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Data Assimilation to Extract Soil Moisture Information From SMAP Observations

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Motivation

Objective:
Efficiently assimilate SMAP observations into the NASA Catchment model.

Issue:
Localized observation rescaling removes some independent information from very skillful SMAP retrievals.

Compare which rescaling method uses independent satellite information most efficiently.

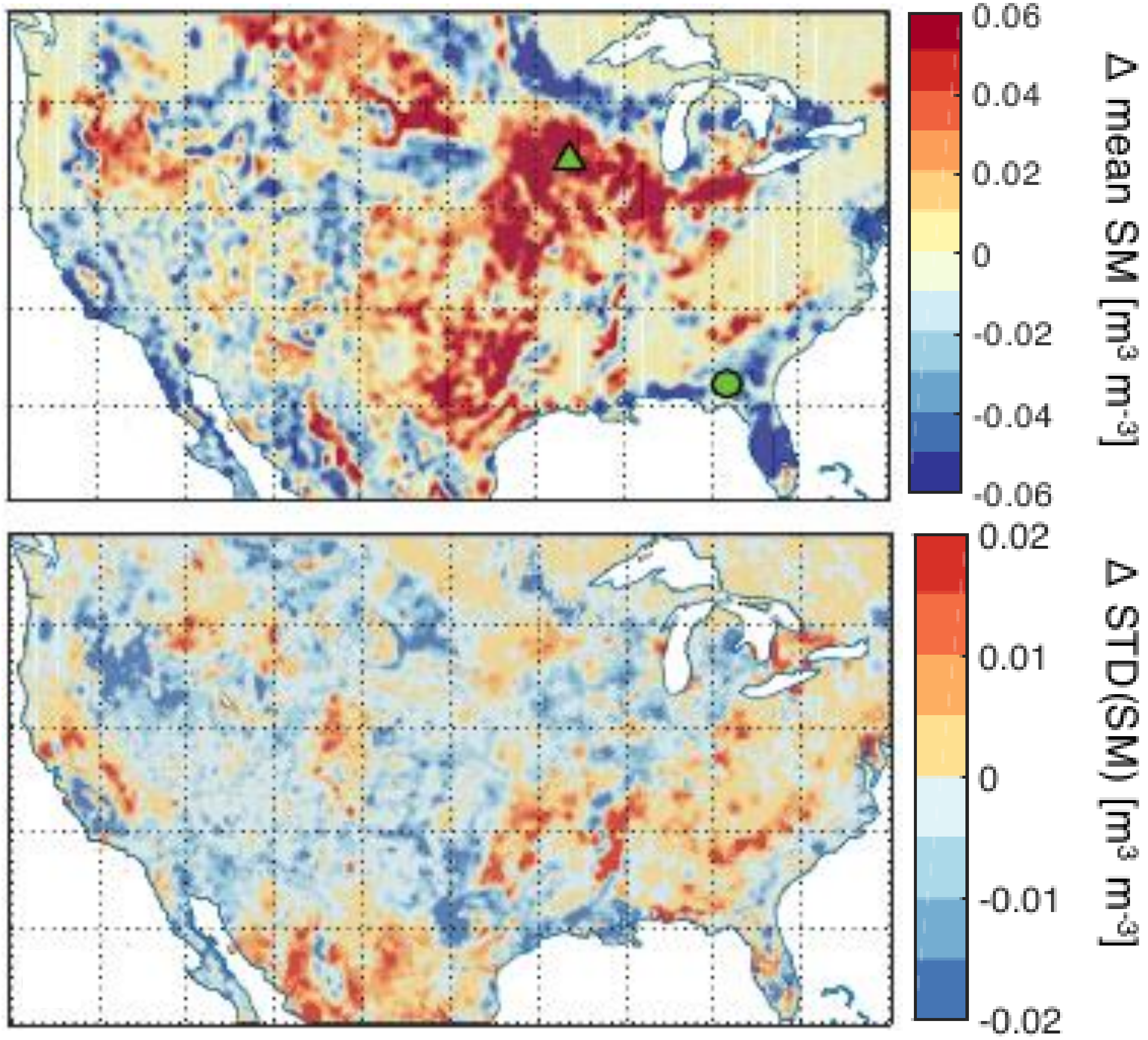


Fig 1. *Effect of localized bias correction (CDF-matching) on soil moisture retrieval.*

SMAP Neural Network Retrievals

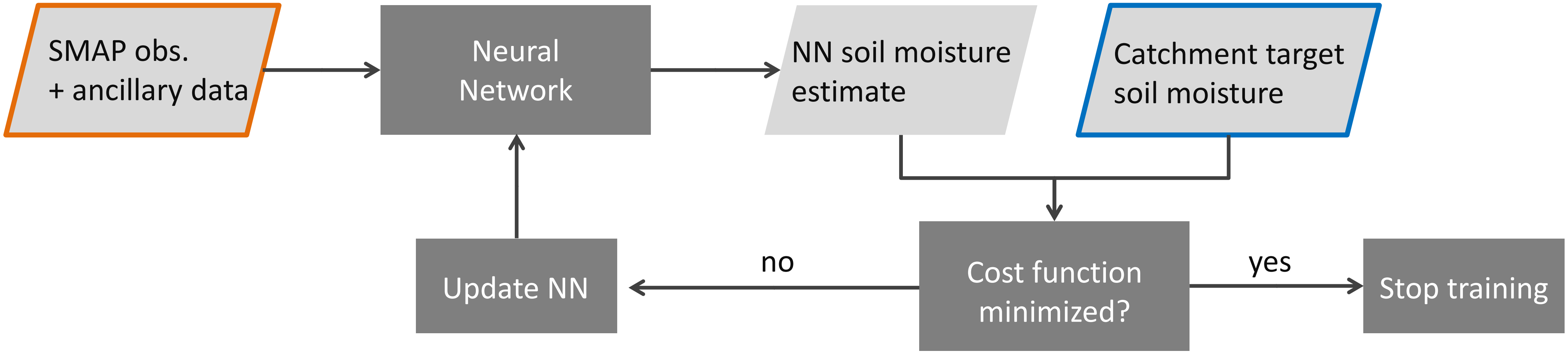


Fig 2. *NN training procedure.*

- Neural Networks (NN) retrieve soil moisture in model climatology (mean, variance, higher moments) *(Kolassa et al. 2017, in review)*
- **Global** dynamic range and bias from model (GEOS-5)
- Spatial and temporal patterns from observations (SMAP + ancillary data)

Can NN retrievals reduce the need for further bias correction prior to assimilation and thus avoid removing independent satellite information?

SMAP Soil Moisture Assimilation

Experiments

• OL	Model-only simulation (no assimilation)
• DA-NN:	Assimilate NN retrievals **without further bias correction**
• DA-NN-CDF:	Assimilate NN retrievals with **local bias correction**
• DA-L2P-gCDF:	Assimilate L2 passive retrievals *(O'Neill et al., 2015)* with **global bias correction**
• DA-L4:	Assimilate **locally rescaled brightness temperatures in SMAP L4_SM system**

- April 2015 – March 2017
- 9 km EASE v2 grid
- Contiguous United States
- 3-hourly analysis

→ Assess skill improvements of DA over OL at SMAP core validation sites

(Jackson et al., 2016; Colliander et al., 2017)

Impact on Soil Moisture Climatology

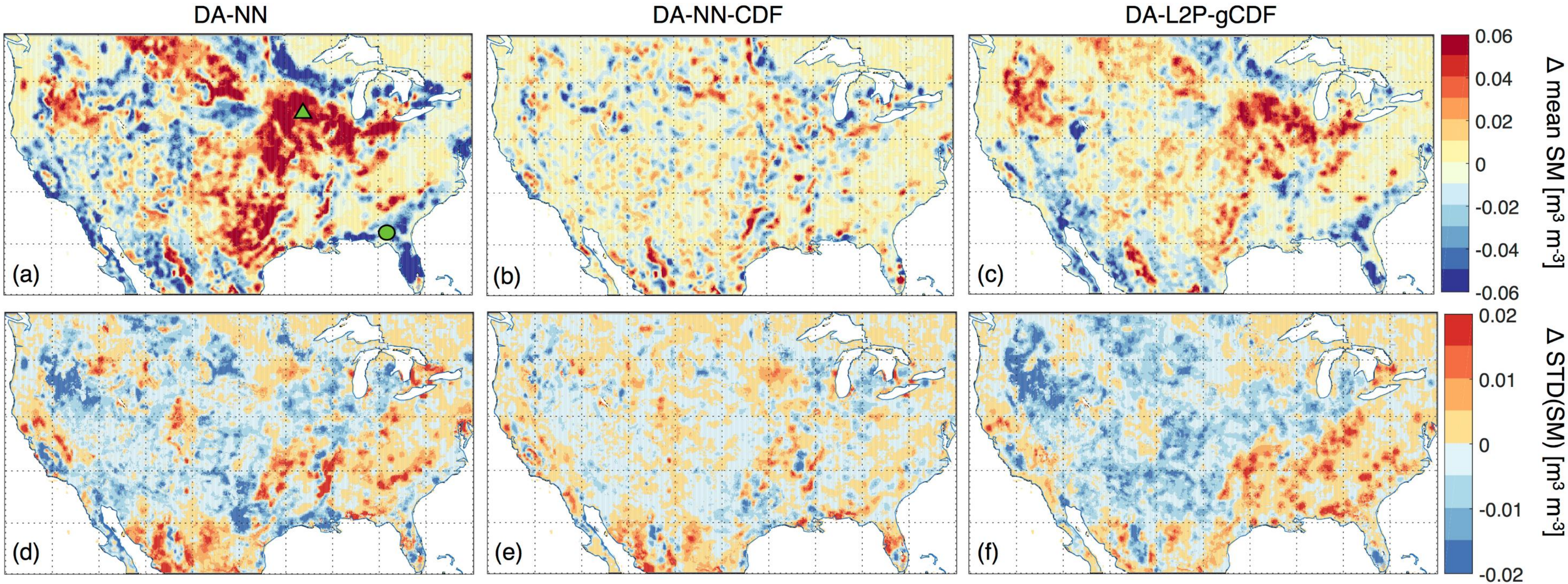


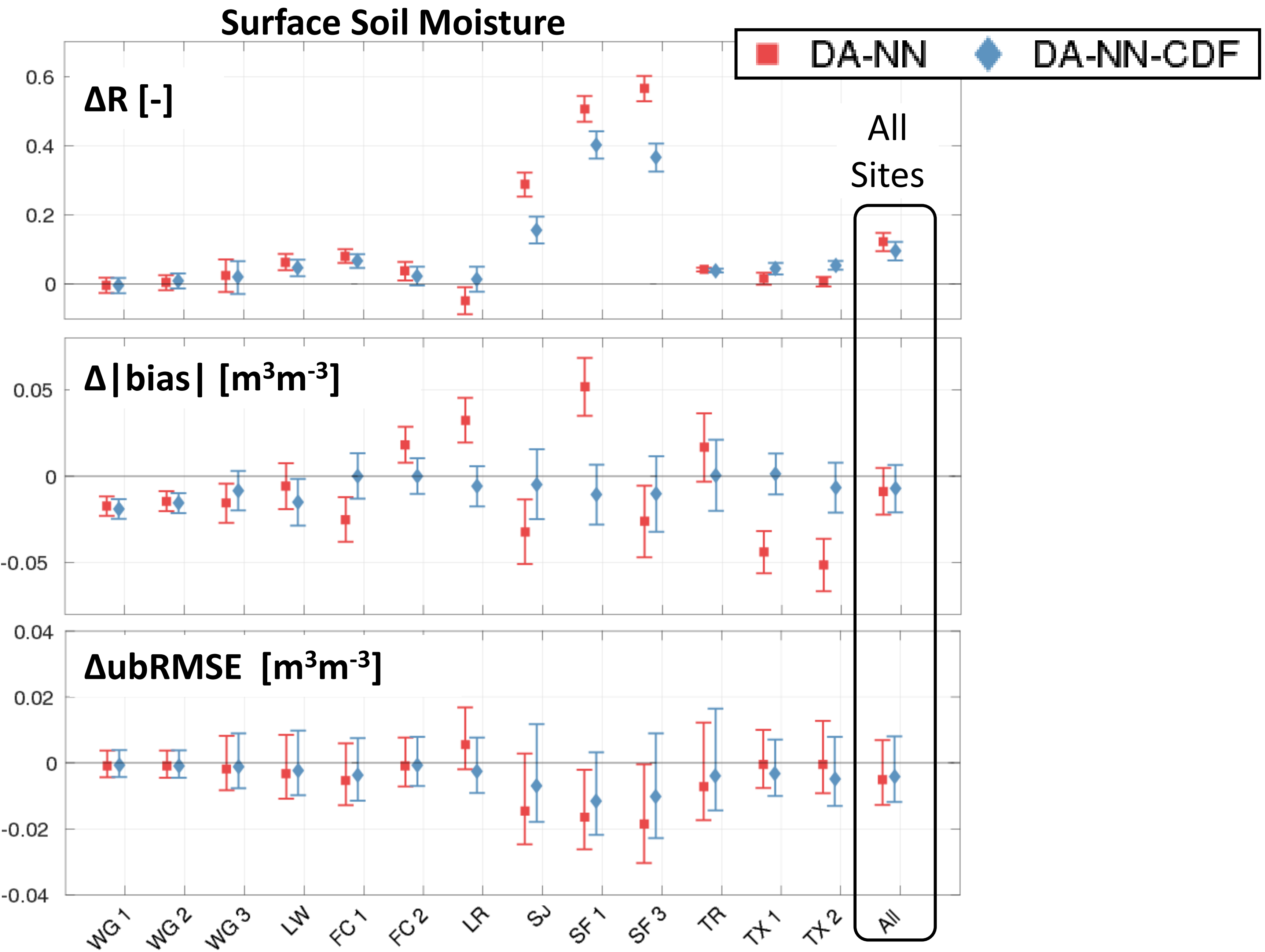
Fig 3. *Difference (OL minus DA) in soil moisture (top row) mean and (bottom row) standard deviation.*

Global rescaling experiments introduce more of the SMAP retrieval information.

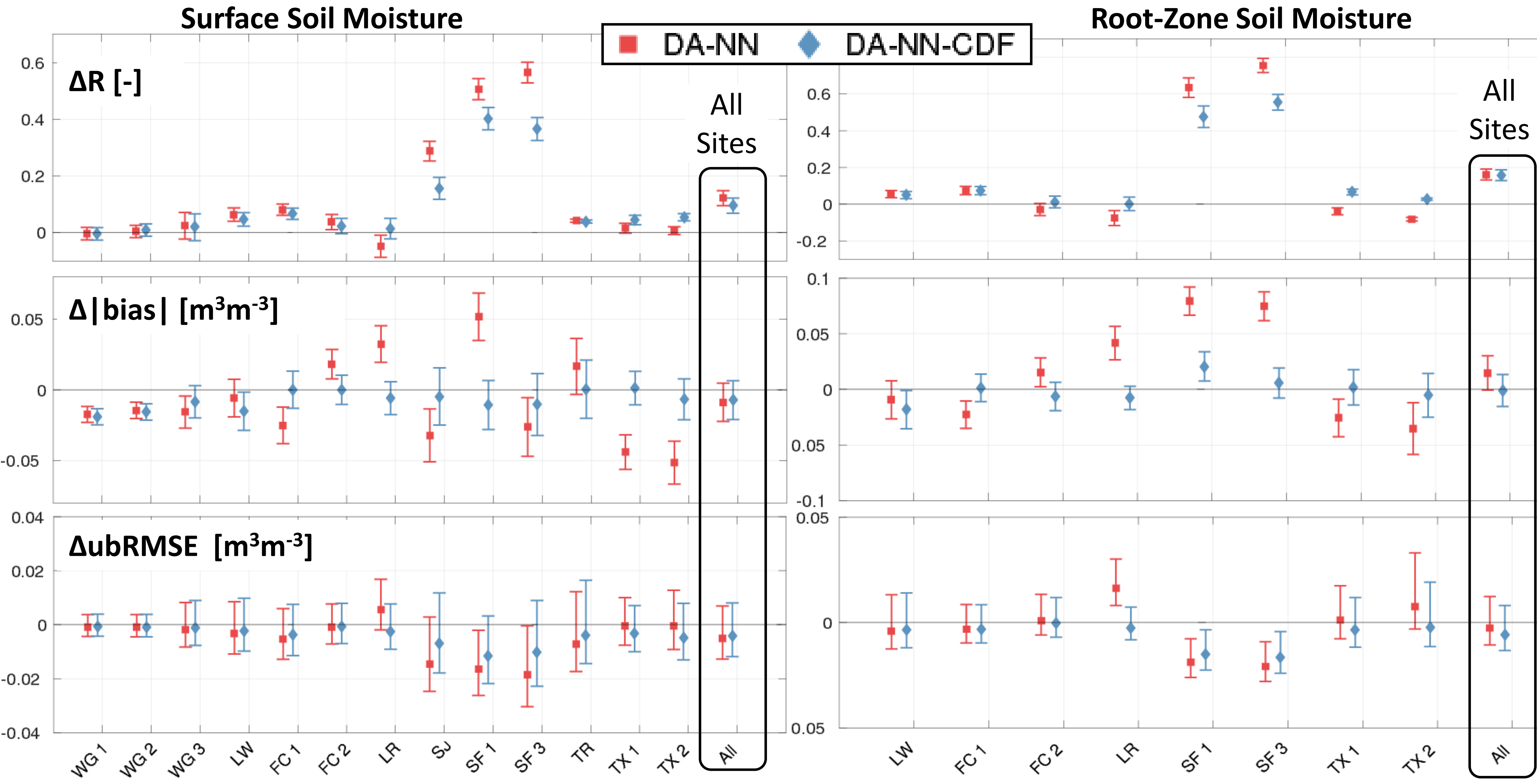
△ South Fork watershed

⬭ Little River watershed

Evaluation vs. In Situ Measurements: Global vs. Local Rescaling



Evaluation vs. In Situ Measurements: Global vs. Local Rescaling



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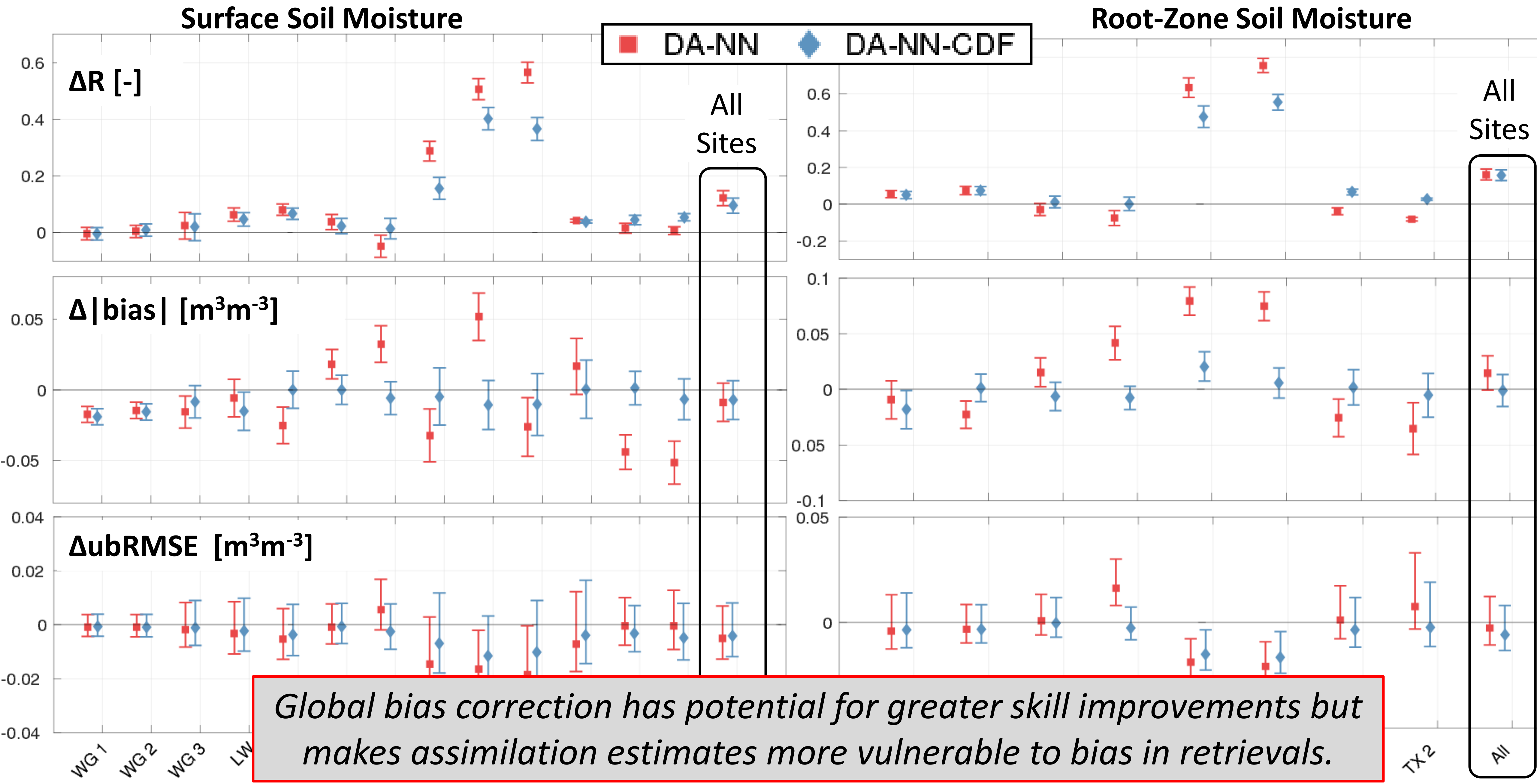
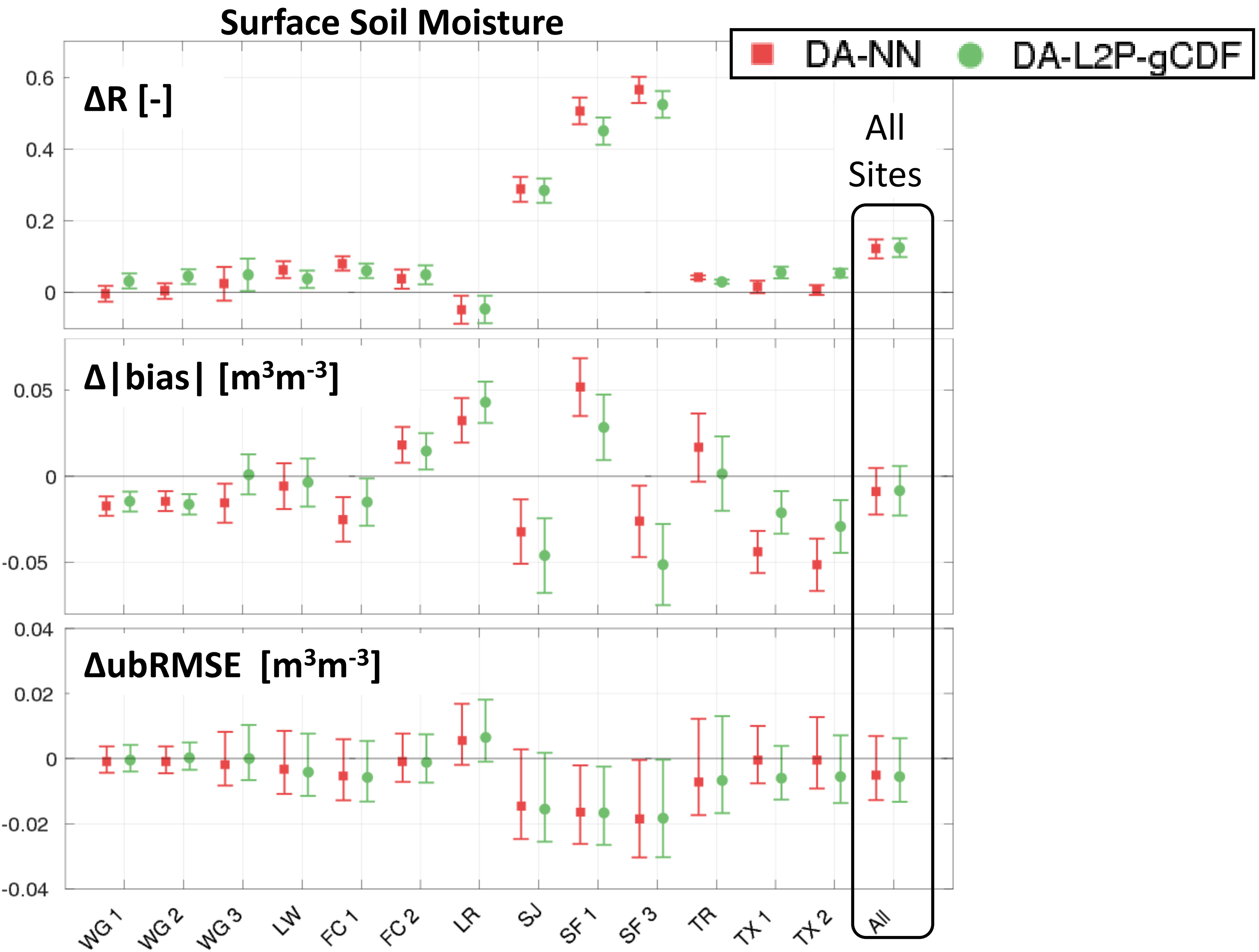
Evaluation vs. In Situ Measurements: Global vs. Local Rescaling

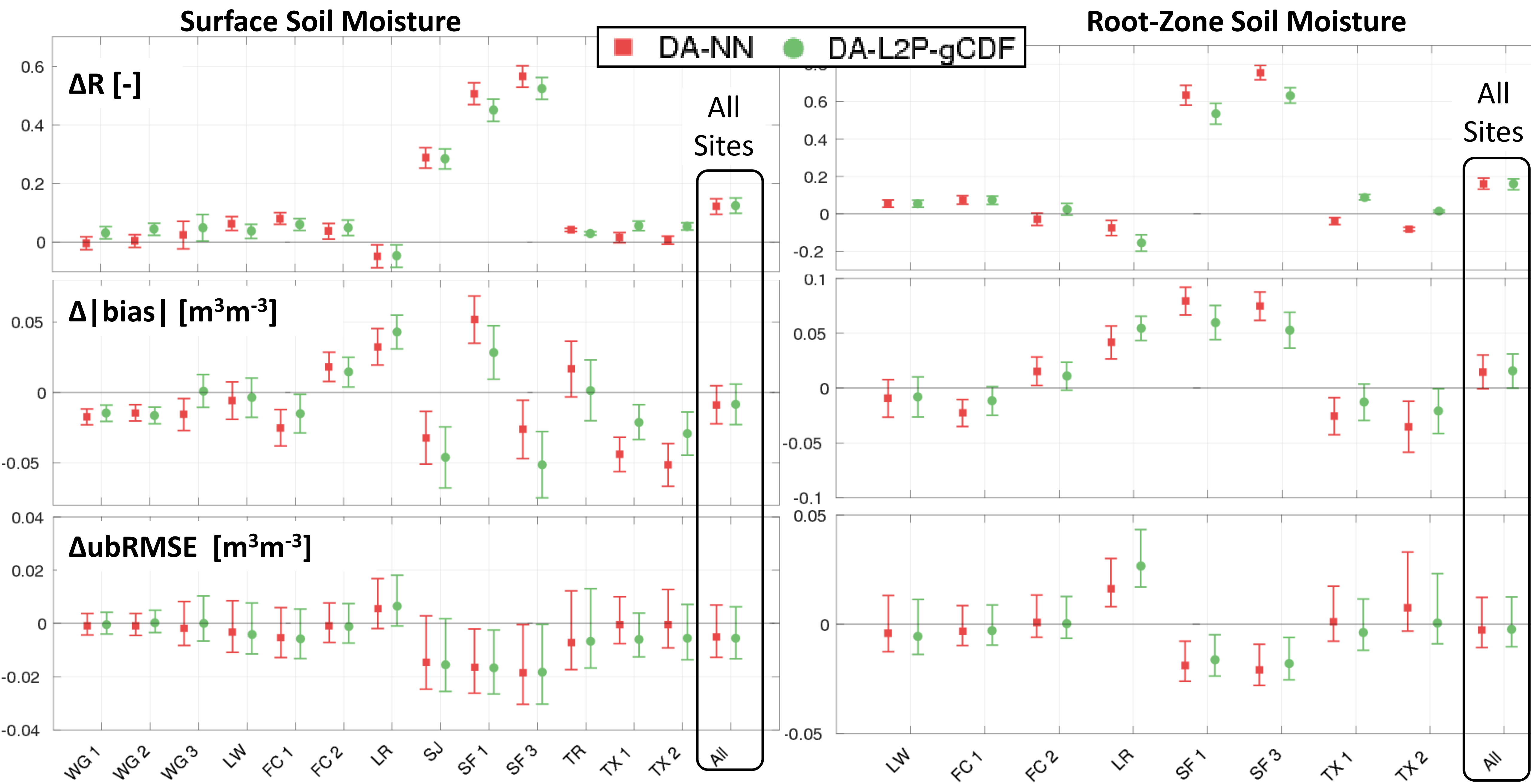


Global bias correction has potential for greater skill improvements but makes assimilation estimates more vulnerable to bias in retrievals.

Evaluation vs. In Situ Measurements: NN vs. L2P Assimilation



Evaluation vs. In Situ Measurements: NN vs. L2P Assimilation



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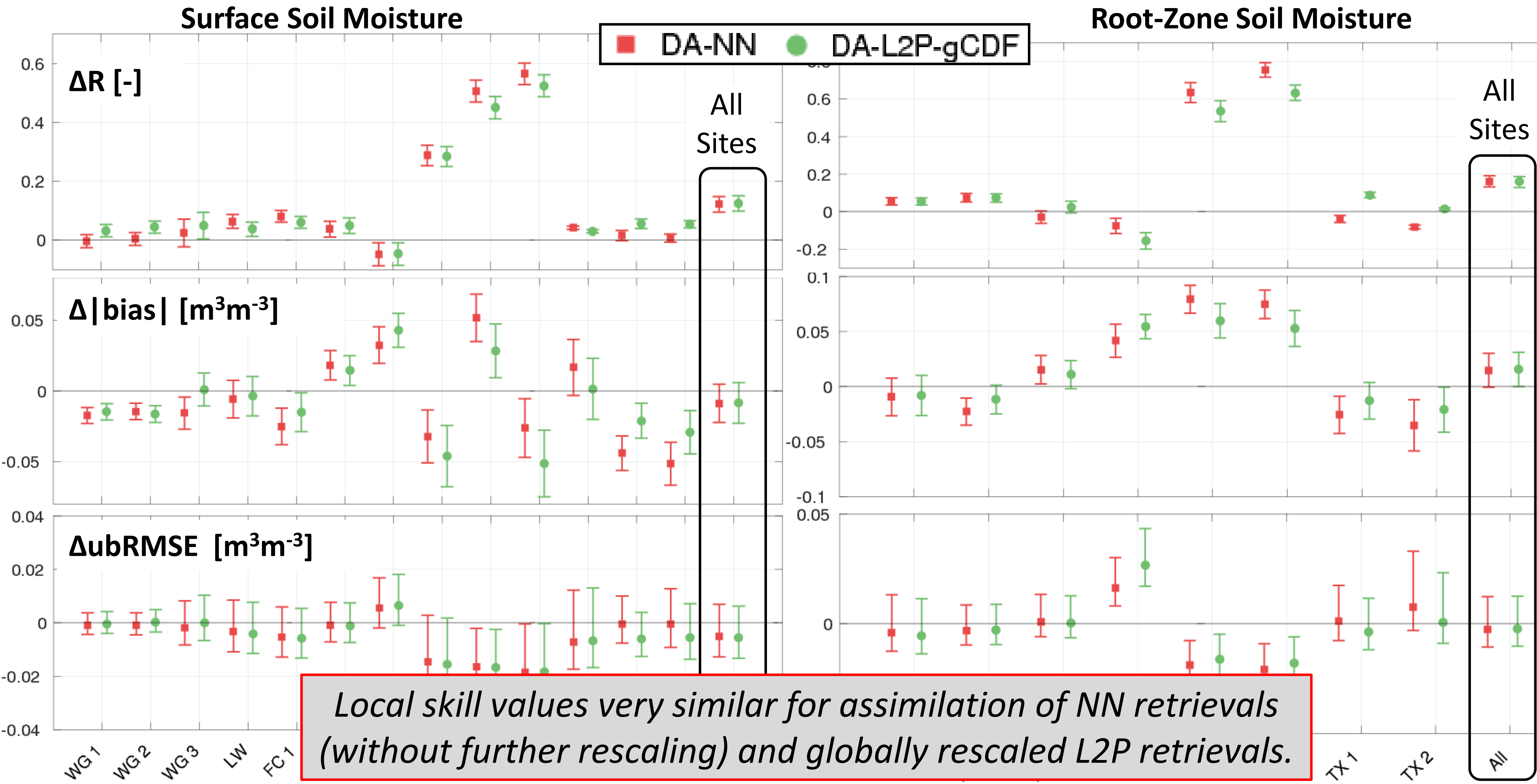
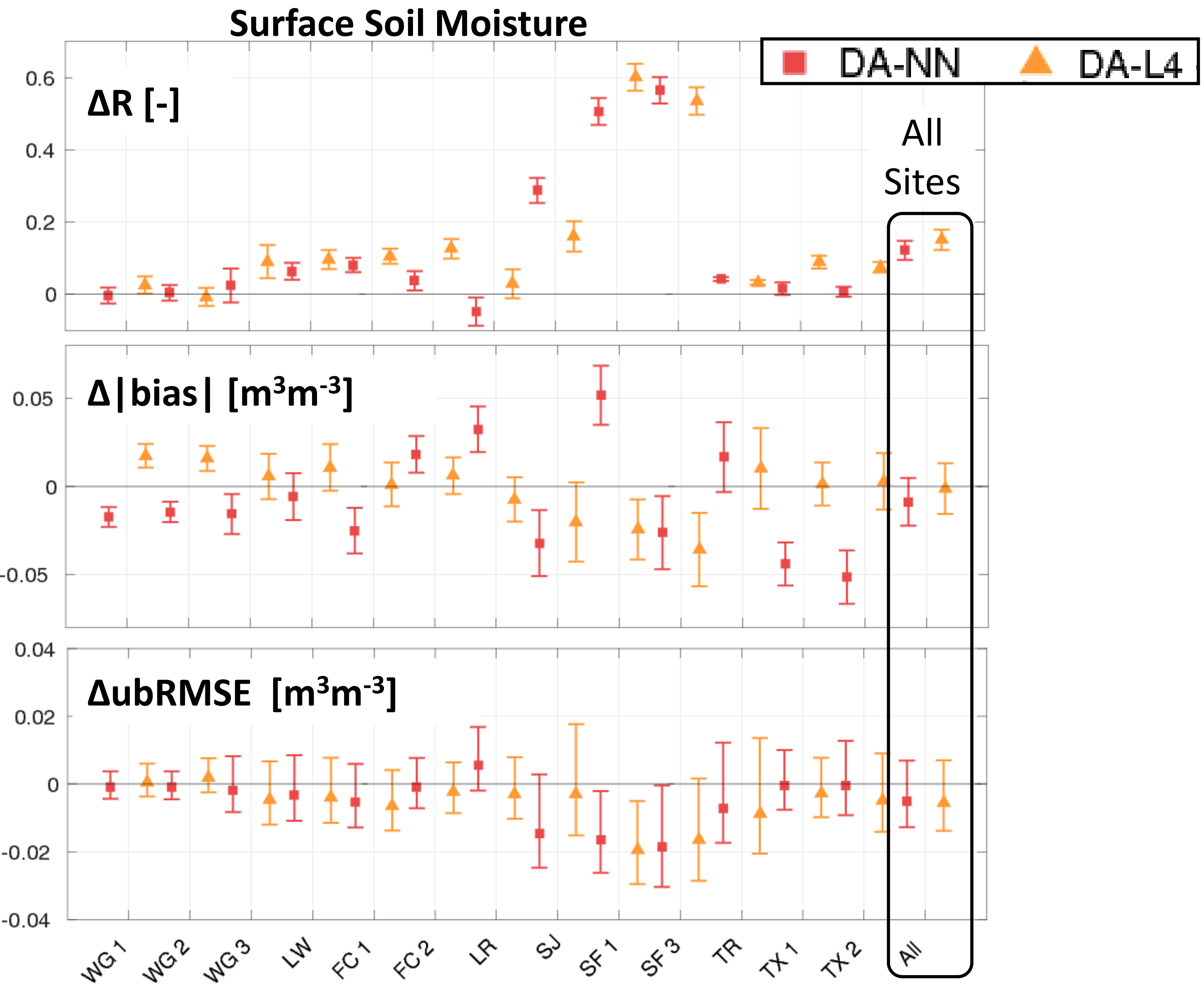
Evaluation vs. In Situ Measurements: NN vs. L2P Assimilation

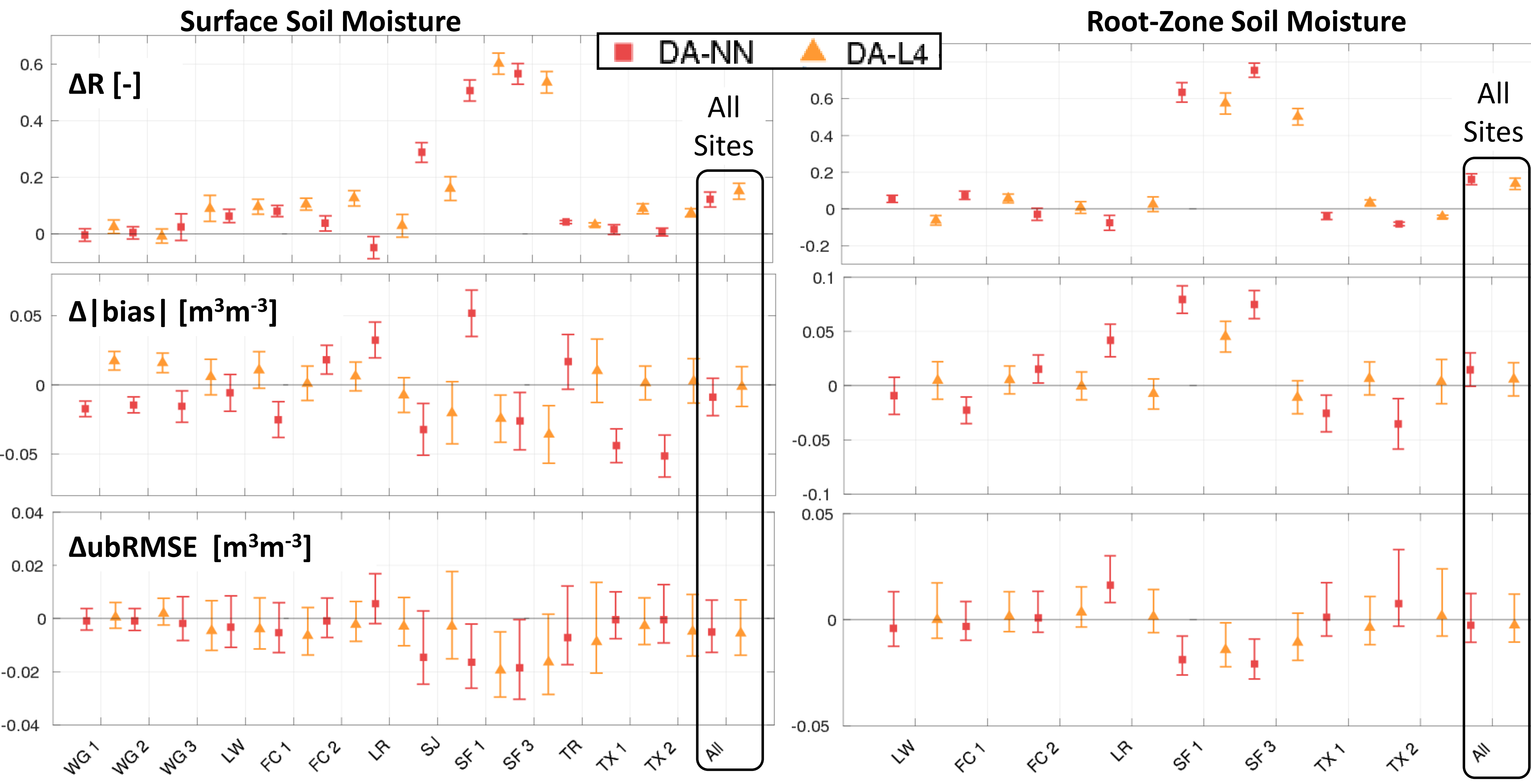


Local skill values very similar for assimilation of NN retrievals (without further rescaling) and globally rescaled L2P retrievals.

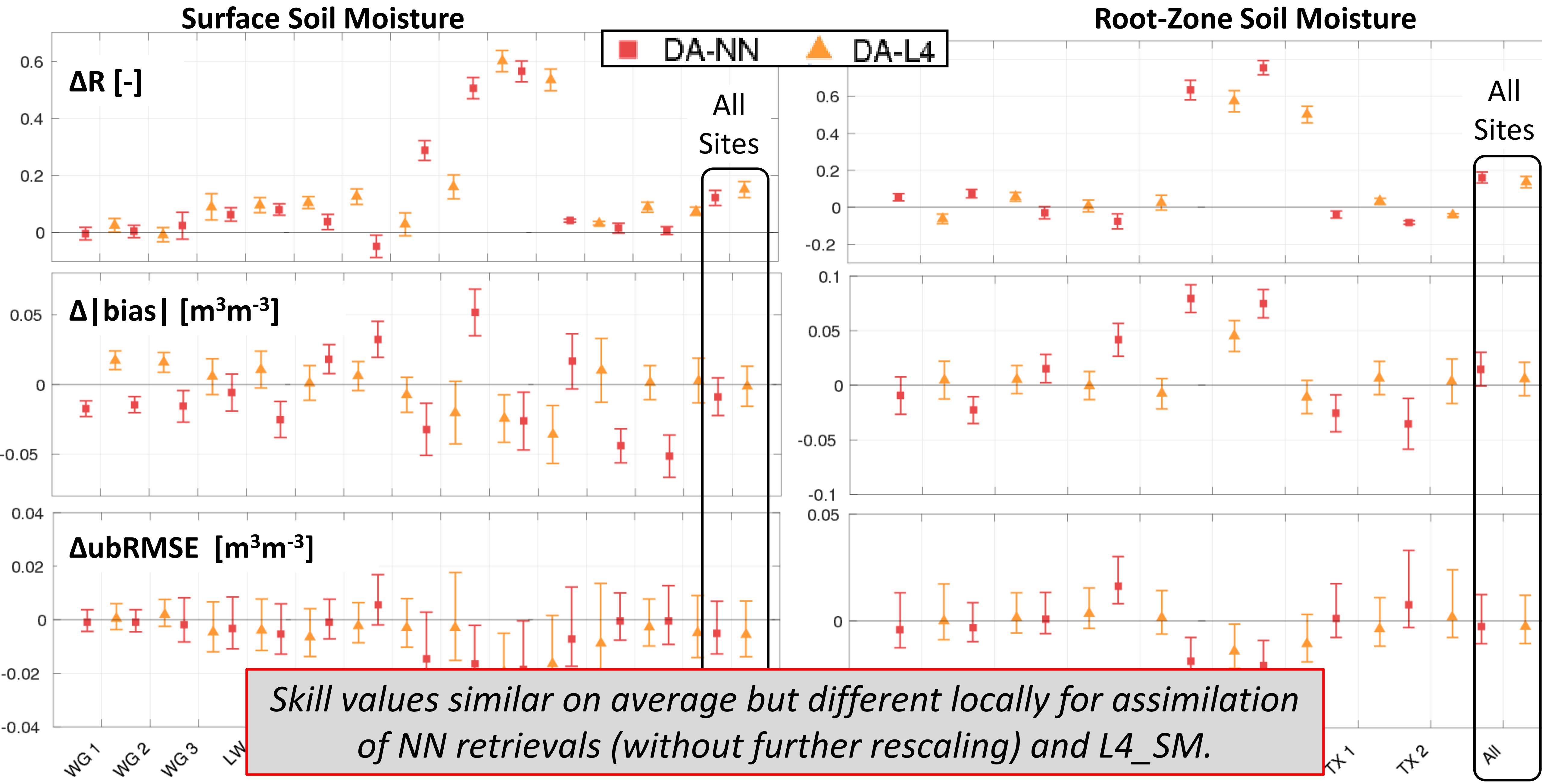
Evaluation vs. In Situ Measurements: NN vs. Tb Assimilation



Evaluation vs. In Situ Measurements: NN vs. Tb Assimilation

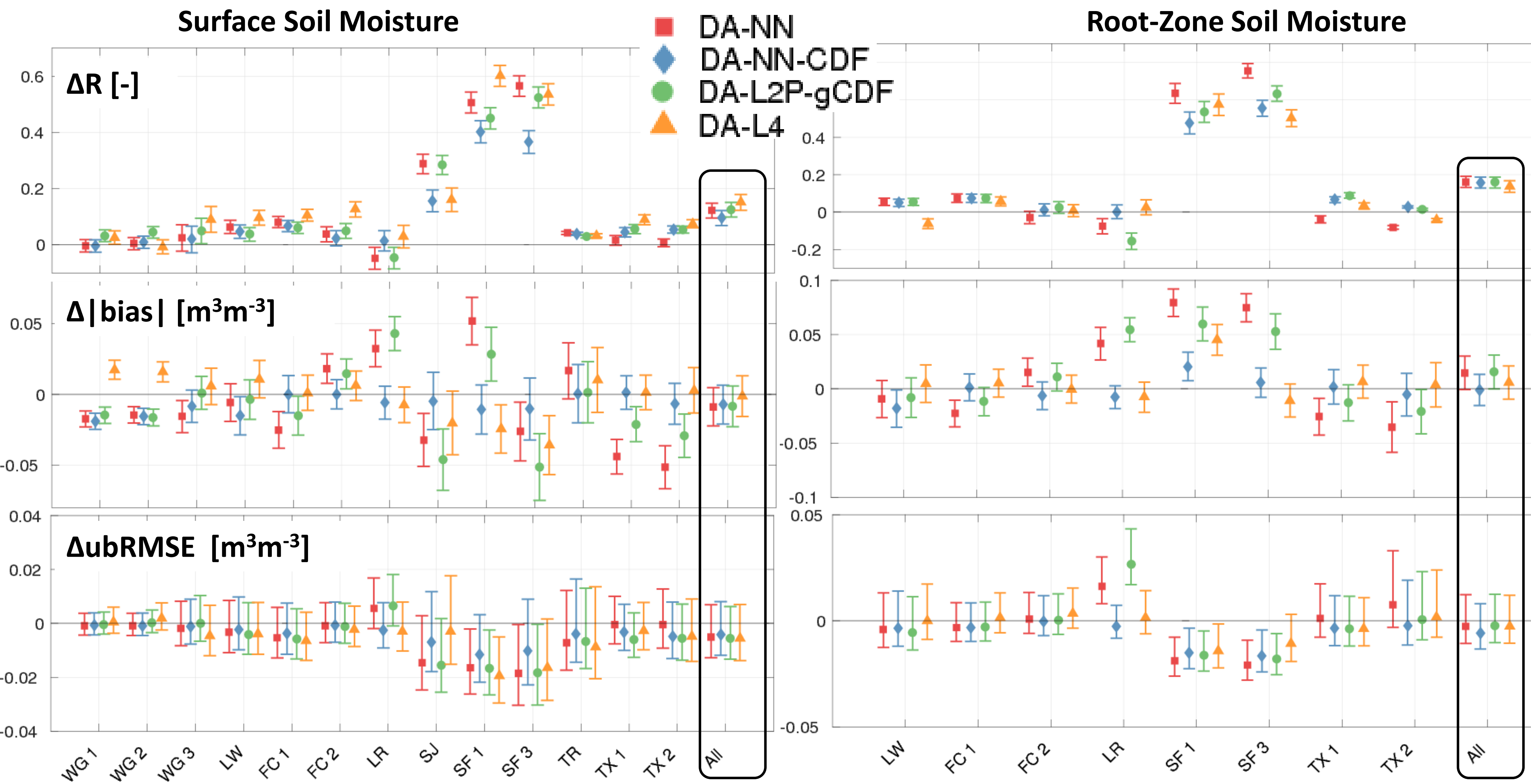


Evaluation vs. In Situ Measurements: NN vs. Tb Assimilation



Skill values similar on average but different locally for assimilation of NN retrievals (without further rescaling) and L4_SM.

Evaluation vs. In Situ Measurements



Impact on Evapotranspiration and Runoff

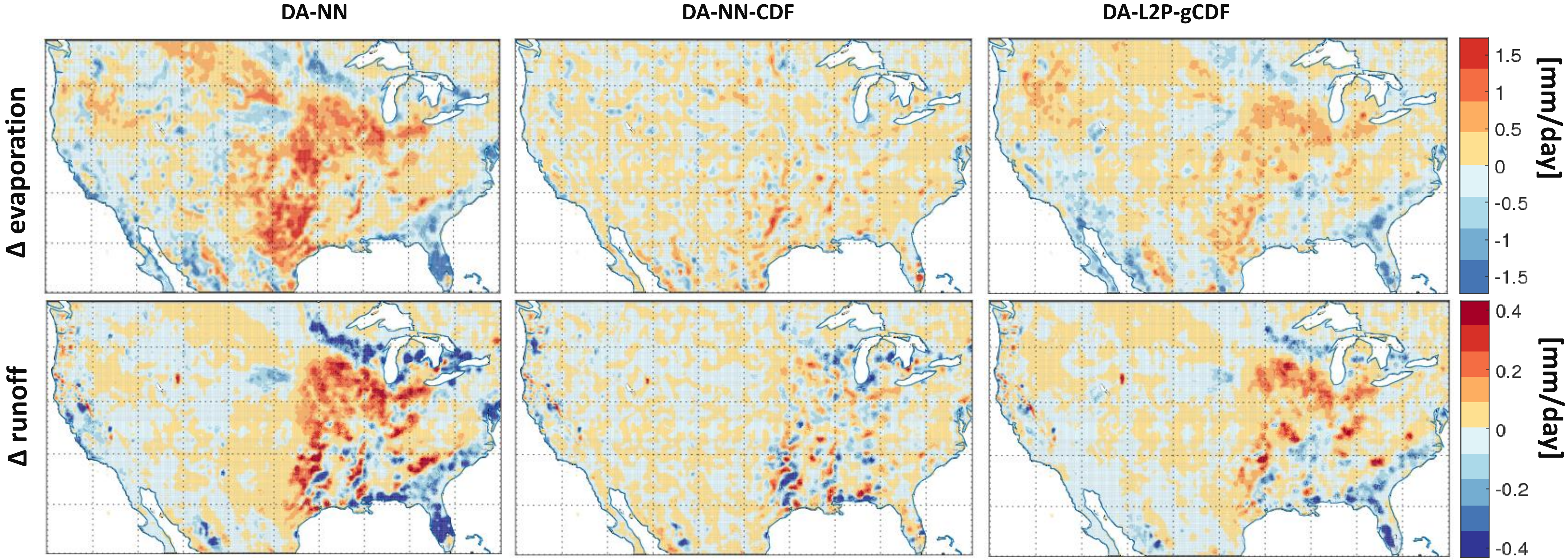


Fig 5. *Difference (OL minus DA) in mean evaporation and runoff.*

Evaporation and runoff changes reflect changes in soil moisture patterns where fluxes are sensitive to soil moisture.

Conclusions

- Global bias correction retains more independent satellite information.
  - Potential for greater improvements over model skill.
  - Assimilation skill more sensitive to retrieval bias.
  - Good QC and error characterization is crucial.
- Assimilation of NN and L2P retrievals (w/ global rescaling) results in very similar local skill values.
- Soil moisture and Tb assimilation have similar average skill with local differences.
- Evaporation and runoff changes reflect changes in soil moisture patterns.

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