Uncertainty Assessment of Space-Borne Passive Soil Moisture Retrievals

Jan Quets, Gabriëlle De Lannoy, Rolf Reichle, Michael Cosh, Robin Van der Schalie, Jean-Pierre Wigneron
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:
  o regular (i.e. non-mpdi-based) or mpdi-based algorithm
  o species included in cost function (CF): H-pol, V-pol, which angle(s), how many angles?
  o whether to include prior soil moisture information in the CF
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\(\rightarrow\) 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
    \( h: 0.11 \rightarrow 0.16; \omega: 0.05 \rightarrow 0.07; b_h \& b_v: 0.1 \rightarrow 0.11 \)
  - 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)
Methods: ensemble sets

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- 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)

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

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 \( SM_{CLSM} \)
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
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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

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angle choice:

E(short-term ens var) [m³/m³]²
Results: retrieval uncertainty

Part 1: sensitivity analysis

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polarization choice:

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

angle
polarization
parmaps
inv. algorithm

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Results: retrieval uncertainty

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RTM parameterization choice:

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inversion algorithm choice:

\[
E(\text{short-term ens var}) \, [\, \text{m}^3/\text{m}^3]^2
\]

angle
polarization
decimation
inv. algorithm

\[
\begin{align*}
\text{short-term ensemble variance} & \quad 0 & \quad 0.00008 & \quad 0.0016 \\
\text{long-term mean ensemble variance} & \quad 0 & \quad 0.00008 & \quad 0.0016 \\
\end{align*}
\]
Results: retrieval uncertainty

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

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

Part 2: total uncertainty estimation

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

ensemble verification

Talagrand diagram

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SMW2017, Vienna
Results: retrieval uncertainty

Part 2: total uncertainty estimation

→ (1) find a properly verified ensemble set

ensemble verification

Talagrand diagram

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

9.6

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

5.4

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

Part 2: total uncertainty estimation

→ (1) find a properly verified ensemble set

ensemble verification

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

9.6

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5.4

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1.1
Results: retrieval uncertainty

Part 2: total uncertainty estimation

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σ(ens set) = 

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

Part 2: total uncertainty estimation

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

ensemble verification

Talagrand diagram

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

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

time-averaged ensemble variance of verified ensemble set = 78% of variance of \textit{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

- **ubRMSE:**
  - no CLSM constraint in CF
  - CLSM constraint in CF

- **bias:**
  - no CLSM constraint in CF
  - CLSM constraint in CF

- **R:**
  - no CLSM constraint in CF
  - CLSM constraint in CF

- **R-anomaly:**
  - no CLSM constraint in CF
  - CLSM constraint in CF

Ensemble set:
- CF: single species
- CF: all H-species
- CF: all V-species
- CF: all H&V-species
Results: skills of ensemble means

Inclusion of CLSM sm in the CF generally improves every skill
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→ inclusion of CLSM sm in the CF generally improves every skill
→ especially when including all species in the CF

Skill metrics of ensemble means VS ensemble sets

Ensemble set:
- CF: single species
- CF: all H-species
- CF: all V-species
- CF: all H&V-species
Results: skills of ensemble means

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

Inclusion of CLSM 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!