Strongly Coupled Land-Atmosphere Data Assimilation and Its influence on Near-surface Weather Forecasting

Zhaoxia Pu
Department of Atmospheric Sciences, University of Utah

With acknowledgments to:
Liao-Fan Lin, JunKai Liu, Qien Huang
University of Utah

NOAA/NCEP/EMC
NOAA JTTI and NGGPS Programs

Weeks 3-4/S2S Webinar
NOAA Weather Program office
April 3, 2023

Outline

- Background
- Understanding covariances between the land surface and atmospheric states.
- Strongly vs. Weakly coupled land-atmosphere data assimilation in short-range weather forecasting
- Developing strongly coupled land-atmosphere data assimilation with GSI-based EnKF
- Recent development in strongly coupled land-atmosphere data assimilation with UFS (with Noah-MP) and JEDI
- Concluding remarks

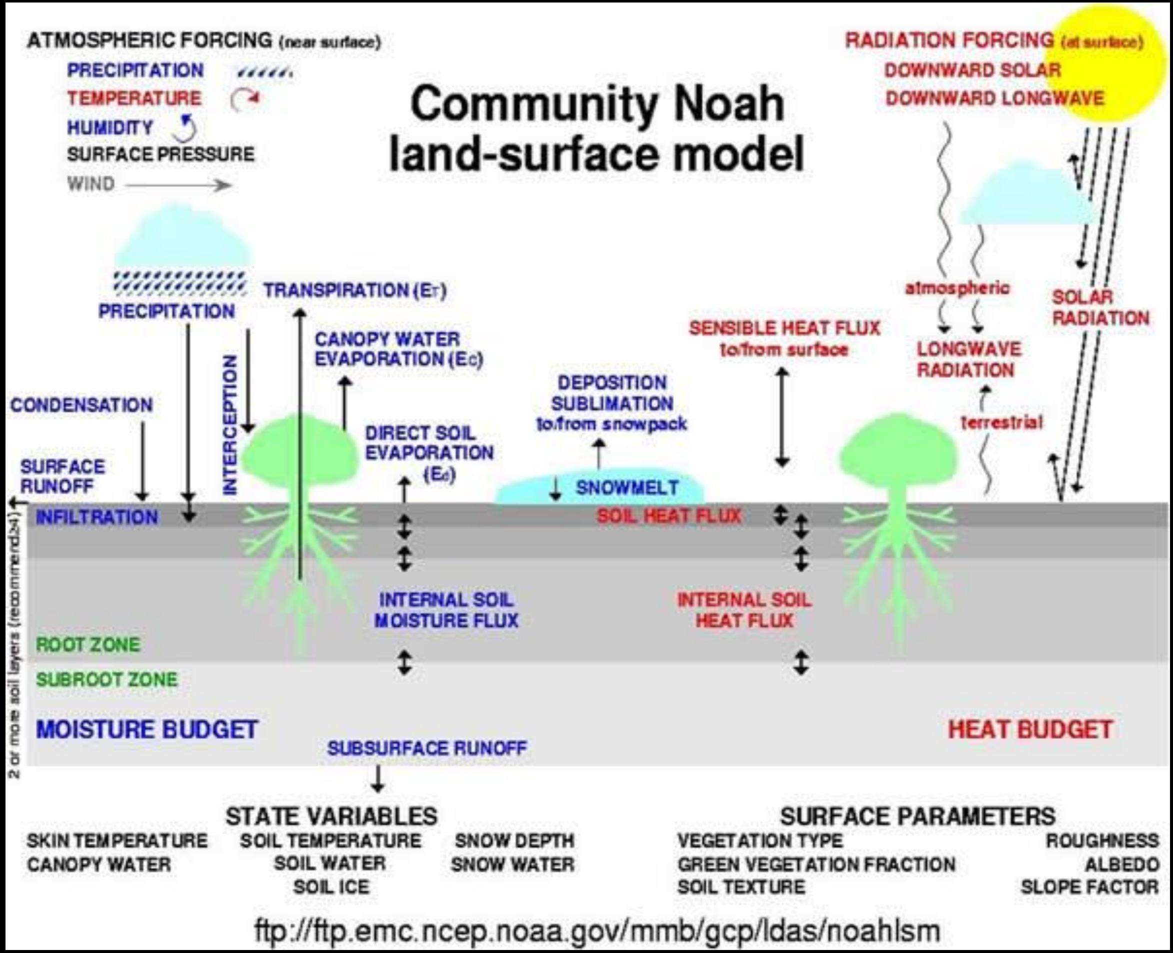
Land-atmosphere Interactions in Numerical Weather and Climate Prediction

Coupled land-atmosphere model
Land surface parameterization

- Poor representation of land surface processes can contribute to prediction biases in weather and climate models
  [Viterbo and Beljaars, 1995; Beljaars et al., 1996; Xue et al., 1996, 2010; Lawrence et al., 2007].

- Biases in land-atmosphere coupling in climate models can contribute to climate prediction biases (Williams et al. 2016)

- Soil moisture can influence climate prediction and weather forecasting
  [e.g., Shukla and Mintz, 1982; Koster et al., 2006, 2010] [Chen and Dudhia 2001; Ek et al. 2004; Santanello et al. 2018]

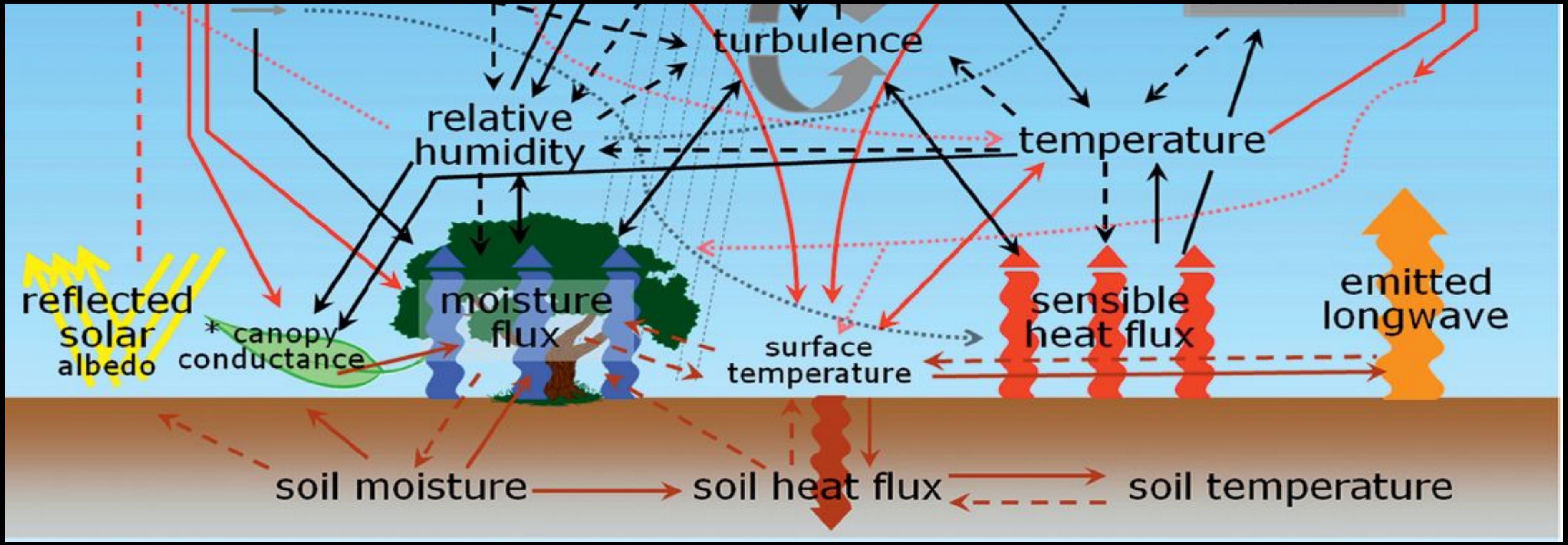


Improved observations, model parameterization, and **data assimilation** are the typical ways to mitigate the biases and uncertainties

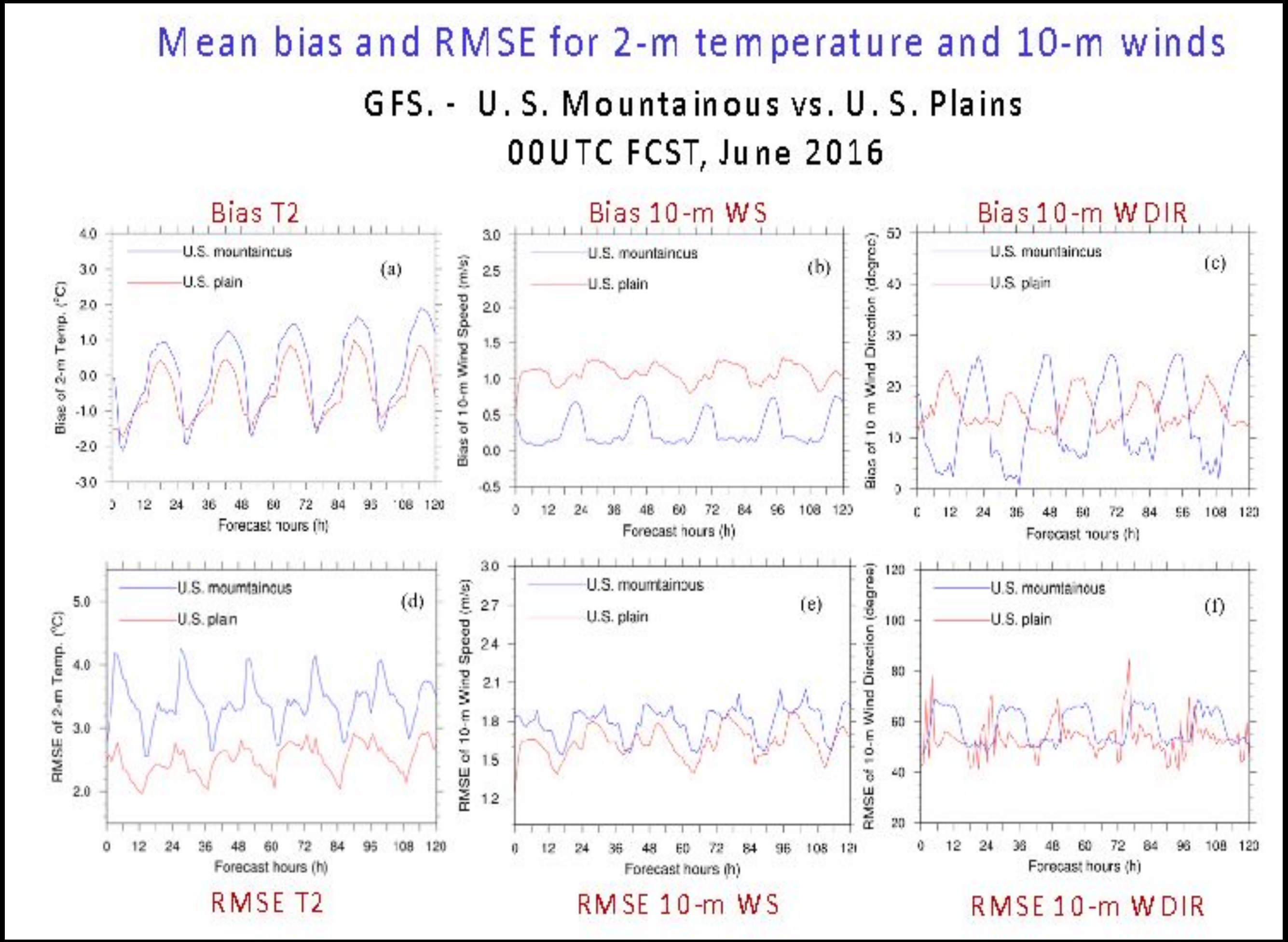
Land-Atmosphere Coupling is Essential in Near-Surface and Boundary Layer

- Near-Surface atmosphere and boundary layer are strongly influenced by land-atmosphere interaction. However,

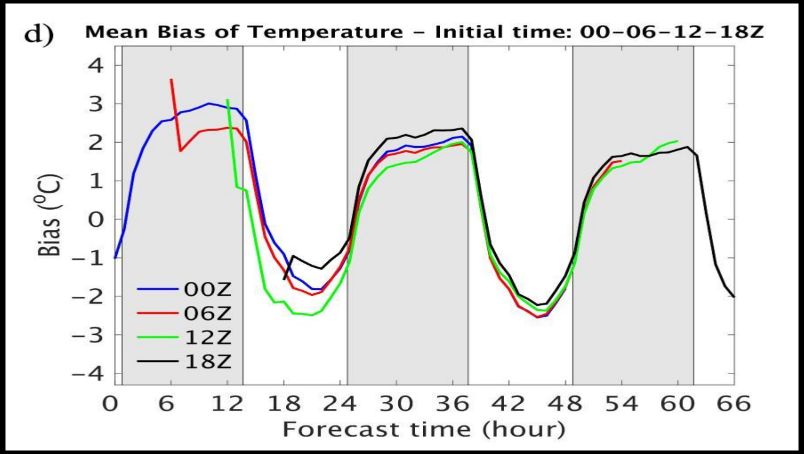
- Uncertainties in land-atmosphere coupling cause significant errors in weather and climate predictions



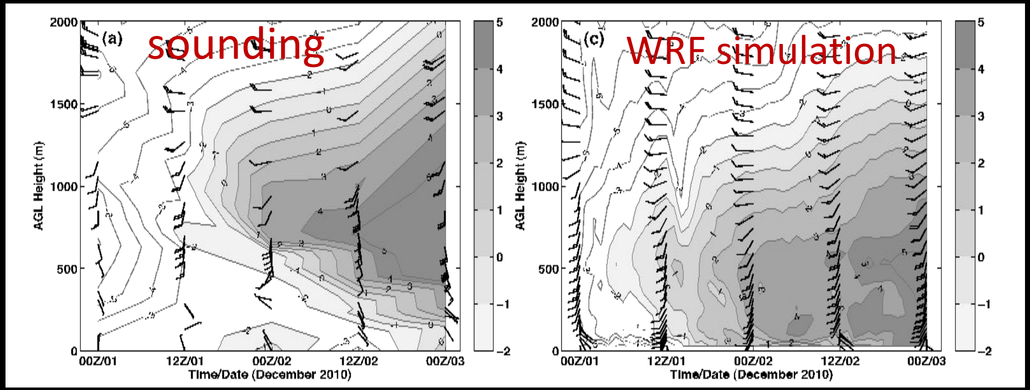
Near-surface weather forecast errors are significant in numerical weather prediction!



Sep-Oct 2012: Mean bias of 2-m Temp.
Dugway Proving Ground, Utah



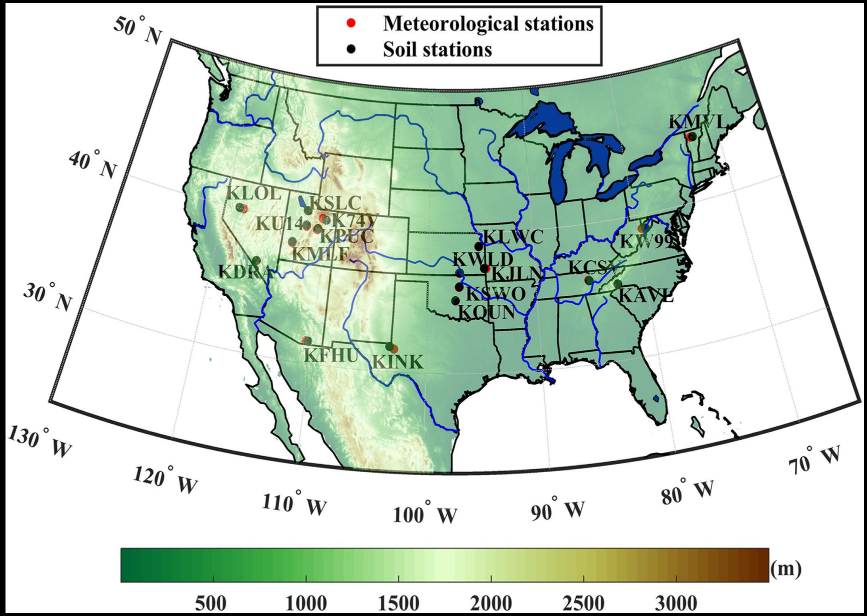
The persistent inversion over
Salt Lake Valley (Dec. 2010)



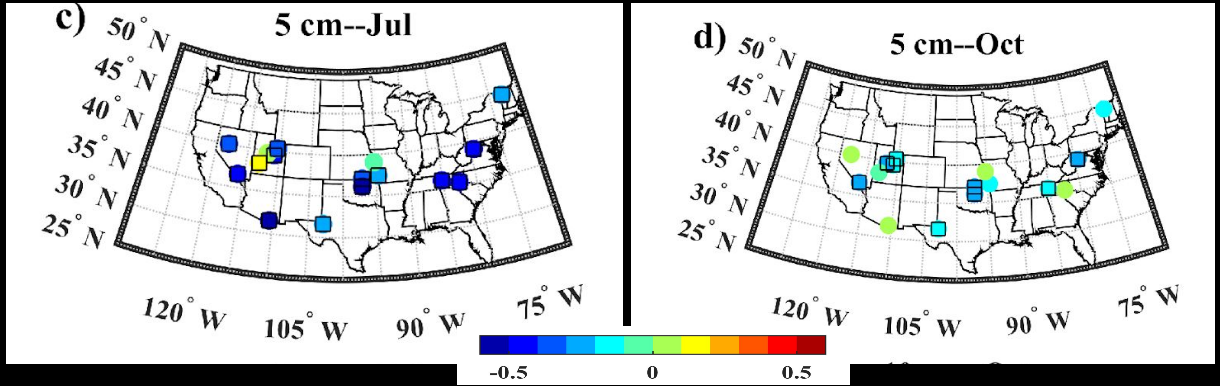
Does Soil Moisture Have an Influence on Near-Surface Temperature?

(Liu and Pu 2019, JGR)

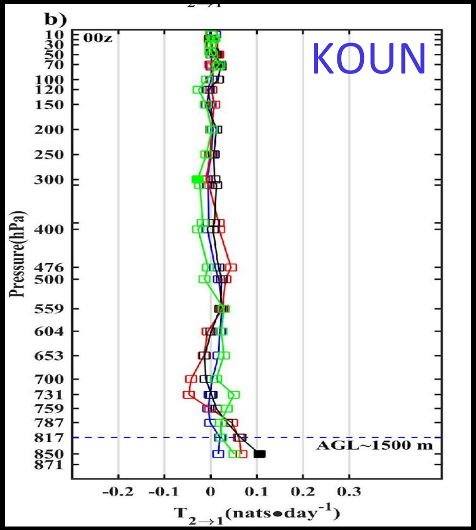
16 soil moisture, 16 meteorological stations, 2 sounding stations (2008-2016)

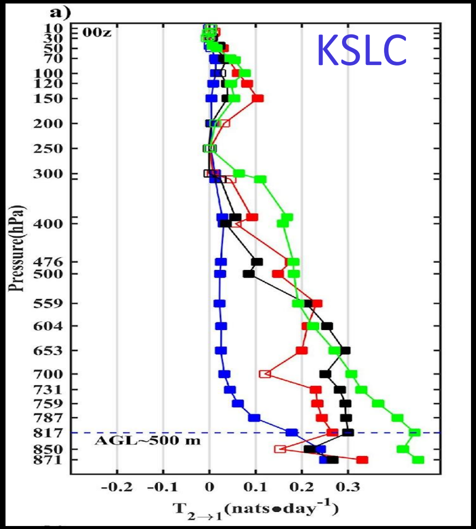


Correlation between soil moisture and T2 (R<0.6)



- There is an interaction between topsoil layer and atmosphere; Impacts of soil moisture on near-surface temperature are significant.





Information flows from sounding temperature to T2.

Interaction between near surface variables with upper atmosphere conditions

- Flow dependent
- Seasonal variability
- Land use and land cover dependencies

Correlations between soil and atmospheric states

(Liu and Pu 2019, JGR)

-- A single column model study with the Weather Research and Forecasting (WRF) model

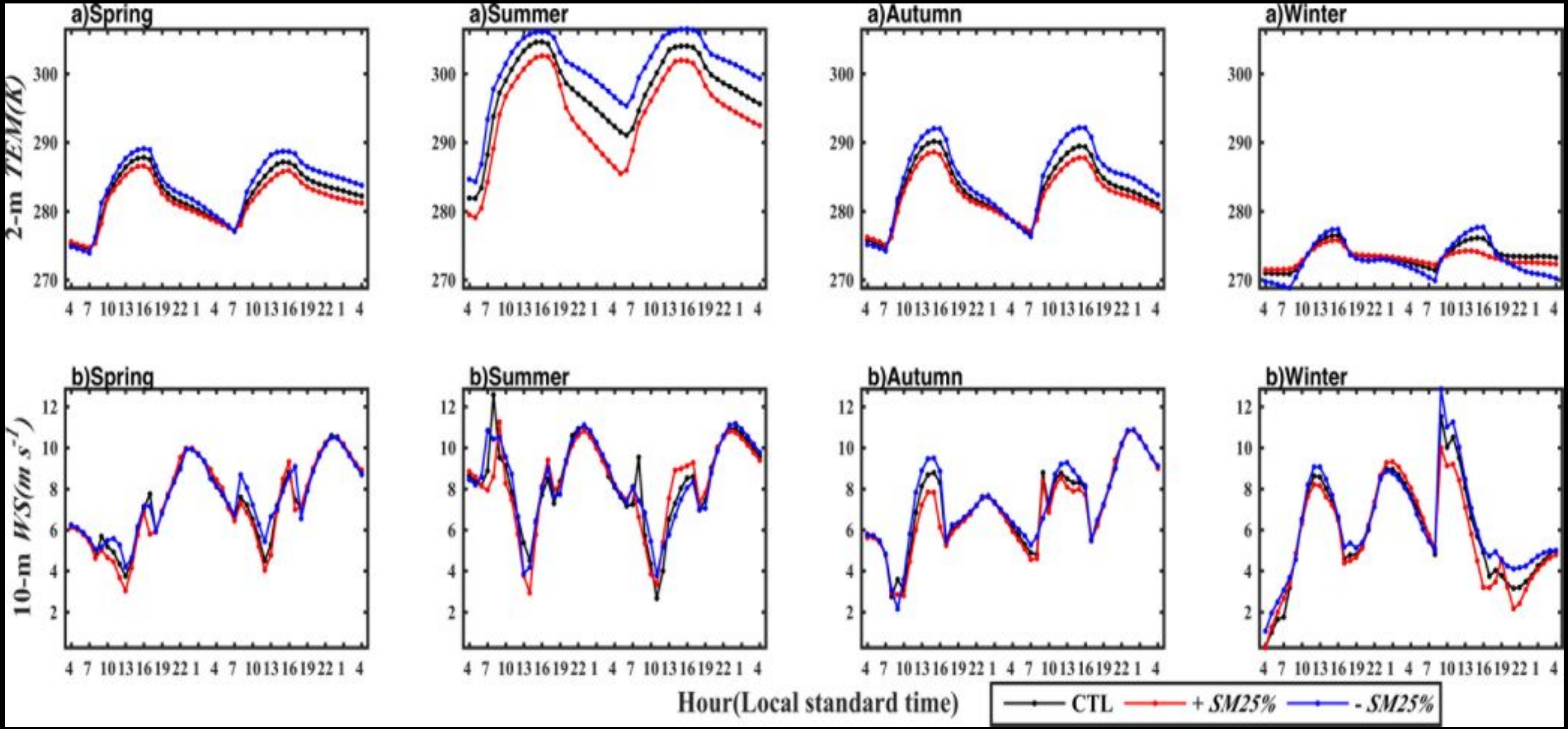
- WRF single column model coupled with Noah Land Surface model
- RRTM longwave radiation/ Dudhia shortwave radiation/ YSU PBL / WSM-6 microphysics

Sensitivity of near-surface weather forecasting to the changes in soil moisture

Spring Summer Autumn Winter

2-m T

10-m WS



Understanding covariances between soil and atmospheric states in a strongly coupled land-atmosphere data assimilation

(Lin and Pu 2018, JAMC)

Monthly estimates of B for 2015-2017 WRF-Noah simulations

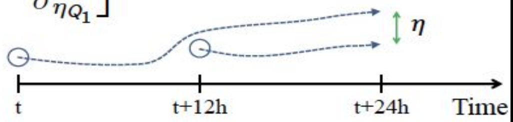
Data Assimilation =
optimal solution of
(model simulations + Observations)
weighted by error statistical

$$J(\delta \mathbf{x}) = \frac{1}{2}\delta \mathbf{x}^{T}\mathbf{B}^{-1}\delta \mathbf{x} + \frac{1}{2}(\mathbf{H}\delta \mathbf{x} - \mathbf{d})^{T}\mathbf{R}^{-1}(\mathbf{H}\delta \mathbf{x} - \mathbf{d})$$

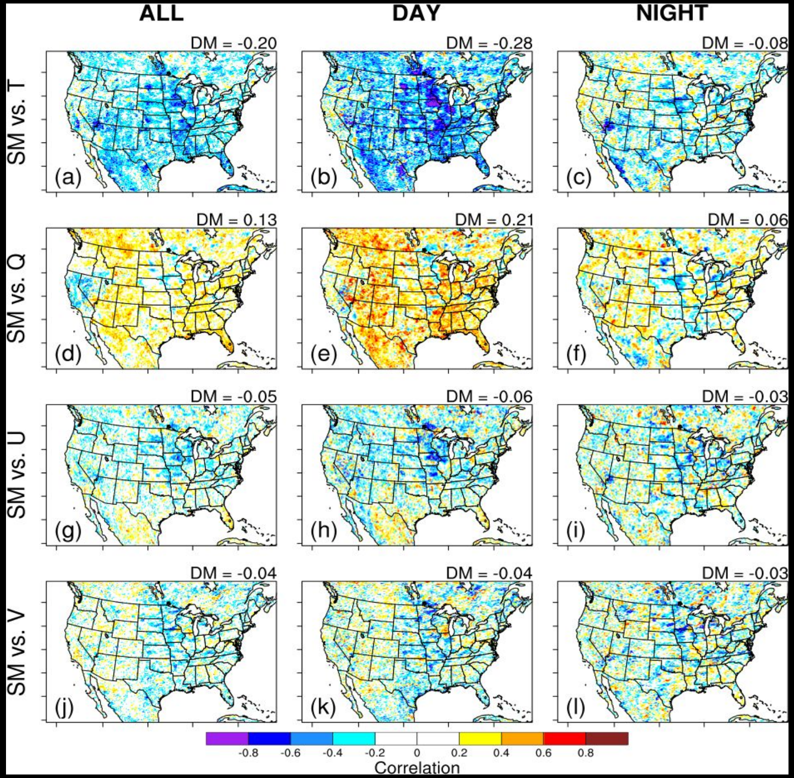
Variational Approach: $\mathbf{B} = \overline{\eta\eta^{T}} = \mathbf{\Sigma C \Sigma}$

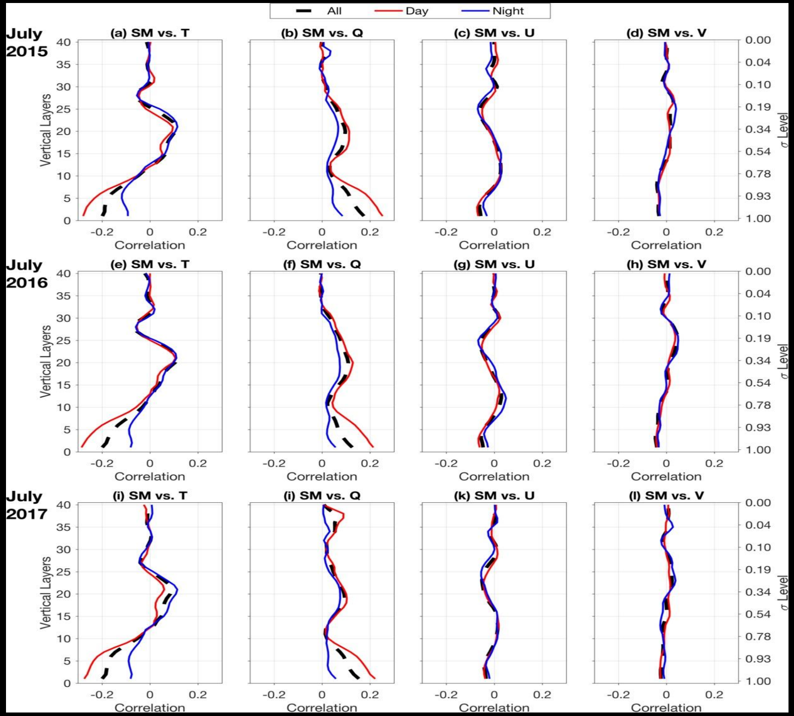
$$\mathbf{C} = \begin{bmatrix} 1 & \rho_{\eta SM_1,\eta T_1} & \rho_{\eta SM_1,\eta Q_1} \\ \rho_{\eta T_1,\eta SM_1} & 1 & \rho_{\eta T_1,\eta Q_1} \\ \rho_{\eta Q_1,\eta SM_1} & \rho_{\eta Q_1,\eta T_1} & 1 \end{bmatrix}$$

$$\mathbf{\Sigma} = \begin{bmatrix} \sigma_{\eta SM_1} & 0 & 0 \\ 0 & \sigma_{\eta T_1} & 0 \\ 0 & 0 & \sigma_{\eta Q_1} \end{bmatrix}$$



The error correlations between top-layer soil moisture (SM) and bottom-layer atmospheric T, Q, U, and V in July 2016.

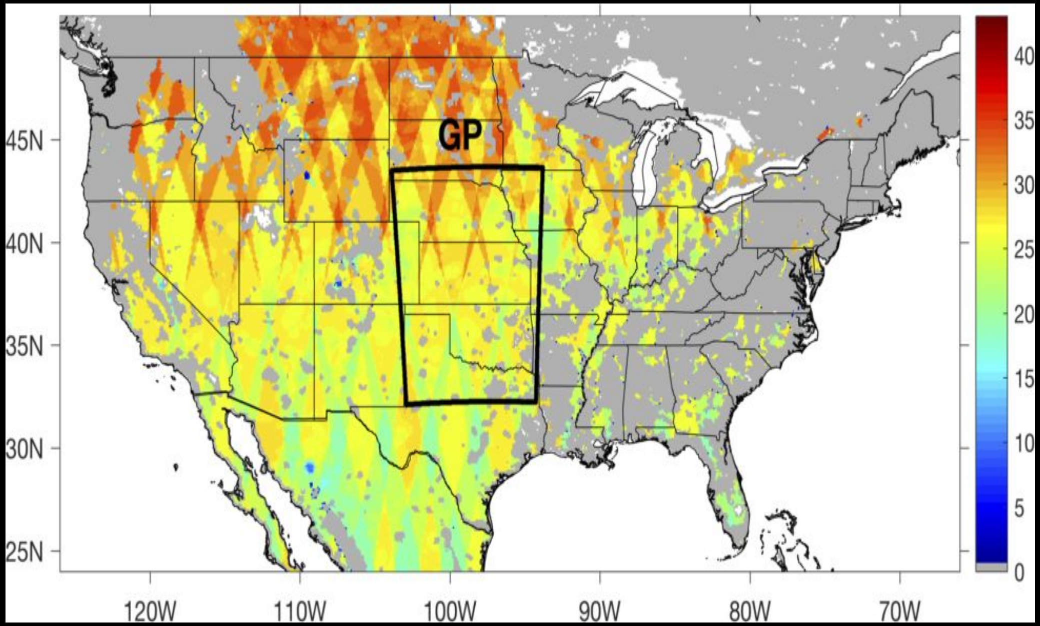




The domain mean error correlation between the top 10-cm soil moisture and atmospheric states at vertical levels in July from 2015 to 2017.

Notable correlations between soil moisture in near-surface and boundary layer temperature and humidity

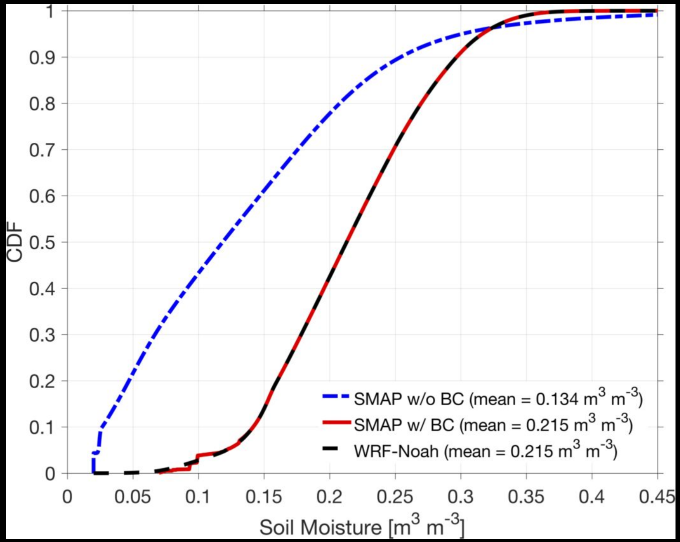
The influence of SMAP soil moisture data assimilation (DA) on short-range weather forecasting with WRF-Noah: Strongly vs. Weakly Coupled DA



The sample of both descending and ascending data from SMAP, 1-27 July 2016

Experiments are performed from 1-28 July 2016

- Open Loop (OPL): no data assimilation
- Weakly coupled DA (WCDA): update only top-layer soil moisture using bias-corrected SMAP soil moisture (SM)
- Strongly Coupled DA (SCDA): update SM and T/Q using bias-corrected SMAP SM



Bias Correction

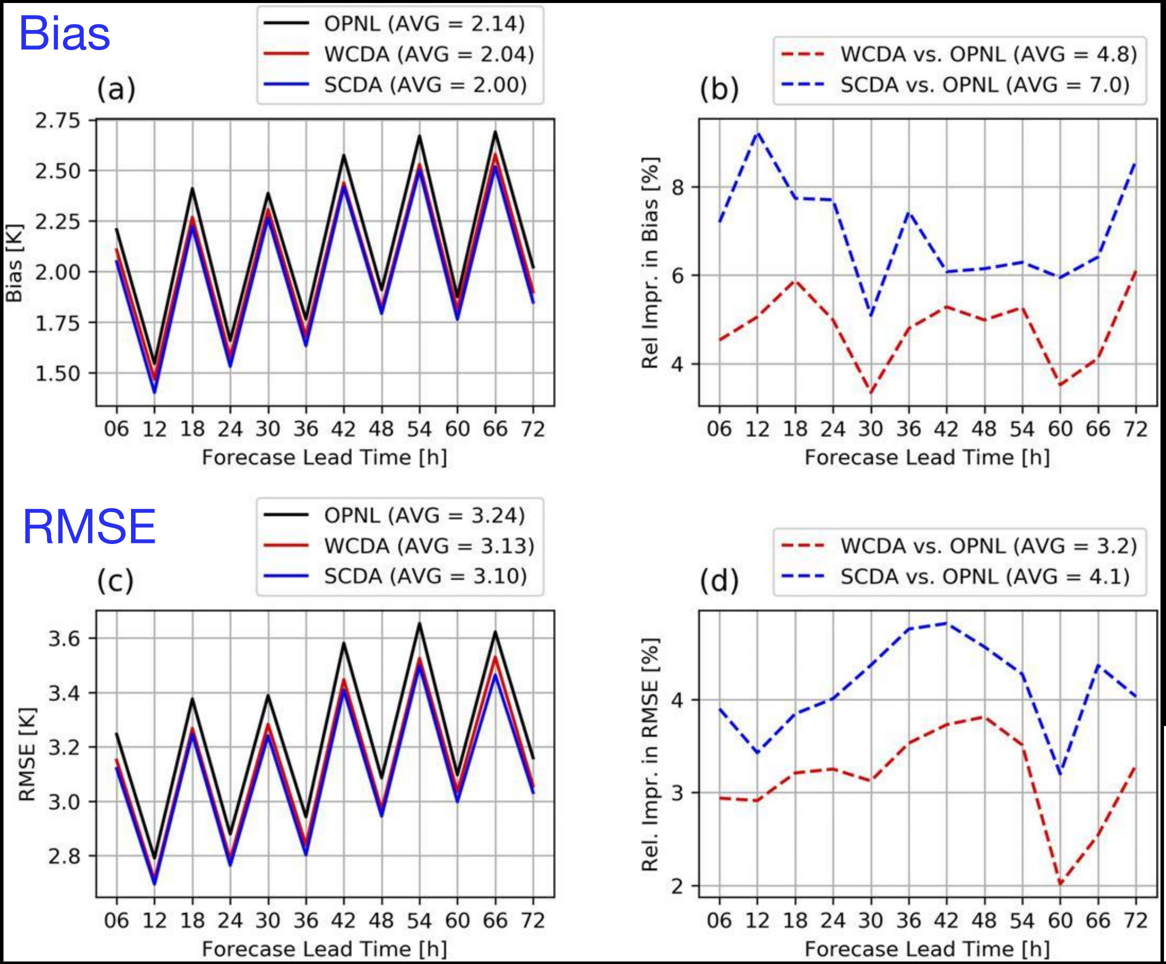
The soil moisture from Noah and SMAP SM before and after rescaling in July 2016 over the regions of interest Cumulative distribution function (CDF) matching

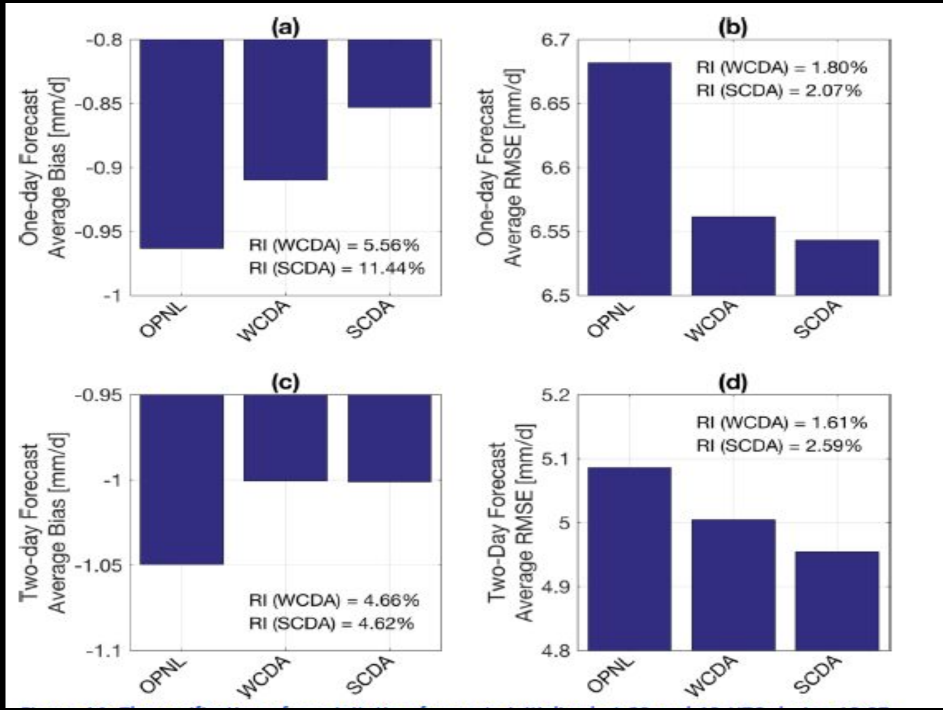
(Lin and Pu 2019, MWR)

SCDA vs. WCDA

2-m temp. forecasts against the METAR weather stations

(10-27 July 2016)





24 h FCST

48 h FCST

Verification of precipitation against Stage IV data.

Forecast initialized at 00 and 12 UTC during 10-27 July 2016

$$RI_{Bias} = \left(1 - \left|\frac{Bias_{DA}}{Bias_{OL}}\right|\right) \times 100\%$$

$$RI_{RMSE} = \frac{RMSE_{OL} - RMSE_{DA}}{RMSE_{OL}} \times 100\%$$

The relative improvements

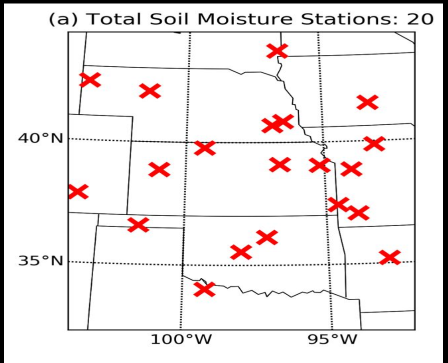
SCDA > WCDA

Strongly coupled land-atmosphere data assimilation within the GSI-EnKF

- Simultaneously assimilate (correct) soil moisture and atmospheric observations (states)

No.	Experiment	Control States	Assimilated Observations
0	OPNL	-	-
1	VarwoSM_CONV	T, Q, U, V, MU	Conventional data
2	VarwoSM_CONV_T2	T, Q, U, V, MU	Conventional data + T2
3	VarwoSM_CONV_Q2	T, Q, U, V, MU	Conventional data + Q2
4	VarwoSM_CONV_T2Q2	T, Q, U, V, MU	Conventional data + T2 + Q2
5	VarwSM_CONV	T, Q, U, V, MU, SM	Conventional data
6	VarwSM_CONV_T2	T, Q, U, V, MU, SM	Conventional data + T2
7	VarwSM_CONV_Q2	T, Q, U, V, MU, SM	Conventional data + Q2
8	VarwSM_CONV_T2Q2	T, Q, U, V, MU, SM	Conventional data + T2 + Q2
9	VarwSM_CONV_SM	T, Q, U, V, MU, SM	Conventional data + SM
10	VarwSM_CONV_T2Q2SM	T, Q, U, V, MU, SM	Conventional data + T2 + Q2 + SM

US SPG Region

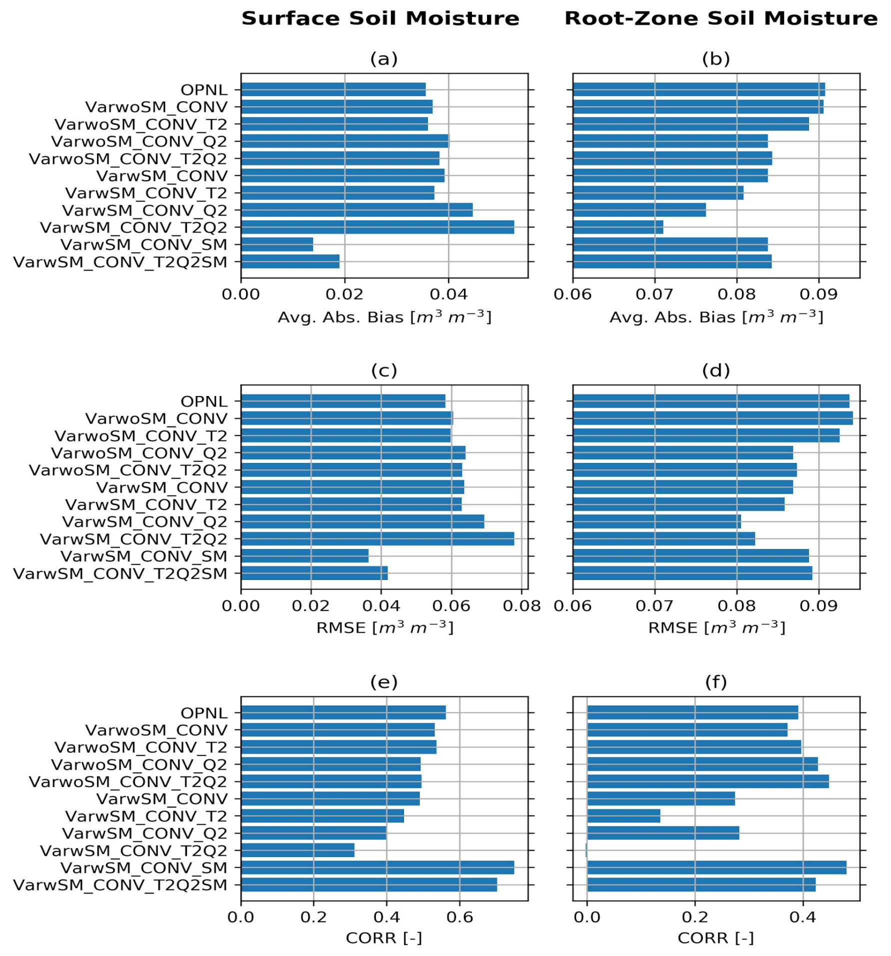


- **1-28 July 2018 (Exp. Period)**
- **Simultaneously assimilate soil moisture and atmospheric data**
- **Significant improvement on the prediction of short-range weather prediction (near-surface atmospheric conditions) and soil moisture.**

	Temperature		Humidity	
	RMSE (K)	RI (%)	RMSE ($g\,kg^{-1}$)	RI (%)
OPNL	1.459	—	1.912	—
CNTL	1.388	4.8%	1.867	2.4%
VarwSM_CONV	1.321	9.5%	1.811	5.3%
VarwoSM_CONV_Q2	1.300	10.9%	1.758	8.1%
VarwSM_CONV_Q2	1.232	15.6%	1.707	10.8%
VarwoSM_CONV_T2Q2	1.303	10.7%	1.763	7.8%
VarwSM_CONV_T2Q2	1.229	15.7%	1.708	10.7%

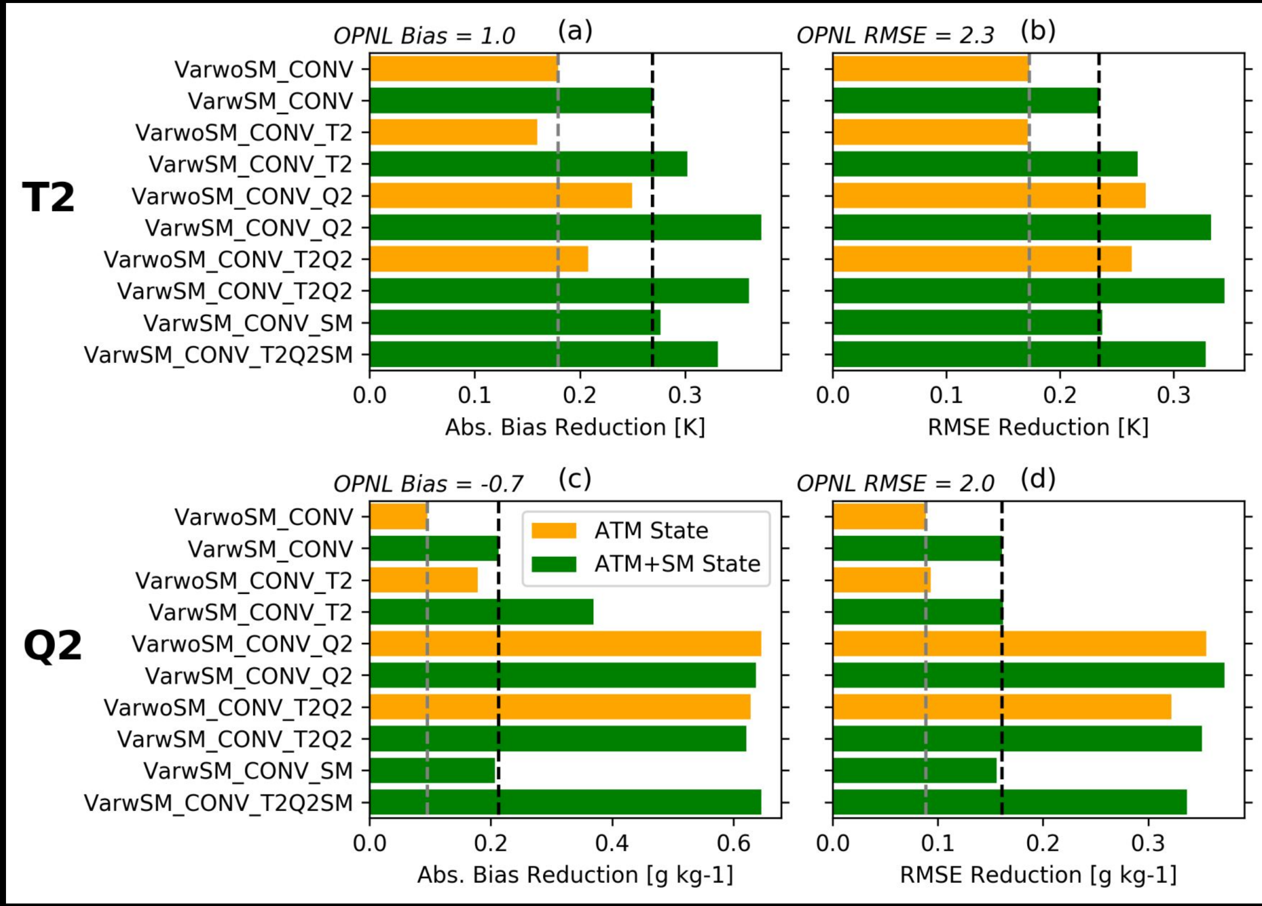
(Lin and Pu 2020, MWR)

Verification of Soil Moisture Analysis Against ISMN



Assimilation of Soil Moisture and Q2 improves the surface soil moisture analysis

Verification of T2 and Q2 Against METAR Stations



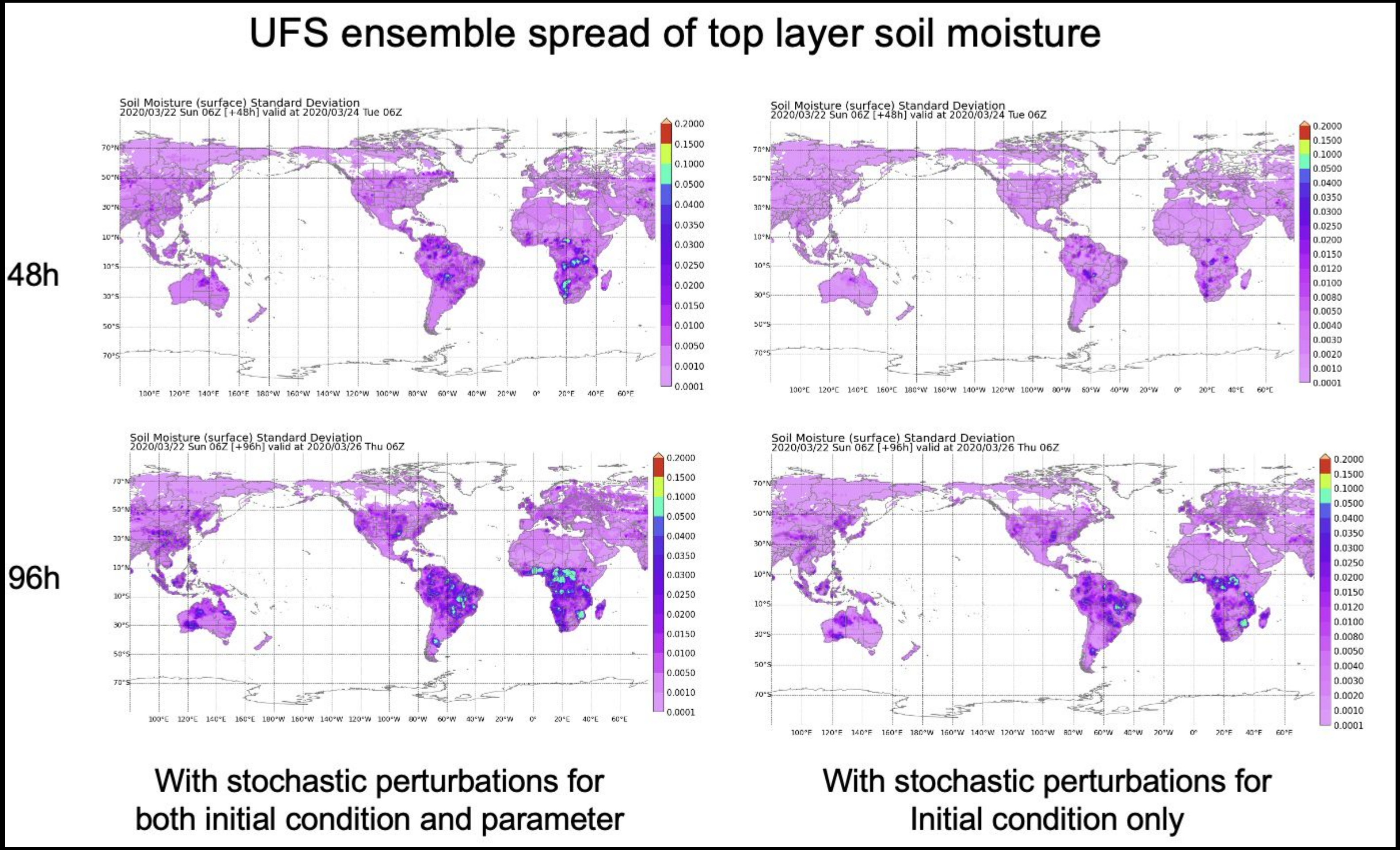
Assimilation of soil moisture enhances accuracies of analysis and forecasts of near-surface weather variables

A recent development with UFS and JEDI

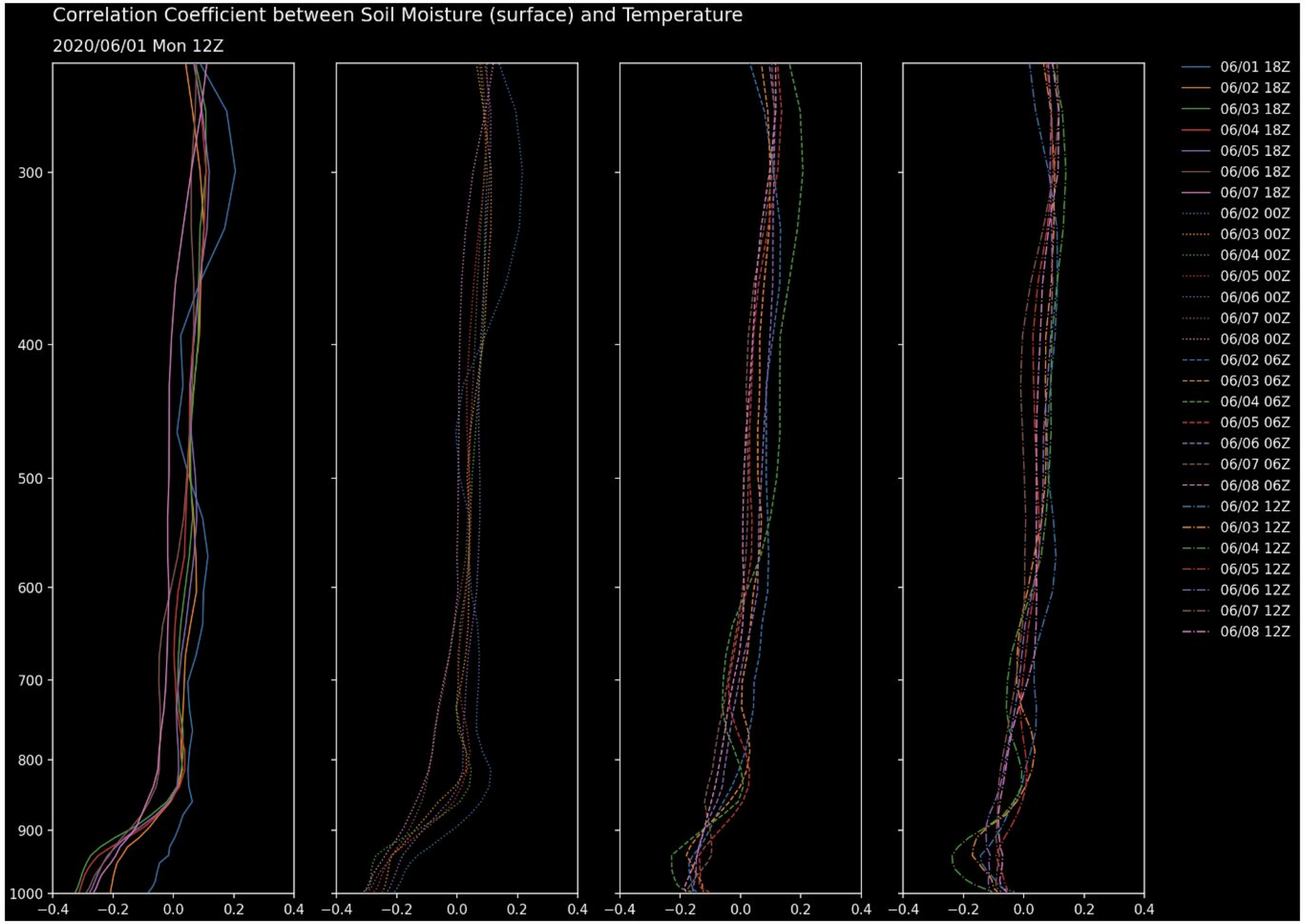
NOAA Unified Forecast System (UFS)

Joint Effort for Data Assimilation Integration (JEDI)

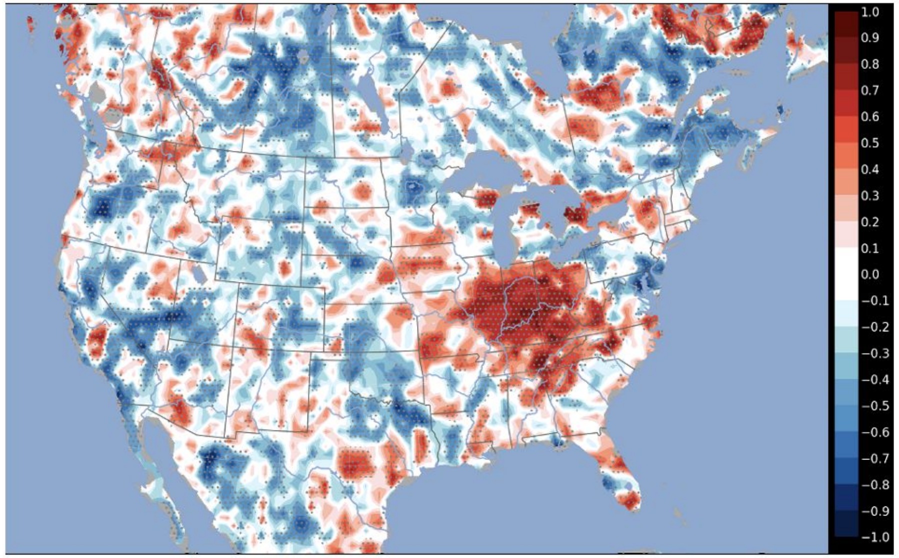
- LETKF data assimilation method



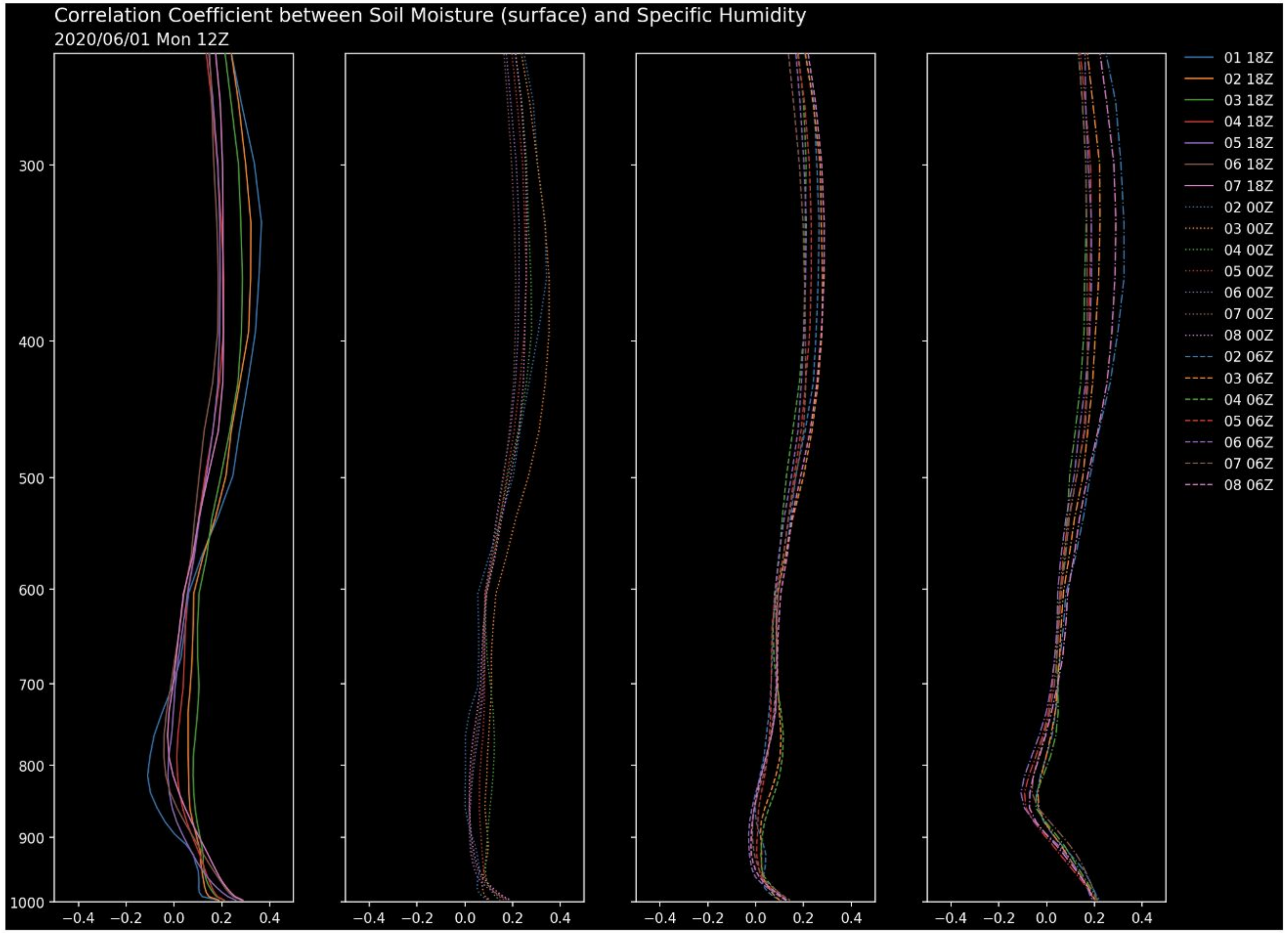
Correlation between soil moisture and temperature in UFS



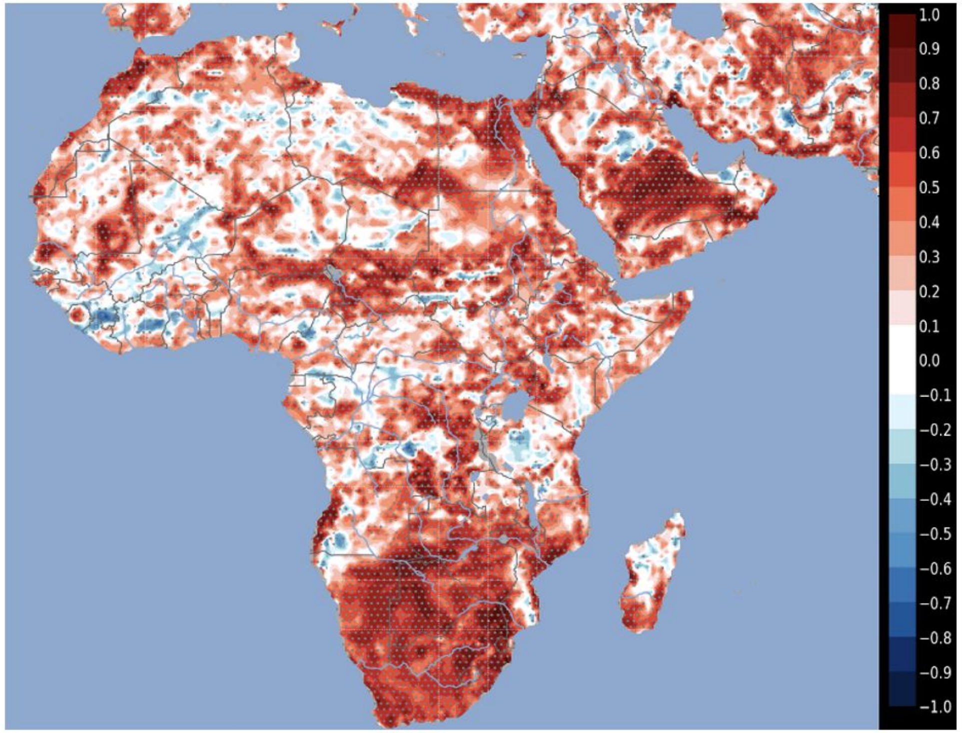
Correlations between soil moisture and temperature at the lowest model level of atmosphere



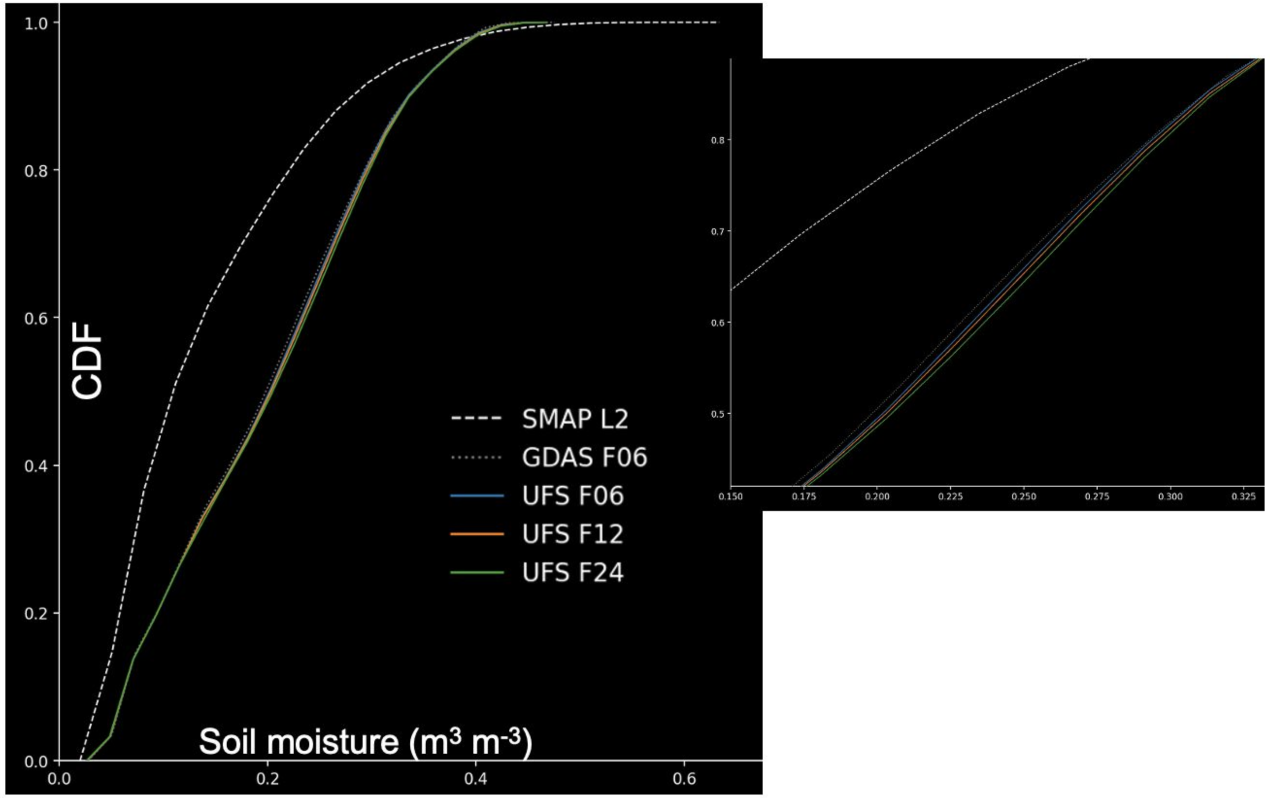
Correlation between soil moisture and humidity in UFS



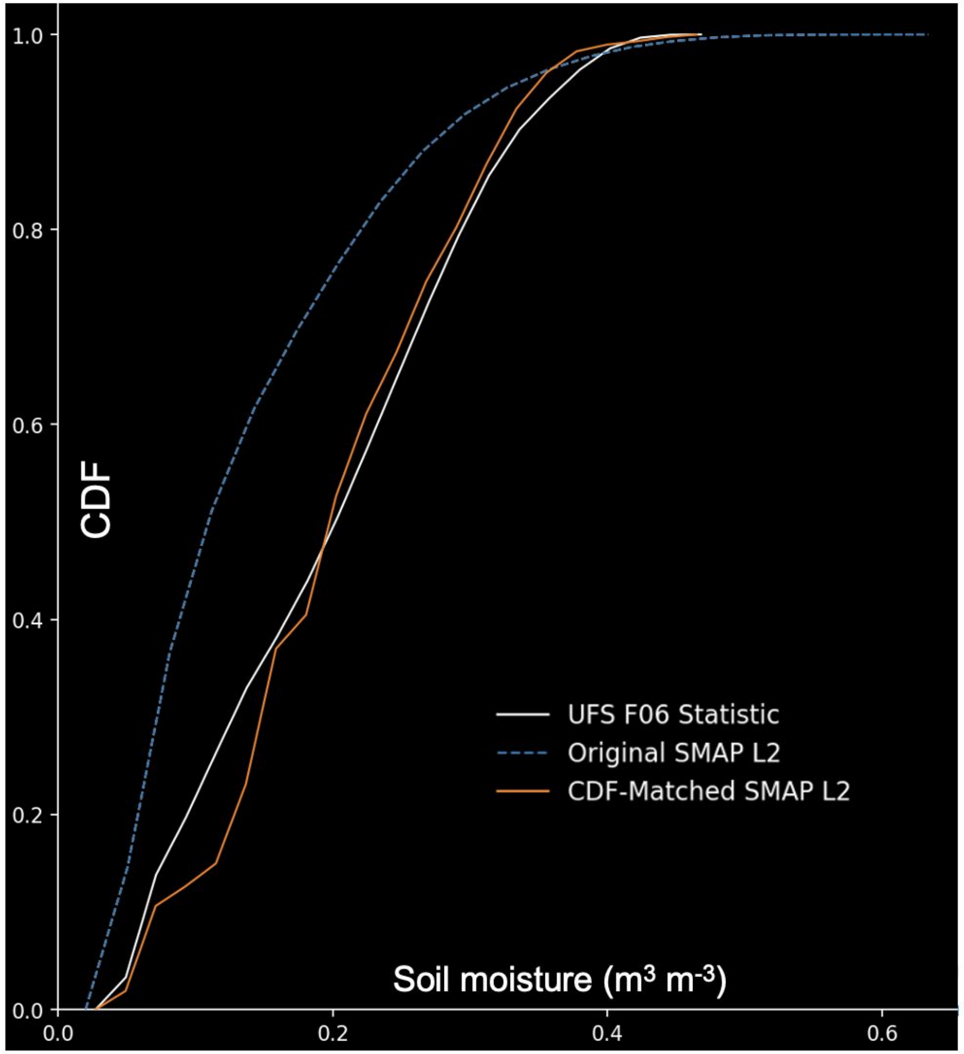
Correlations between soil moisture and humidity at the lowest model level of atmosphere



Soil Moisture Bias Correction - CDF Match

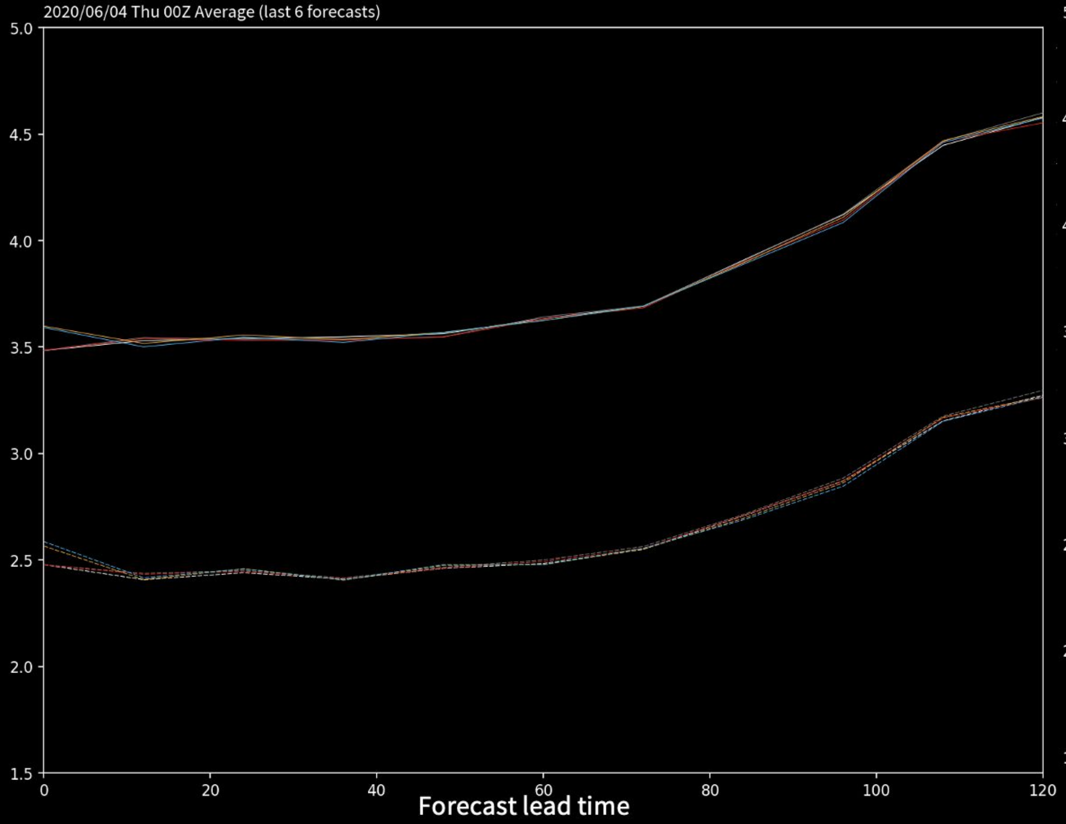


June 2020

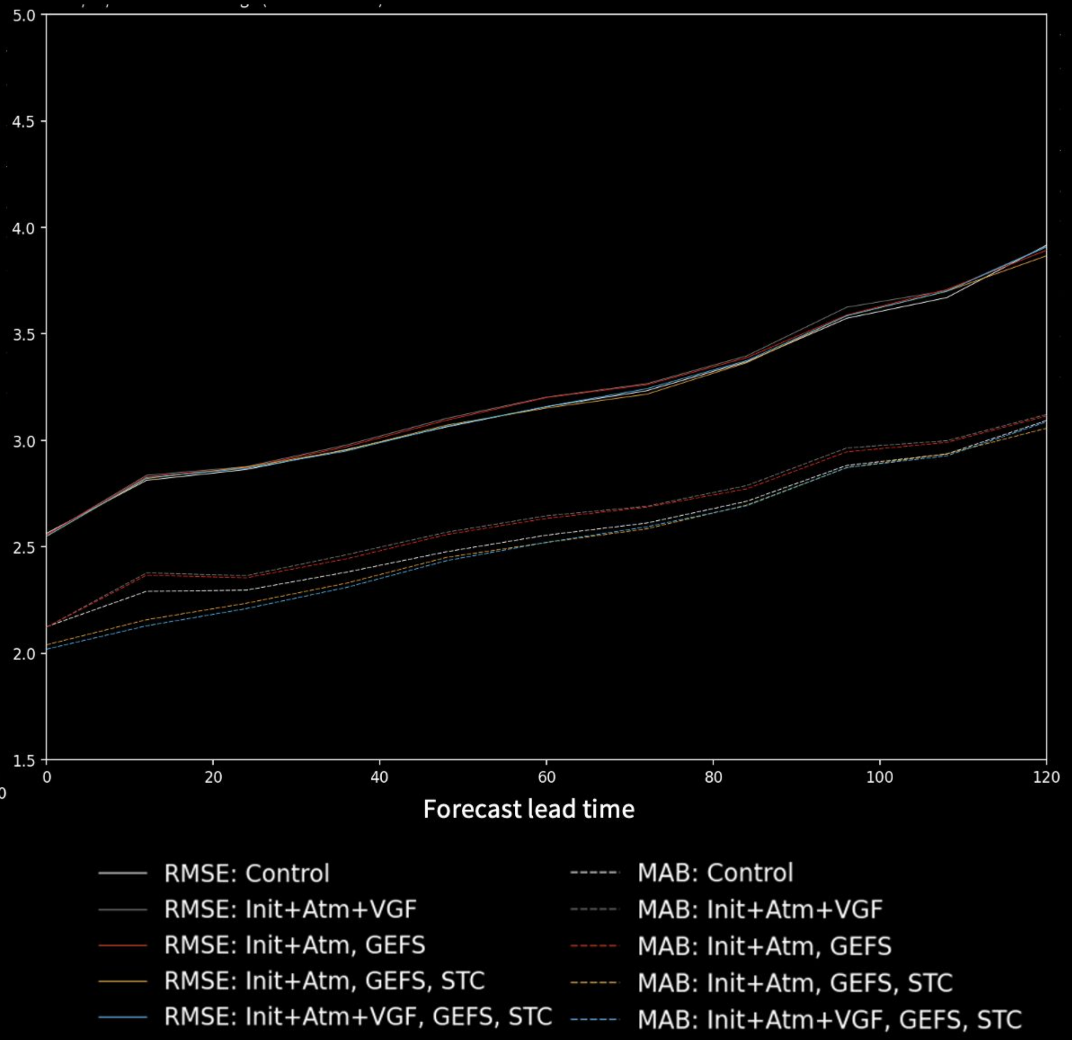


Soli moisture DA influence on UFS forecasts: Verify against METAR

Surface Dew Point (2020/06/04 00Z – 06/06 12Z)



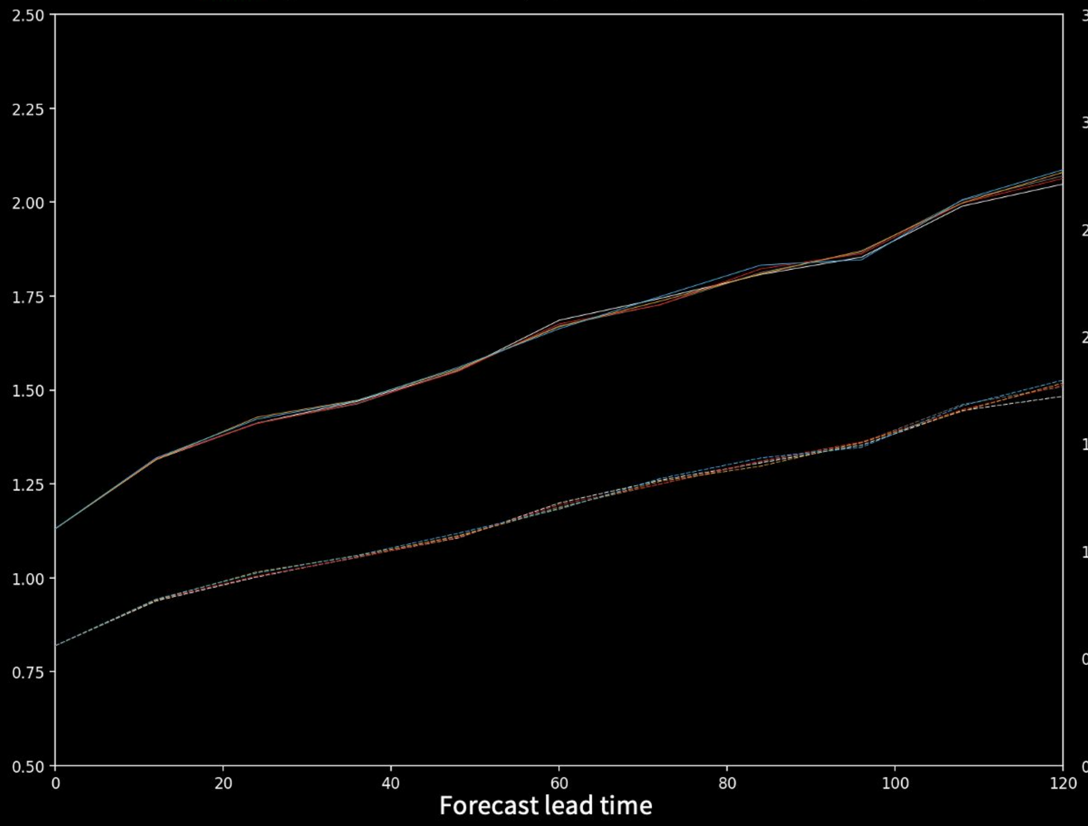
Surface Temperature (2020/06/04 00Z – 06/06 12Z)



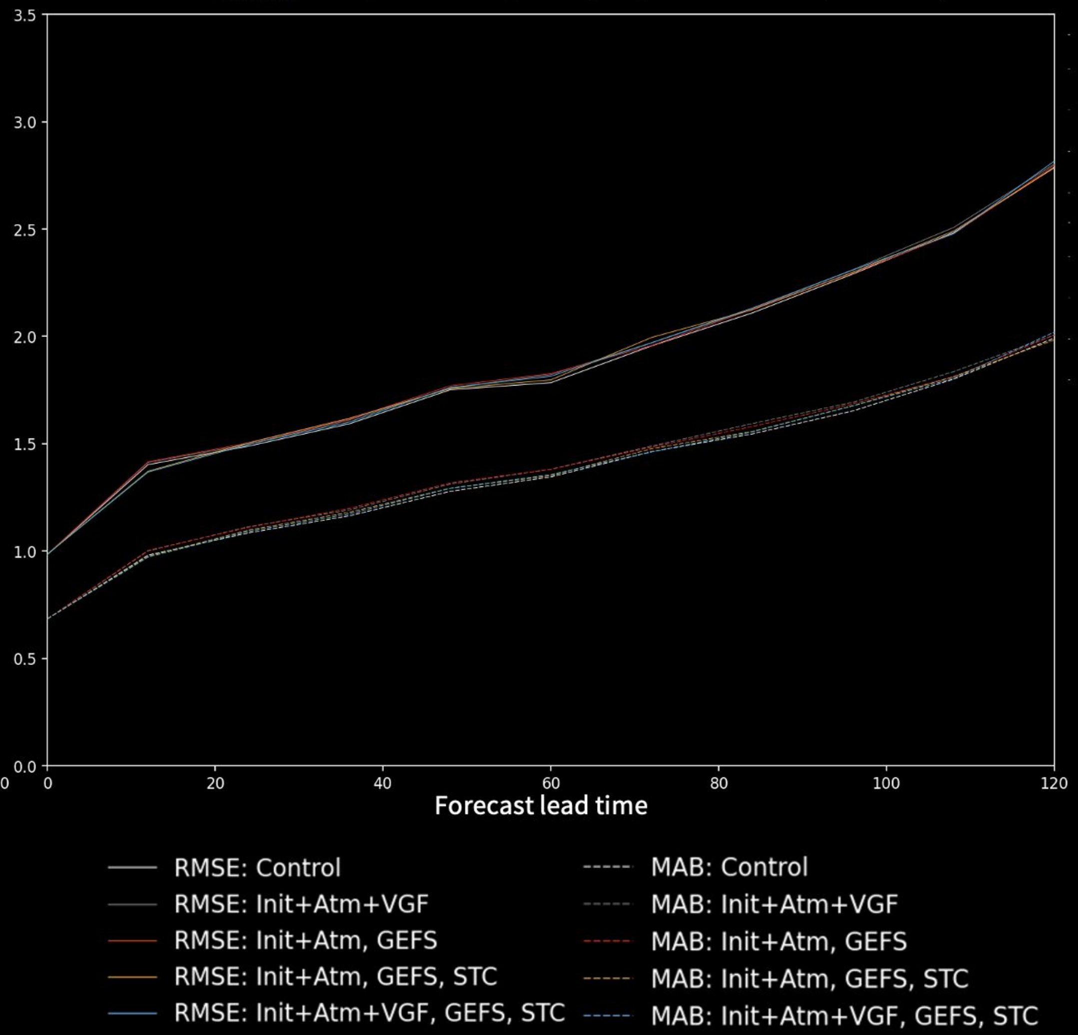
STC experiments sightly improve the surface temperature forecast.

Soli Moisture DA Influence on UFS forecasts: Verify against Soundings

850 hPa Specific Humidity (2020/06/04 00Z – 06/06 12Z)



850 hPa Temperature (2020/06/04 00Z – 06/06 12Z)



No significant improvement or deterioration compared with the control.

Concluding remarks

- There are correlations between soil and atmospheric states. A strongly coupled land-atmospheric data assimilation is recommended. The strongly coupled land-atmosphere data assimilation outperforms the weakly coupled data assimilation.

- A strongly coupled system with GSI EnKF demonstrates potential benefits in predicting near-surface atmospheric conditions and soil moisture.

- Recent development in strongly-coupled land-atmosphere data assimilation with UFS/JEDI is in progress.

- Evaluations of influences of strongly coupled land-atmosphere data assimilation on medium-range weather prediction and 3-4 weeks/S2S are ongoing or under the plan.

Thank you!

Zhaoxia.Pu@utah.edu