NN retrieval of soil moisture


and co-authors...
Physical retrieval algorithm

• Inverse problem:

  SM = Soil Moisture
  Z = other geophysical parameters: veg., soil prop., Ts, etc.

  For each observation TB, we search SM such that: \( \text{RTM}(SM, Z) = TB \)
  where RTM is Radiative Transfer Model

• Classical approaches: Iterative, Optimal Interpolation, Bayesian, etc.

  \[
  SM^* = SM_{fg} + \left[ A^\dagger S_\varepsilon^{-1} A + S_{fg}^{-1} \right]^{-1} A^\dagger S_\varepsilon^{-1} (TB_\varepsilon - A \cdot SM_{fg})
  \]

• Limitations: requires simulations RTM(X,Z) but uncertainties on:
  - \textit{A priori} information on surface parameters Z
  - Radiative Transfer Model (RTM)

• Question: RTM modeling not satisfactory. Other solution?
Neural networks retrieval

It is a parametric nonlinear regression model

Remark: The NN model is applied at pixel level, not as image processing (≠deep learning)
Advantages of NNs:
- *Fast* in operational mode, low memory required
- Multivariate, *high-dimension* space
- *Nonlinear*: situation-dependent, saturation effects
- *Flexible*: No rigid assumptions, can take realistic and complex specifications (FG, instr. noise, model errors, etc.) and various ways to introduce *a priori* information
- Global inversion model, no need for further inversion scheme
- Exploit *synergy*
- *Information content* tool to quantify the impact of: FG, noise, regime-dependence, number and location of channels, compression errors, fusion of information, etc.

Limitations of NNs:
- Needs to be *re-trained* if conditions change (new instrument, noise characteristics, etc.)
- Need a high-quality *learning dataset*
Building a learning dataset: *in situ* solution

**In situ measurements**

<table>
<thead>
<tr>
<th>Region</th>
<th>Station</th>
<th>Surface</th>
<th>Frequency</th>
<th>Period</th>
<th>Depth</th>
</tr>
</thead>
<tbody>
<tr>
<td>Illinois</td>
<td>19</td>
<td>grass</td>
<td>1-3/m</td>
<td>All year</td>
<td>10cm</td>
</tr>
<tr>
<td>Iowa</td>
<td>6</td>
<td>corn</td>
<td>2/m</td>
<td>Growing</td>
<td>7.8cm</td>
</tr>
<tr>
<td>Russia</td>
<td>171</td>
<td>cereal</td>
<td>3/m</td>
<td>All year</td>
<td>20cm</td>
</tr>
<tr>
<td>India</td>
<td>11</td>
<td>grass</td>
<td>4/m</td>
<td>All year</td>
<td>xxcm</td>
</tr>
<tr>
<td>Mongolia</td>
<td>42</td>
<td>Pasture</td>
<td>3/m</td>
<td>Spring</td>
<td>10cm</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Weat</td>
<td></td>
<td>summer</td>
<td></td>
</tr>
</tbody>
</table>

**Global Soil Moisture Data Bank**

(Robock et al., BAMS, 2000)

**Real satellite observations**

**Problems:**
- not enough *in situ* observations to represent well the spatial and temporal variability of soil moisture
- Spatial coherency of *in situ* data
- The measured SM might not be the same as what the satellite observes
- After launch only
Building a learning dataset: RTM simulations

**Global SM from model**

- Multiple years
- Global coverage
- We choose the SM we want from the model

**Simulated Observations**

**Advantage:**
- Can be done before launch

**Problem:**
- What is our confidence on the Radiative Transfer Model?
Building a new learning dataset for historical measurements

Global SM from retrieval

Real SMOS observations

- Multiple years
- Global coverage

Advantage:
- Independent from Surface Model

Problem:
- Need to rely on an *a posteriori* retrieval, which is based on a RTM
Building a learning dataset: Our approach

Global SM from model

Real satellite observations

Problems/questions:
- Is the land model SM good enough?
- Are the SM really related to the Obs?
- Are we just reproducing the SM from the model when teaching the retrieval with this dataset?
- After launch only
Applications:
1) **Information content analysis, and synergy**
2) **Remote sensing**: No need of RTM, or *in situ* measurements
3) **Consistency checking method**: Check consistency of model output with satellite observations, help model development
4) **Variational assimilation applications**: Define a link between observations and model (link coherent with model) but need to specify uncertainties

(Aires, Prigent, Rossow, Soil moisture at a global scale. II – Global Statistical relationships, JGR, 2005)
Application 1) – Information content & synergy

Visible and Near-IR (NOAA/AVHRR) (NDVI)

Thermal IR (ISCCP) (diurnal Ts amplitude) (Aires, Prigent and Rossow, 2004, JGR)

Passive microwave (DMSP / SSM/I) (surface emissivities) (Prigent, Aires, and Rossow, 2006, JGR)

Active microwave (ERS scatterometer) (backscattering coefficient)

Soil moisture at a global scale I, Prigent, Aires, Rossow, JGR, 2005

Soil Moisture retrieval from multi-instrument observations: information content and retrieval methodology, Kolassa, Aires, Polcher, Prigent, Jimenez, Pereira, JGR, 2013

Soil moisture retrieval from AMSR-E and ASCAT microwave observations synergy Part 1: Satellite data analysis, Kolassa, Gentine, Prigent, Aires, RSE, 2016

Information content
Data fusion and synergy

Accumulating Predictors

<table>
<thead>
<tr>
<th></th>
<th>RMS</th>
<th>CORR.</th>
<th>RMS</th>
<th>CORR.</th>
</tr>
</thead>
<tbody>
<tr>
<td>IR Norm Ts Amp.</td>
<td>0.069</td>
<td>0.753</td>
<td>0.057</td>
<td>0.833</td>
</tr>
<tr>
<td>ERS small ang.</td>
<td>0.055</td>
<td>0.792</td>
<td>0.054</td>
<td>0.876</td>
</tr>
<tr>
<td>NDVI</td>
<td>0.052</td>
<td>0.819</td>
<td>0.052</td>
<td>0.704</td>
</tr>
<tr>
<td>SSMR E37V-H</td>
<td>0.059</td>
<td>0.830</td>
<td>0.059</td>
<td>0.724</td>
</tr>
<tr>
<td>SSMR E18V-H</td>
<td>0.069</td>
<td>0.832</td>
<td>0.050</td>
<td>0.735</td>
</tr>
<tr>
<td>SSMR E19V</td>
<td>0.059</td>
<td>0.833</td>
<td>0.050</td>
<td>0.737</td>
</tr>
<tr>
<td>SSMR E56V-H</td>
<td>0.069</td>
<td>0.833</td>
<td>0.050</td>
<td>0.738</td>
</tr>
</tbody>
</table>
Application 2) - Soil moisture retrieval

ECMWF

Global Soil Moisture Data Bank, Robock et al., 2000

Evaluation

Local temporal variability assessed

- Spatial and temporal variability of the retrieval is based on the observations
- The NN retrieval does not reproduce the model patterns, it can even correct it!

Several spatial/temporal metrics are used

SM retrieval from AMSR-E & ASCAT MW observation synergy Part 2: Product evaluation, Kolassa, Gentine, Prigent, Aires, Ale., RSE, 2017
Application 3) – Consistency checking

Consistency checking between model output and satellite observations:
- ECMWF closer to EO observations
- This tool can help model development

Higher incoherencies model/observations

NCEP

ECMWF

Synthetic tests:

Shifting the SM seasonal cycle in some basins

NN retrieval is able to correct season where necessary

Application 4) - Variational assimilation

- Assimilation in NWP centres of:
  1. Raw observations: need a RTM, good auxiliary parameters
     - Ask to the system to “perform” the retrieval, data fusion
  2. Retrieved SM: need uncertainty characterization Ri

- Solution (1) has been privileged because easier to specify errors in raw observations (supposed to be constant) than on retrieved products (state-dependent). But difficulty to rely on the RTM...

Advantages of (2):
- Retrieval is coherent with model SM
- We can “help” the retrieval when necessary
- No need for aux. parameters

\[
J(x_0) = \frac{1}{2}(x_0 - x_0^b)^T B^{-1}(x_0 - x_0^b) \\
+ \frac{1}{2} \sum_{i=0}^{n} (x(t_i) - x_i^r)^T R_i(x(t_i))^{-1}(x(t_i) - x_i^r)
\]

Aires, F., et al. (2005), Sensitivity of satellite microwave and infrared observations to SM at a global scale: 2. Global statistical relationships, JGR.
Application 4) - Variational assimilation

• Is NN retrieval independent enough from the model?

• Our approach:
  - One general “CDF matching”

• Classical approach:
  - One CDF matching for each pixel

Data assimilation to extract soil moisture information from SMAP observations, Kolassa et al., RS, 2017.

- Spatial pattern of EO data is changed
- Dynamic behaviour too

The NN retrieval is less model-dependent

Global bias-calibration better than localized ones for assimilation!
Assimilation experiments at ECMWF with SMOS

First retrieval:

- SMOS data
- NDVI
- Soil texture...


Assimilation:

- Neural Network training and application
- SMOS NN SM data assimilation in a land surface model & atmospheric impact, Rodriguez-Fernandez, de Rosnay, Albergel, Richaume, Aires, Prigent, Kerr, RS, 2019

In parallel, SMAP assimilation at NASA:

- Data assimilation to extract soil moisture information from SMAP observations, Kolassa et al., RS, 2017.
- Merging active & passive MW observations in SM data assimilation, Kolassa, Reichle, Draper, RSE 2017.

Forecast skills of T850
**Downscaling of SM**

NN downscaling scheme

![Figure 1. Two levels of spatial grids used for training and retrieval steps in the NN algorithm. While both steps have similar grid structures, the spatial resolutions are different as listed here.](image)

**Inputs using in each of the downscaling scheme:**

<table>
<thead>
<tr>
<th>No.</th>
<th>Usage</th>
<th>Input 1</th>
<th>Input 2</th>
<th>Input 3</th>
<th>Input 4</th>
<th>Input 5</th>
<th>Input 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>R1</td>
<td>Training</td>
<td>SM at 45 km</td>
<td>NDVI at 45 km</td>
<td>NDVI at 9 km for target pixel</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>Retrieval</td>
<td>SM at 11.25 km</td>
<td>NDVI at 11.25 km</td>
<td>NDVI at 2.25 km for target pixel</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>R2</td>
<td>Training</td>
<td>SM at 45 km</td>
<td>NDVI at 45 km</td>
<td>NDVI at 9 km for target pixel</td>
<td>NDVI at 45 km for 1.25 km grid</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>Retrieval</td>
<td>SM at 11.25 km</td>
<td>NDVI at 11.25 km</td>
<td>NDVI at 2.25 km for target pixel</td>
<td>NDVI at 2.25 km for 1.25 km grid</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>R3</td>
<td>Training</td>
<td>SM at 45 km</td>
<td>NDVI at 45 km</td>
<td>NDVI at 9 km for target pixel</td>
<td>Tl at 45 km</td>
<td>Tl at 9 km for target pixel</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>Retrieval</td>
<td>SM at 11.25 km</td>
<td>NDVI at 11.25 km</td>
<td>NDVI at 2.25 km for target pixel</td>
<td>Tl at 11.25 km</td>
<td>Tl at 2.25 km for target pixel</td>
<td>–</td>
</tr>
<tr>
<td>R4</td>
<td>Training</td>
<td>SM at 45 km</td>
<td>NDVI at 45 km</td>
<td>NDVI at 9 km for target pixel</td>
<td>Tl at 45 km</td>
<td>Tl at 9 km for target pixel</td>
<td>NDVI at 45 km for all pixels at 9 km</td>
</tr>
<tr>
<td></td>
<td>Retrieval</td>
<td>SM at 11.25 km</td>
<td>NDVI at 11.25 km</td>
<td>NDVI at 2.25 km for target pixel</td>
<td>Tl at 11.25 km</td>
<td>Tl at 2.25 km for target pixel</td>
<td>NDVI at 11.25 km for all pixels at 2.25 km</td>
</tr>
</tbody>
</table>

- **ASCAT SM (45 or 11 km)**
- **NDVI (45 and 9km)**
- **Tl**: Time Index

• What we learned:
  – This is perfect technique to **build long-term record of SM**
    - Calibration over long time record
    - Technique flexible enough for all kind of instruments
    - Exploit synergy for better SM retrieval
  – Good approach for **SM assimilation** (& other surface products?)

• Assimilation in NWP centres:
  – ECMWF
  – NASA

• **Uncertainty characterization** to improve usability of SM product & facilitate assimilation

  - State-dependency of retrieval errors
  - Similar work should be done for SM
Perspectives

• Build long-term record of SM using all the available EO:

- Data fusion better synergy than a posteriori combination:
  - Aires, Aznay, Prigent, Paul, Bernardo, JGR, 2012
  - SM retrieval from AMSR-E & ASCAT MW observations synergy Part 1: Satellite data analysis, Kolassa, Gentine, Prigent, Aires, RSE, 2016

► Merging EO data a priori better than a posteriori combination of a SM products
Thank you!