Data Assimilation to Extract Soil Moisture Information From SMAP Observations

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• Motivation

• Method
  o SMAP NN Retrievals
  o Data Assimilation Experiments

• Results
  o Impact on Soil Moisture Climatology
  o Evaluation vs. In Situ Measurements
  o Impact on Evaporation and Runoff

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

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

Comparison:
Compare which rescaling method uses independent satellite information most efficiently.

Motivation

Fig 1. Effect of localized bias correction (CDF-matching) on soil moisture retrieval.
Fig 2. NN training procedure.

- Neural Networks (NN) retrieve soil moisture in model climatology (mean, variance, higher moments) \((Kolassa \text{ et al. 2017, in review})\)
- **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?
**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*)
Global rescaling experiments introduce more of the SMAP retrieval information.

Fig 3. Difference (OL minus DA) in soil moisture (top row) mean and (bottom row) standard deviation.
Evaluation vs. In Situ Measurements: Global vs. Local Rescaling

Surface Soil Moisture

ΔR [-]

Δ|bias| [m³m⁻³]

ΔubRMSE [m³m⁻³]

All Sites

DA-NN  DA-NN-CDF

WG 1, WG 2, WG 9, LW, FC 1, FC 2, LIH, SJ, SF 1, SF 3, TR, TX 1, TX 2
Evaluation vs. In Situ Measurements: Global vs. Local Rescaling

Surface Soil Moisture

- $\Delta R [-]$
- $\Delta |bias| [m^3 m^{-3}]$
- $\Delta ubRMSE [m^3 m^{-3}]$

Root-Zone Soil Moisture

- All Sites

Legend:
- DA-NN
- DA-NN-CDF

Sites:
- WG 1, WG 2, WG 3, LW, FC 1, FC 2, LR, SJ, SF 1, SF 3, TR, TX 1, TX 2

All Sites

Rescaling comparison for surface and root-zone soil moisture measurements.
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

- Surface Soil Moisture

- $\Delta R$ [-]

- $\Delta |\text{bias}|$ [m$^3$m$^{-3}$]

- $\Delta ubRMSE$ [m$^3$m$^{-3}$]

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

Surface Soil Moisture

Δ\(R\) [-]

Δ|bias| [m\(^3\)m\(^{-3}\)]

ΔubRMSE [m\(^3\)m\(^{-3}\)]

Root-Zone Soil Moisture

All Sites
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

Surface Soil Moisture

ΔR [-]

Δ|bias| [m³m⁻³]

ΔubRMSE [m³m⁻³]
Evaluation vs. In Situ Measurements: NN vs. Tb Assimilation

Surface Soil Moisture

- ΔR [-]
- Δ|bias| [m³ m⁻³]
- ΔubRMSE [m³ m⁻³]

Root-Zone Soil Moisture

- All Sites

| Site | ΔR | Δ|bias| | ΔubRMSE |
|------|----|---------|---------|
| WG1  |    |         |         |
| WG2  |    |         |         |
| WG3  |    |         |         |
| LW   |    |         |         |
| FC1  |    |         |         |
| FC2  |    |         |         |
| LR   |    |         |         |
| SJ   |    |         |         |
| SF1  |    |         |         |
| SF2  |    |         |         |
| TR   |    |         |         |
| TX1  |    |         |         |
| TX2  |    |         |         |
Evaluation vs. In Situ Measurements: NN vs. Tb Assimilation

Surface Soil Moisture

Root-Zone Soil Moisture

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

Surface Soil Moisture

ΔR [-]

Δ|bias| [m$^3$m$^{-3}$]

ΔubRMSE [m$^3$m$^{-3}$]

Root-Zone Soil Moisture

DA-NN
DA-NN-CDF
DA-L2P-gCDF
DA-L4

WG 1, WG 2, WG 3, LW, FC 1, FC 2, LR, SJ, SF 1, SF 3, TR, TX 1, TX 2
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.
  o Potential for greater improvements over model skill.
  o Assimilation skill more sensitive to retrieval bias.
  o 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.

Kolassa, J., et al. (2017b), Data assimilation to extract soil moisture information from SMAP observations (in preparation).


Jackson, T.J., et al. (2016), Calibration and Validation for the L2/3 SM P Version 3 Data Products, SMAP Project, JPL D-93720, Jet Propulsion Laboratory, Pasadena, CA.