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 $\not\rightarrow$ 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 proir soil moisture information in the CF

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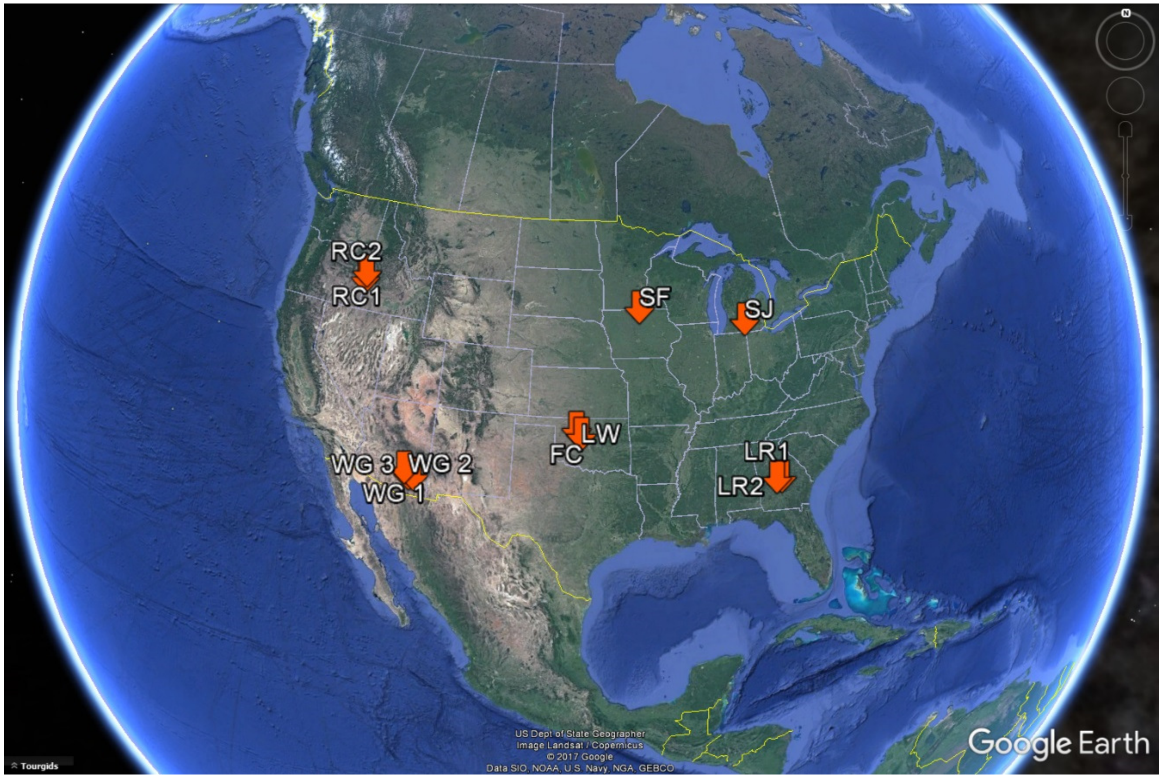
→ note: uncertainty = systemic error + random error

- 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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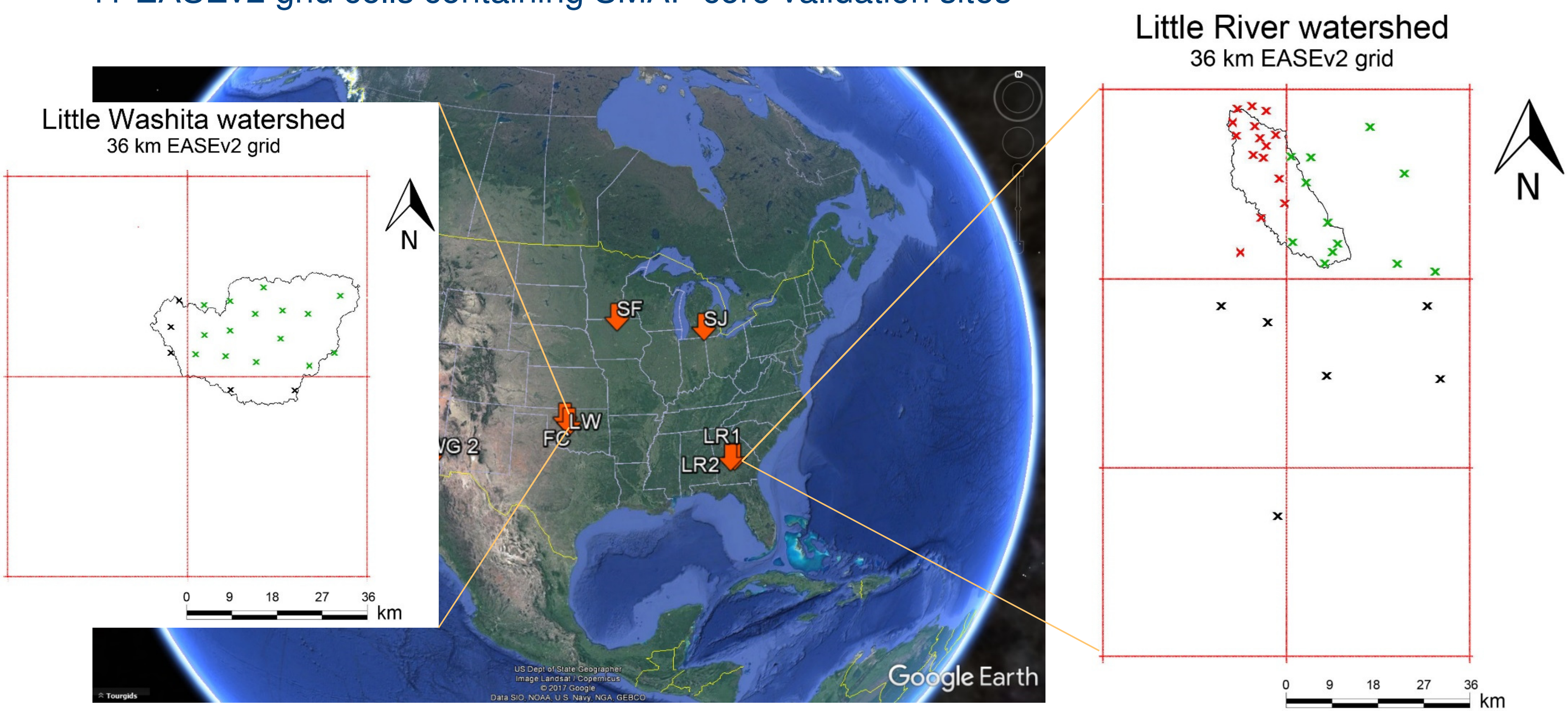

→ in situ soil moisture observations to which SM retrievals will be compared (May 2010→June2015)

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Methods: ensemble sets

- 4 choices in RTM parameterization
  - Lit1: based on SMAP L2 — h: 0.11→0.16; ω: 0.05→0.07; b_h&b_v: 0.1→0.11
  - Lit2: based on LMEB L2 — h: 0.10→0.70; ω: 0.05→0.05; b_h&b_v: 0.15→0.3
  - Lit3: based on ECMWF — h: 1.66→1.66; ω: 0.00→0.05; b_h&b_v: 0.15→0.3
  - Lit4: based on SMAP L4 — h: 0.00→0.97; ω: 0.00→0.13; b_h&b_v: 0.07→0.4
- 4 perturbations for each h_{min}, h_{max}, ω, 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)

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- 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**

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Methods: Cost Function (CF)

$$\boldsymbol{CF} = (\boldsymbol{Tb_{sim}} - \boldsymbol{Tb_{obs}})^{\boldsymbol{T}} \boldsymbol{C}^{-\boldsymbol{1}} \, (\boldsymbol{Tb_{sim}} - \boldsymbol{Tb_{obs}}) + \frac{\boldsymbol{1}}{\boldsymbol{0{,}02^2}} (\boldsymbol{SM_{retr}} - \boldsymbol{SM_{CLSM}})^{\boldsymbol{2}}$$

with $\boldsymbol{C}$ = 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

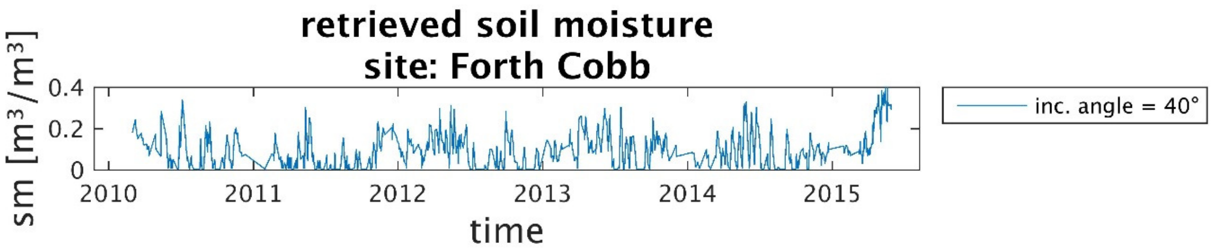
- model-only SM_{CLSM}

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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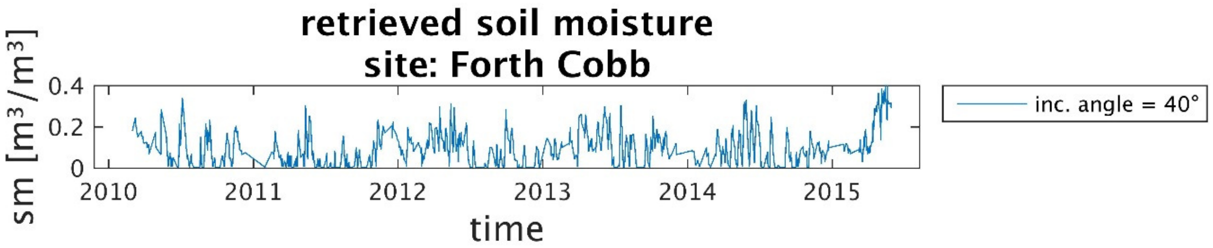

HOW?

- **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

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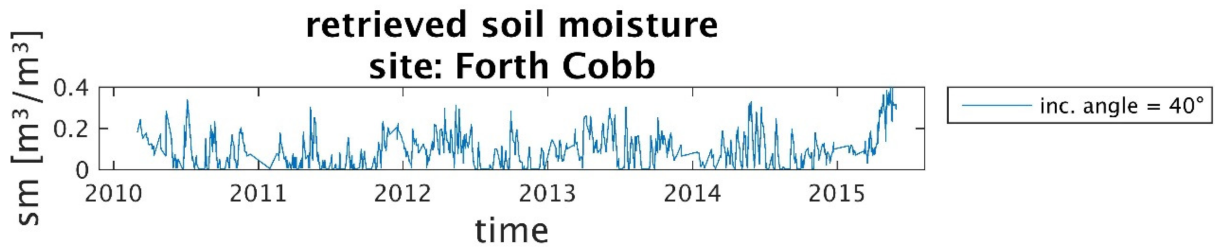
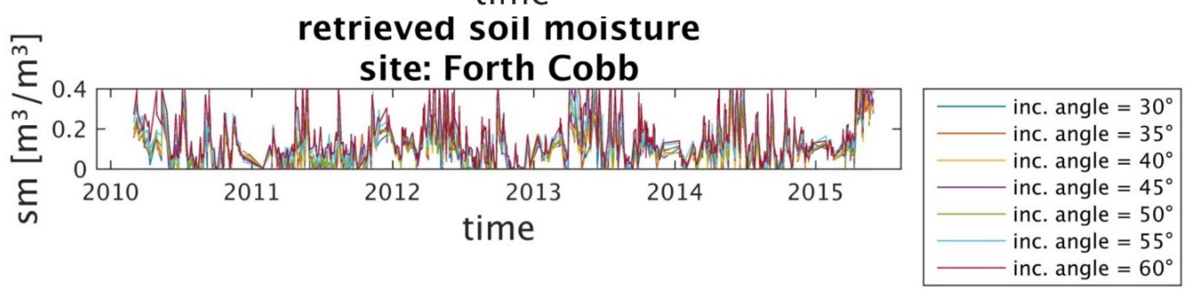
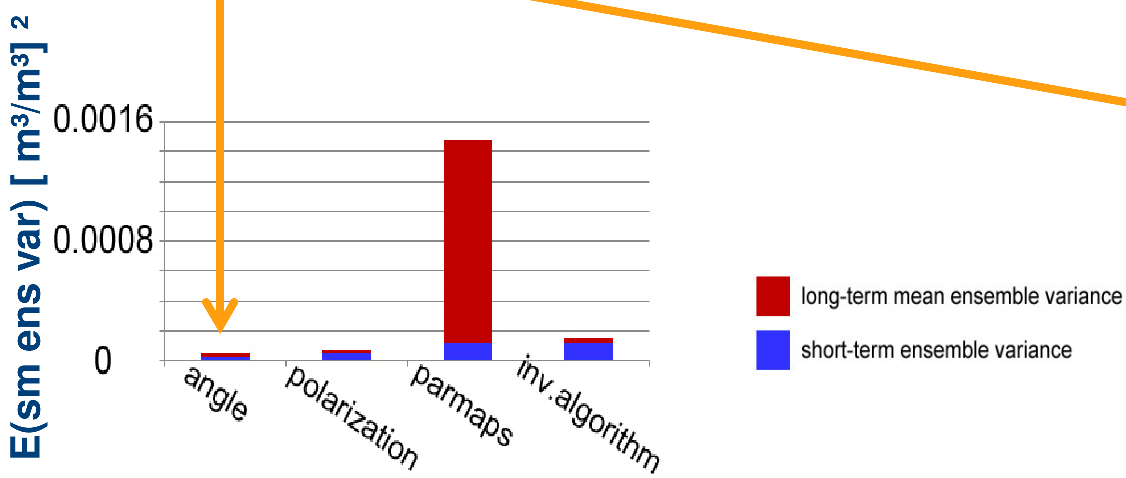
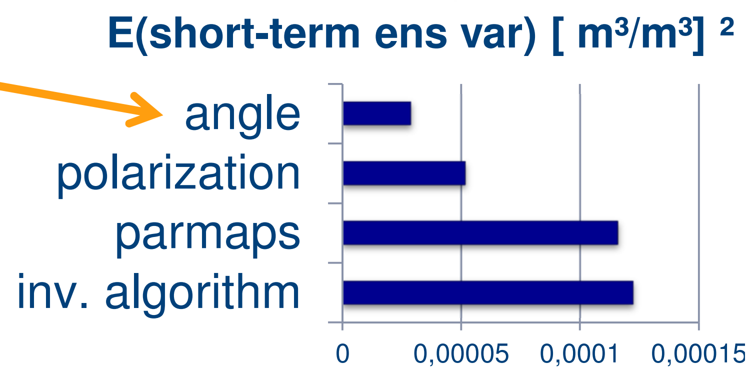




angle choice:





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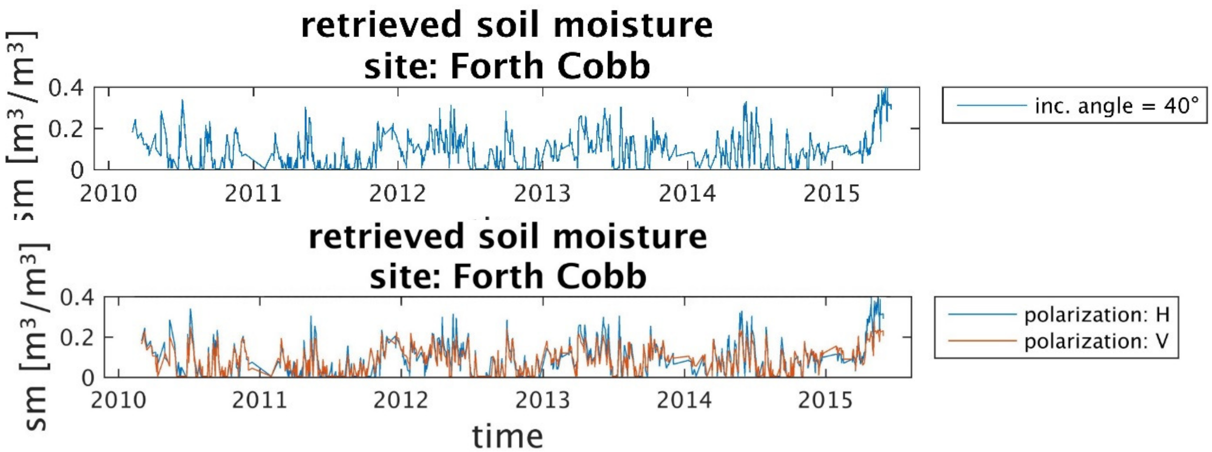
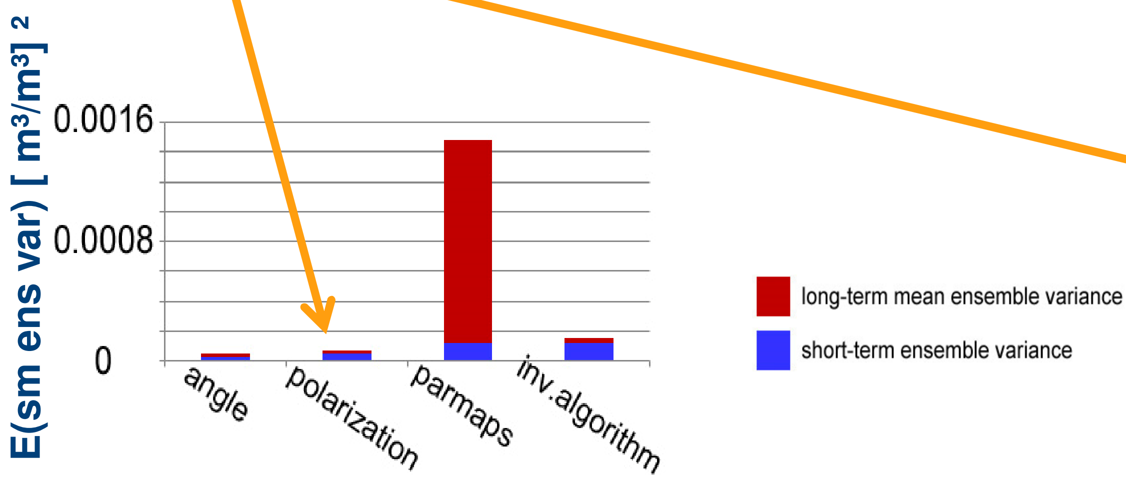
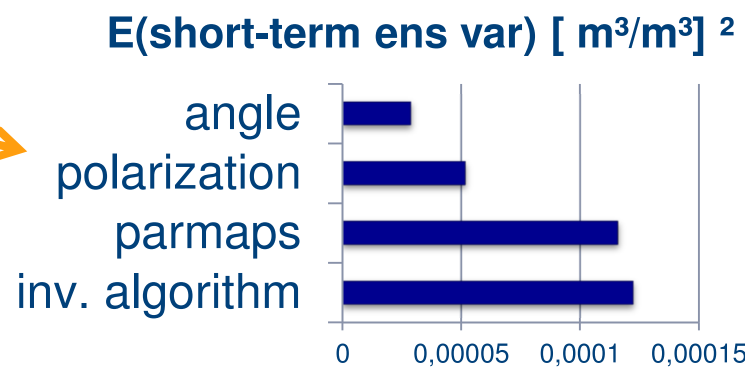


polarization choice:





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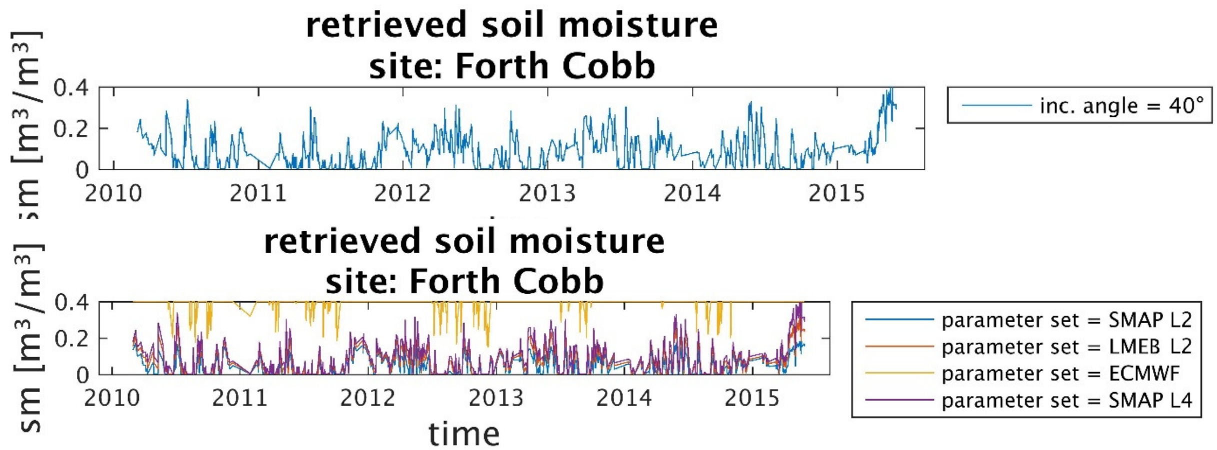
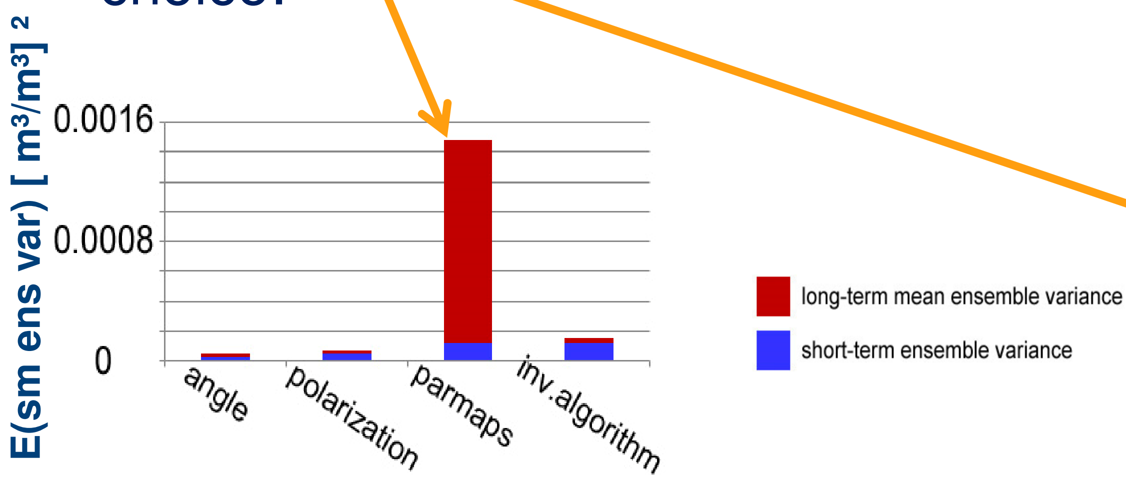
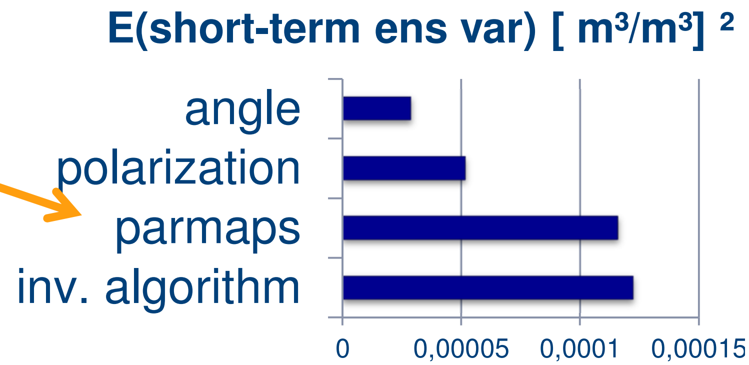


RTM parameterization choice:





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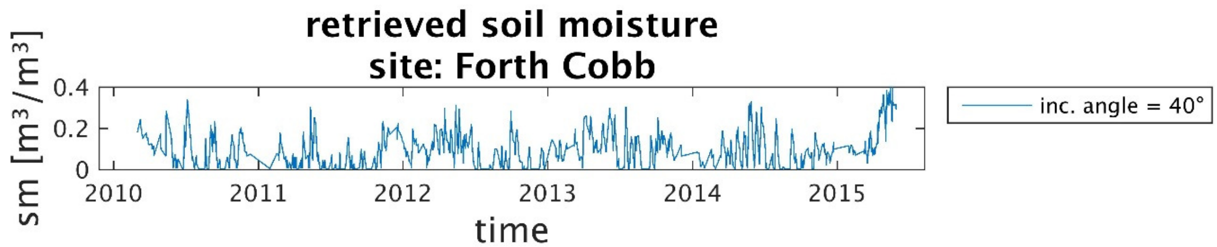
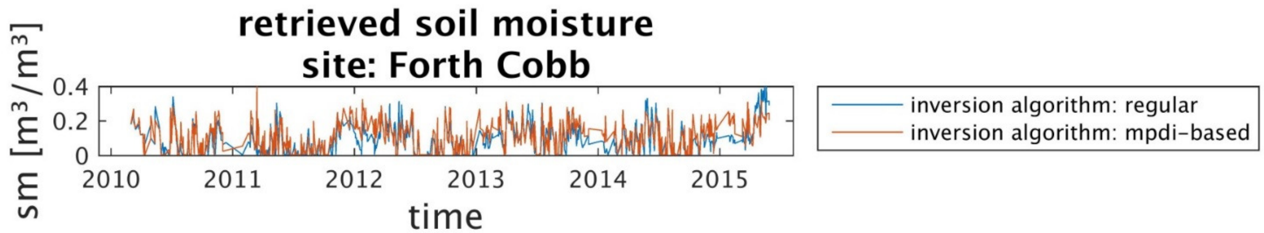
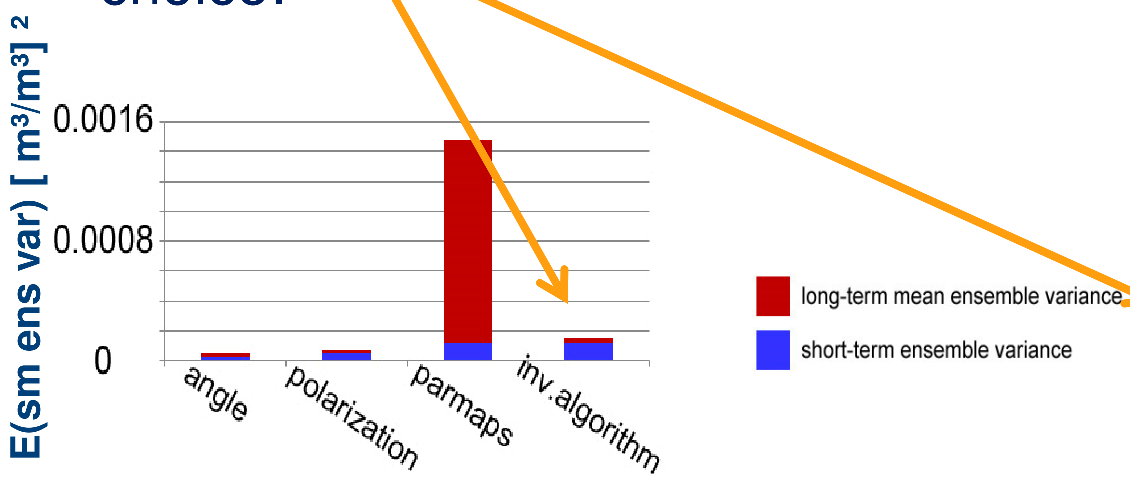
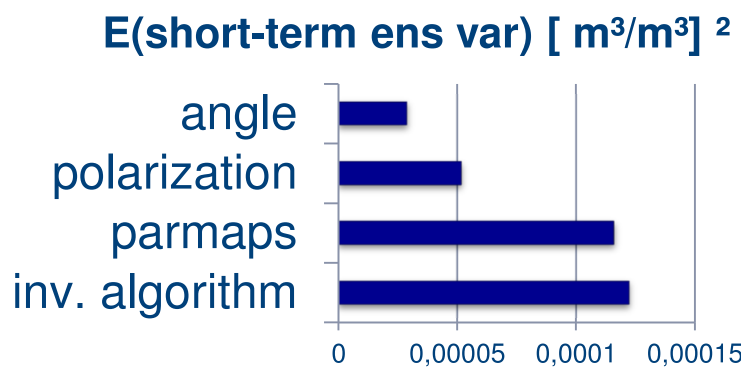




inversion algorithm choice:





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

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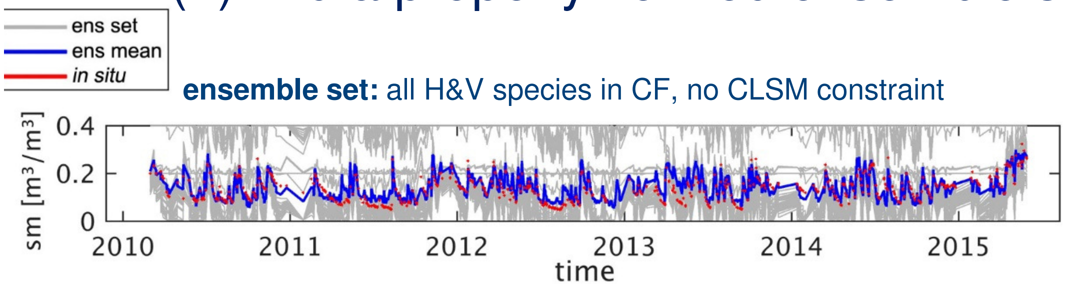
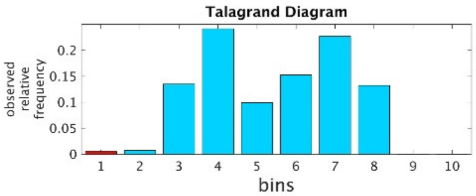
ensemble verification

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



Talagrand diagram



$$\frac{\sigma(ens\ set)}{MSE(ens\ mean, obs)}$$

9.6

Results: retrieval uncertainty

Part 2: total uncertainty estimation

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Talagrand diagram

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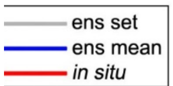

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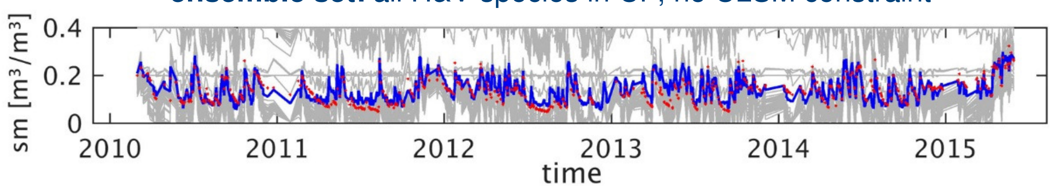

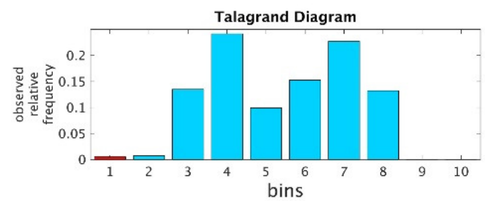

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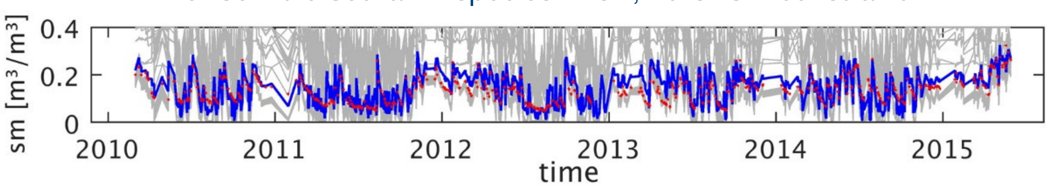

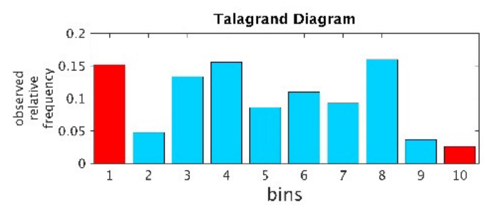

5.4

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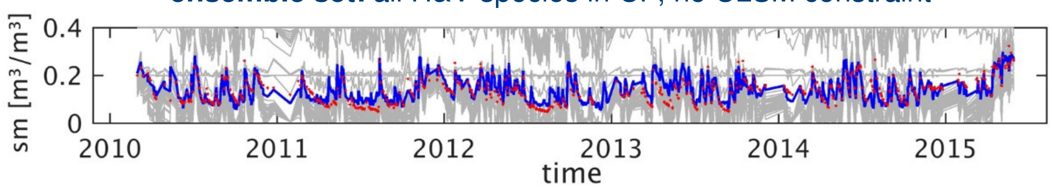

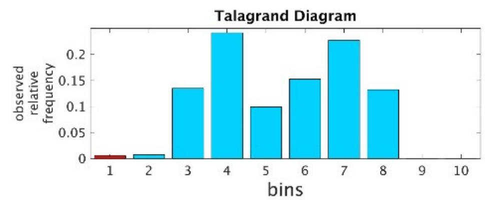

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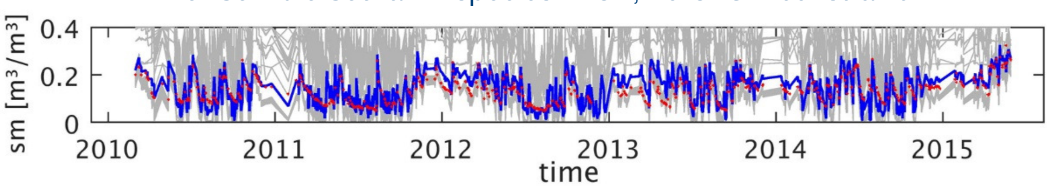

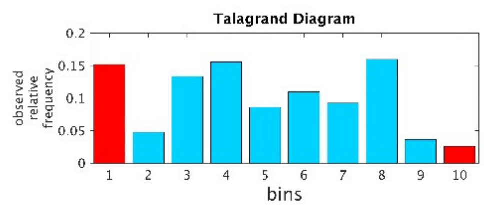

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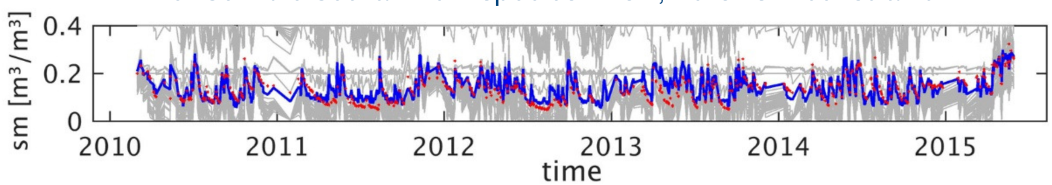

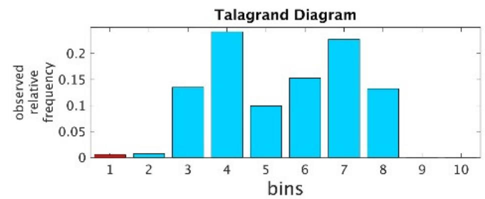

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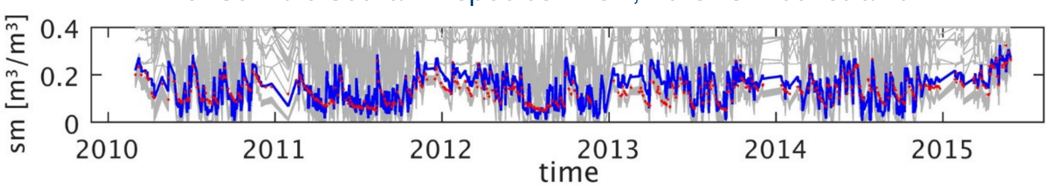
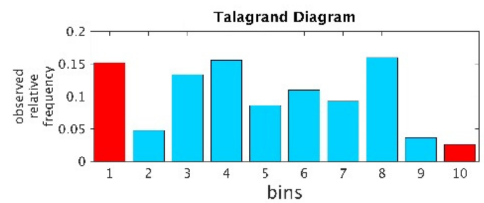
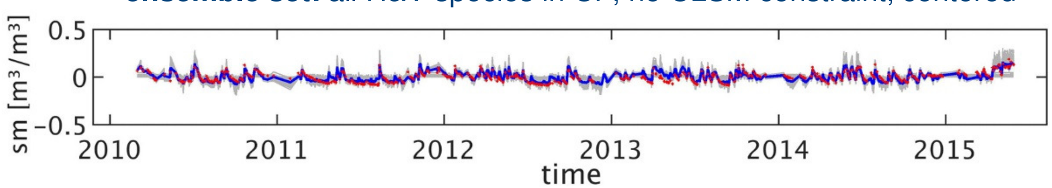
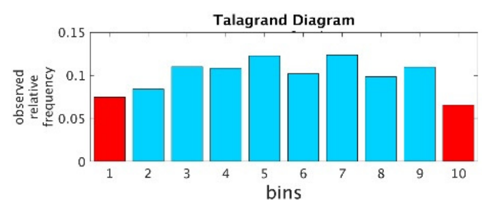




5.4

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





1.1

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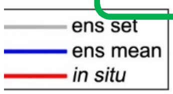

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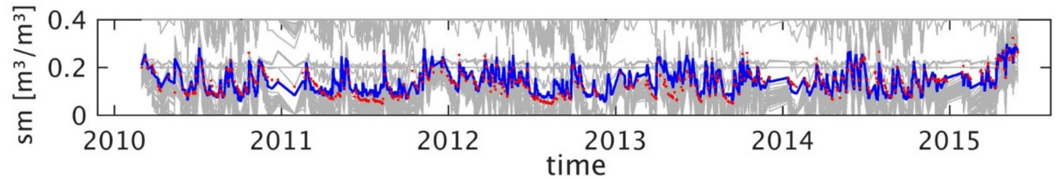

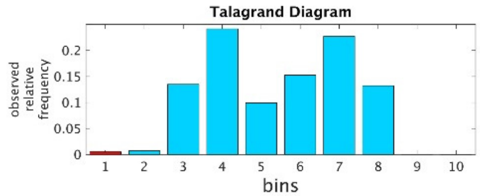

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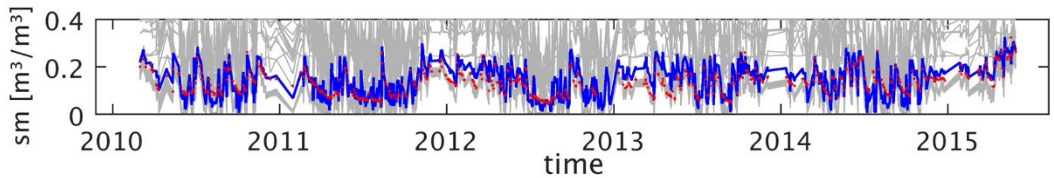

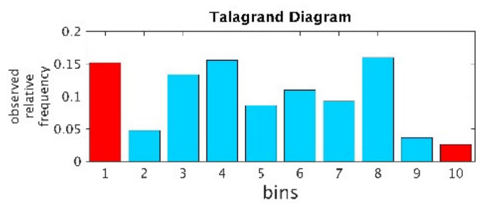

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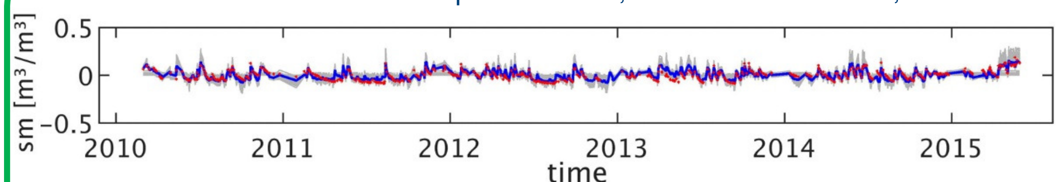

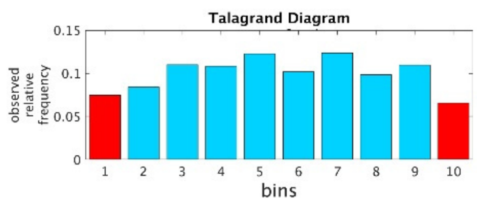

1.1

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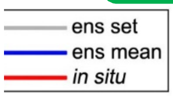

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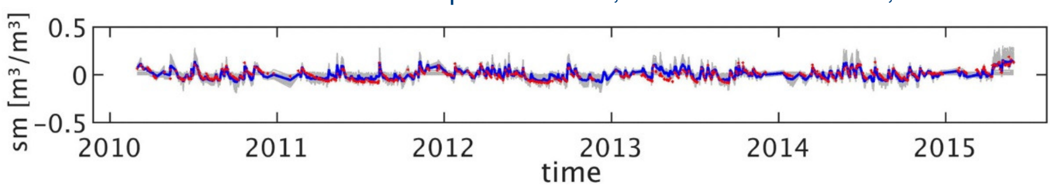
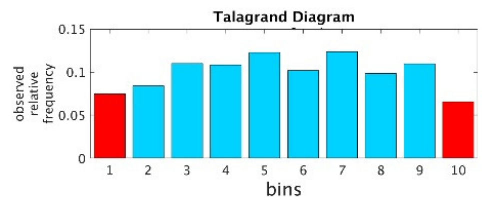


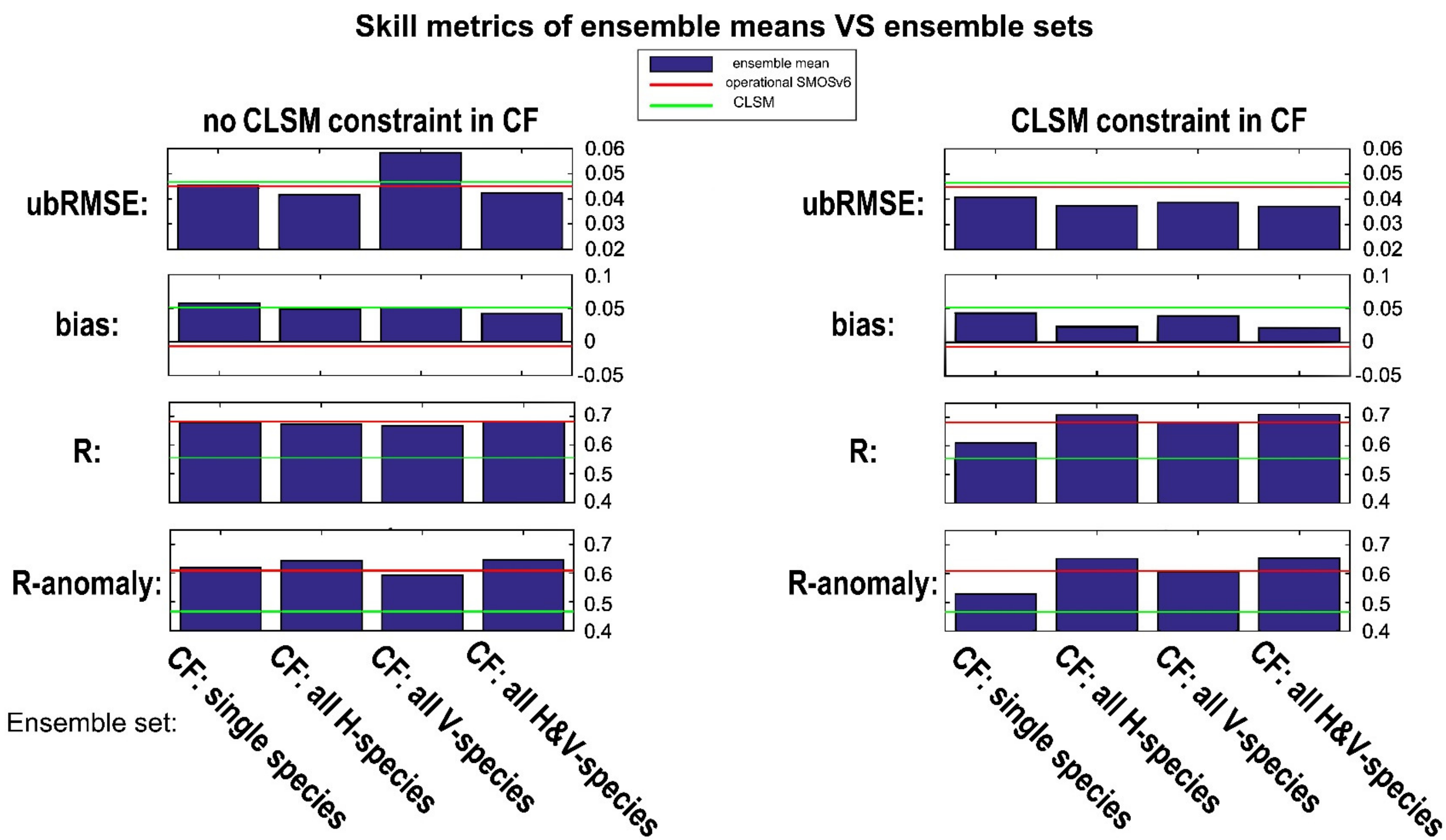


1.1

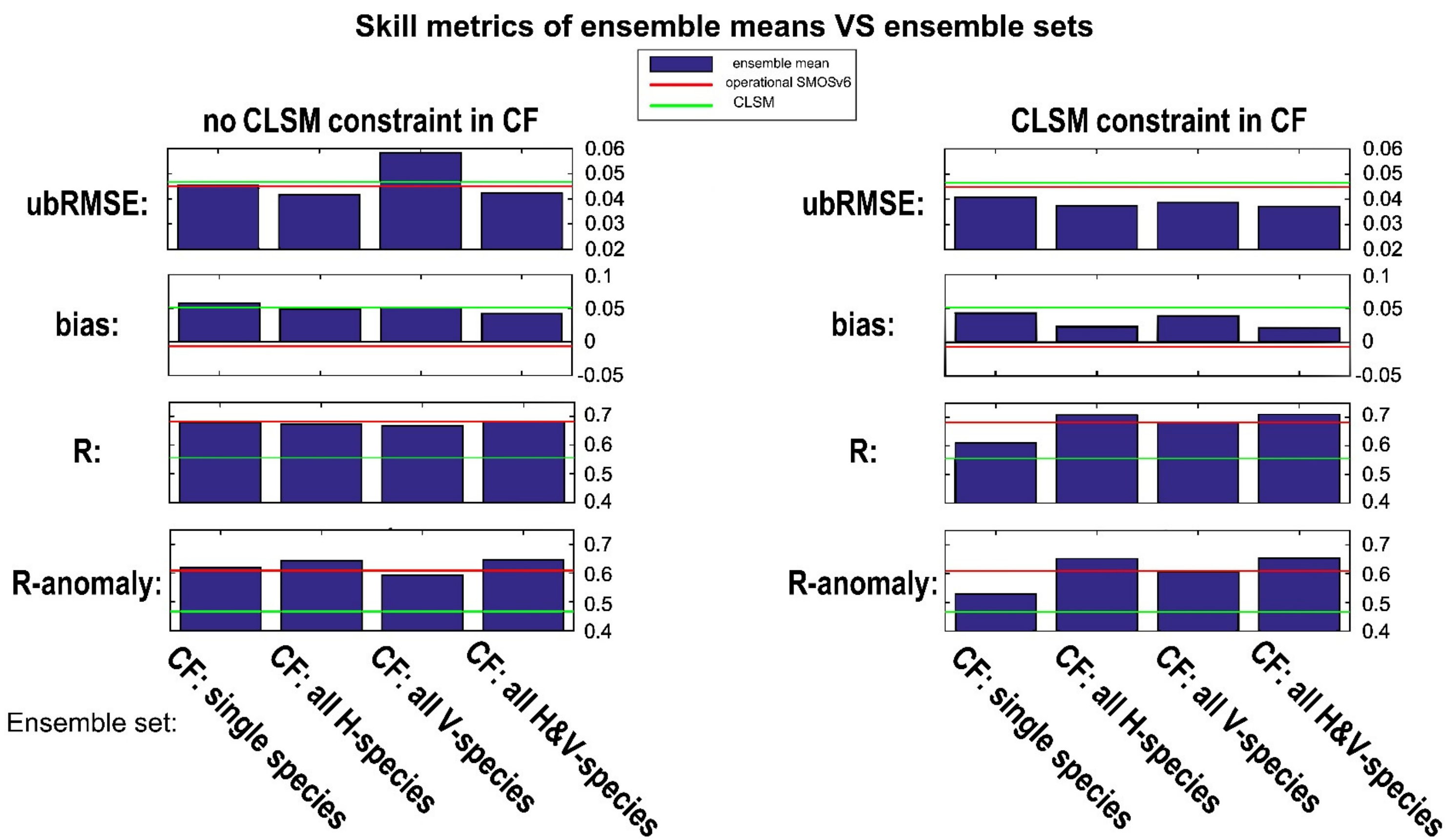
time-averaged **ensemble variance** of verified ensemble set =**78%**
of variance of *in situ* observations

Results: ranked skills of ensemble retrievals

Results: skills of ensemble means



Results: skills of ensemble means



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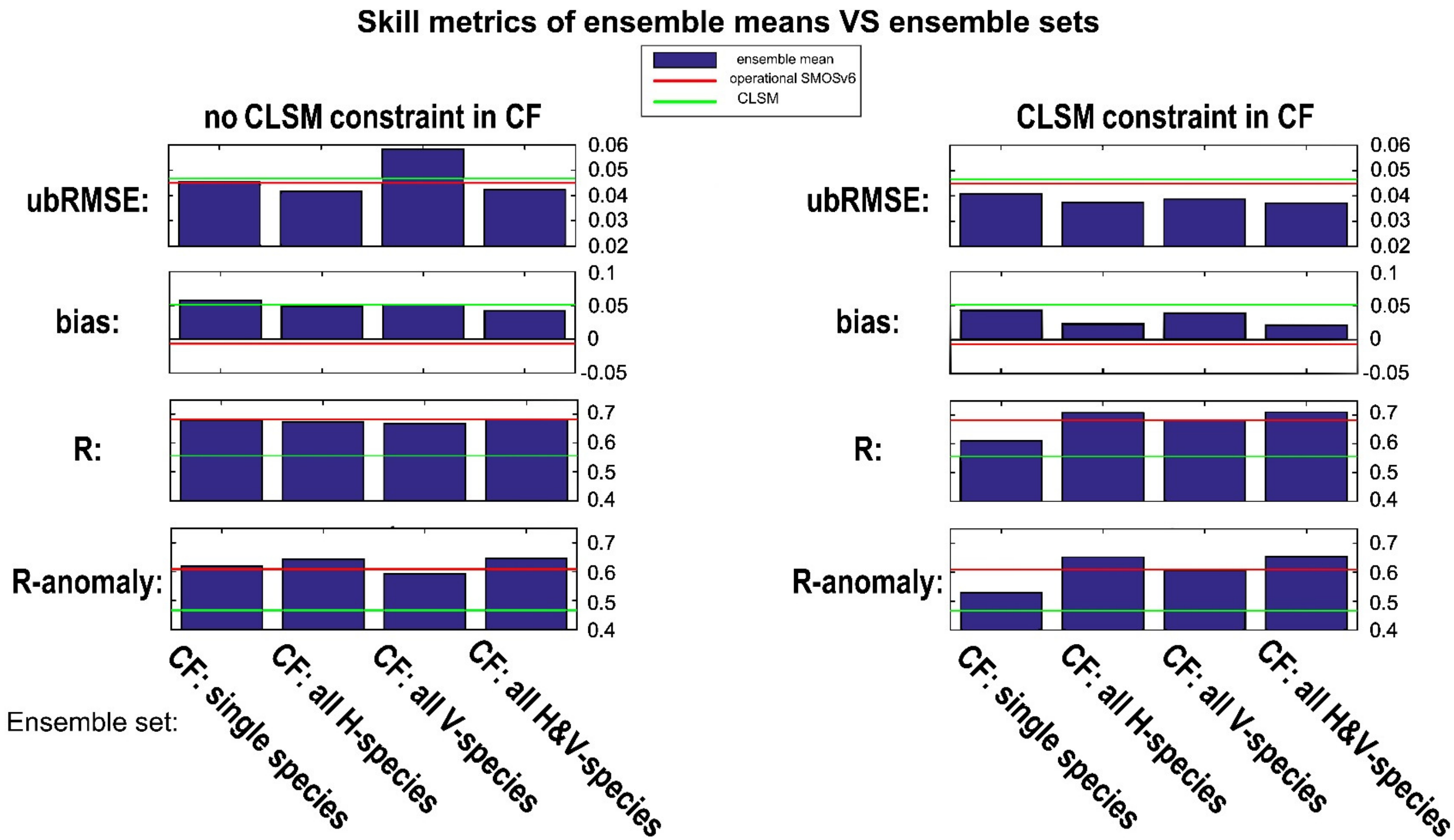

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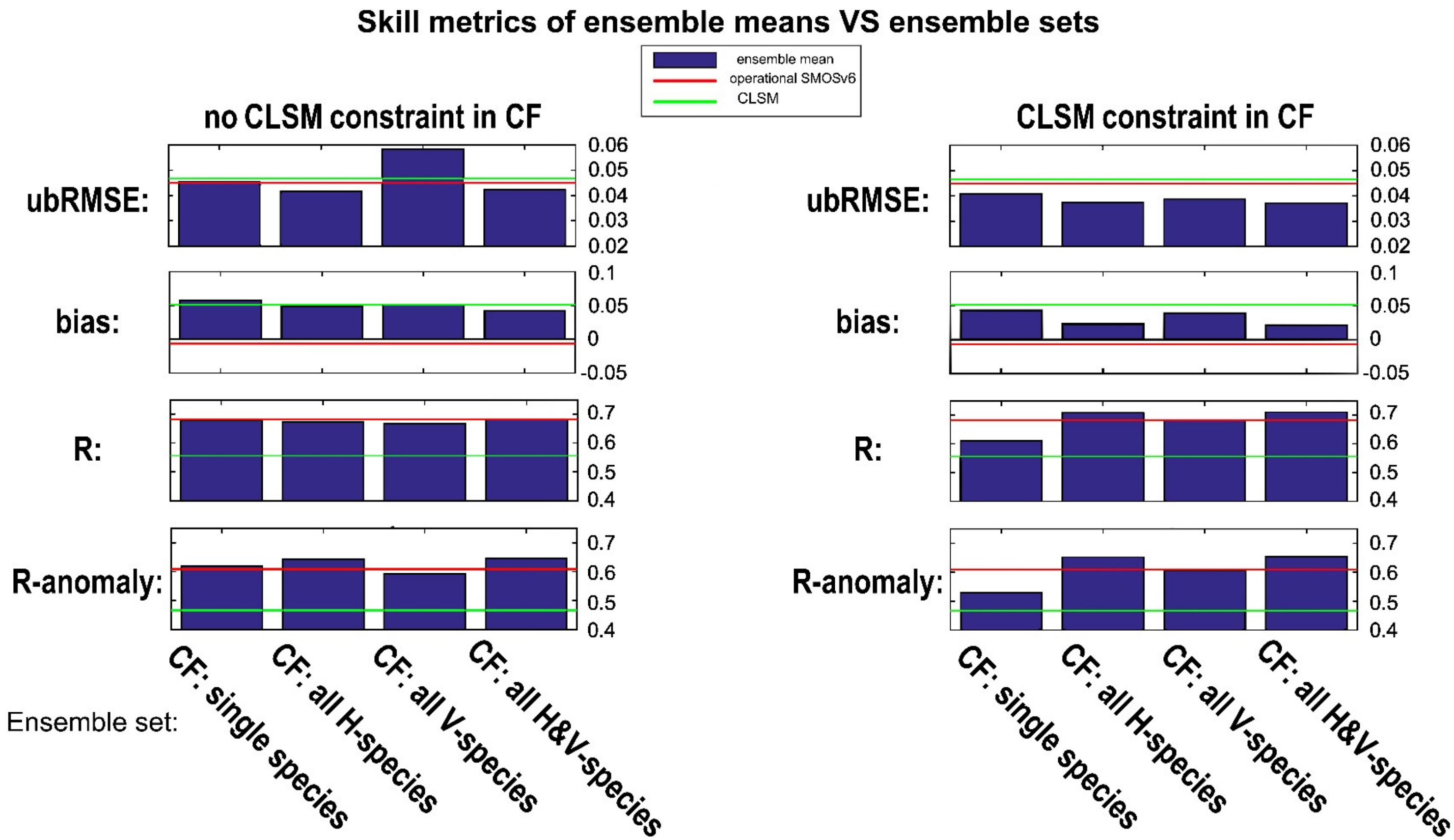

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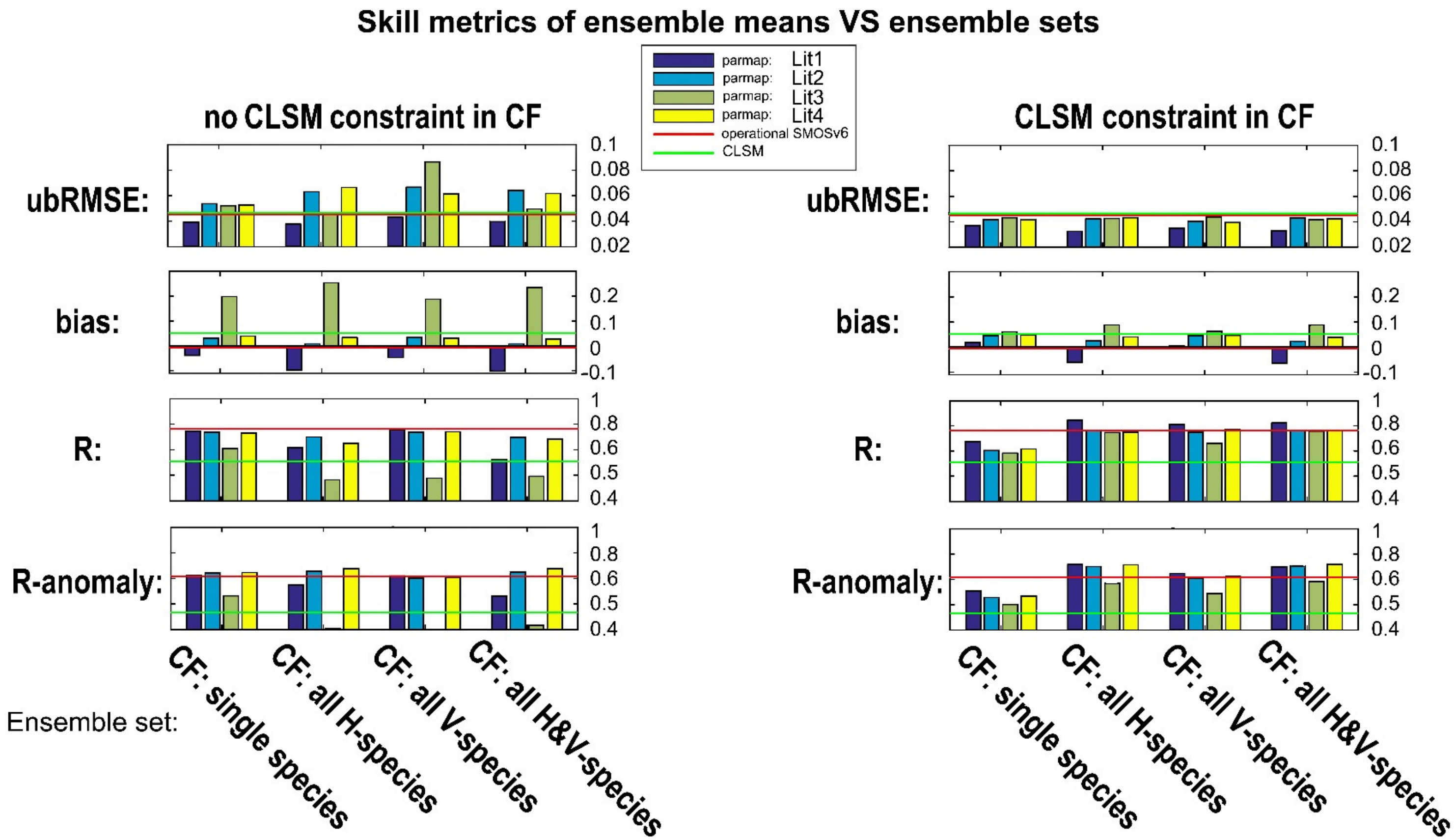

→ inclusion of CLSM sm in the CF generally improves every skill
→ independent of the used RTM parameterization

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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!

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