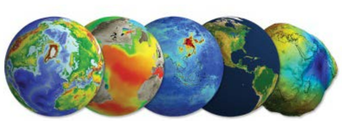
# SMOS measurements in forecasting systems: A quantitative assessment of skill

**M.Drusch and S.Mecklenburg (ESA)**

with contributions from:
J. Munoz-Sabater and P. de Rosnay, ECMWF
H. Lievens and N. Verhoest, Gent University
Y. Kerr, CESBIO
and the SMOS + Hydrology
Science Team



# From scientific challenges to societal benefit

**new observation systems** | **novel measurements**

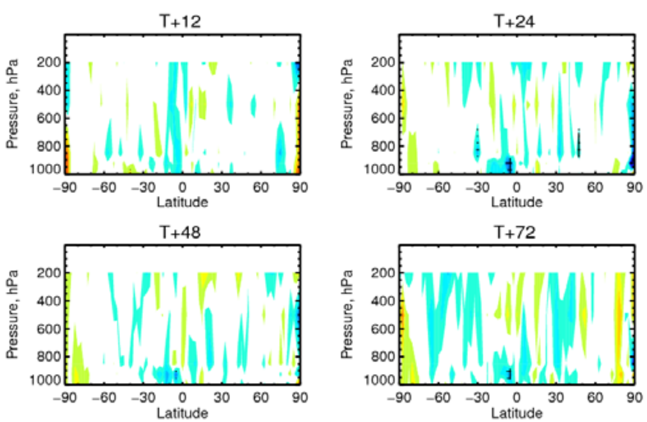
↓ **data assimilation** ↓

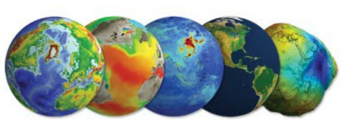
**high quality analyses and improved initial conditions**

↓ **forecast** ↓

**increased predictive skill** | **improved risk mitigation** | **societal benefit**

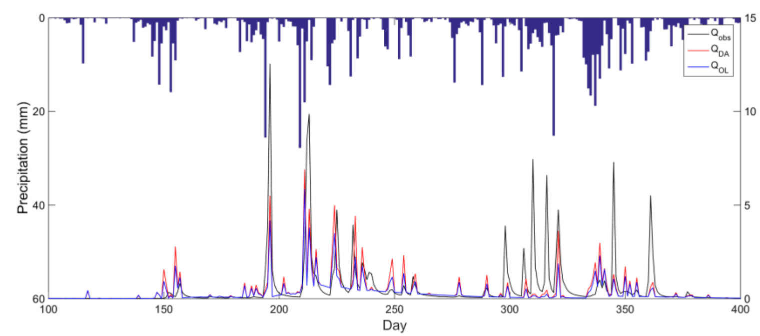
## EXAMPLE 1: NWP - Assimilating SMOS TB



**The impact on weather is neutral to positive (blue) (ECMWF)**

## EXAMPLE 2: PREDICTING STREAMFLOW




**The impact on stream flow is positive. (U. Gent)**

# EXAMPLE 1: ECMWF – Developments and Spin–offs

Activities started in 2003:

**Pre-launch**

- Development of the simplified Extended Kalman Filter (sEKF).
- Radiative transfer model (CMEM) implemented as Forward Operator.
- Development of Bias Correction scheme based on CDF matching.

**Technical improvements**

- Implementation of operational data monitoring.
- Quality control wrt RFI and data thinning.
- More efficient task scheduling.

**Adjusting models**

- Improved model physics in the land surface scheme (H-TESSEL).

**Skill assessment**

- DA experiment tuning the sEKF.
- Analysis of forecast impact (on-going).

## Simplified Extended Kalman Filter:

For each grid point, analysed state vector $\boldsymbol{x}_a$:

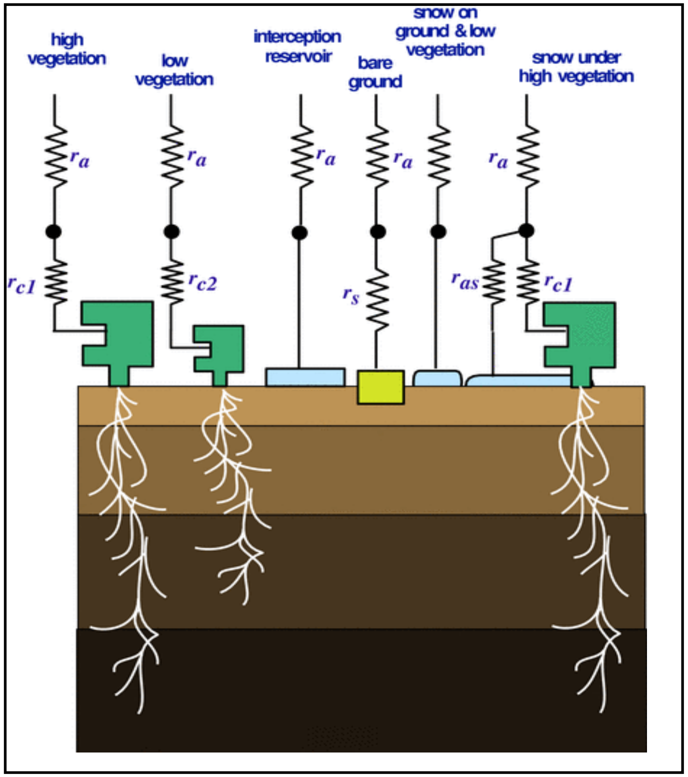
$$\boldsymbol{x}_a = \boldsymbol{x}_b + \mathbf{K}\,(\boldsymbol{y} - H\,[\boldsymbol{x}_b])$$

$\boldsymbol{x}_b$ : background state vector,

$\boldsymbol{y}$ : observation vector

H : non linear observation operator

**K** : Kalman gain matrix: $\mathbf{K} = [\mathbf{B}^{-1} + \mathbf{H}^T\mathbf{R}^{-1}\mathbf{H}]^{-1}\mathbf{H}^T\mathbf{R}^{-1}$




**LSM : HTESSEL** 0-7cm, 7-28cm, 28-100cm (100-289cm)

**Three experiments:**

- **Screen Level Variable (SLV) :** assimilation of $T^{2m}$, $RH^{2m}$
- **SMOS**: assimilation of only SMOS $T_B$ CDF corrected
- **SMOS+SLV**: assimilation of $T^{2m}$, $RH^{2m}$ and SMOS $T_B$ CDF

# Summer validation (JJA) ; TOP LAYER (0-7 cm)

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## SMOS+SLV: best analysis/representation of soil moisture when compared to in-situ

→ The worst among the 3 expt.

→ Neither the best nor the worse

→ The best among the 3 expt.

| Network | SLV Bias | SLV RMSD | SLV R | SMOS Bias | SMOS RMSD | SMOS R | SMOS + SLV Bias | SMOS + SLV RMSD | SMOS + SLV R | N |
|---|---|---|---|---|---|---|---|---|---|---|
| SMOSMANIA | -0.017 | 0.067 | 0.77 | -0.043 | 0.085 | 0.71 | -0.015 | 0.064 | 0.78 | 9 |
| TWENTE | 0.024 | 0.097 | 0.77 | -0.013 | 0.099 | 0.71 | 0.005 | 0.095 | 0.76 | 18 |
| SCAN | -0.088 | 0.137 | 0.55 | -0.076 | 0.132 | 0.55 | -0.082 | 0.135 | 0.57 | 98 |
| USCRN | -0.079 | 0.115 | 0.67 | -0.072 | 0.116 | 0.64 | -0.074 | 0.115 | 0.69 | 61 |
| MAQU | 0.027 | 0.067 | 0.75 | 0.064 | 0.089 | 0.79 | 0.026 | 0.067 | 0.74 | 16 |
| SWATMEX | -0.080 | 0.095 | 0.80 | -0.126 | 0.138 | 0.74 | -0.082 | 0.098 | 0.79 | 8 |
| VAS | -0.082 | 0.105 | 0.48 | -0.072 | 0.079 | 0.53 | -0.085 | 0.099 | 0.59 | 1 |
| OZNET | -0.104 | 0.122 | 0.69 | -0.098 | 0.118 | 0.72 | -0.104 | 0.122 | 0.71 | 30 |
| REMEDHUS | -0.065 | 0.093 | 0.57 | -0.058 | 0.080 | 0.73 | -0.068 | 0.092 | 0.61 | 17 |
| UMBRIA | -0.153 | 0.159 | 0.65 | -0.207 | 0.210 | 0.47 | -0.153 | 0.159 | 0.67 | 2 |
| HOBE | -0.052 | 0.076 | 0.70 | -0.031 | 0.066 | 0.57 | -0.033 | 0.067 | 0.69 | 30 |

*Bias ($m^3m^{-3}$); RMSD ($m^3m^{-3}$)*

# Summer validation (JJA) ; ROOT ZONE (0-100 cm)

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- Validation undertaken over 77 (SCAN) and 50 (USCRN) stations ($p$-value$<0.05$)
- Observations are averaged over 5, 10, 20, 50 cm (and 100 cm also for USCRN)
- Model SM is averaged over the three layers (7, 28, 100 cm)

**SLV**

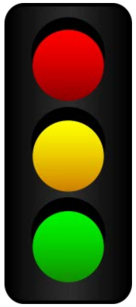
| Network | Bias ($m^3m^{-3}$) | RMSD ($m^3m^{-3}$) | R | N |
|---|---|---|---|---|
| SCAN | -0.041 | 0.113 | 0.72 | 77 |
| USCRN | -0.072 | 0.111 | 0.66 | 50 |

**SMOS**

| Network | Bias ($m^3m^{-3}$) | RMSD ($m^3m^{-3}$) | R | N |
|---|---|---|---|---|
| SCAN | -0.027 | 0.119 | 0.72 | 77 |
| USCRN | -0.064 | 0.106 | 0.70 | 50 |

**SMOS + SLV**

| Network | Bias ($m^3m^{-3}$) | RMSD ($m^3m^{-3}$) | R | N |
|---|---|---|---|---|
| SCAN | -0.040 | 0.115 | 0.73 | 77 |
| USCRN | -0.066 | 0.109 | 0.69 | 50 |



→ The worst among the 3 expt.

→ Neither the best nor the worse

→ The best among the 3 expt.

**SMOS+SLV/SMOS: neutral to good analysis/representation of soil moisture**

**Summary: integrating SMOS data improves soil moisture analysis**

# Forecast Impact and Skill
## *(What does SMOS add?)*

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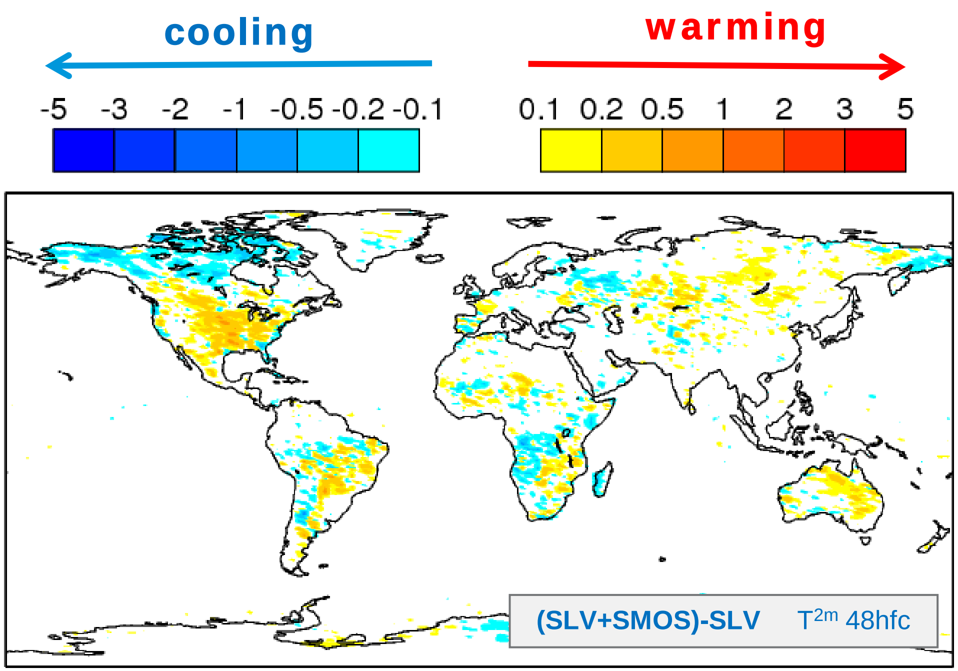
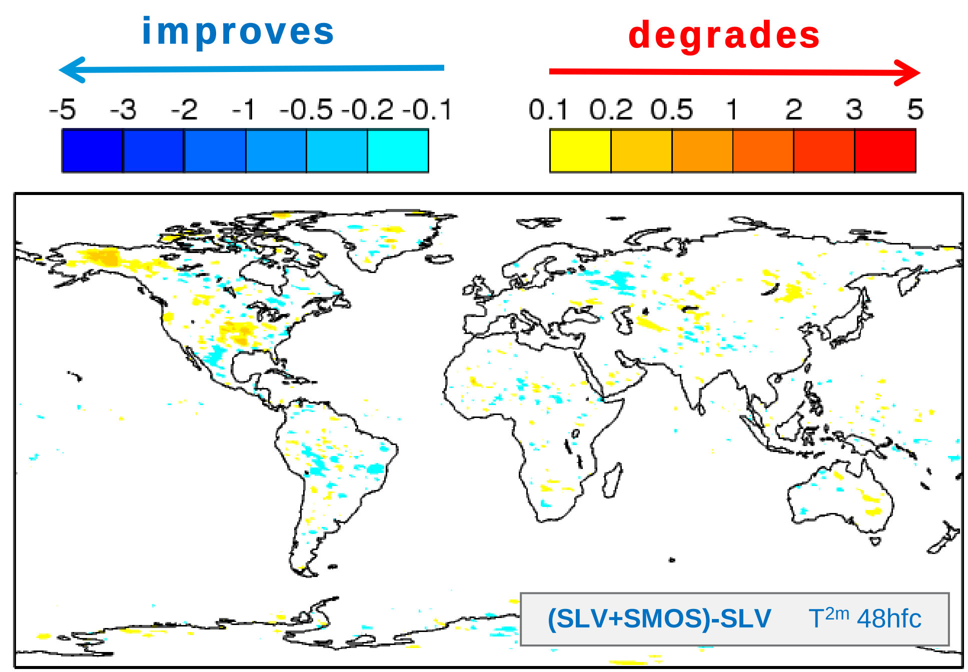
### $T_{2m}$ differences




### FC impact / $T_{2m}$ error differences

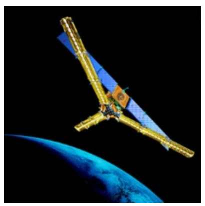


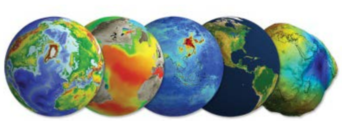

- LEFT: SMOS increments produce warmer and drier atmosphere in central US, Sahel, South of Africa and Australia (→ hot-spots for NWP impact).
- RIGHT: Neutral to slightly negative regional impact in the skill of the forecast by assimilating SLV+SMOS.
- **More experiments needed with the target for initial operational implementation: Maintain positive impact in the soil moisture analysis with a neutral impact in low level atmospheric parameters.**

# Balancing Uncertainties …

**Operational set-up (CTRL):**

**Obs Err**: $\sigma(T_{2M}) = 1$ K; $\sigma(RH_{2M}) = 4\%$; $\sigma(SM_{ASCAT}) = 0.05\ m^3m^{-3}$

| | Config.1 | Config.2 | Config.3 | |
|---|---|---|---|---|
| SMOS Obs Err  | $\sigma(T_B) = 6 +$ rad_acc ~ [8.5-10] K | $\sigma(T_B) = 6 +$ rad_acc ~ [8.5-10] K | $\sigma(T_B) = 6 +$ 3xrad_acc ~ [13.5-18] K | |
| Model Err | $\sigma = 20\%$ WHC [0.03-0.08] $m^3m^{-3}$ | $\sigma = 10\%$ WHC [0.015-0.04] $m^3m^{-3}$ | $\sigma = 10\%$ WHC [0.015-0.04] $m^3m^{-3}$ | layer-1: 7 cm |
| | $\sigma = 10\%$ WHC [0.015-0.04] $m^3m^{-3}$ | $\sigma = 5\%$ WHC [0.008-0.02] $m^3m^{-3}$ | $\sigma = 5\%$ WHC [0.008-0.02] $m^3m^{-3}$ | layer-2: 21 cm |
| | $\sigma = 5\%$ WHC [0.008-0.02] $m^3m^{-3}$ | $\sigma = 5\%$ WHC [0.008-0.02] $m^3m^{-3}$ | $\sigma = 5\%$ WHC [0.008-0.02] $m^3m^{-3}$ | layer-3: 72 cm |



* WHC = Water Holding Capacity of the soil

# Atmospheric Impact(1)

DRMSE: Normalized difference in rmse of the forecast

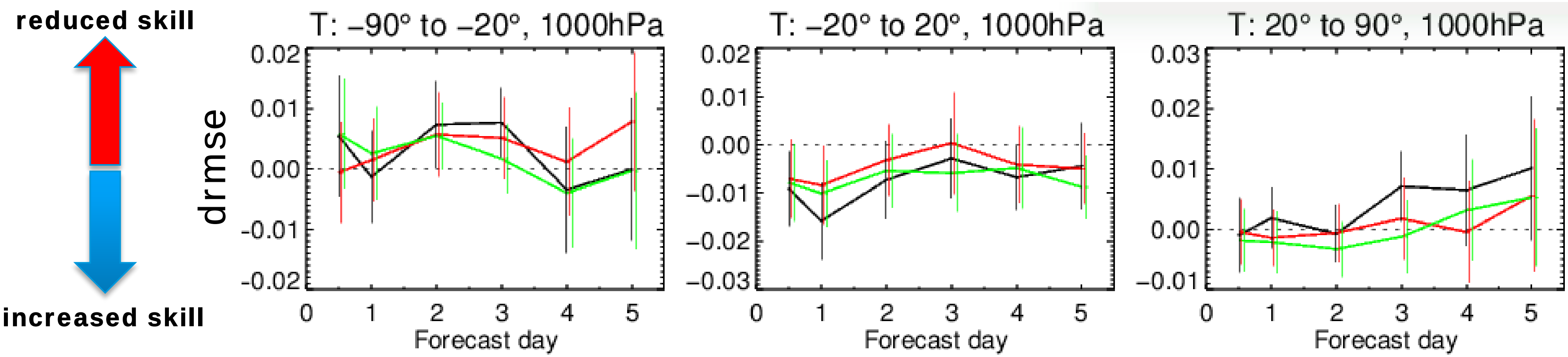
drmse > 0: expt worse than ctrl

drmse < 0: expt better than ctrl

Config.1

Config.2

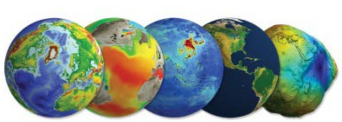
Config.3




*SH- extratropics* *Tropics* *NH- extratropics*

For air temperature: Neutral to positive impact for **Config.3.** depending on region.

For air humidity: some significant improvement, around 1% for Config.3.



# Summary I (ECMWF: NWP)

- SMOS data successfully integrated into the ECMWF coupled land-atmospheric forecasting system and land data assimilation scheme,

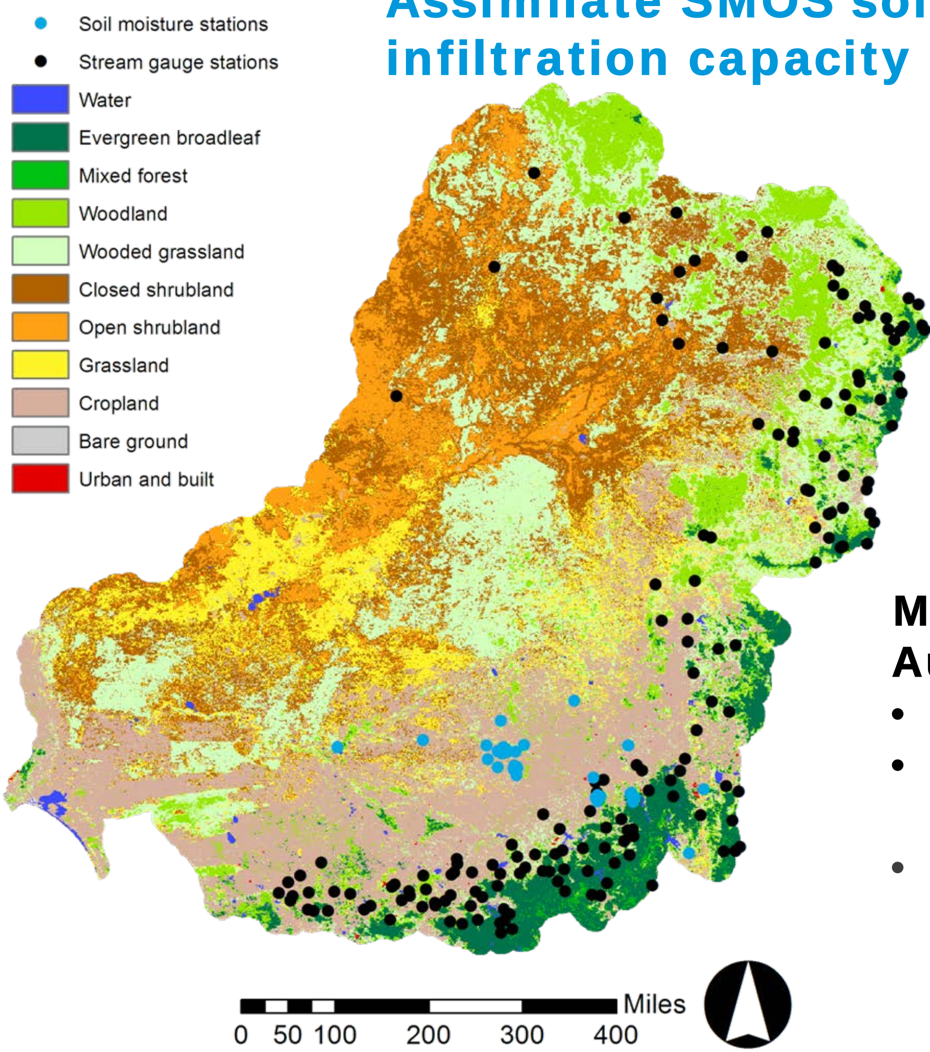
- Seasonal summer experiments (with baseline observation and background error) show that, compared to the op. system, the SMOS signal tends to dry out the soil (in average),

  - positive results in terms of shallow, root-zone soil moisture analysis (and forecast),
  - limited atmospheric impact (with some degradations)

- Several diagnostics and sensitivity experiments (see configuration 1-3) show that components of the assimilation system can and should be adjusted in order to optimize the use of SMOS information in the coupled land-atmospheric forecasting system,

  - The integration of SMOS $T_B$ in the ECMWF operational LDAS is feasible and planned.

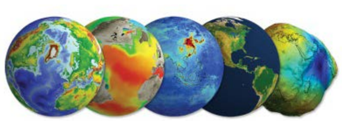
# EXAMPLE 2: Predicting Streamflow
# The Catchment




## Assimilate SMOS soil moisture into a the variable infiltration capacity (VIC) model to predict streamflow


**Murray-Darling catchment / SE Australia:**

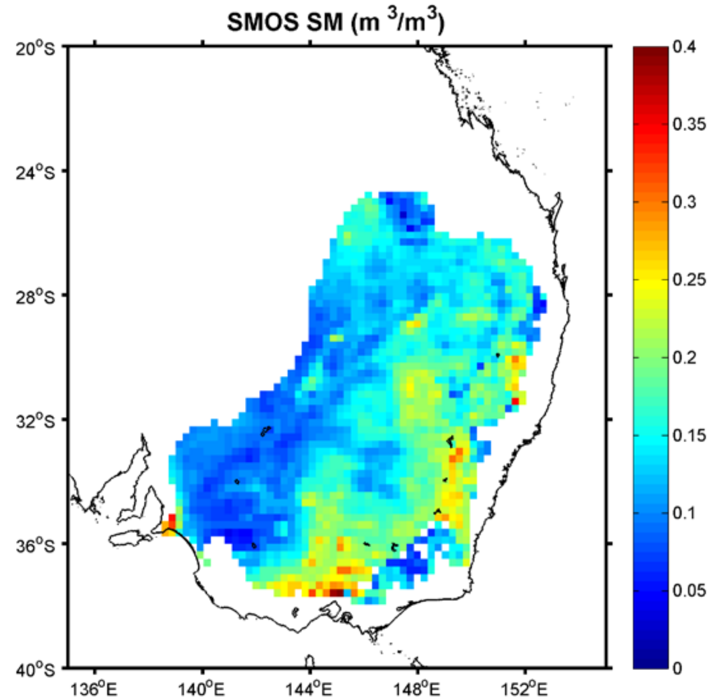
- Variety of land cover
- Well equipped with SM and stream flow stations
- Validation data (2010-2011):
  - 169 stream gauge stations
  - 49 OzNet soil moisture stations



smos+hydrology
support to science element

# Data Assimilation Experiments

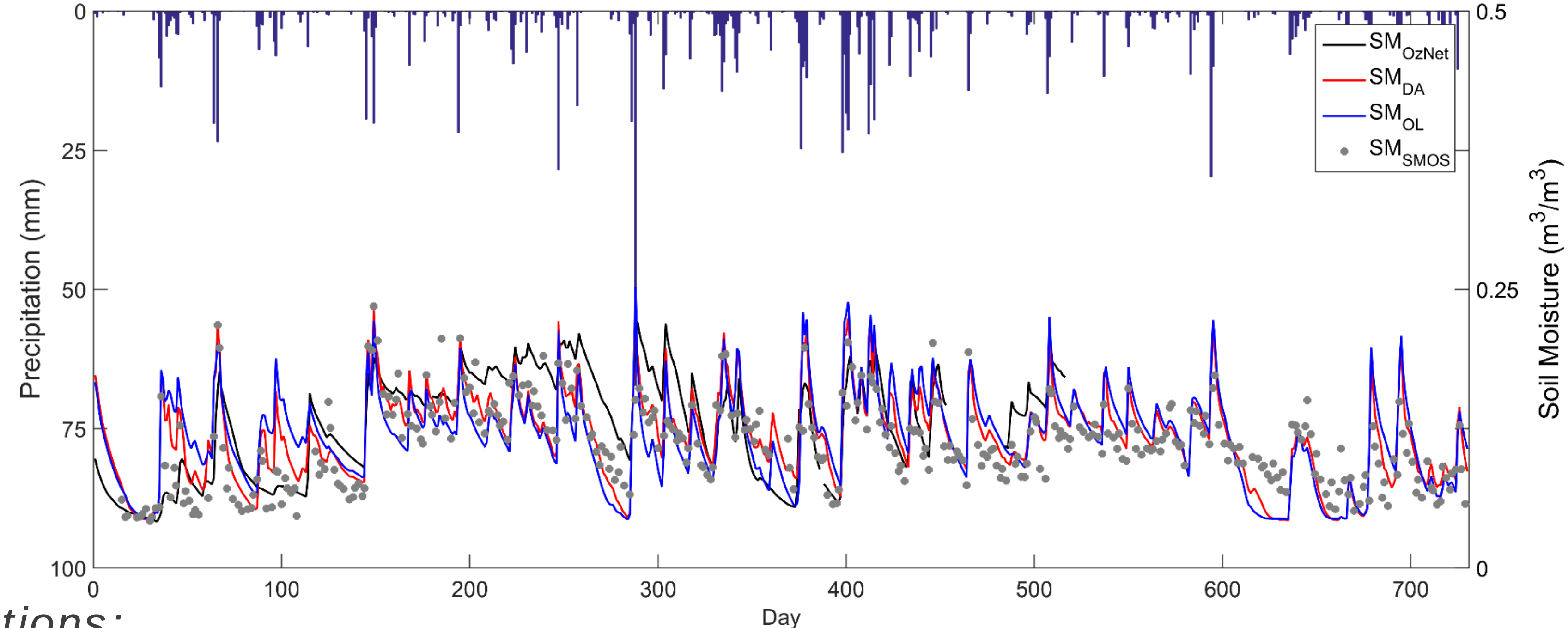
- **Observations**
  - CATDS Level 3 SMOS SM
  - 2010-2011
  - 25 km grid
  - Extracted for MDB




- **Ensemble Kalman Filter** (with gain nudging)
- **Bias correction**
  - Rescaling of the SMOS observations to the model climatology
  - 3 methods are tested:
    1. *mean*: correction of mean
    2. *var*: correction of mean and variance
    3. *cdf*: CDF-matching (correction of mean, variance, and skewness)
- **Data assimilation experiments**:
  - Open Loop (OL) – no observations assimilated
  - $DA_{mean}$ – SMOS with bias correction of the mean (1)
  - $DA_{var}$ – SMOS with bias correction of the mean and variance (2)
  - $DA_{cdf}$ – SMOS with cdf-matching bias correction (3)

# Soil Moisture Analyses

*Example: Yanco 3 with DA cdf*



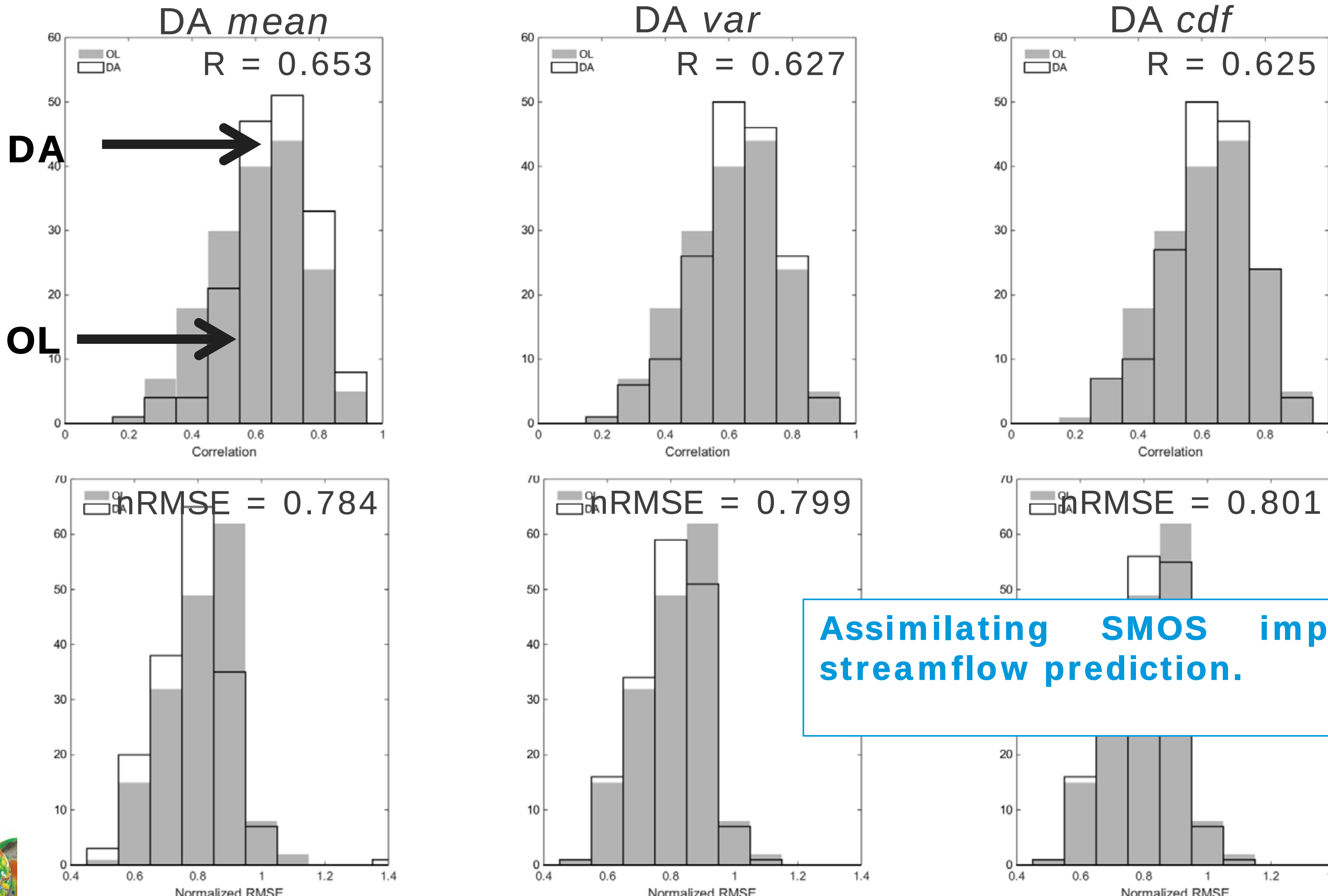

*All stations:*

| SM record | RMSE *cdf* ($m^3/m^3$) | R *cdf* (-) |
|---|---|---|
| VIC OL | 0.058 | 0.549 |
| VIC DA *mean* | 0.045 | 0.713 |
| VIC DA *var* | 0.048 | 0.677 |
| VIC DA *cdf* | 0.048 | 0.686 |

SMOS adds skill to the soil moisture analysis. Best results are obtained when only adjusting for the mean keeping the variability in the observation data set.

# Streamflow Predicition

*OL: R = 0.608 / nRMSE = 0.812*




**Assimilating SMOS improves streamflow prediction.**

# Summary II (Hydrology)

- Assimilation of coarse scale SMOS SM improves soil moisture simulations

- Improved antecedent soil moisture conditions increase performance of stream flow simulations

- Most improvements are in peak runoff simulations

- Bias correction largely impacts the magnitude of improvements:
    - CDF matching loses info on observational variability
    - Best results with mean bias correction

# Summary (3)

- Constraining a well-calibrated model – data assimilation system with a new observation type is a significant task.
- The assimilation of SMOS brightness temperatures improves the soil moisture analyses in the ECMWF forecasting system and the VIC model.
- The impact on the subsequent forecasts for atmospheric parameters and streamflow are neutral and slightly positive, respectively.
- Future work must focus on model physics and parameterizations to make optimal use of the new observation type.
- Additional applications that could benefit from L-band observations are related to sea ice thickness, hurricane wind speeds, and the global carbon cycle.