Uncertainty Assessment of Space-Borne Passive Soil Moisture Retrievals

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Problem statement

unique Tb observation → unique SM retrieval
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Because:

- choice in RTM parameterization (e.g. SMAP L2, LMEB L2, ECMWF, SMAP L4)
- choice in inversion algorithms:
  - regular (i.e. non-mpdi-based) or mpdi-based algorithm
  - species included in cost function (CF): H-pol, V-pol, which angle(s), how many angles?
  - whether to include prior soil moisture information in the CF
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→ note: uncertainty = systemic error + random error
  - random error may be focus (e.g. in data assimilation studies)
Methods: site information

11 EASEv2 grid cells containing SMAP core validation sites
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→ in situ soil moisture observations to which SM retrievals will be compared (May 2010→June 2015)
Methods: ensemble sets

- 4 choices in RTM parameterization
  - Lit1: based on SMAP L2
    - $h$: 0.11 → 0.16; $\omega$: 0.05 → 0.07; $b_h$ & $b_v$: 0.1 → 0.11
  - Lit2: based on LMEB L2
    - $h$: 0.10 → 0.70; $\omega$: 0.05 → 0.05; $b_h$ & $b_v$: 0.15 → 0.3
  - Lit3: based on ECMWF
    - $h$: 1.66 → 1.66; $\omega$: 0.00 → 0.05; $b_h$ & $b_v$: 0.15 → 0.3
  - Lit4: based on SMAP L4
    - $h$: 0.00 → 0.97; $\omega$: 0.00 → 0.13; $b_h$ & $b_v$: 0.07 → 0.4
- 4 perturbations for each $h_{\text{min}}$, $h_{\text{max}}$, $\omega$, and $b_h$, $b_v$ (-50%, -25%, +25%, +50%)
- 7 angles in CF (i.e. $30^\circ$, $35^\circ$, $40^\circ$, $45^\circ$, $50^\circ$, $55^\circ$, $60^\circ$), either separately or together
- 2 polarizations (i.e. H-pol, V-pol)
- 2 different RTM-inversion algorithms (i.e. mpdi-based or non-mpdi-based)
Methods: ensemble sets

- 4 choices in RTM parameterization
  - Lit1: based on SMAP L2  $h: 0.11 \rightarrow 0.16; \omega: 0.05 \rightarrow 0.07; b_h & b_v: 0.1 \rightarrow 0.11$
  - Lit2: based on LMEB L2  $h: 0.10 \rightarrow 0.70; \omega: 0.05 \rightarrow 0.05; b_h & b_v: 0.15 \rightarrow 0.3$
  - Lit3: based on ECMWF  $h: 1.66 \rightarrow 1.66; \omega: 0.00 \rightarrow 0.05; b_h & b_v: 0.15 \rightarrow 0.3$
  - Lit4: based on SMAP L4  $h: 0.00 \rightarrow 0.97; \omega: 0.00 \rightarrow 0.13; b_h & b_v: 0.07 \rightarrow 0.4$
- 4 perturbations for each $h_{\text{min}}, h_{\text{max}}, \omega,$ and $b_h, b_v$ (-50%, -25%, +25%, +50%)
- 7 angles in CF (i.e. 30°, 35°, 40°, 45°, 50°, 55°, 60°), either separately or together
- 2 polarizations (i.e. H-pol, V-pol)
- 2 different RTM-inversion algorithms (i.e. mpdi-based or non-mpdi-based)
- Many ensemble sets tested, ranging between 28 and 2456 members
- Not all combinations possible
Methods: Cost Function (CF)

\[ CF = (T_b_{sim} - T_b_{obs})^T C^{-1} (T_b_{sim} - T_b_{obs}) + \frac{1}{0.02^2} (S_{retr} - S_{CLSM})^2 \]

with \( C = \) Tb error covariance matrix, representing:
- Tb error variances \((6^2 K^2)\)
- correlations between Tb errors of different incidence angles

with prior SM information included
- model-only \( S_{CLSM} \)
Results: retrieval uncertainty

Part 1: sensitivity analysis

default retrieval:
- single species in CF: 40° Hpol
- Lit4 RTM parameterization
- non-mpdi-based inversion algorithm
- =basically SCA
Results: retrieval uncertainty

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HOW?
  • **step1**: choosing angle, polarization, RTM-parameters, inversion algorithms separately
  • **step2**: calculating ensemble variances of these experiments
  • **step3**: dividing this variance in long-term mean ensemble variance and short-term ensemble variance
**Results: retrieval uncertainty**

**Part 1: sensitivity analysis**

**default retrieval:**
- single species in CF: 40° Hpol
- Lit4 RTM parameterization
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**angle choice:**

![Graph showing E(short-term ens var) vs. angle, polarization, parmaps, inv. algorithm.](image)

![Chart showing retrieved soil moisture at Forth Cobb with different incidence angles.](image)
Results: retrieval uncertainty

Part 1: sensitivity analysis

default retrieval:
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polarization choice:
Results: retrieval uncertainty

Part 1: sensitivity analysis

default retrieval:
• single species in CF: $40^\circ$ Hpol
• Lit4 RTM parameterization
• non-mpdi-based inversion algorithm
• =basically SCA

RTM parameterization choice:

\[
E(\text{short-term ens var}) \ [m^3/m^3]^2
\]
Results: retrieval uncertainty

Part 1: sensitivity analysis

default retrieval:
- single species in CF: 40° Hpol
- Lit4 RTM parameterization
- non-mpdi-based inversion algorithm
  = basically SCA

inversion algorithm choice:

![Graph showing soil moisture retrieval over time](image)

- $E_{\text{short-term ens var}}$ [m$^3$/m$^3$]$^2$
- angle
- polarization
- parmaps
- inv. algorithm

$E_{\text{short-term ens var}} = 0.00005$ to $0.0001$

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Results: retrieval uncertainty

Part 2: total uncertainty estimation
Results: retrieval uncertainty

Part 2: total uncertainty estimation
→ (1) find a properly verified ensemble set
Results: retrieval uncertainty

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→ (1) find a properly verified ensemble set
→ (2) its ensemble variance characterizes total retrieval uncertainty
Results: retrieval uncertainty

Part 2: total uncertainty estimation

(1) find a properly verified ensemble set

ensemble set: all H&V species in CF, no CLSM constraint

Talagrand diagram

\[ \sigma(\text{ens set}) = \frac{\text{MSE}(\text{ens mean}, \text{obs})}{9.6} \]
Results: retrieval uncertainty

Part 2: total uncertainty estimation

→ (1) find a properly verified ensemble set

ensemble verification

Talagrand diagram

\[ \frac{\sigma(\text{ens set})}{\text{MSE}(\text{ens mean, obs})} \]

9.6

ensemble set: all H species in CF, no CLSM constraint

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**ensemble verification**

\[
\sigma(\text{ens set}) \quad \text{MSE(ens mean, obs)}
\]

\[
\begin{align*}
\sigma(\text{ens set}) & = 9.6 \\
\text{MSE(ens mean, obs)} & = 5.4
\end{align*}
\]

**ensemble set:** all H&V species in CF, no CLSM constraint

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Results: retrieval uncertainty

Part 2: total uncertainty estimation

→ (1) find a properly verified ensemble set

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ensemble set: all H&V species in CF, no CLSM constraint, centered
Results: retrieval uncertainty

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→ (1) find a properly verified ensemble set

→ (2) its ensemble variance characterizes total retrieval uncertainty

ensemble set: all H&V species in CF, no CLSM constraint, centered

time-averaged ensemble variance of verified ensemble set = 78% of variance of in situ observations
Results: ranked skills of ensemble retrievals

Ranked Skills (n=2856)

ubRMSE

bias

R

anomaly R

inversion algorithm/
polarization

RTM-parameterization

angle

with/without prior

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Results: skills of ensemble means

Skill metrics of ensemble means VS ensemble sets

no CLSM constraint in CF

ubRMSE:

bias:

R:

R-anomaly:

CLSM constraint in CF

ubRMSE:

bias:

R:

R-anomaly:

Ensemble set:
Results: skills of ensemble means

→ inclusion of CLSM sm in the CF generally improves every skill
Results: skills of ensemble means

Inclusion of CLSM sm in the CF generally improves every skill, especially when including all species in the CF.
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Results: skills of ensemble means

The inclusion of CLSM sm in the CF generally improves every skill independent of the used RTM parameterization.
Take home messages

1. **passive L-band SMOS soil moisture retrievals are uncertain**
   - ... and most sensitive to RTM parameterizations (e.g. roughness parameters and surface albedo)
   - ... with the ensemble variance of a verified set amounting to **78%** of in situ temporal variance
   - ... choice of RTM-parameter set strongly influences the bias

2. **constraining a CF with CLSM-simulated soil moisture improves the retrieval skill**
   - even though CLSM skills are generally worse than retrieval skills
   - main reason: constrain extreme high and low values

3. **ensemble means of ensemble sets**
   - ensemble means of ensemble sets outperform operational SMOS by about up to **9%** for ubRMSE and more than **6%** for anomaly R
   - best performance reached by including as many as possible species in the CF (i.e. 14 species)

4. next: compare to SMOS-IC or other alternatives
Thank you for your attention!