Global Soil Moisture Estimation from L-Band Satellite Data: Impact of Radiative Transfer Modeling in Assimilation and Retrieval Systems

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Land surface:

Observing and modeling:

KU Leuven HPC Tier2:
L-band (1.4 GHz) brightness temperatures ($T_b$) are sensitive to soil moisture and temperature in the surface layer (5 cm).

L-Band Data

NASA SMAP
ESA SMOS

brightness temperature

RTM (parameters)

forward (assimilation)

inverse (retrieval)

soil temperature
soil moisture
vegetation

Model
Parameters
Complexities
SMOS Retrieval
SMOS Assimilation
Conclusions
Tb increases with drier soil moisture (sfmc)

Tb increases with more vegetation ($\tau$)

Tb strongly depends on parameters (e.g. h, roughness)
Parameter Estimation

**Lookup tables: per vegetation class**

- SMAP L2
- SMOS IC

**Calibrated: per grid cell**

- SMAP L4

- Based on optimizing SMOS Tb versus simulated Tb, using simulated soil moisture (De Lannoy et al., 2013, 2014)

- Based on field experiments; optimizing retrievals vs in situ soil moisture

- Can this also be used for forward modeling (DA experiments)?

- Can this also be used for inverse modeling (retrievals)?
Complexities

Enhance the RTM for specific land cover types, e.g. peatlands:

- **Soil moisture dynamics:**
  improved physical processes in peatland

- **RTM w/ dielectric model:**

- **Open water:**
  incl. open water reduces bias in Tb forward modeling

\[ Tb = f_{land}.T_{b\,land} + f_{SOW}.T_{b\,SOW} + f_{DOW}.T_{b\,DOW} \]

land + static (land mask) + dynamic open water (AMSR2)
- Dielectric model only has minor impact (Bircher vs Wang & Schmugge)
- PEAT-CLSM outperforms CLSM for both soil moisture and Tb simulations
- Adding dynamic open water fraction further improves the results

(Michel Bechtold)
SMOS Retrievals
Global Soil Moisture (SM) and VOD Retrievals

- **SMOS (quasi-)operational retrieval products:**
  - **SMOS L2/L3**
    - only retrieval for nominal fraction, low vegetation/forest
    - \((SM, VOD) = f(Tb^{SMOS}, MODIS LAI, ECMWF Ts, Tb^{ECMWF notnominal}, RTM)\)
  - **SMOS-IC (Fernandez-Moran et al., 2017)**
    - homogenous pixels
    - \((SM, VOD) = f(Tb^{SMOS}, ECMWF Ts, RTM)\)
  - **SMOS-LPRM** in ESA CCI
    - homogenous pixels
    - \(VOD = f(MPDI^{SMOS}, \omega), \text{ and } SM = f(Tb^{SMOS}, VOD, \text{model Ts, RTM})\)

- **SMOS research products:** physically-based, neural network, various RTMs, ...
  - homogenous pixels
  - \(VOD = f(Tb^{SMOS}, \text{MERRA2 Ts, MERRA2 SM, RTM}), \text{ or } SM = f(Tb^{SMOS}, \text{MERRA2 Ts, MERRA2 LAI, RTM})\)
In situ validation (CalVal sites)

- All operational products do better than model simulations.
- Much simpler SMOS-IC product performs as good as complex SMOS L2.
- RTM calibrated for forward modeling could serve for SM retrievals.
- Lit3 (fwd modeling) is inferior for retrievals.

(Jan Quets)
Representative site evaluation (11 vegetation classes)

- limited (anomaly) correlations: L-band VOD contains other information than optical vegetation indices (VI)
- SMOS-IC performs better than operational SMOS L2 (anomaly R)
- RTM calibrated for forward modeling could serve for \( \tau \) retrievals
- Lit3 (fwd modeling) is inferior for retrievals

(Michiel Van Gompel)
SMOS Data Assimilation
Data Assimilation

SMOS Obs (footprint)

NASA GEOS-5 Land Surface Modeling (36 km)

- Catchment land surface model
- MERRA surface meteorology

Observation operator:
- spatial aggregation
- radiative transfer model*
  only in case of Tb assimilation

SMOS Obs (footprint) and NASA GEOS-5 Land Surface Modeling (36 km) with observation operator details.
**Data Assimilation**

<table>
<thead>
<tr>
<th>SMOS Obs (footprint)</th>
<th>NASA GEOS-5 Land Surface Modeling (36 km)</th>
</tr>
</thead>
<tbody>
<tr>
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**Observation operator:**
- spatial aggregation
- radiative transfer model*
  - only in case of Tb assimilation

**Data Assimilation**
- 3D EnKF
- bias mitigation*
- filter parameters*

- Surface soil moisture (∼ top 5 cm)
- Root zone soil moisture (∼ top 1 m)
- Other consistent geophysical fields, with error estimates

⇒ * calibration using long-term SMOS record
Land Surface Modeling

Prognostic LSM

- conservation mass and energy
- convection, diffusion
- Richards equation

Diagnostic RTM

- radiative transfer
- NN, regression
Innovations
(a) O-F SM \([m^3.m^{-3}]\)

(b) \(\Delta w_{tot} [mm]\)

 Increments
Analysis
(c) sfmc \([m^3.m^{-3}]\)

(d) rzmc \([m^3.m^{-3}]\)

- Observation-minus-forecast (O-F, innovation), footprint-scale
- Increment, model grid
- Analysis, model grid
- 3D EnKF: smooth transitions, no swath edges in analysis

(30 April 2015, 12 UTC)
Tb Data Assimilation

Innovations
(a) O-F Tb$_H$ [K]  (b) O-F Tb$_V$ [K]

Increments
(c) $\Delta$wtot [mm]  (d) $\Delta$tp1 [K]

Analysis
(e) sfmc [m$^3$.m$^{-3}$]  (f) rzmc [m$^3$.m$^{-3}$]  (g) tp1 [K]

(30 April 2015, 12 UTC)
SM Observation or Innovation Bias

SM is relatively stationary

Example: at one location, at any time, replace an observed SM of 0.08 m$^3$/m$^3$ with a value of 0.10 m$^3$/m$^3$

- CDF based on 5 years, all seasons
- separate rescaling for ascending (6 am) and descending (6 pm) times
Tb Observation or Innovation Bias

Tb has a strong seasonal pattern

Example: at one location,
- **at pentad 7**, correct the observed $T_b^H$ for a bias of 237-241 K
- **at pentad 36**, correct the observed $T_b^H$ for a bias of 262-260 K
- **at pentad ...**, correct ...

model-SMOS $<T_b^H(40^o)>$ [K], Asc, pentad 36

Little River

- mean-only, 5 year-average, per pentad
- separate rescaling for ascending (6 am) and descending (6 pm), 7 angles, 2 polarizations
Normalized Tb or SM Innovations

Tb_7ang DA
(a) $m=1.14$, $s=0.35$ [K/K]

SM DA
(b) $m=1.23$, $s=0.41$ [-]

\[
\text{std}(O-F/\sqrt{\sigma_F^2 + \sigma_O^2}),
\]
with $\sigma_F^2$ and $\sigma_O^2$ determined by DA design parameters (ensemble perturbations).

Target value = 1

\(< \quad \text{DA system} \quad \text{>}

\text{overestimates} \quad \text{underestimates}

\text{actual uncertainty}
**Δwtot Increments**

### Tb_7ang DA

(a) $m=0.46$, $s=0.11$ [-]

(b) $m=0.76$, $s=0.19$ [-]

### SM DA

(c) $m=6.86$, $s=3.65$ [mm]

(d) $m=4.17$, $s=1.93$ [mm]
\( \Delta w_{tot} \) Increments

**Tb_7ang DA**

(a) \( m=0.46, s=0.11 \) [-]

Less Tb data than SM data assimilated

More increments than observations: spatial filter

(b) \( m=0.76, s=0.19 \) [-]

**SM DA**

(c) \( m=6.86, s=3.65 \) [mm]

(d) \( m=4.17, s=1.93 \) [mm]
Δw_tot Increments

**Tb_7ang DA**
(a) $m=0.46$, $s=0.11$ [-]

**SM DA**
(b) $m=0.76$, $s=0.19$ [-]

Less Tb data than SM data assimilated

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(c) $m=6.86$, $s=3.65$ [mm]  
(d) $m=4.17$, $s=1.93$ [mm]

std(Δw_tot) for Tb DA larger than SM DA

due to relatively higher Tb O-F, more info in Tb O-F
\( \Delta \)wtot Increments (mm)

- unbiased system
- Tb DA introduces more large increments than SM DA
  \sim Tb DA has larger innovations than SM DA
- different information extracted during Tb DA and SM retrieval process?

(De Lannoy and Reichle, 2016, HESS)
In Situ Evaluation

Tb_{7}ang DA
(a) $\Delta \text{RMSD}_{ub} = -0.004 \text{ [m}^3/\text{m}^3\text{]}$
(153/187 improved)

(b) $\Delta \text{RMSD}_{ub} = -0.003 \text{ [m}^3/\text{m}^3\text{]}$
(143/187 improved)

SM retrieval DA
(c) $\Delta \text{RMSD}_{ub} = -0.002 \text{ [m}^3/\text{m}^3\text{]}$
(125/187 improved)

(d) $\Delta \text{RMSD}_{ub} = -0.001 \text{ [m}^3/\text{m}^3\text{]}$
(121/187 improved)

Surface s.m.

Root-zone s.m.

Blue=better
Red=worse
In Situ Evaluation

- Surface Soil Moisture
  - favorable: anomR [\text{-}] 0.4, 0.5, 0.6
  - non-favorable: anomR [\text{-}] 0.4, 0.5, 0.6
  - N=98(24), N=83(22)

- Root-Zone Soil Moisture
  - favorable: anomR [\text{-}] 0.4, 0.5, 0.6
  - non-favorable: anomR [\text{-}] 0.4, 0.5, 0.6
  - N=98(24), N=83(22)

- open loop, Tb_7ang DA, Tb_fit DA, SM DA

- largest soil moisture improvements in favorable areas
- similar averaged skill statistics for Tb and SM DA

(De Lannoy and Reichle, 2016)
Effect of RTM on Tb DA

Repeat the Tb_7ang DA experiment, but with lookup table RTM parameters:

- **Calibrated**
- **Lookup (SMAP L2)**

**Effect on Tb obs predictions:**
- primary: different seasonal bias → Tb rescaling
- secondary: different anomalies?

(Alexander Gruber)
Effect of RTM on Tb DA

Repeat the Tb_7ang DA experiment, but with lookup table RTM parameters:

- Lower roughness → lower Tb
- Lower vegetation opacity → lower Tb

Effect on Tb obs predictions:
- primary: different seasonal bias → Tb rescaling
- secondary: different anomalies?

(Alexander Gruber)
- obvious seasonal bias RTM calib vs lookup
- after rescaling: similar Tb anomalies for RTM calib and lookup
- different variance in Tb obs and Tb fct anomalies (for both RTM calib and lookup)
- Tb anomaly innov variance is slightly larger for RTM calib (not over forests)
\[ \Delta \text{wtot} \] Increments

- unbiased system
- both Tb DA schemes correct soil moisture trajectories similarly
- calibrated RTM introduces more large increments than lookup RTM
- \( \sim \) Tb (anomaly) innovation variance
In situ surface and root-zone soil moisture (ISMN, not strictly QC-ed)

- In situ surface soil moisture (SCAN+USCRN, strictly QC-ed)

- DA always performs better than OL (even when forced with qualitative MERRA2)
- Similar averaged skill statistics for Tb DA using RTM calib and lookup

(Alexander Gruber)
Conclusions

SMOS (or SMAP) Tb to soil moisture via radiative transfer modeling
- very different RTM parameterizations available for forward and inverse modeling
  - optimized parameters for retrievals work for data assimilation (fwd RTM)
  - optimized parameters for fwd modeling work for retrievals (inverse RTM)
- Tb estimates much improved when accounting for open water in RTM

Data assimilation:
- SM DA and Tb DA both improve surface and root-zone soil moisture
- SM DA and Tb DA add different increments to products
- seasonal bias mitigation in Tb DA effectively overcomes shortcomings in RTM parameterization (calibrated or not)
- to do: spatio-temporal optimization of Tb (obs and forecast) errors