金星大気の観測・シミュレーション・データ同化に関する研究会

A Machine Learning Approach To The Observation Operator For Satellite Radiance Data Assimilation

Jianyu (Richard) Liang

Koji Terasaki

Takemasa Miyoshi

Data Assimilation Research Team, RIKEN Center for Computational Science

Data assimilation

Data assimilation (DA) is the combination of **model** and **observations**

DA gives the optimal estimate of the initial condition of the model.

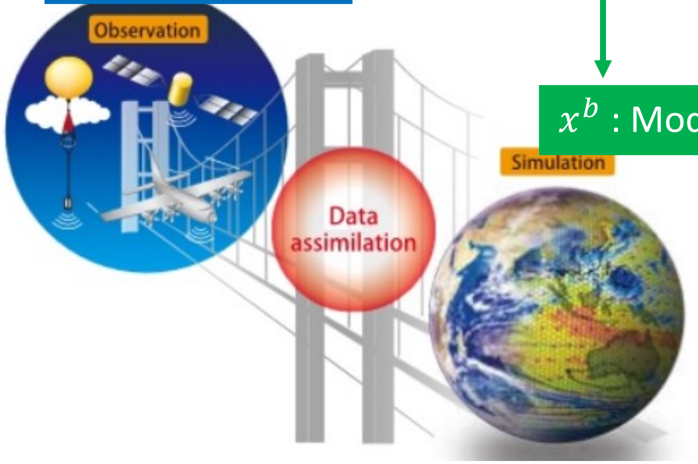
$$x^a = x^b + K(y - H(x^b))$$

K: weight matrix

x^a : analysis (optimal estimate)

e.g. radiance

Y: Observations



x^b : Model simulations

e.g. pressure, temperature

we need an observation operator (satellite simulator) **H,** to take the difference between model variables and observations

e.g. pressure, temperature

x^b : Model simulations

radiance

$H(x^b)$: Model equivalent of the observations

compare

radiance

y: Observations

Review observation operator (satellite simulator)

Current observation operator (RTM: RTTOV)

$< y - h(x) > \neq 0$

Let $h'(x) = h(x) + b^{scan} + \beta_o + \sum_{i=1}^{N} \beta_i p_i(x)$

$< y - h'(x) > = 0$

It usually takes time to build observation operator and start using the new data after launching the satellites.

x^b : Model simulations

H() : RTTOV and bias correction

$\boldsymbol{H}(x^b)$: Model equivalent of the brightness temperature

Use machine learning (ML) as the observation operator

$< \boldsymbol{y} - h_{ML}(\boldsymbol{x}) > = 0$

(1) Training

x^b : Model simulations

y: Observations

- Run a DA experiment
- using the model output and observations to train the machine learning model

(2) Testing, DA experiment

x^b : Model simulations

H(): Machine learning model

$\boldsymbol{H}(x^b)$: Model equivalent of the brightness temperature

compare

y: Observations

Use machine learning as observation operator

1. In this research, physically-based observation operator (RTM) is used to train the machine learning model
2. We are currently considering other methods to train the ML model without using the RTM

Advantages:
1. No explicit coding of the physically-based model and no separate bias correction procedure
2. Similar infrastructure can be used for other observations so we can use them quickly

Disadvantages:
1. need a lot of data to train the ML model
2. need to re-train the ML model if the configuration of the numerical model is changed
3. need to update the ML model regularly using the most up-to-date data

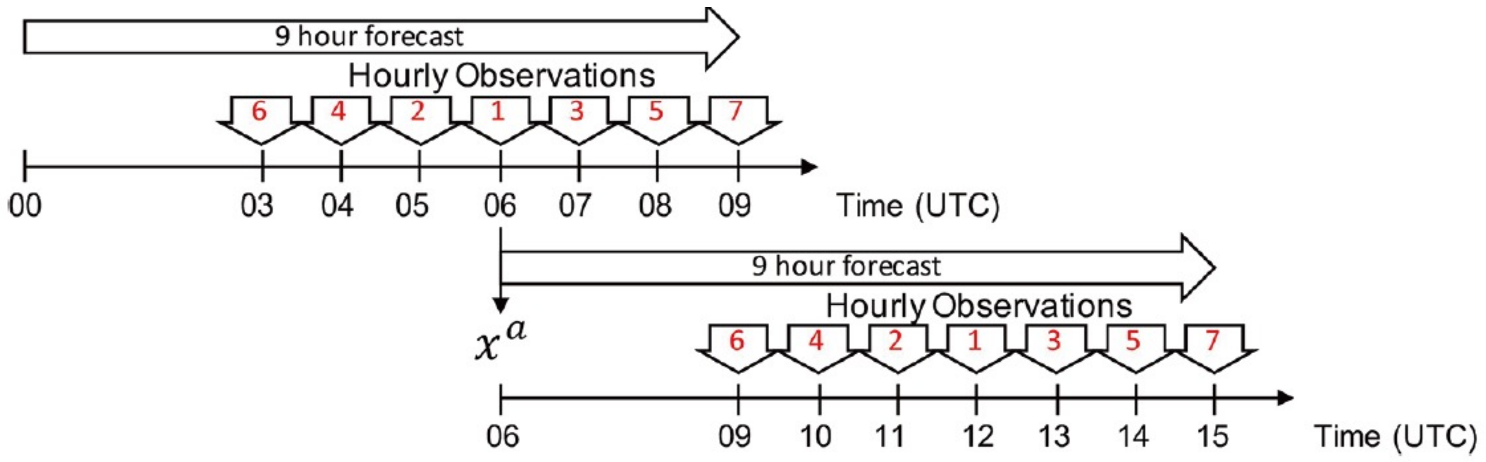
Data assimilation system

Non-hydrostatic icosahedral atmospheric model (NICAM)

- horizontal resolution: 250 km
- 78 vertical levels
- RTTOV is the observation operator for radiance data assimilation

Local ensemble transform Kalman filter (LETKF)

- Assimilate conventional observations and satellite radiance every 6 hours
- 64 members



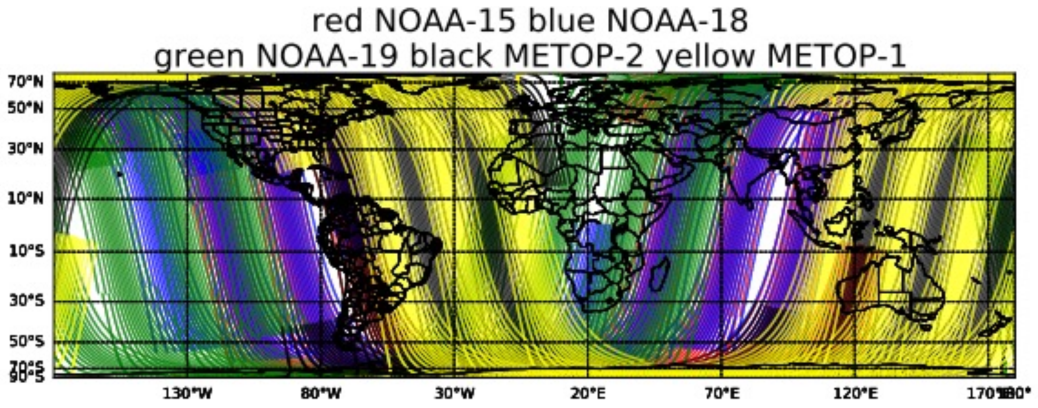
Radiance data

Brightness temperatures (BT) from the Advanced Microwave Sounding Unit (AMSU-A) on NOAA-15, NOAA-18, NOAA-19, METOP-2,and METOP-1 satellites. 2~3 channels were used.

Radiometric characteristics of the AMUS-A

Channel Number	Frequency (GHz)	Polarization (at nadia)	Number of Bands	Instrument Sensitivity NEDT (K)	Primary function
6	54.4	Horizontal	1	0.25	Tropospheric temperature
7	54.94	Vertical	1	0.25	Tropospheric temperature
8	55.5	horizontal	1	0.25	Tropospheric temperature

AMSU-A radiances during a 6-h period before thinning

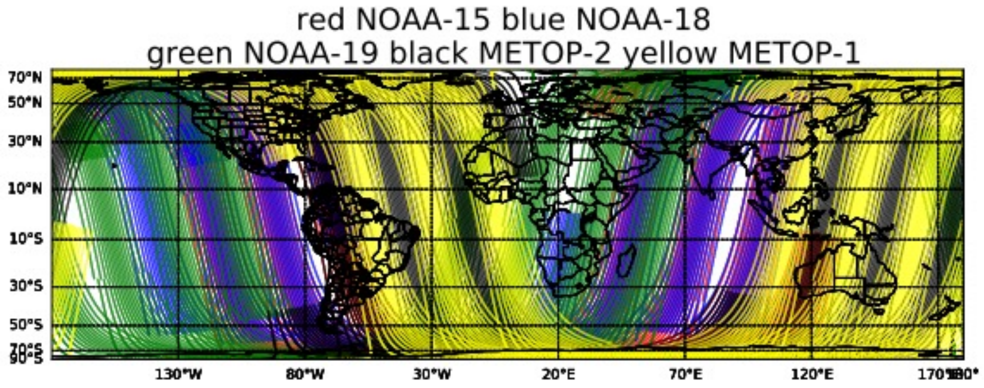


Experiment

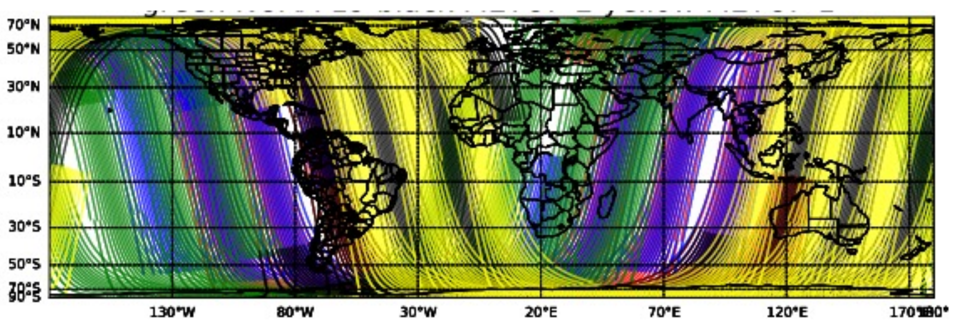
	2015.01.01 ~ 2015.01.31	2015.02.01 ~2015.02.28 (training)	2016.01.01 ~ 2016.01.31	2016.02.01 ~2016.02.28 (testing)
Data assimilation	DA spin-up conv + radiance(RTTOV)	DA cycle conv + radiance(RTTOV)	DA spin-up conv + radiance(RTTOV)	Control conv + radiance(RTTOV)
Machine learning		(1) generate the training data (80% train+ 20% validation) (2) Build the ML model		Test conv + radiance(ML)

Machine learning

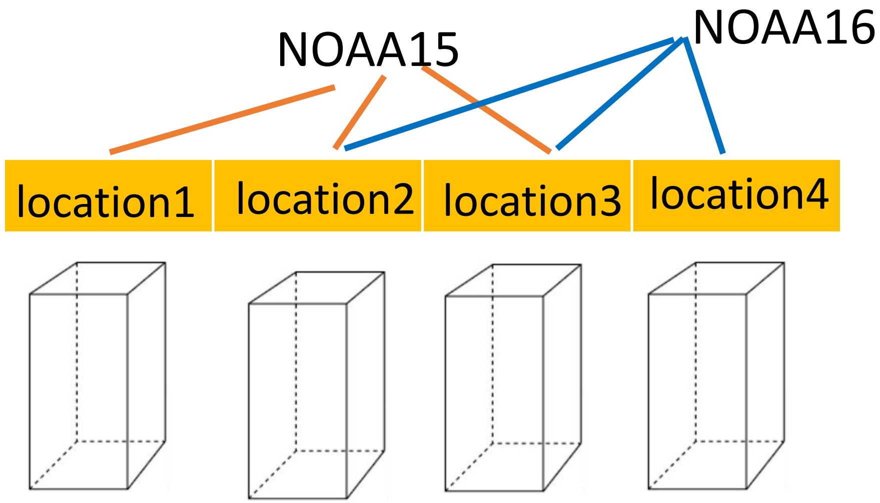
$$\boldsymbol{y} = h_{ML}(\boldsymbol{x^b}) + \varepsilon$$
$$< \varepsilon > = 0$$



select every 2 points



Interpolate model variables at the model grids to observation locations



Machine learning

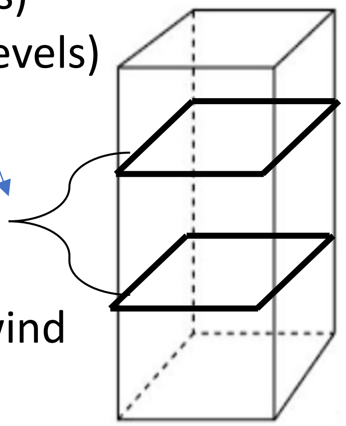
$$y = h_{ML}(x^b) + \varepsilon$$

$$\langle \varepsilon \rangle = 0$$

Input: x^b

3D variables:
pressure (78 levels)
temperature (78 levels)
specific humidity (40 levels)

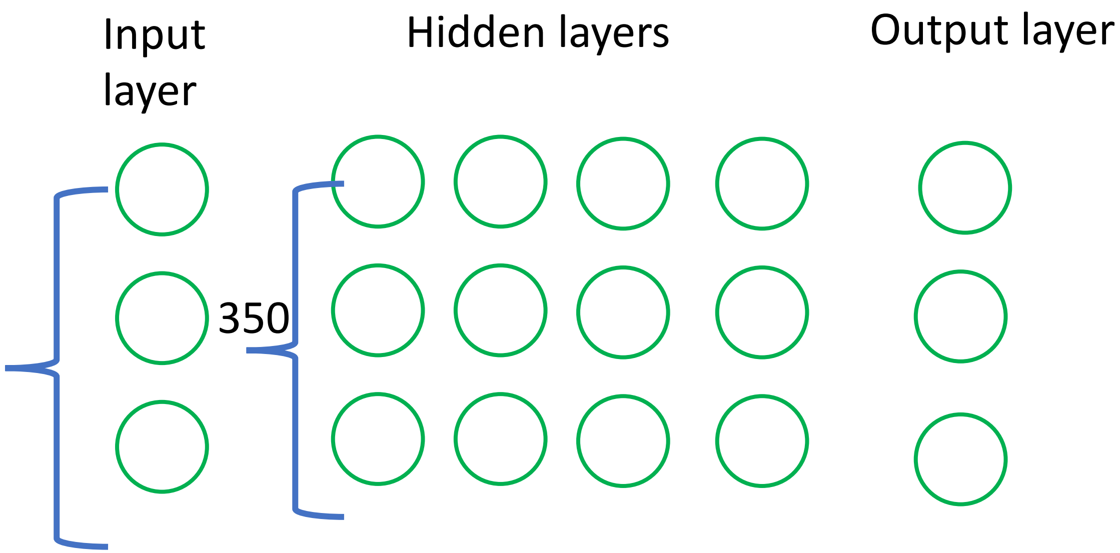
2D variables:
surface pressure
surface temperature
10-meter u-wind and v-wind
2-meter temperature
2-m specific humidity
other bias predictor: Satellite zenith angle, Scan angle, latitude



Output: y

satellite brightness temperature from channel 6, 7, 8

205 features, includes different levels



Hyperparameters:
activation function: ReLu
learning rate: 1e-04
l2 weight: 1.0e-6

The training data has around 3 million rows for a 1-month period

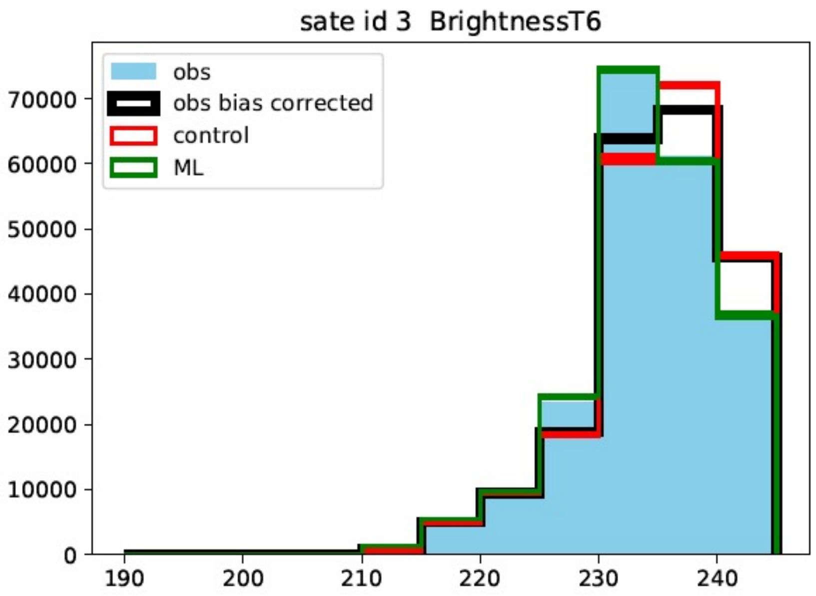
Analyze bias

NOAA-19
1 month data

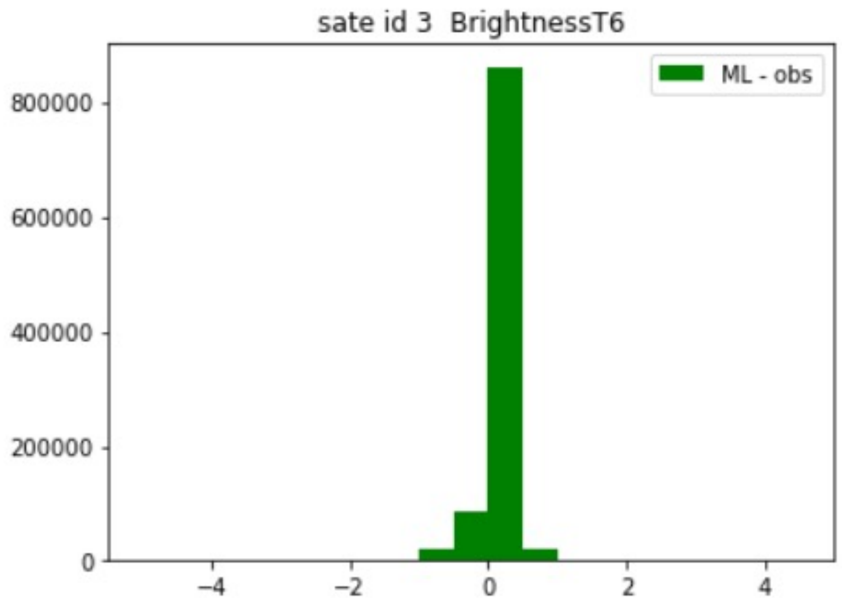
Bias is well handled by machine learning

Average T from observation: 234.11 K
Average T from ML: 234.12 K

Number of observations



Histogram of brightness temperature [K]



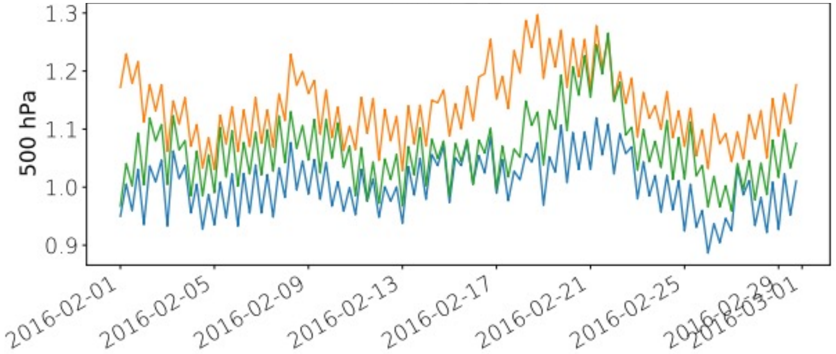
Histogram of brightness temperature difference (ML obs – real obs)[K]

Temperature, zonal wind compared to ERA

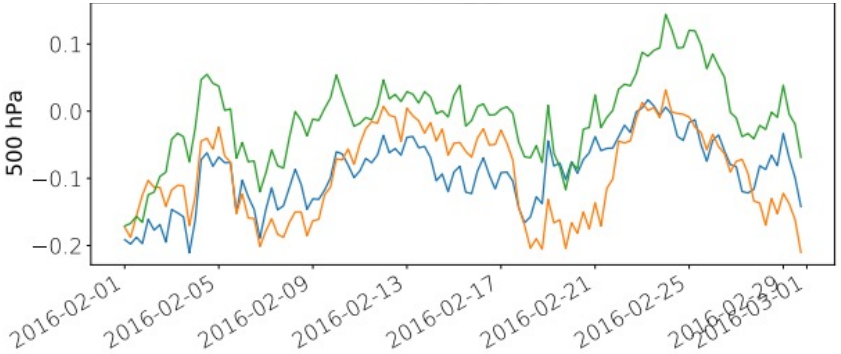
no radiance
RTTOV radiance
ML radiance

Global average of temperature (K) at 500 hPa

RMSD



bias



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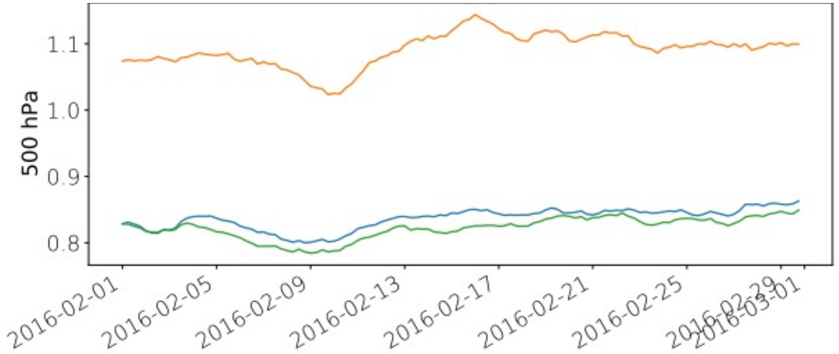
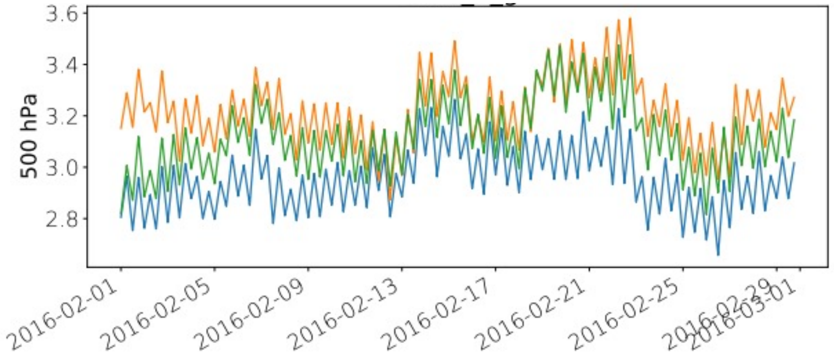
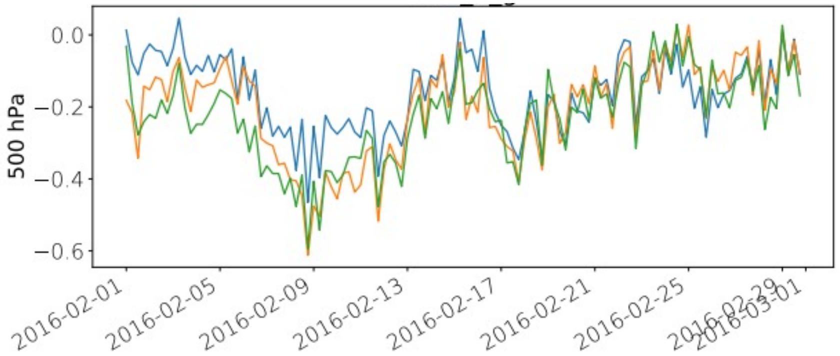


Global average of zonal wind (m/s) at 500 hPa

RMSD



bias



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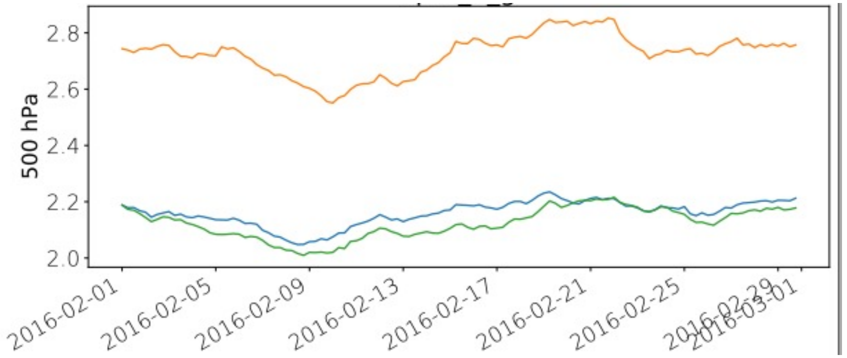


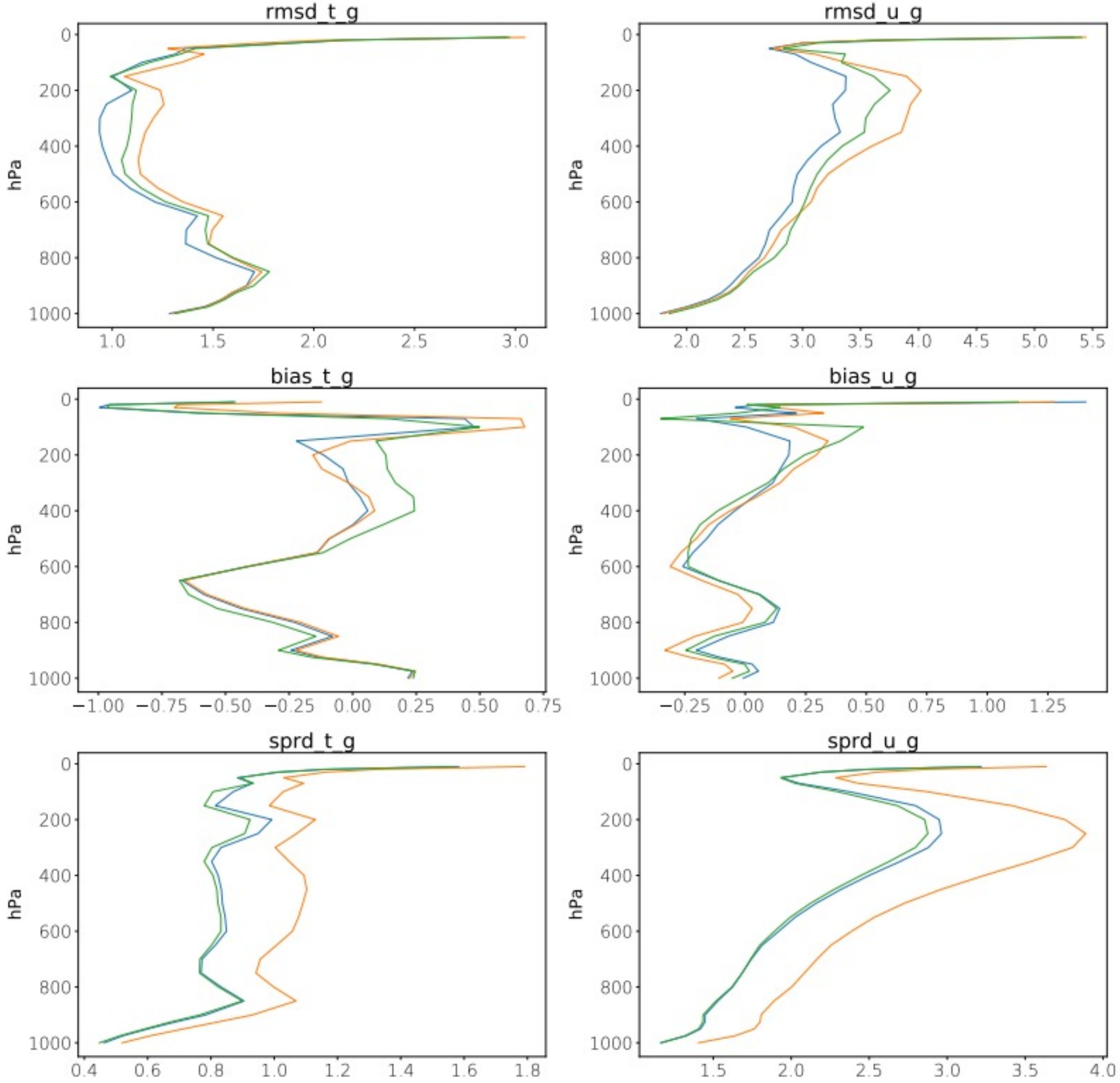
Temperature, zonal wind compared to ERA

1 month average | Global average of temperature [K] | Global average of zonal wind (m/s)

RMSD

bias

spread



no radiance
RTTOV radiance
ML radiance

Summary

(1) ML can be used as the 'observation operator'

(2) ML model treated the bias properly, and its performance was comparable to the control experiment

(3) We are currently considering other methods to train the ML model without using the RTM

(4) Implement ML as observation operator for Akatsuki data, and assimilate them into AFES-Venus model

Email: jianyu.liang@riken.jp