and passiveq).

- Results show that full-var experiment has much more impact when wind fields are sparser than specific humidity.

- The improvement in the full-var experiment comes from the ability of LETKF estimating the covariance between specific humidity and other dynamical variables, such as covariance between winds and humidity fields.

Future plan

- We will assimilate real humidity observations with NCEP GFS system. We will examine the impacts of humidity observations, both from conventional instruments and satellites, on assimilation results