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Soil Moisture Applications in Earth Sciences

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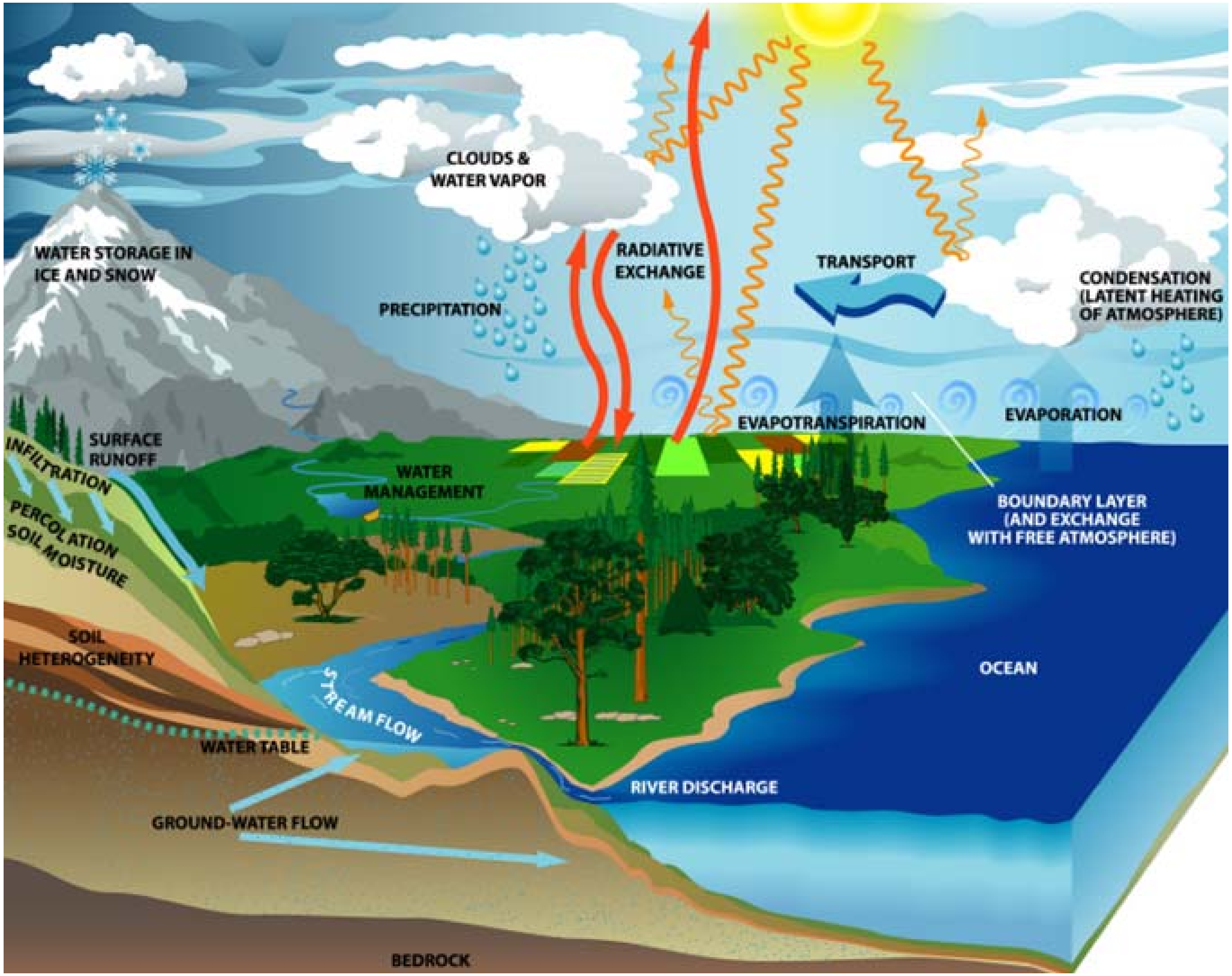
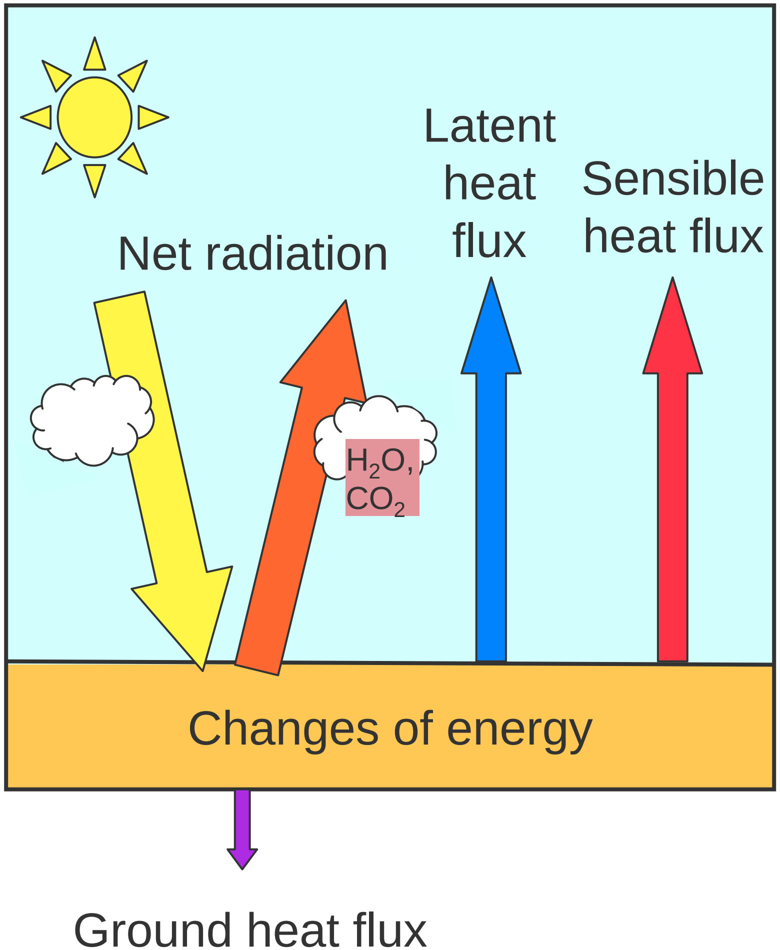
Water Cycle



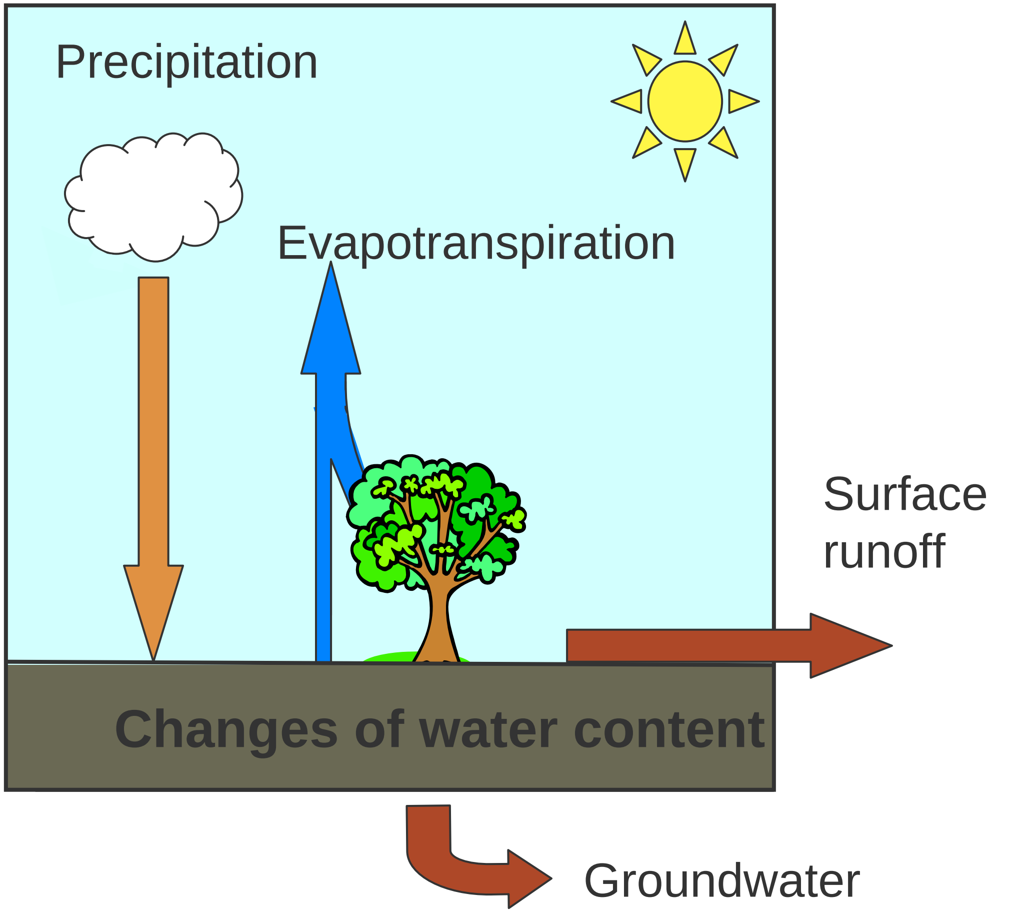
Water Cycle (http://www.usgcrp.gov/usgcrp/images/ocp2003/)

Coupling of Energy and Water Balance

Land energy balance



Land water balance



Seneviratne SI, Corti T, Davin EL, et al. (2010) Investigating soil moisture-climate interactions in a changing climate: A review, Earth-Science Reviews, 99(3-4), 125-161

Relevance of Soil Moisture in Hydrology

- Hydrologists are primarily interested in runoff and water budgets

$$R(\theta) = P - ET(\theta) - \Delta\theta$$

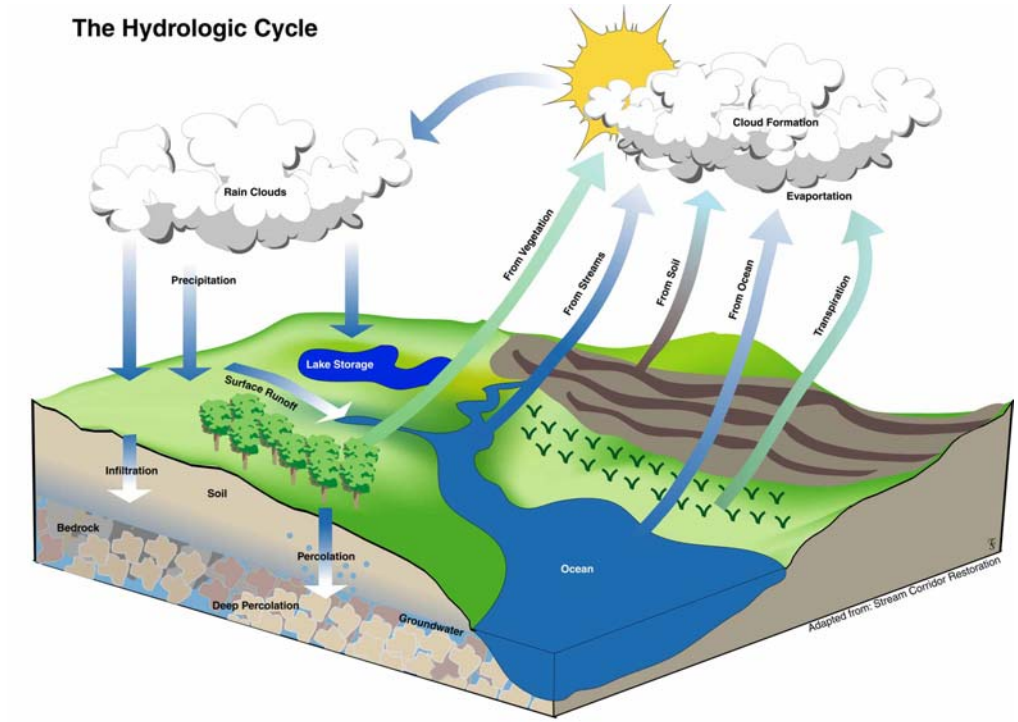
θ … Soil moisture

$\Delta\theta$ ..Change in θ

P …Precipitation

R …Runoff

ET…Evapotranspiration



Relevance of Soil Moisture in Energy Balance

- Soil moisture does not enter the land surface energy balance equation directly

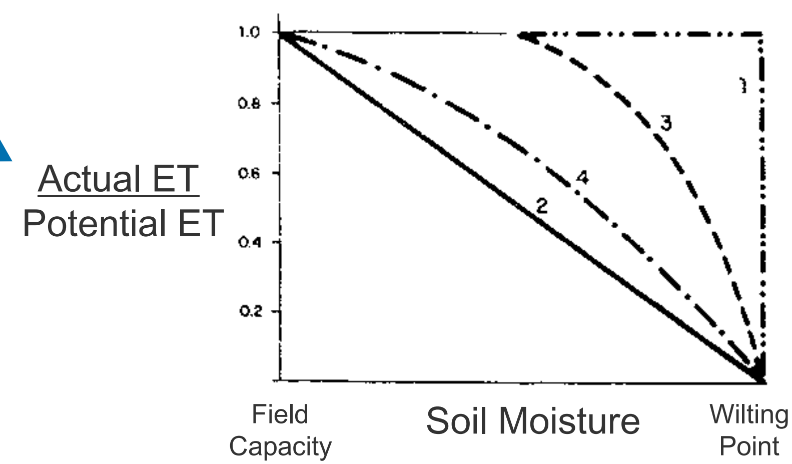
$$\rho C(\theta)\Delta T_s = [1-\alpha(\theta)]S^{\downarrow} + L^{\downarrow} - \varepsilon(\theta)\sigma T_s^4 - H - \lambda \cdot ET(\theta) - G$$

- But strongly influences several terms

Decreasing importance

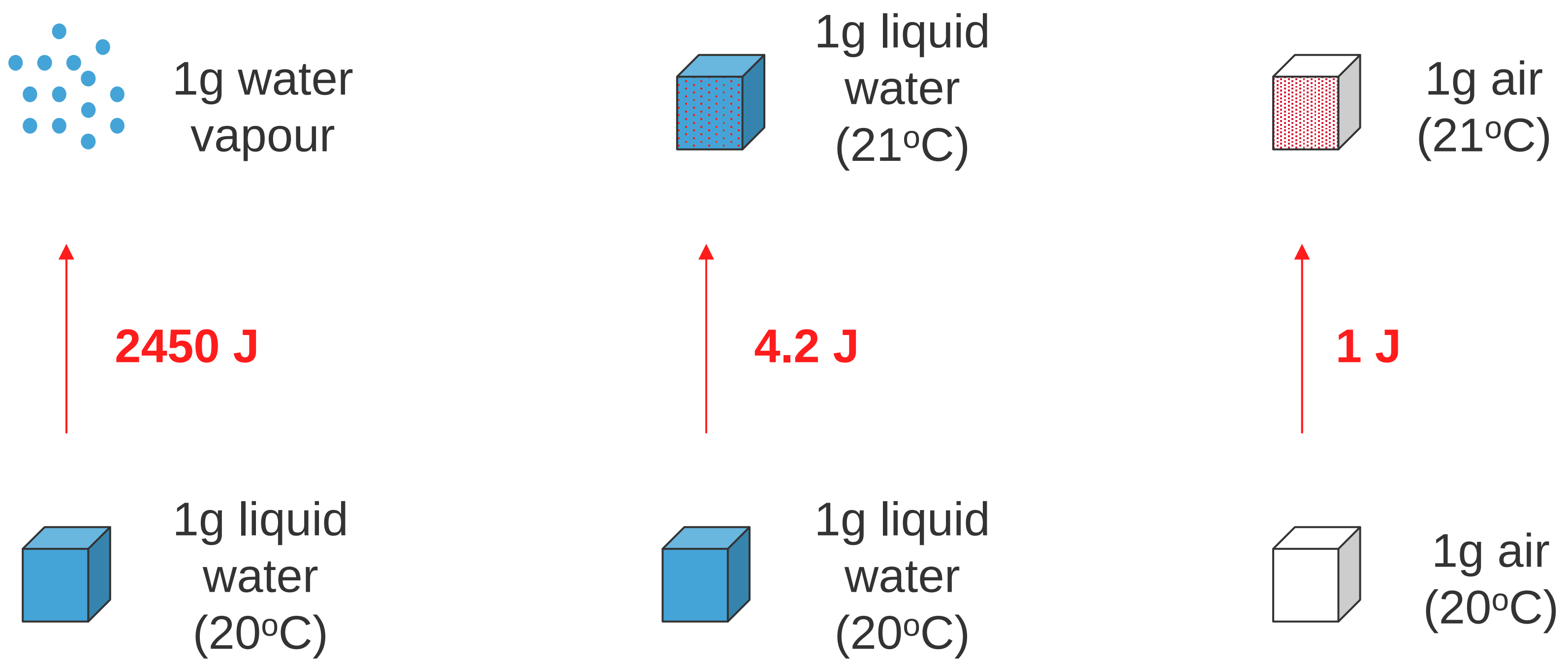
- Evapotranspiration
- Specific heat capacity
  - Soil dry = 800 J/kgK
  - Soil wet = 1480 J/kgK
  - Water = 4180 J/kgK
- Emissivity
- Albedo

Different Models of Actual ET

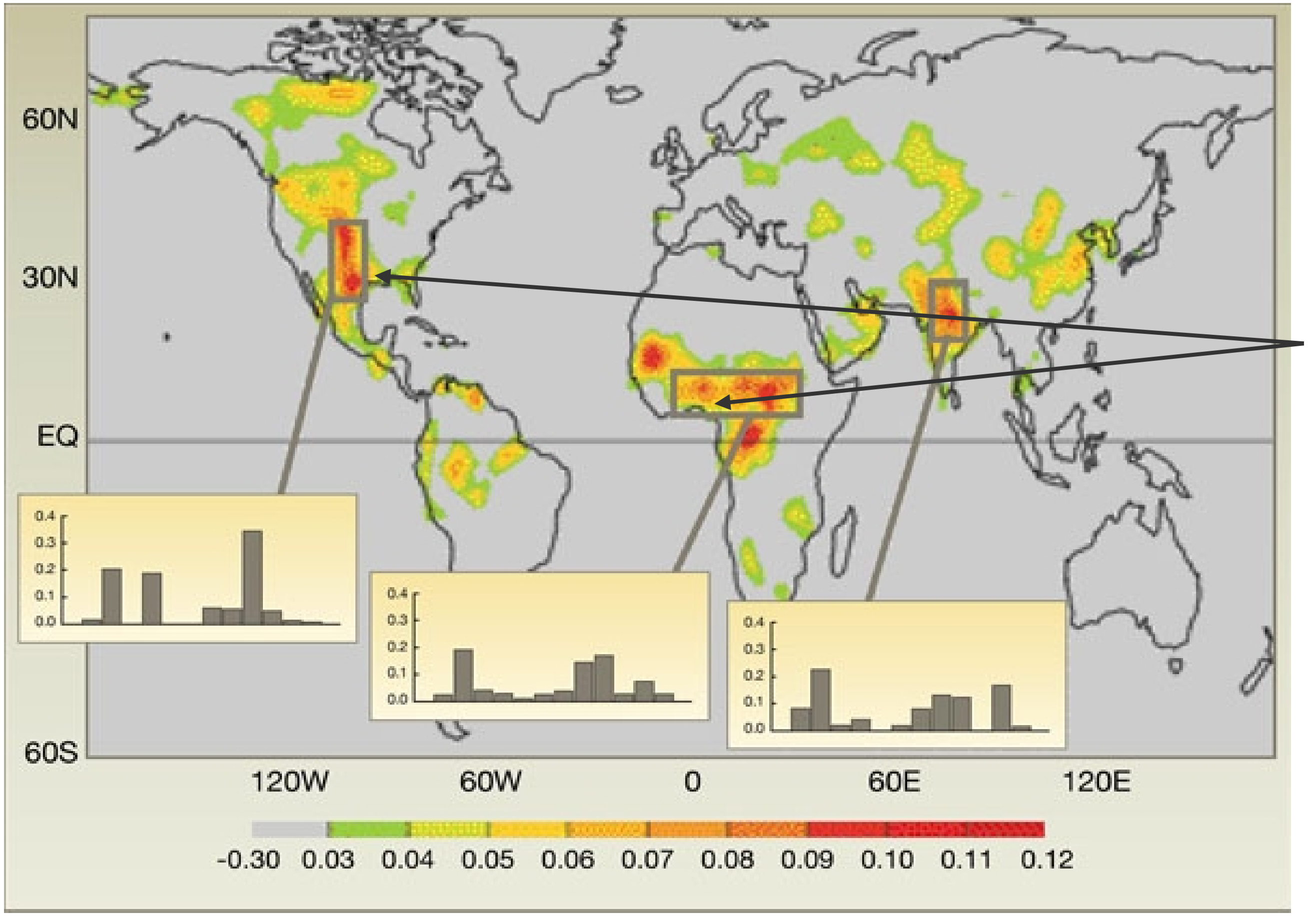


Relevance of Soil Moisture for Meteorology

- Evapotranspiration is associated with a large energy flux



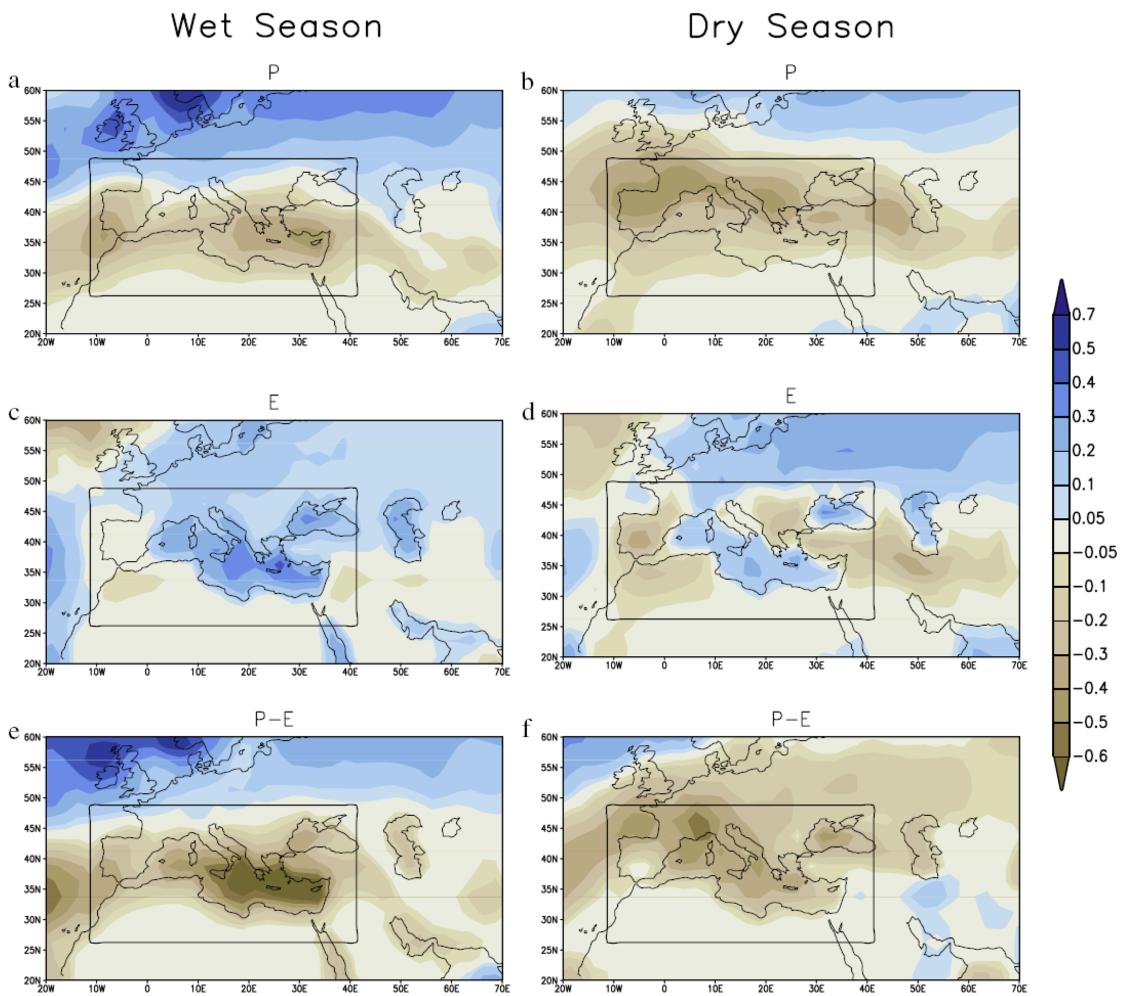
Areas of Strong Land-Atmosphere Coupling



Strong coupling in transitional zones between dry and wet climates

Koster RD, Dirmeyer PA, Guo ZC, et al. (2004) Regions of strong coupling between soil moisture and precipitation, Science, 305 (5687), 1138-1140

Predicted Climate Change Impacts



Precipitation

Evapotranspiration

Precipitation - Evapotranspiration

Mediterranean water cycle changes by 2070–2099 compared to 1950–2000

Mariotti A, Zeng N, Yoon J-H., et al. (2008) Mediterranean water cycle changes: transition to drier 21st century conditions in observations and CMIP3 simulations. Environ. Res. Lett., 3, 044001.

Annual Mean Rainfall on the Po Watershed 1975-2006: 20% Reduction

Need for Global Soil Moisture Observations

- Socioeconomic Perspective (*Nature* from April 2008)
  - Population growth, economic development and climate change put high pressures on water resources
  - Current models suggest that more rain will fall, but less often
  - Crisis from health sector will soon spill over to the energy and agricultural sectors

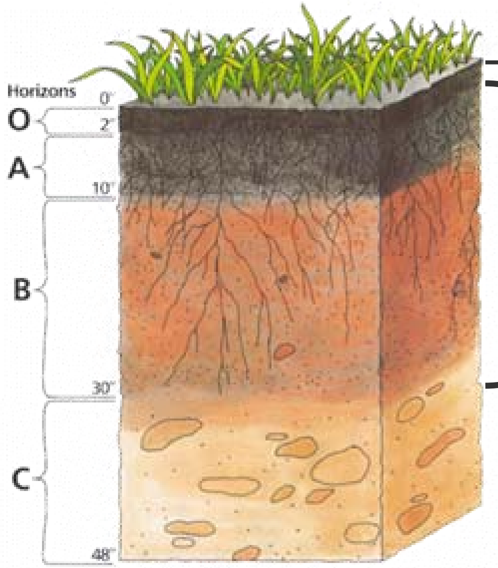
- Model Perspective
  - Model physics at large scale are often not well understood
    - Do we correctly model infiltration, evapotranspiration, etc.?

- Data Perspective
  - Lack and limited representativeness of in-situ soil moisture data
  - Hydrologic soil properties not properly described by soil maps

Estimation of Profile Soil Moisture

- Our method rests upon simple differential model for describing the exchange of soil moisture between surface layer (Θ_s) and the "reservoir" (Θ)
  - T … characteristic time

$$\frac{d\Theta}{dt} = \frac{1}{T}(\Theta - \Theta_s) \quad \Longrightarrow \quad \Theta(t) = \frac{1}{T}\int_{-\infty}^{t} \Theta_s(t')\exp\left[-\frac{t-t'}{T}\right]dt'$$



Thin, remotely sensed soil layer with Θ_s

Root zone with Θ : layer of interest for most applications

Soil profile

Wagner, W., G. Lemoine, H. Rott (1999) A Method for Estimating Soil Moisture from ERS Scatterometer and Soil Data, Remote Sensing of Environment, 70, 191-207.

"Red-Noise" Infiltration Model

- Mathematically, this model corresponds to a first-order Markov process, where
  - $\Theta(t)$ is the process variable
  - $\Theta_s(t)$ is the external forcing
  - *T* is the response time of the system

- The autocorrelation function of $\Theta(t)$ is given by
  - First suggested theoretically for soil moisture by Delworth and Manabe (1988)
  - Confirmed with observations by Robock, Vinnikov, and collaborators

$$r(\tau) = e^{-t/T}$$

- Effects of convolution integral
  - Retarded and smoothed time series

Ceballos, A., K. Scipal, W. Wagner, J. Martínez-Fernández (2005) Validation of ERS scatterometer-derived soil moisture data over the central part of the Duero Basin, Spain, Hydrological Processes, 19, 1549-1566, doi: 10.1002/hyp.5585.

Soil Water Index (SWI)

- SWI is the discrete formulation of the convolution integral

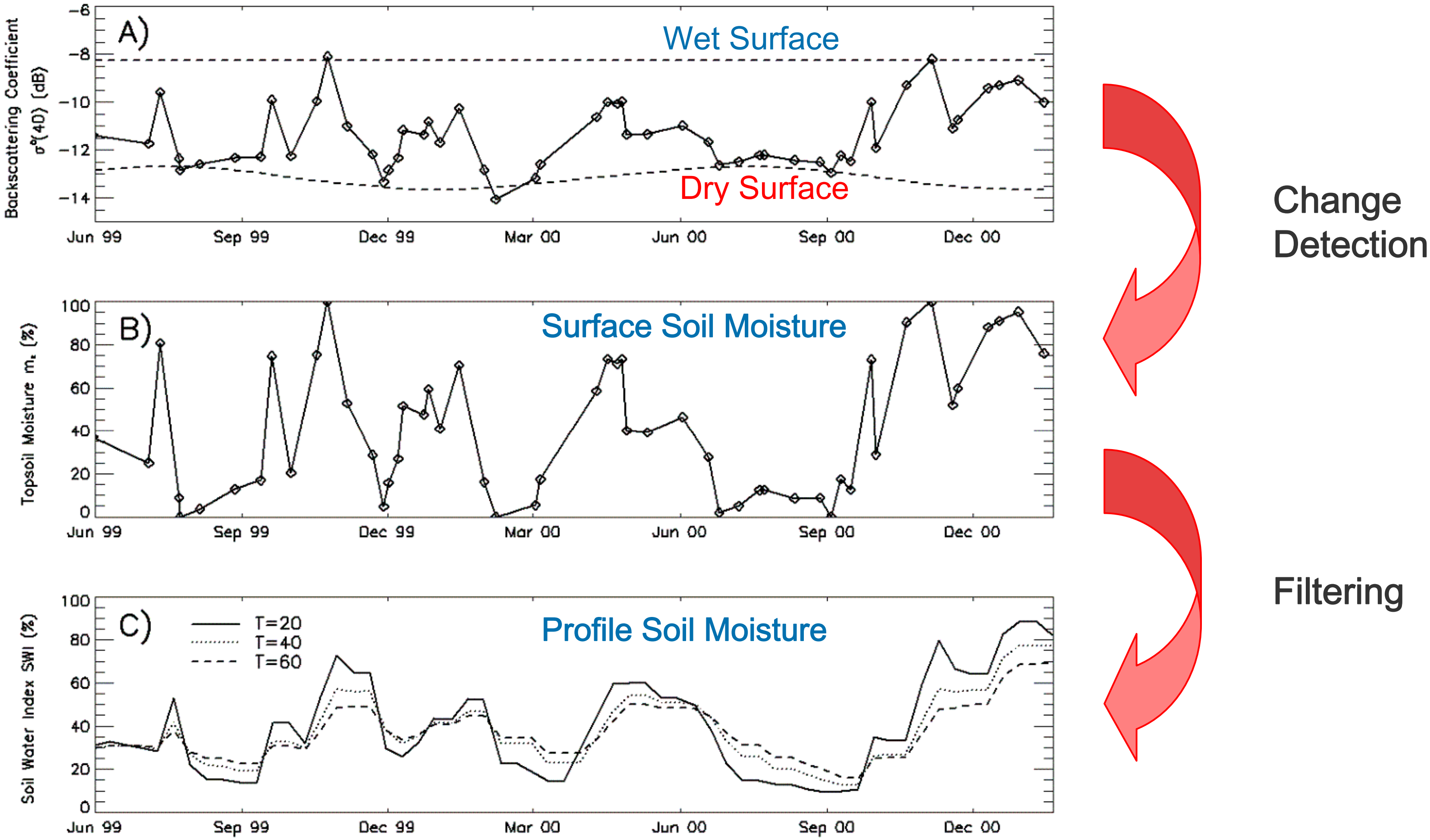
$$SWI(t) = \frac{\sum_i m_s(t_i) e^{-\frac{t-t_i}{t_i}}}{\sum_i e^{-\frac{t-t_i}{t_i}}} \quad \text{for} \quad t_i \le t$$

- Absolute soil moisture values

$$\theta(t) = WL + SWI(t) \cdot \left(\frac{FC + TWC}{2} - WL \right)$$

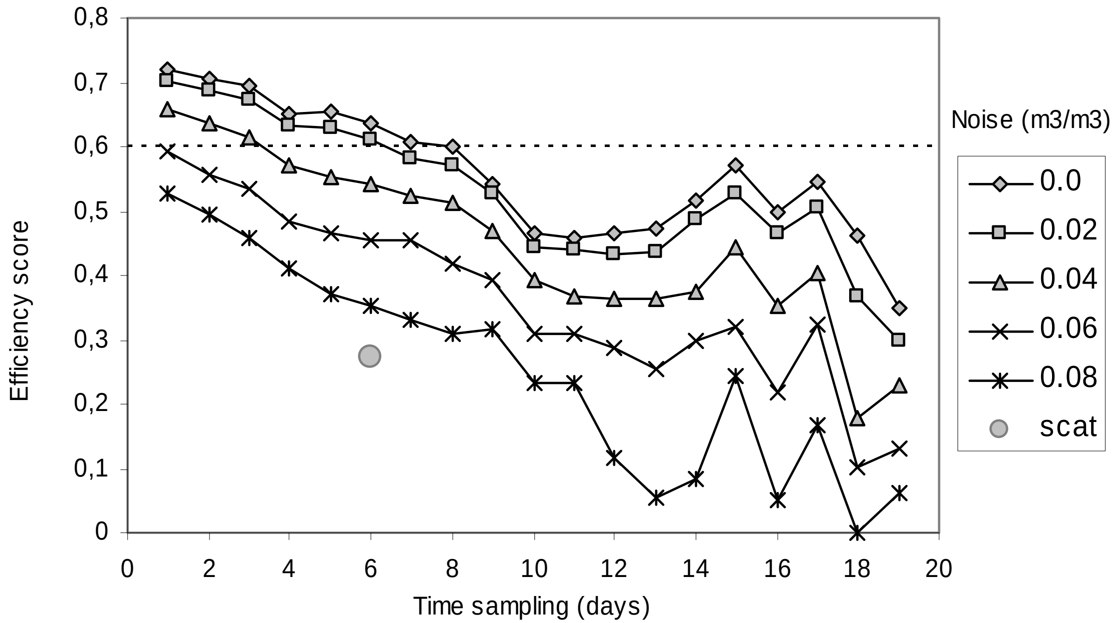
where WL is the wilting point, FC the field capacity and TWC the total water capacity

From Backscatter to Surface and Profile Soil Moisture



Quality of SWI

- The quality of SWI depends critically upon
  - Density of time series
  - Regular sampling
  - Removal of erroneous data (frozen and snow covered soil)



Efficiency based on Model Simulations

Pellarin, T., J.-C. Calvet, W. Wagner (2006) Evaluation of ERS Scatterometer soil moisture products over a half-degree region in Southwestern France, Geophysical Research Letters, 33(17), L17401.

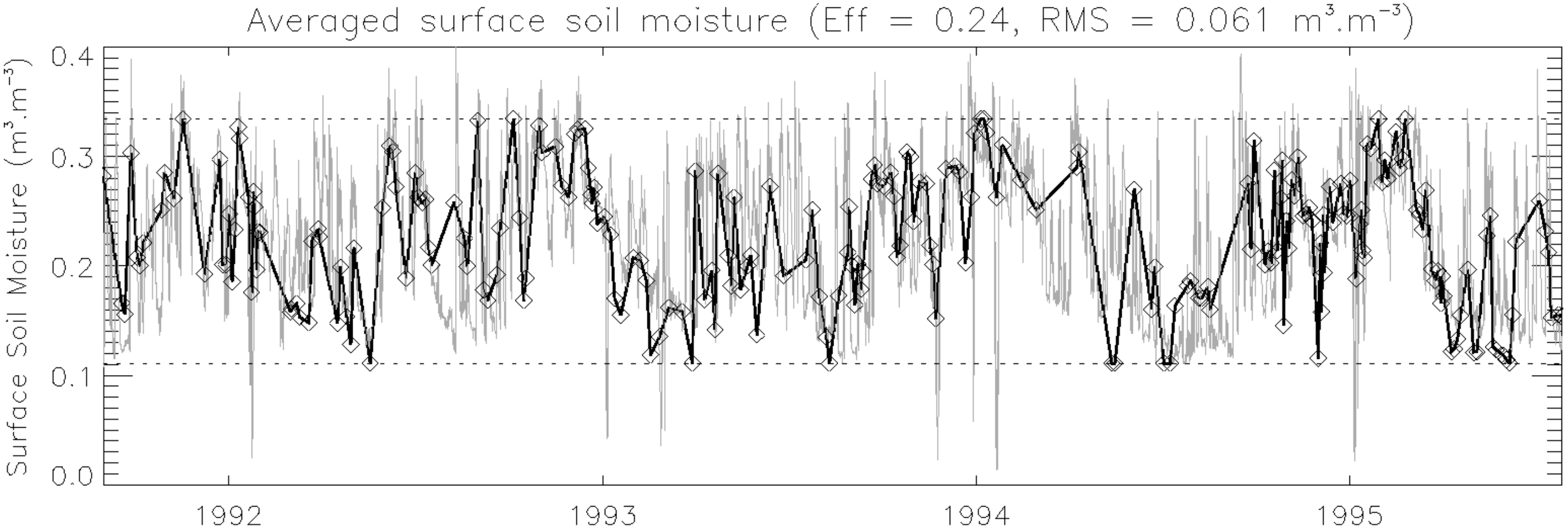
Validation

- No reference data set can provide the absolute truth

- Several independent validation approaches are required
  - Error propagation & Monte Carlo
  - Comparison with in-situ measurements
  - Comparison with modelled soil moisture data
  - Satellite data intercomparison
  - Triple collocation
  - Data assimilation techniques

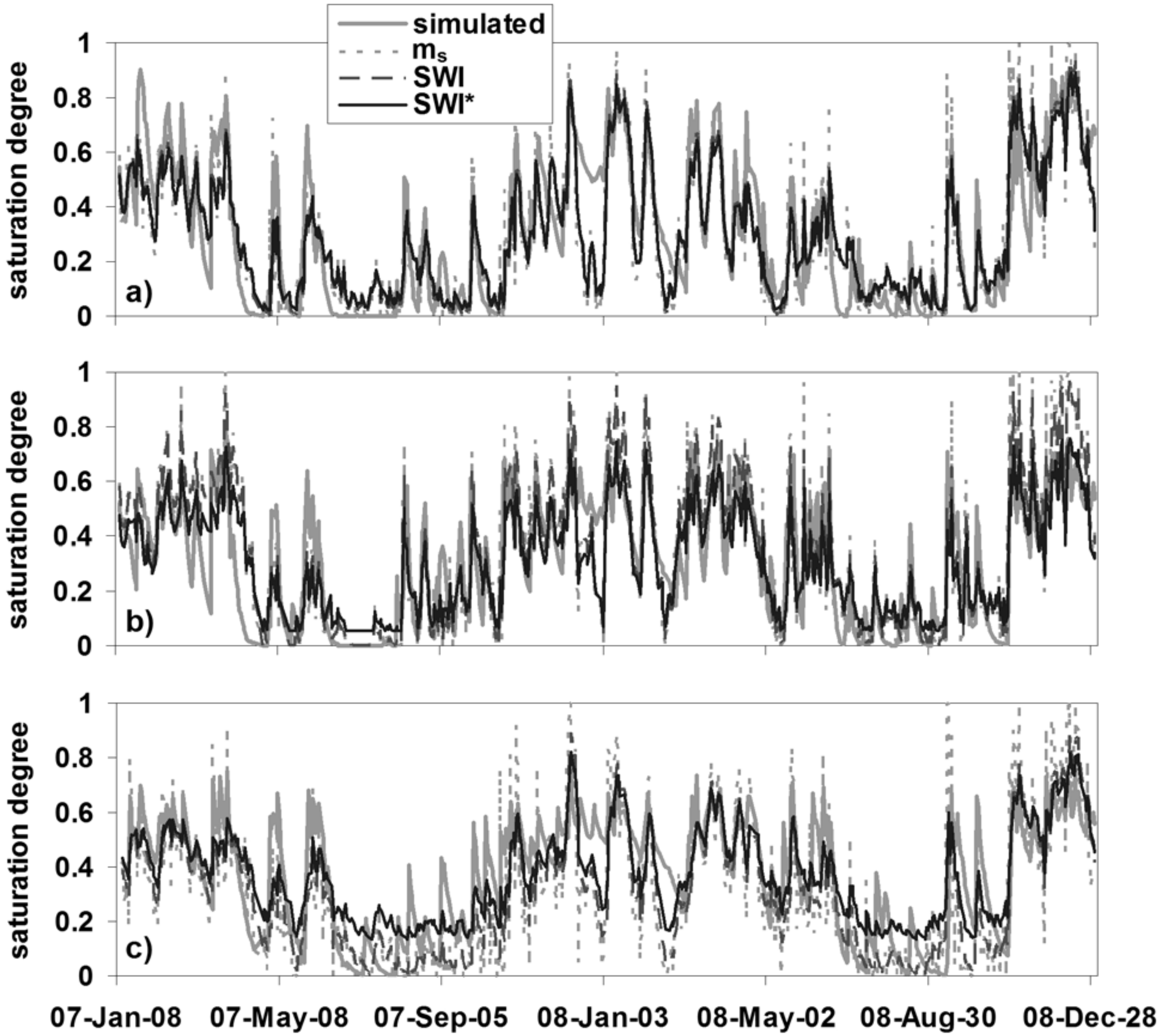
ERS SCAT versus Model

- Comparison of ERS SCAT surface soil moisture with modelled surface soil moisture data
  - South-west France
  - RMSE error ~0.06 m^3m^{-3}



Pellarin, T., J.-C. Calvet, W. Wagner (2006) Evaluation of ERS Scatterometer soil moisture products over a half-degree region in Southwestern France, Geophysical Research Letters, 33(17), L17401.

ASCAT versus Model

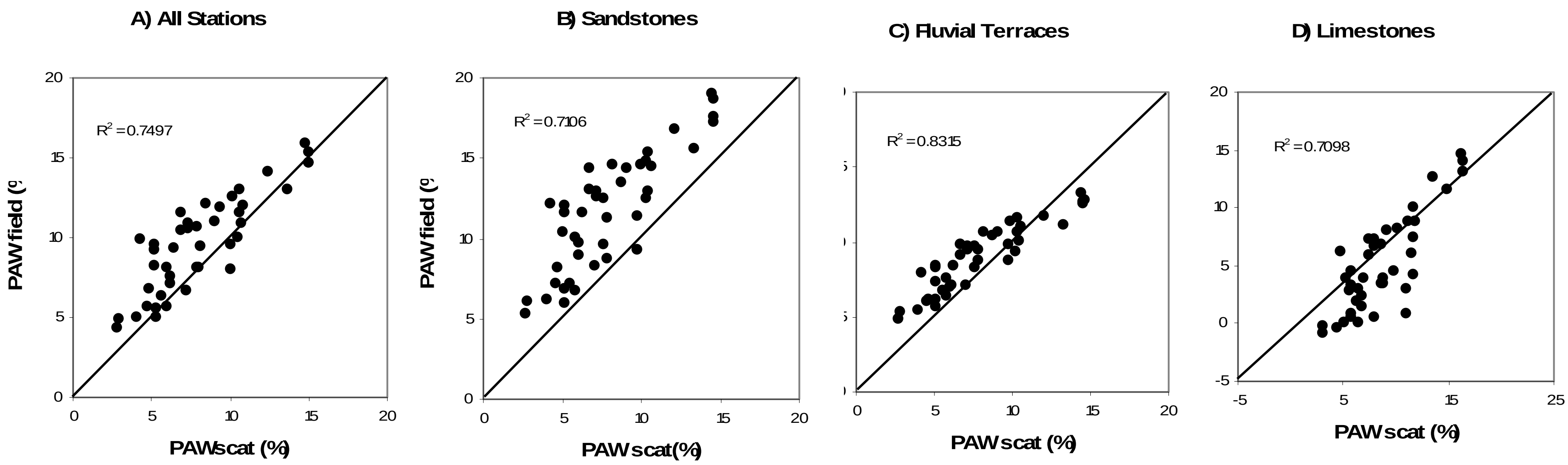


ASCAT versus 3 cm simulated degree of saturation for products, ms, SWI, and SWI* and investigated sites: a) Vallaccia, b) Cerbara, and c) Spoleto.

Brocca, L., F. Melone, T. Moramarco, W. Wagner, S. Hasenauer (2010) ASCAT Soil Wetness Index validation through in-situ and modeled soil moisture data in Central Italy, Remote Sensing of Environment, in press.

ERS SCAT SWI versus In-situ

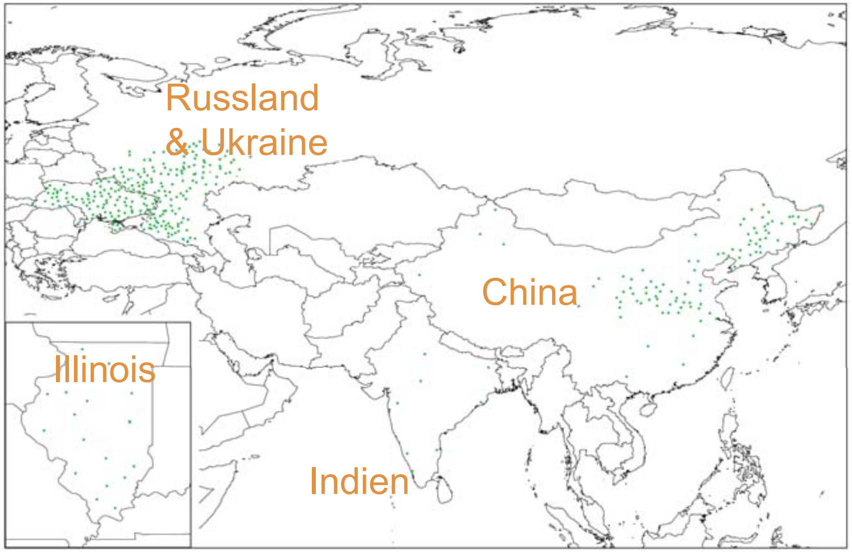
- Duero Basin, Spain, 20 TDR stations
  - Despite scaling problem R2 = 0.71 - 0.83 and RMSE < 4 % vol.



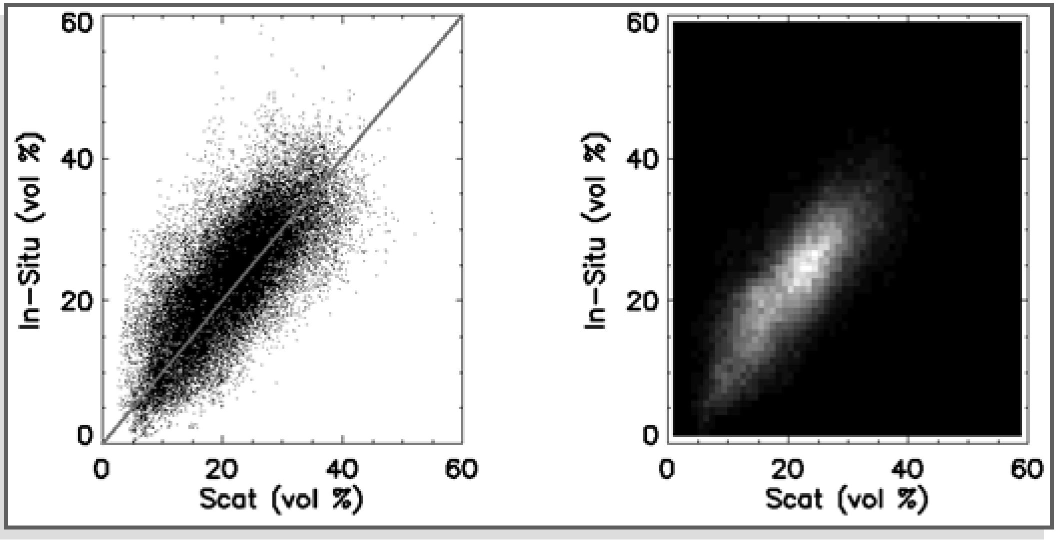
0-100 cm Plant Available Water (PAW) for different soil units in the Duero basin

International Soil Moisture Network

- Gravimetric field measurements of soil moisture
  - 48 000 data points
  - Accuracy of SWI ≈ 5 % vol. for 0-100 cm layer

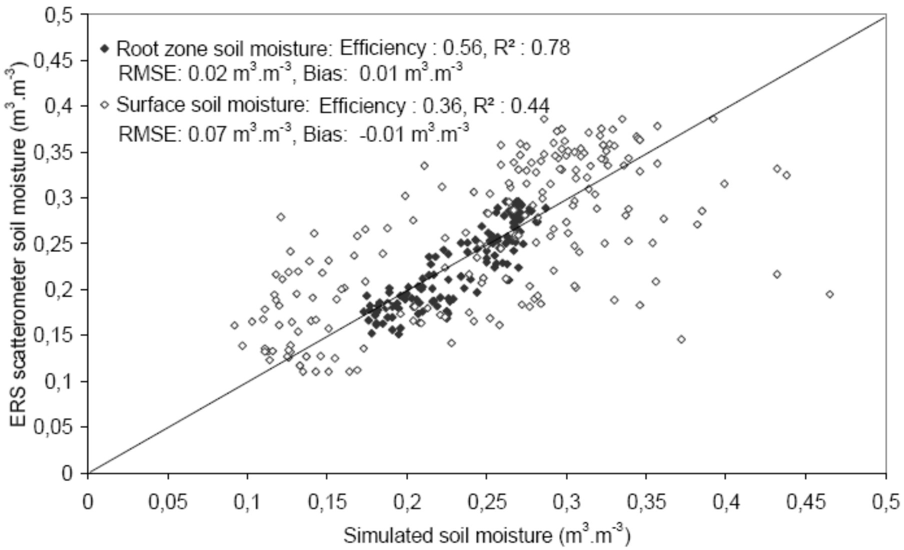


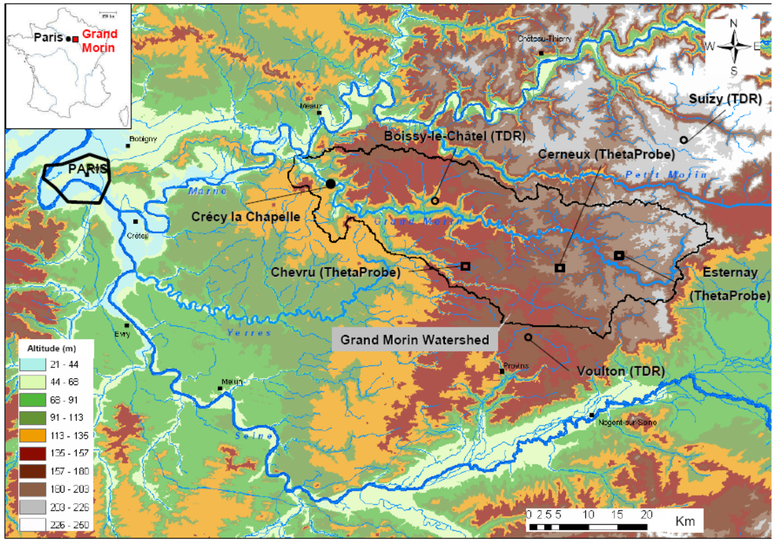
Location of in-situ soil moisture stations



Error of Surface versus Profile Soil Moisture

- Error of surface soil moisture typically larger (4-8 %) than for the estimated profile soil moisture content (2-5 %)

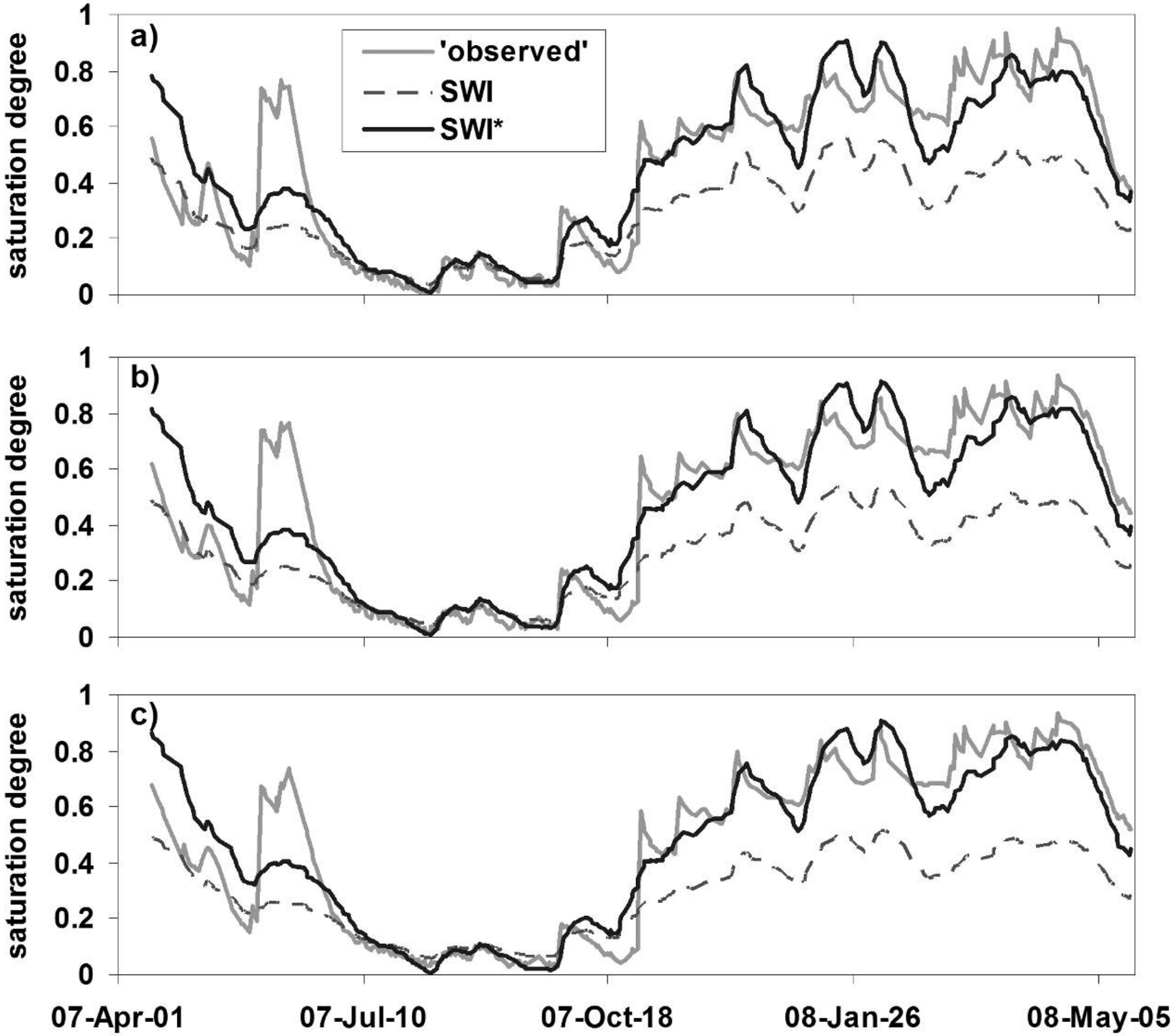




Comparison of surface and root-zone soil moisture (m3 m−3) for ERS scatterometer data (5 cm and 1m depth, respectively) and simulation (1 cm and 1.5m depth, respectively), from June 1997 to November 2000 in Grand Morin watershed near Paris, France.

Paris Anguela, T., M. Zribi, S. Hasenauer, F. Habets, C. Loumagne (2008) Analysis of surface and root-zone soil moisture dynamics with ERS scatterometer and the hydrometeorological model SAFRAN-ISBA-MODCOU at Grand Morin watershed (France), Hydrol. Earth Syst. Sci., 12, 1415-1424.

ASCAT SWI versus In-Situ



SWI and scaled SWI* versus in-situ data from the Vallaccia catchment at

a) 10 cm
b) 20 cm
c) 40 cm

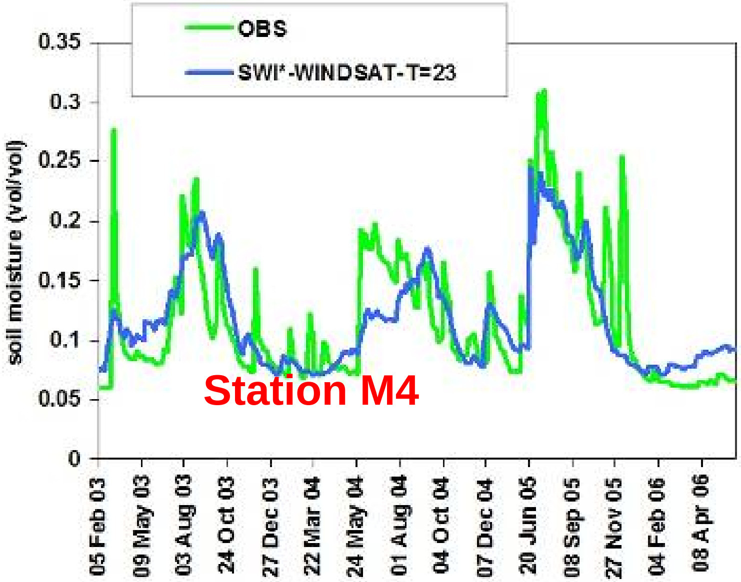
Correlation and RMSE for Surface and SWI

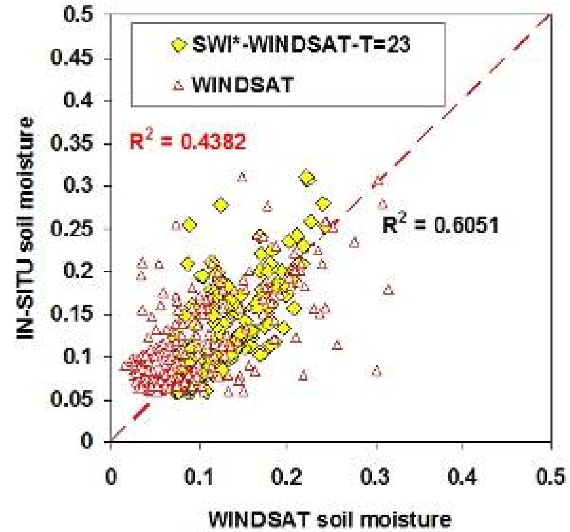
Depth (cm)	N	T (days)	m_s (T=0)			SWI			SWI*
			R	R_{SP}	RMSE	R	R_{SP}	RMSE	RMSE
10	342	19.5	0.672	0.717	0.264	0.921	0.924	0.216	0.114
20	342	23.0	0.643	0.691	0.280	0.925	0.928	0.226	0.110
40	342	29.0	0.605	0.643	0.294	0.938	0.936	0.231	0.105
Anomalies									
10	314	19.5	0.580	0.560	0.831	0.700	0.730	0.635	0.635
20	314	23.0	0.547	0.529	0.862	0.707	0.730	0.626	0.626
40	314	29.0	0.498	0.489	0.907	0.728	0.741	0.598	0.598

Comparison between the in situ and ASCAT degree of saturation for three products: surface soil moisture, m_s, Soil Wetness Index, SWI, and linearly rescaled Soil Wetness Index, SWI*. (N: number of observations, T: characteristic time length, R and RSp: Pearson and Spearman correlation coefficient, RMSE: root mean square error).

Brocca, L., F. Melone, T. Moramarco, W. Wagner, S. Hasenauer (2010) ASCAT Soil Wetness Index validation through in-situ and modeled soil moisture data in Central Italy, Remote Sensing of Environment, in press.

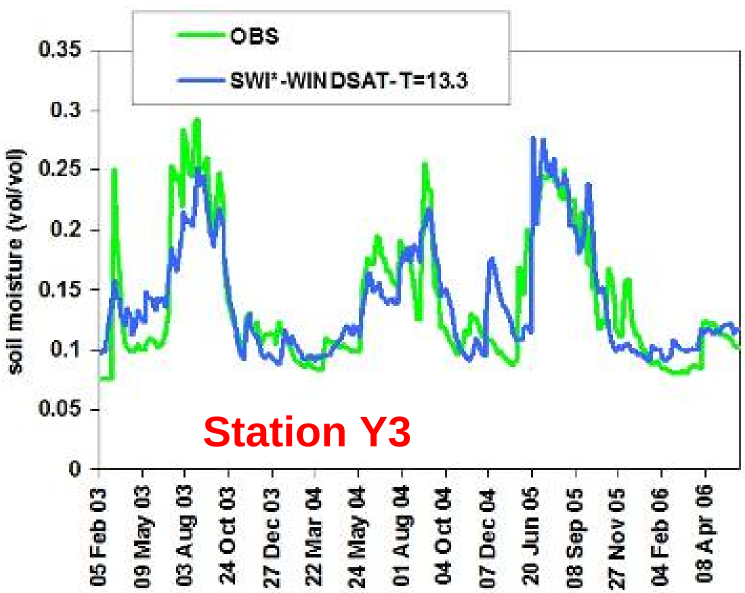
Windsat validation Oznet (Australia)

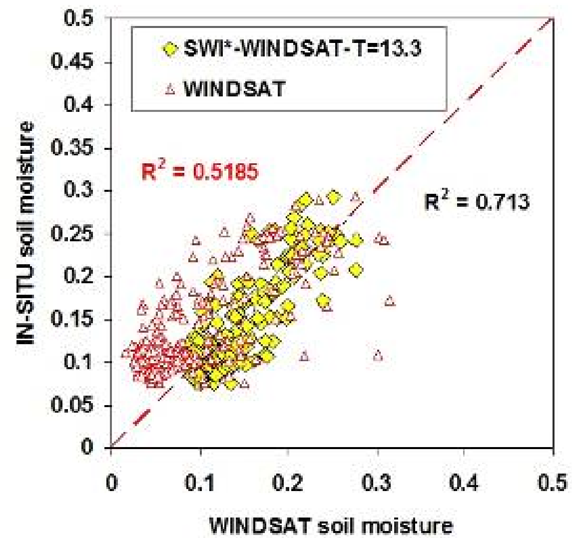




WINDSAT

$R_{ms}=$	0.662
$R_{SWI}=$	0.778
$RMSD_{SWI*}=$	0.034

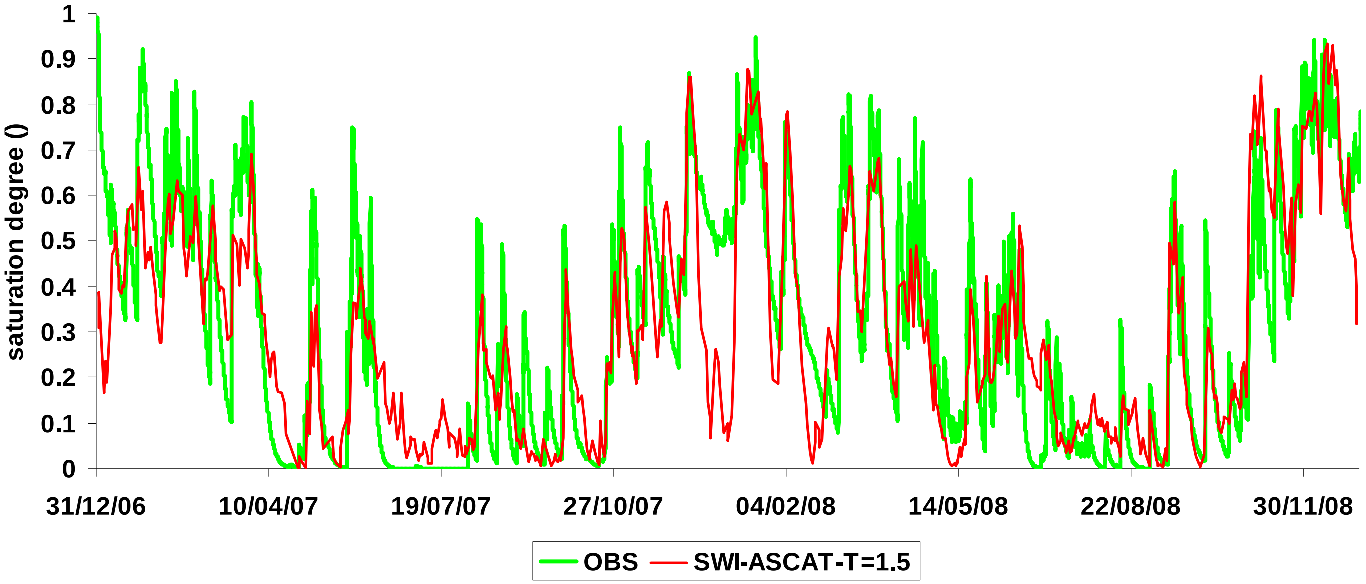


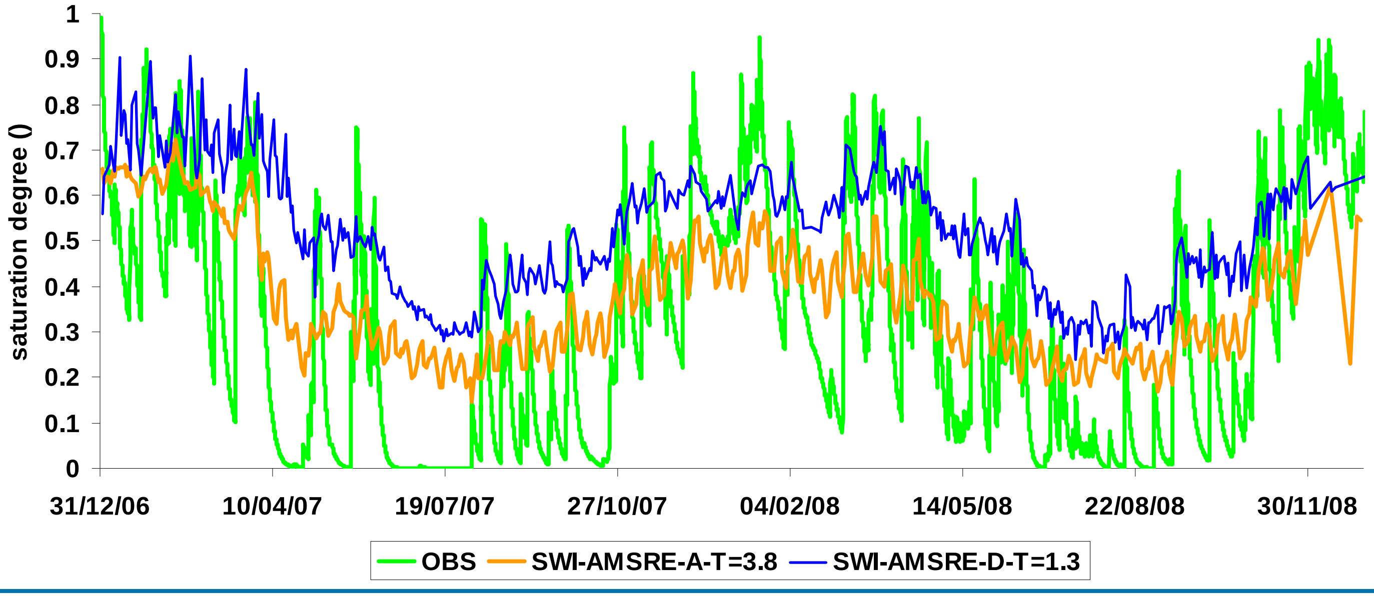


WINDSAT

$R_{ms}=$	0.720
$R_{SWI}=$	0.844
$RMSD_{SWI*}=$	0.030

ASCAT vs AMSR-E (VUA)





ASCAT

R_{ms}= 0.839
R_{SWI}= 0.871
$RMSD_{SWI^*}$= 0.131

AMSRE-A

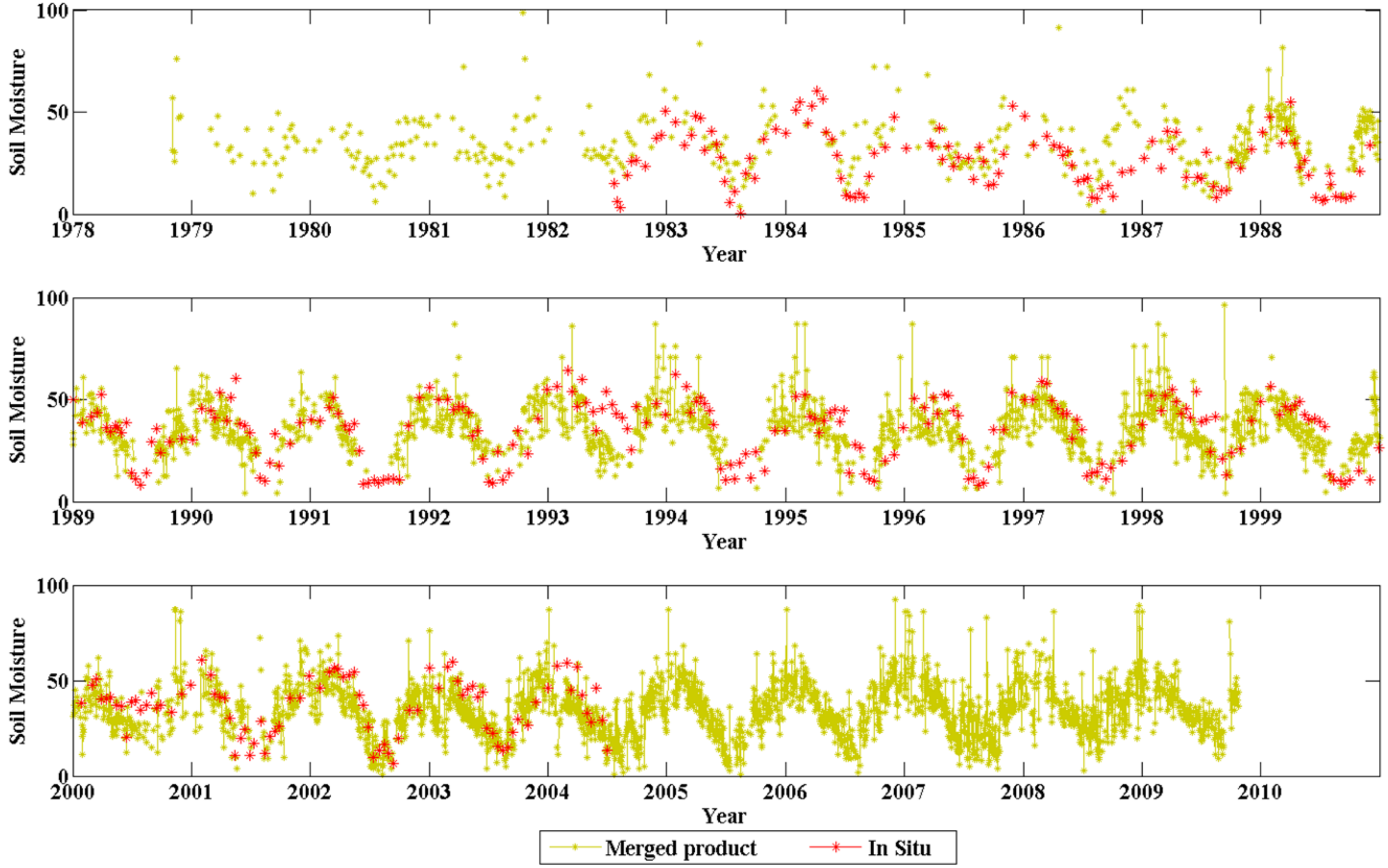
R_{ms}= 0.605
R_{SWI}= 0.748
$RMSD_{SWI^*}$= 0.165

AMSRE-D

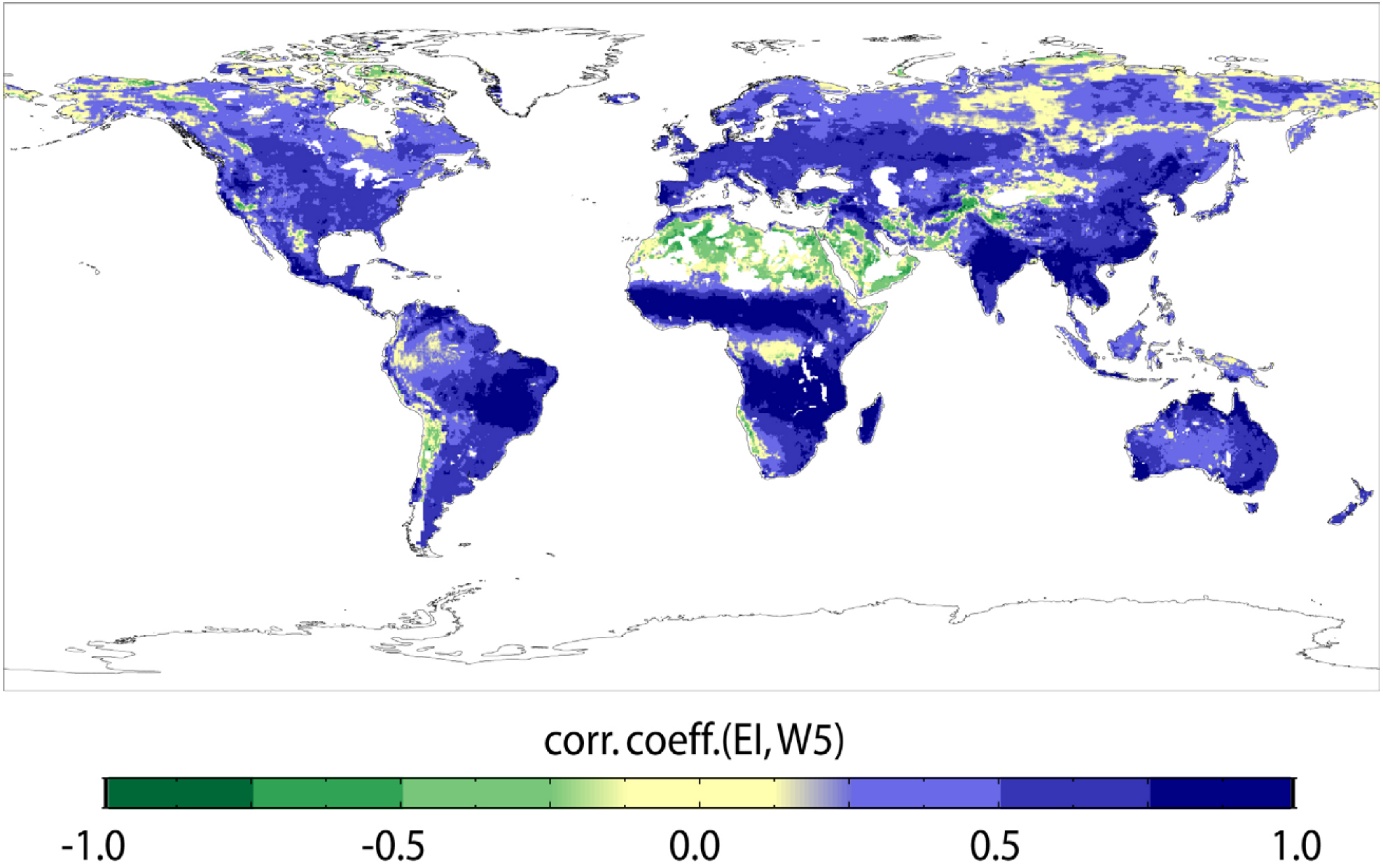
R_{ms}= 0.701
R_{SWI}= 0.719
$RMSD_{SWI^*}$= 0.169

Validation Merged Active/Passive Time Series

- Illinois Climate network



Comparison with ERA Interim Reanalysis



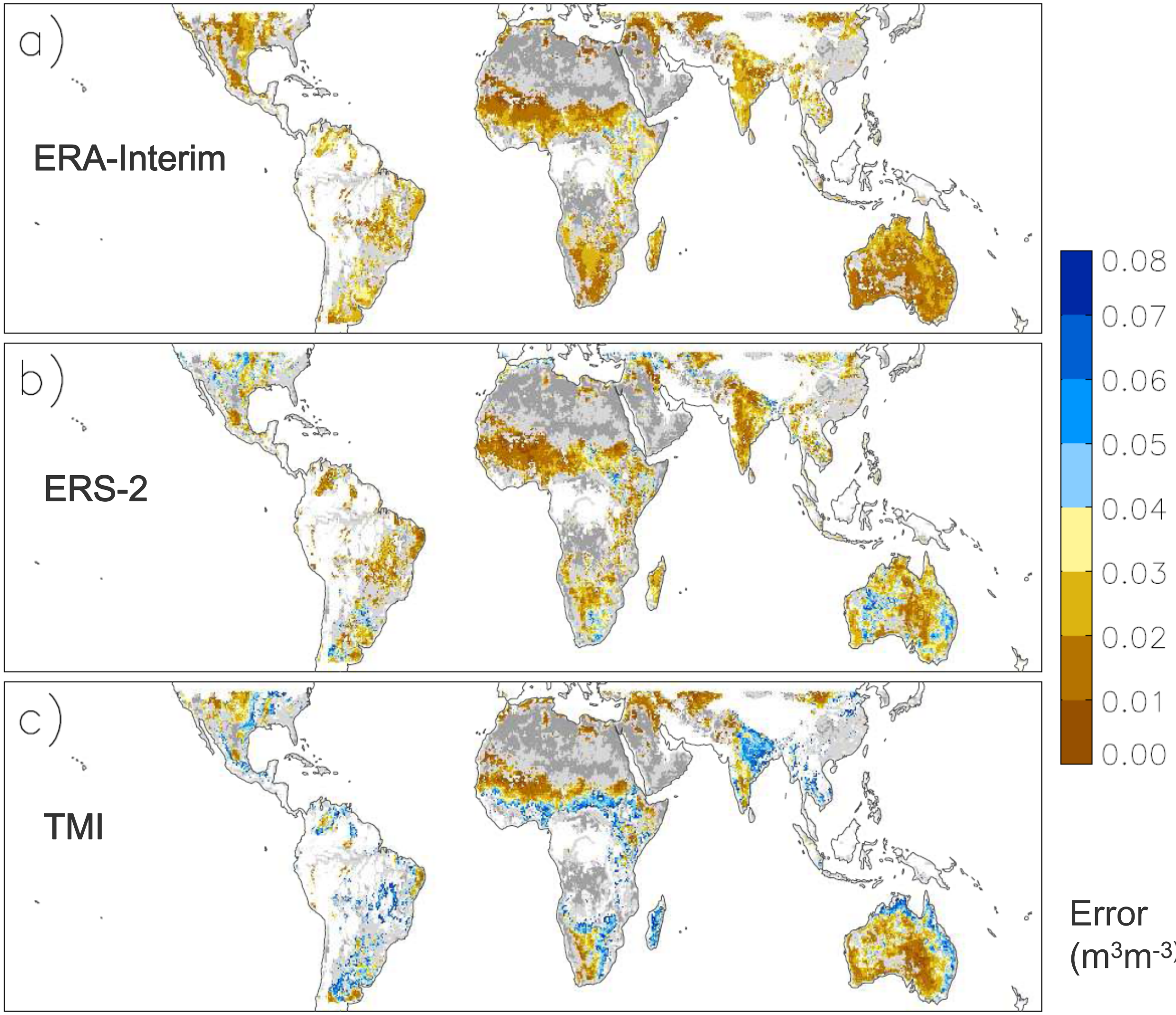
Triple Collocation Error Model

- Error model
- Assumptions
  - Linear and uncorrelated errors

$$e_E^{*2} = \langle (\Theta_E^* - \Theta_S^*)(\Theta_E^* - \Theta_T^*) \rangle$$

$$e_S^{*2} = \langle (\Theta_E^* - \Theta_S^*)(\Theta_S^* - \Theta_T^*) \rangle$$

$$e_T^{*2} = \langle (\Theta_E^* - \Theta_T^*)(\Theta_S^* - \Theta_T^*) \rangle$$

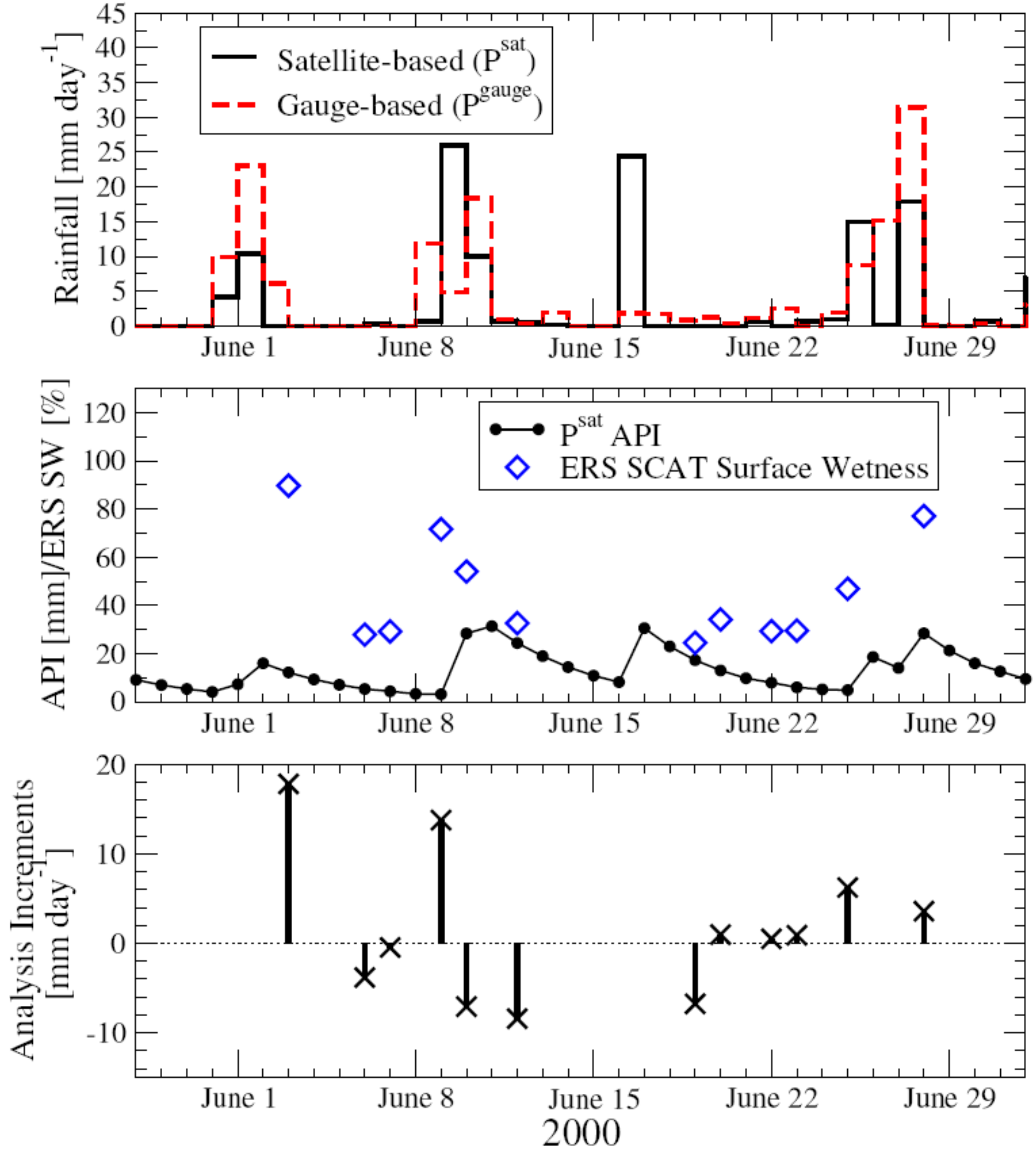


Scipal, K., T. Holmes, R. de Jeu, V. Naeimi, W. Wagner (2008) A possible solution for the problem of estimating the error structure of global soil moisture datasets, Geophysical Research Letters, 35, L24403, doi:10.1029/2008GL035599.

Assimilation

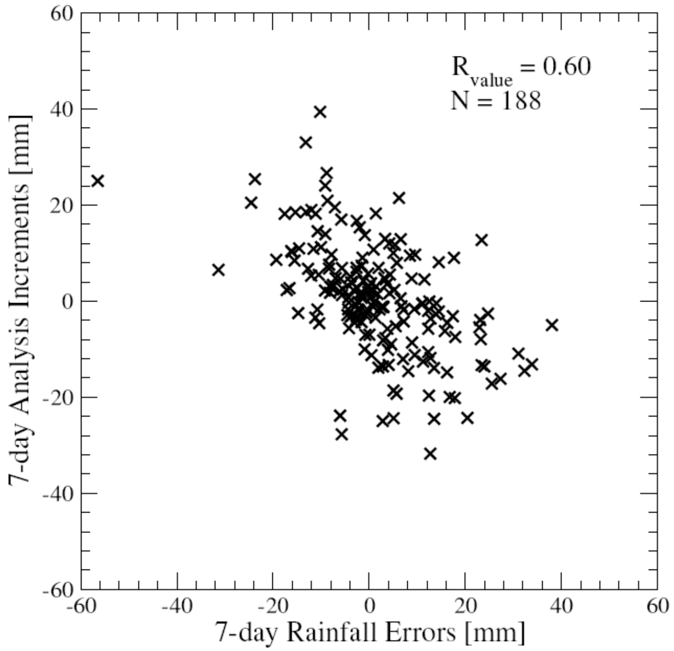
- Models and data are imperfect
- Improve outputs by data assimilation

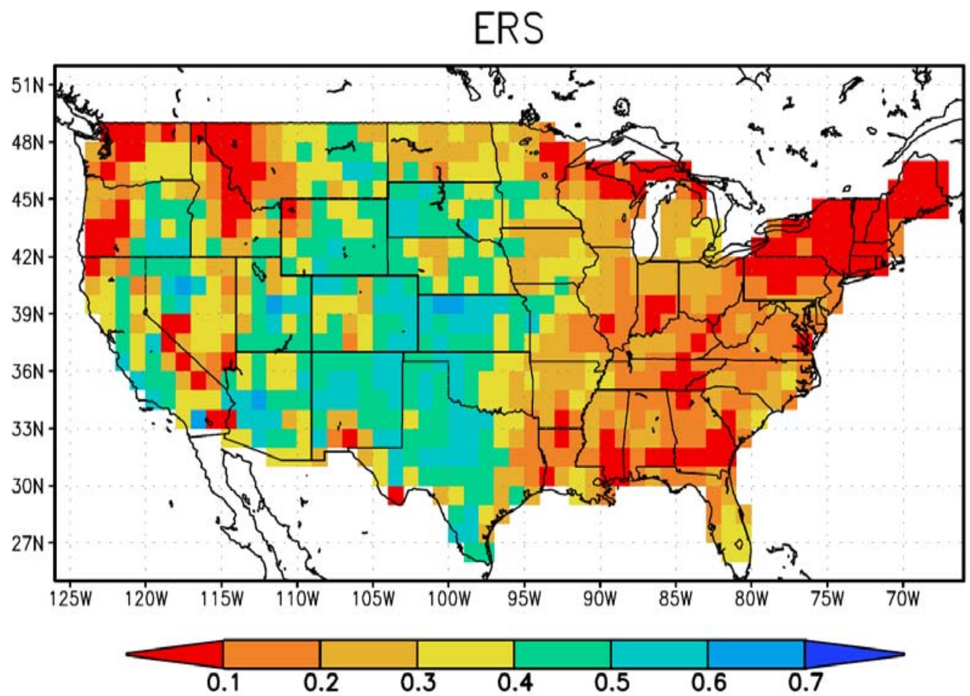
- Satellite soil moisture data can help to correct impact of erroneous precipitation data
  - Wade Crow (2007) Journal of Hydrometeorology



Crow, W.T., and X. Zhan, "Continental-scale evaluation of remotely-sensed soil moisture products," IEEE Geoscience and Remote Sensing Letters, 4(3), 451-455, 2007.

Added Value of SCAT Soil Moisture





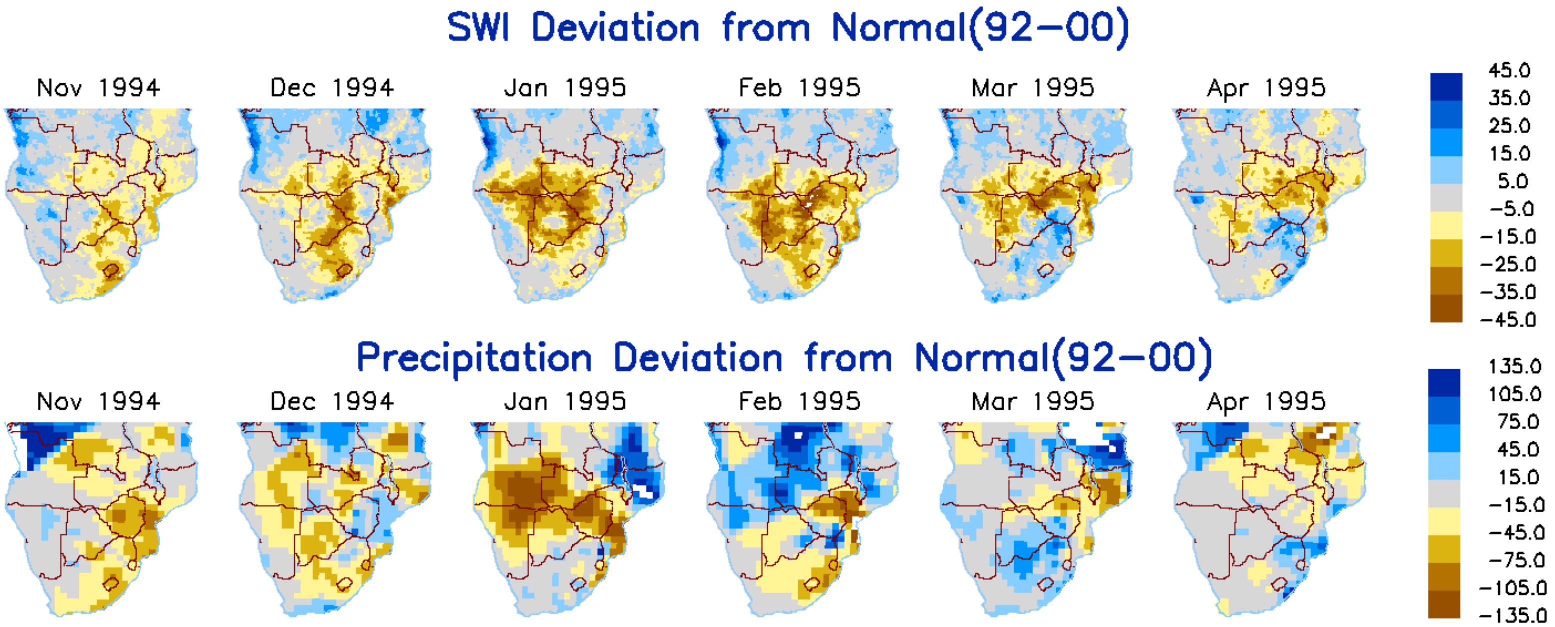
Positive Impact →

Results kindly provided by Wade Crow, USDA

Applications

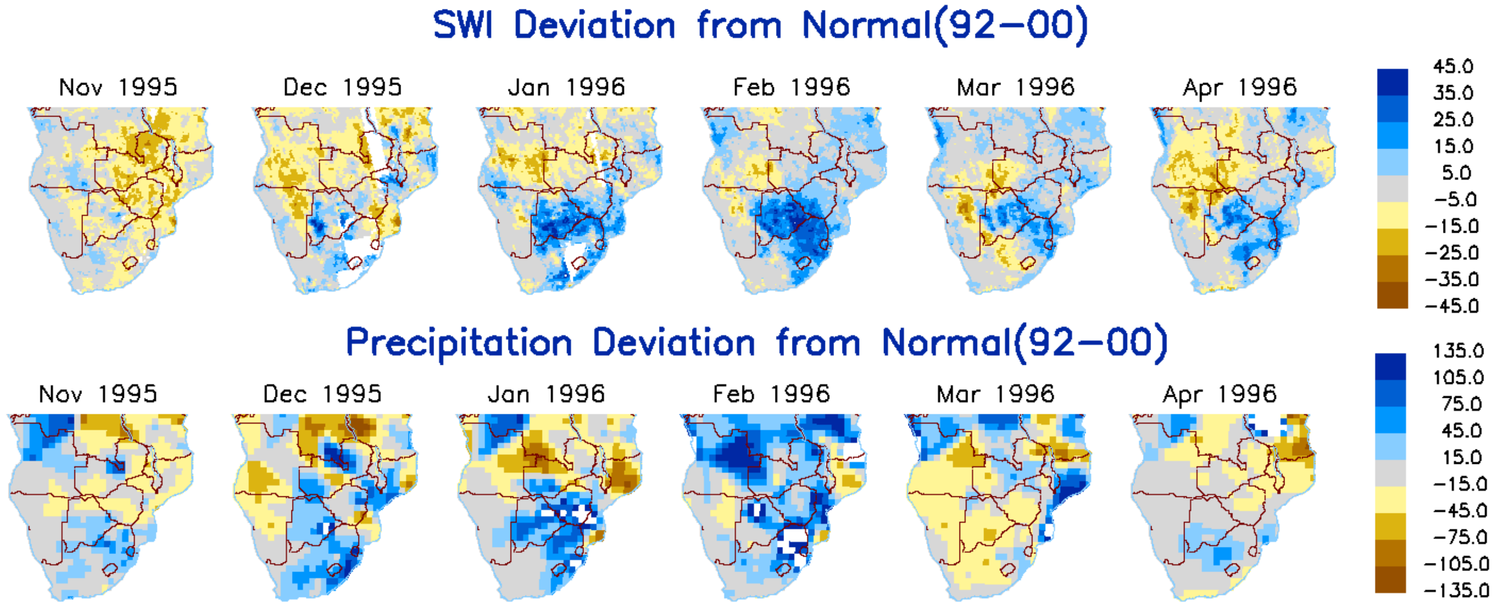
- Early flood warning
- Drought monitoring
- Climate studies
- Runoff forecasting
- Event-based runoff estimation
- Weather forecasting
- Yield monitoring

Droughts in South Africa 1994/95



During the 1994/95 season, a blocking high-pressure system related to warm El Niño events kept southern Africa dry. Most of southern African countries suffered from severe droughts. In the north-western part of Zimbabwe, rainfall during the 1994/1995 season was near the lowest ever recorded. Cereal production fell to 45 percent of the long-term average. USAID reported that over six million people needed emergency assistance because of crop failures and food shortages throughout southern Africa.

Floods in South Africa 1995/96

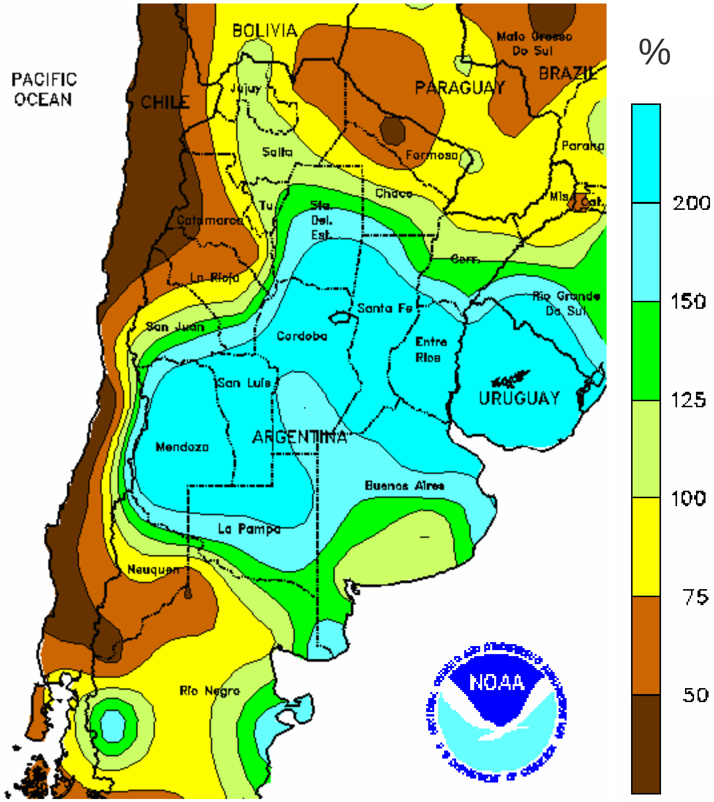


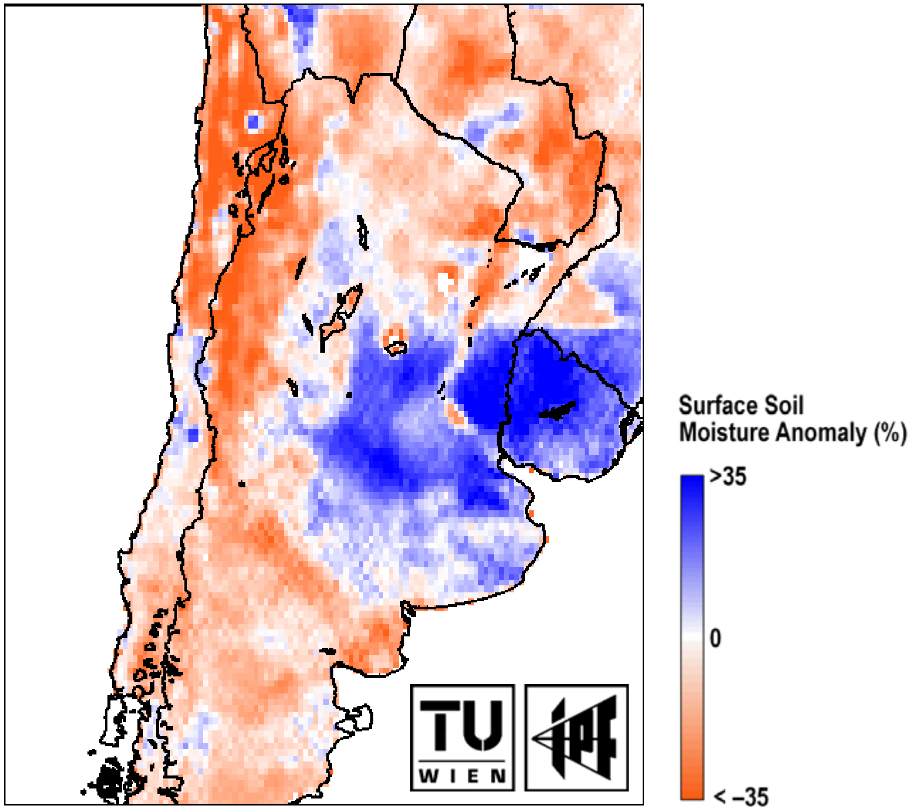
Contrary to the season 1994/95 in the season 1995/96, a progression of Atlantic lows led to a series of storms, bringing heavy rainfall to the area.. According to USAID the excessive rainfalls resulted in floods and consequently in damage to crops and property in the South African areas of Northern Transval and Eastern Cape Provinces and in Mozambique.

Heavy Rains in Northern Argentina/Uruguay

- Comparison with NOAA CPC regional climate map for March 2007.

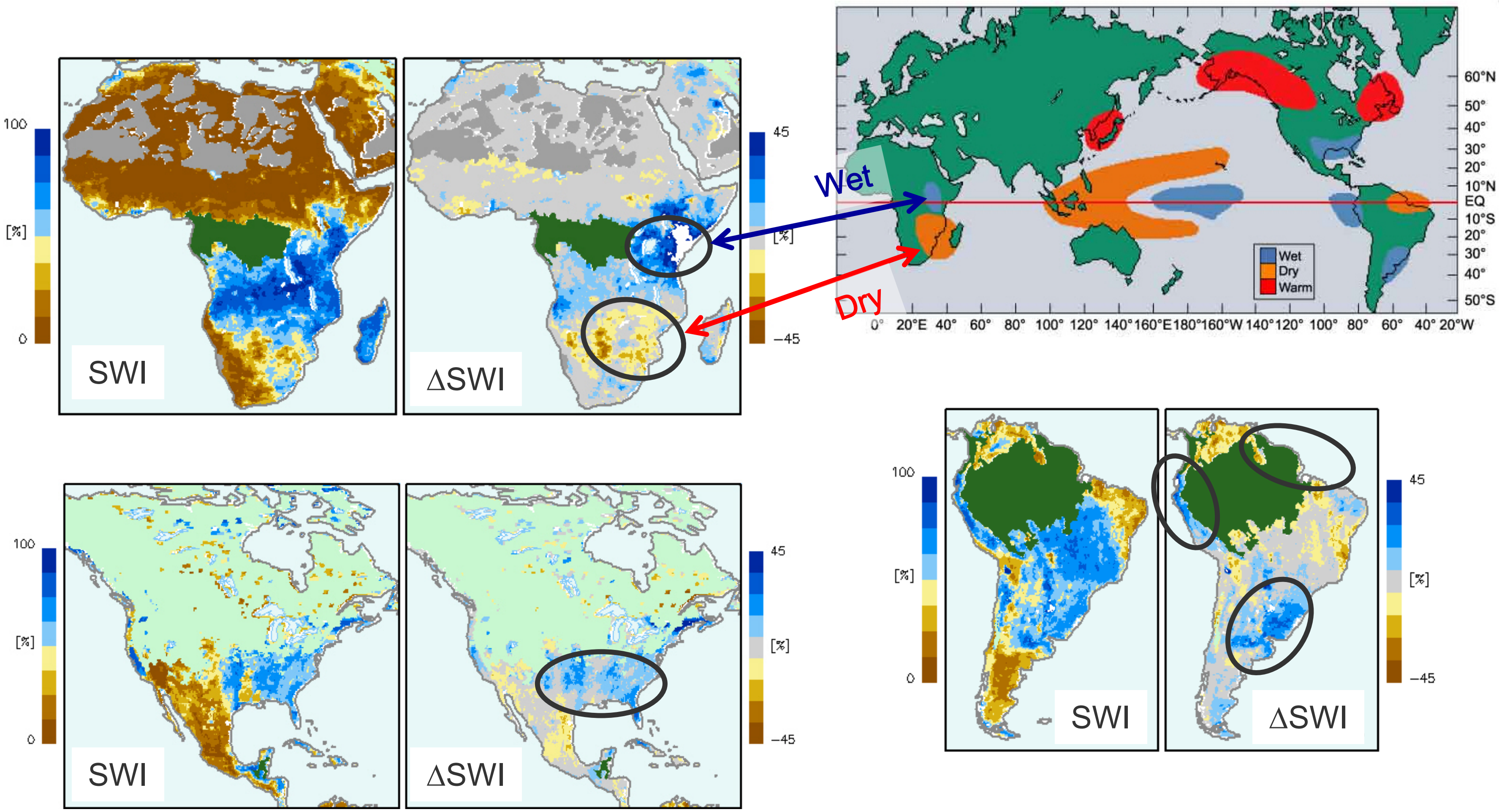
Percent of normal precipitation





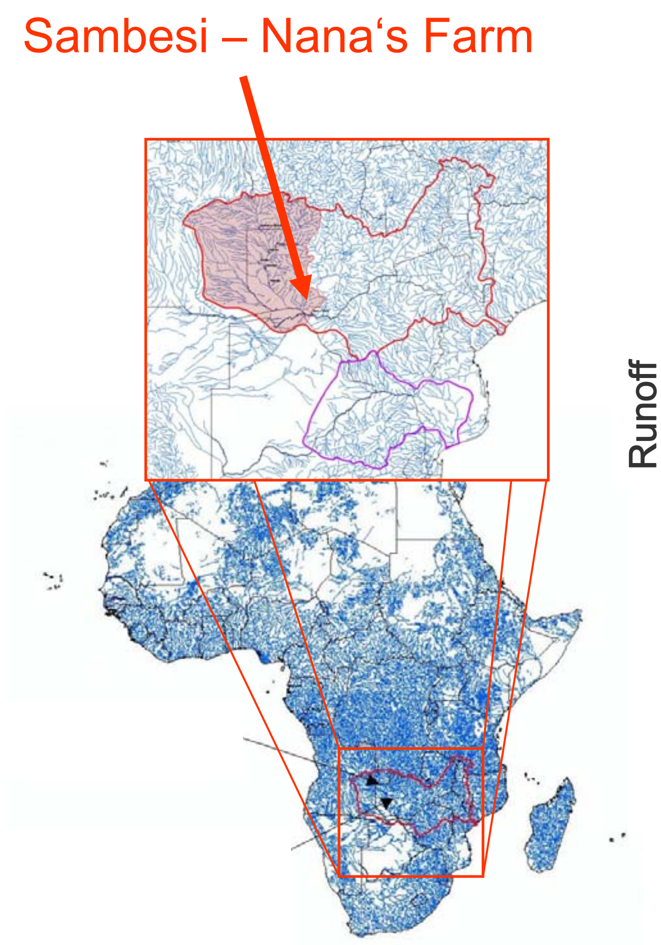
Effects of El Niño 1987-1988

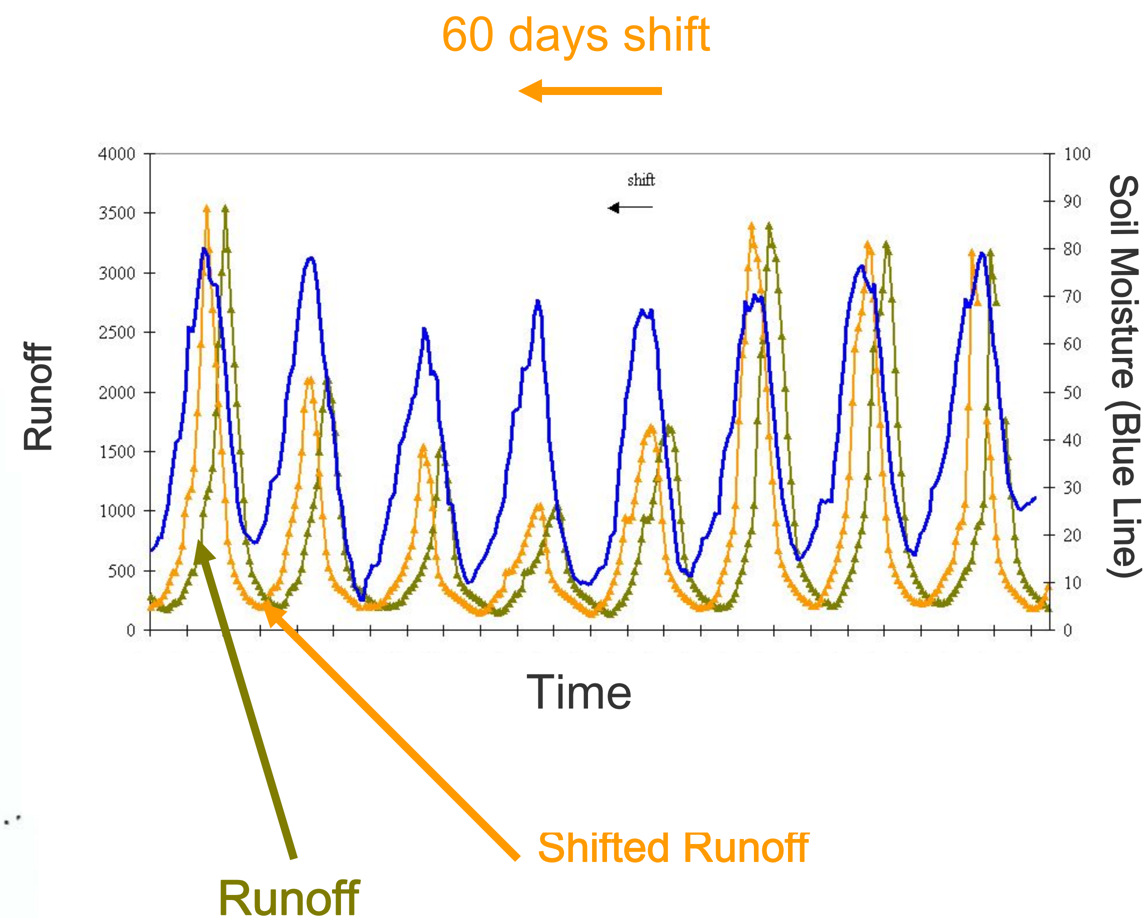
© NOAA



Künzer, C., D. Zhao, K. Scipal, D. Sabel, V. Naeimi, Z. Bartalis, S. Hasenauer, H. Mehl, S. Dech, W. Wagner (2009) El Niño influences represented in ERS Scatterometer derived soil moisture data, Applied Geography, 29(4), 463-477.

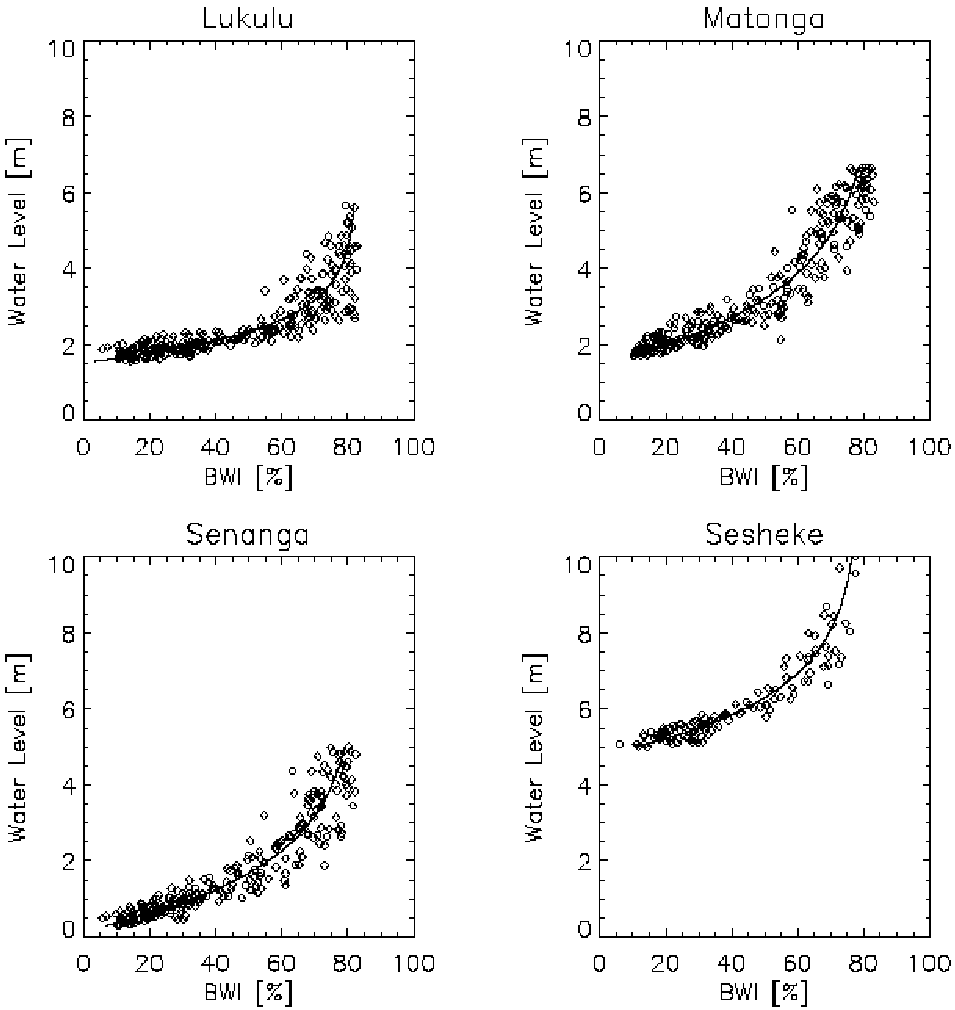
SCAT Soil Moisture versus River Runoff

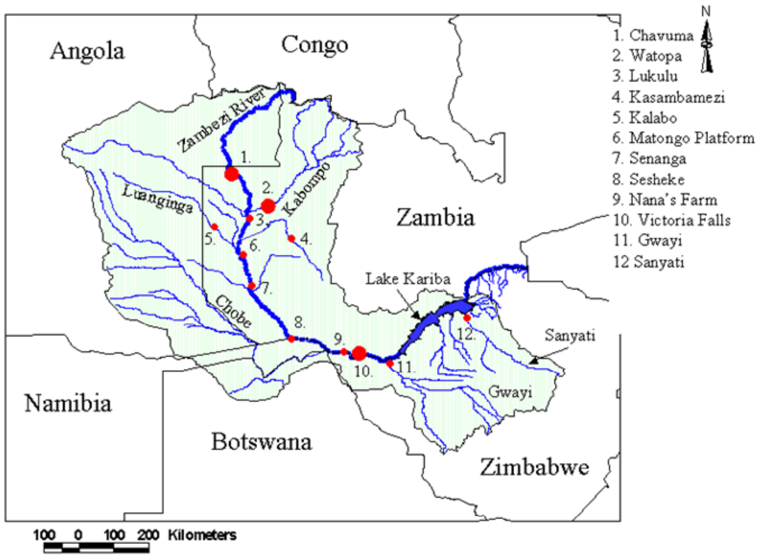


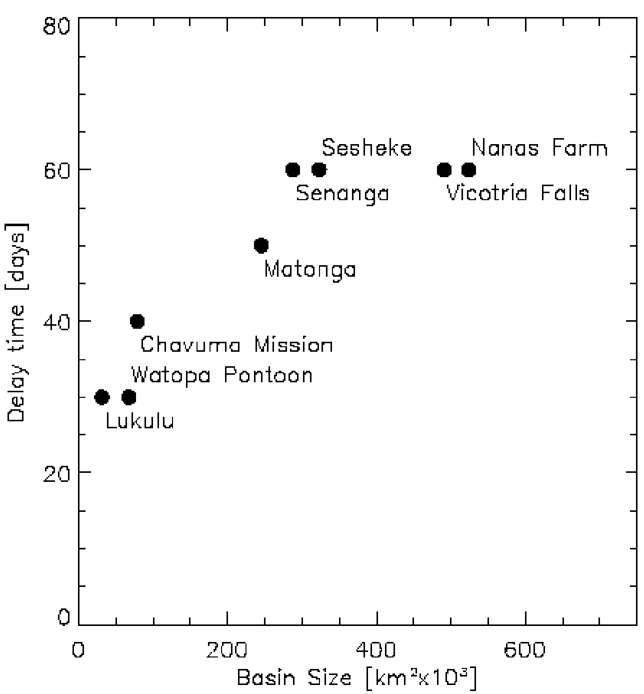


Scipal, K., C. Scheffler, W. Wagner (2005) Soil moisture-runoff relation at the catchment scale as observed with coarse resolution microwave remote sensing, Hydrology and Earth System Sciences, 9(3), 173-183.

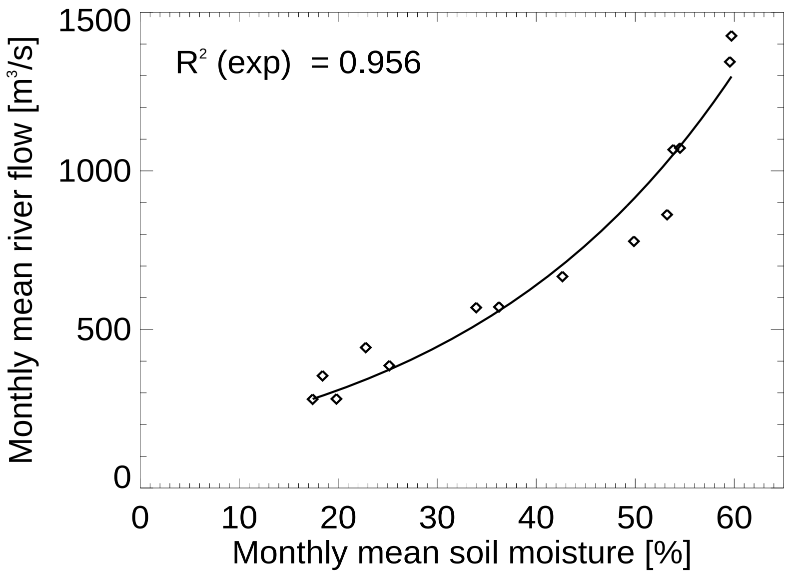
Time Shift and Catchment Size

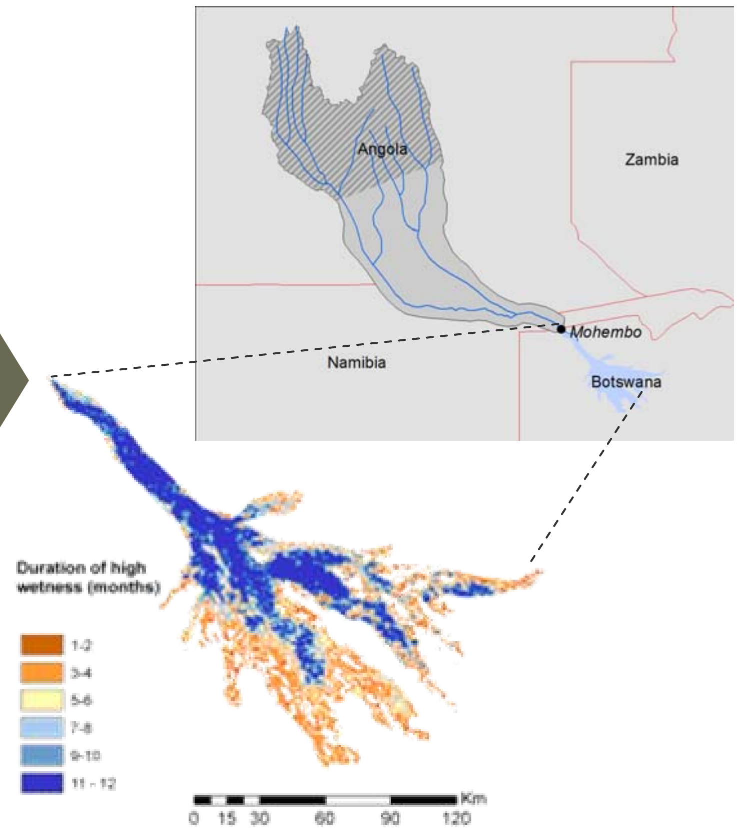




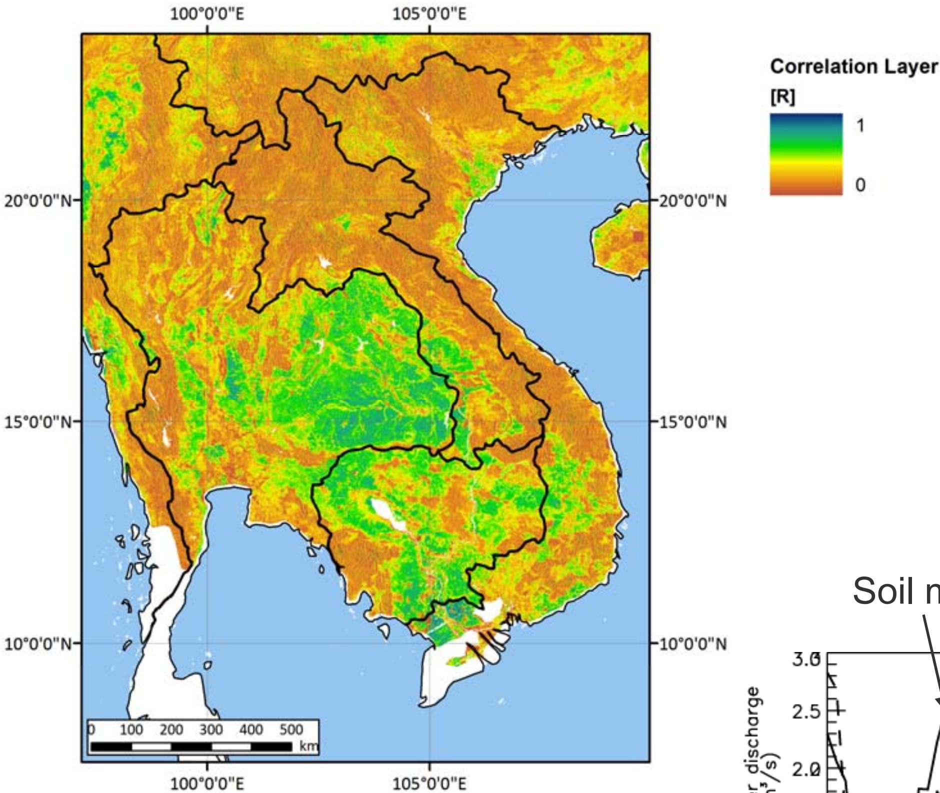


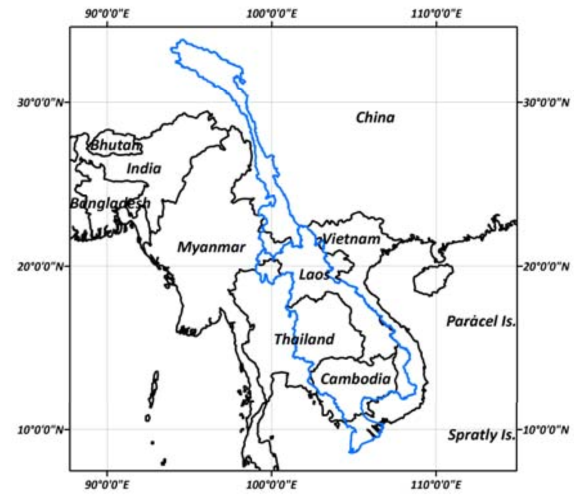
ASAR GM Soil Moisture and Runoff Okavango

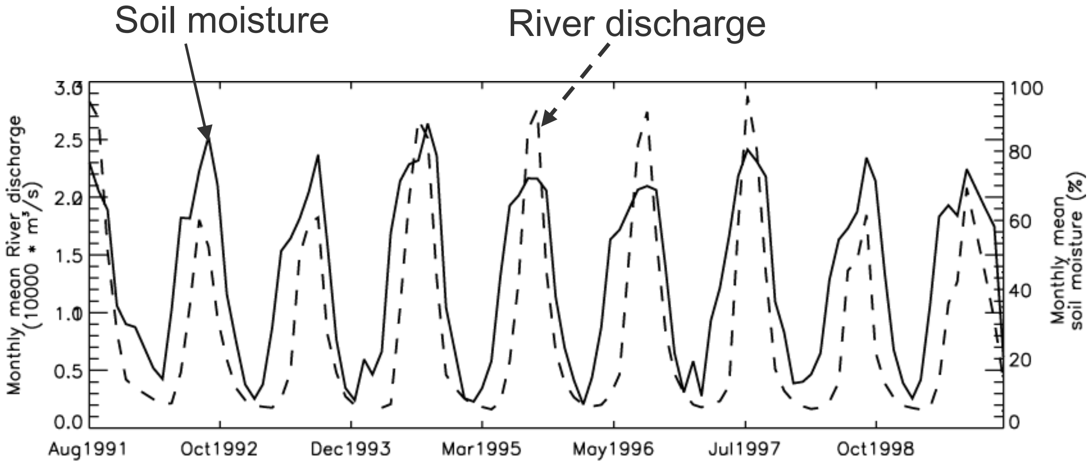




Soil Moisture and Mekong River Runoff







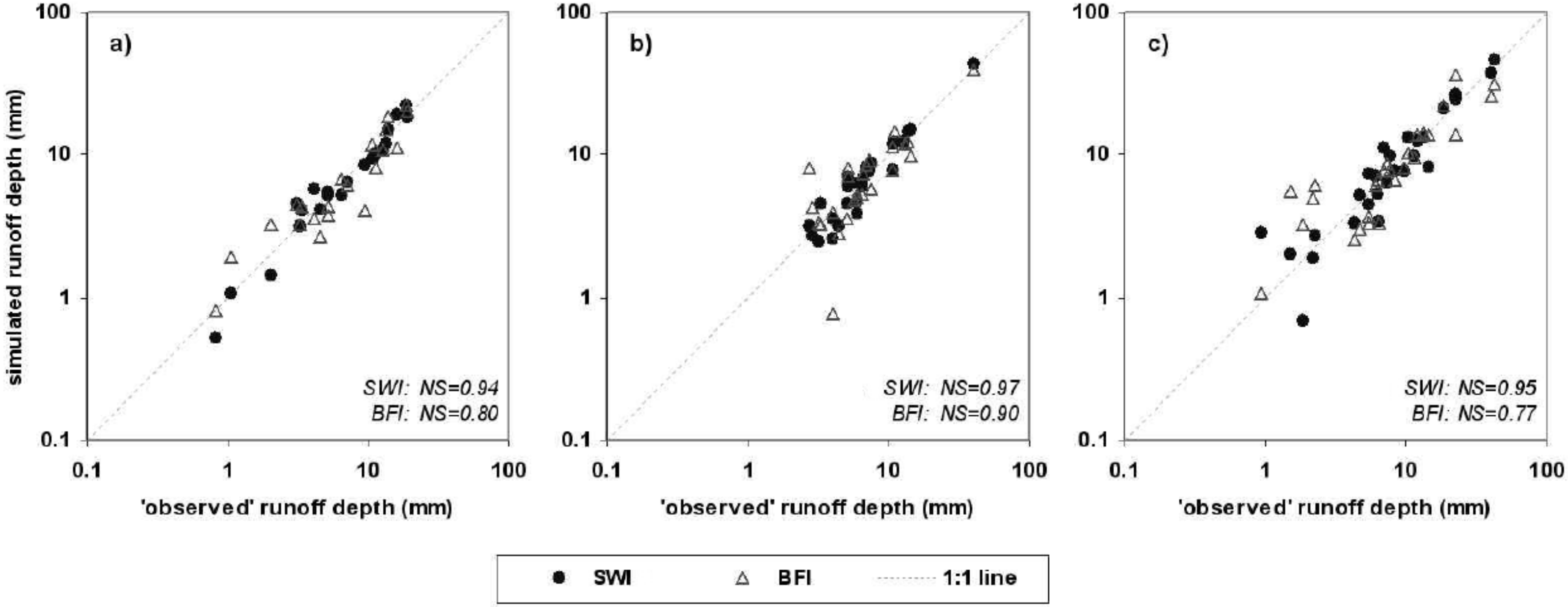
The "correlation layer" is a measure of the temporal correlation between local and regional backscatter dynamics. Red indicates dense vegetation and green/blue colours low vegetation.

Event-based Rainfall-Runoff Modelling

- "Curve Number Method"

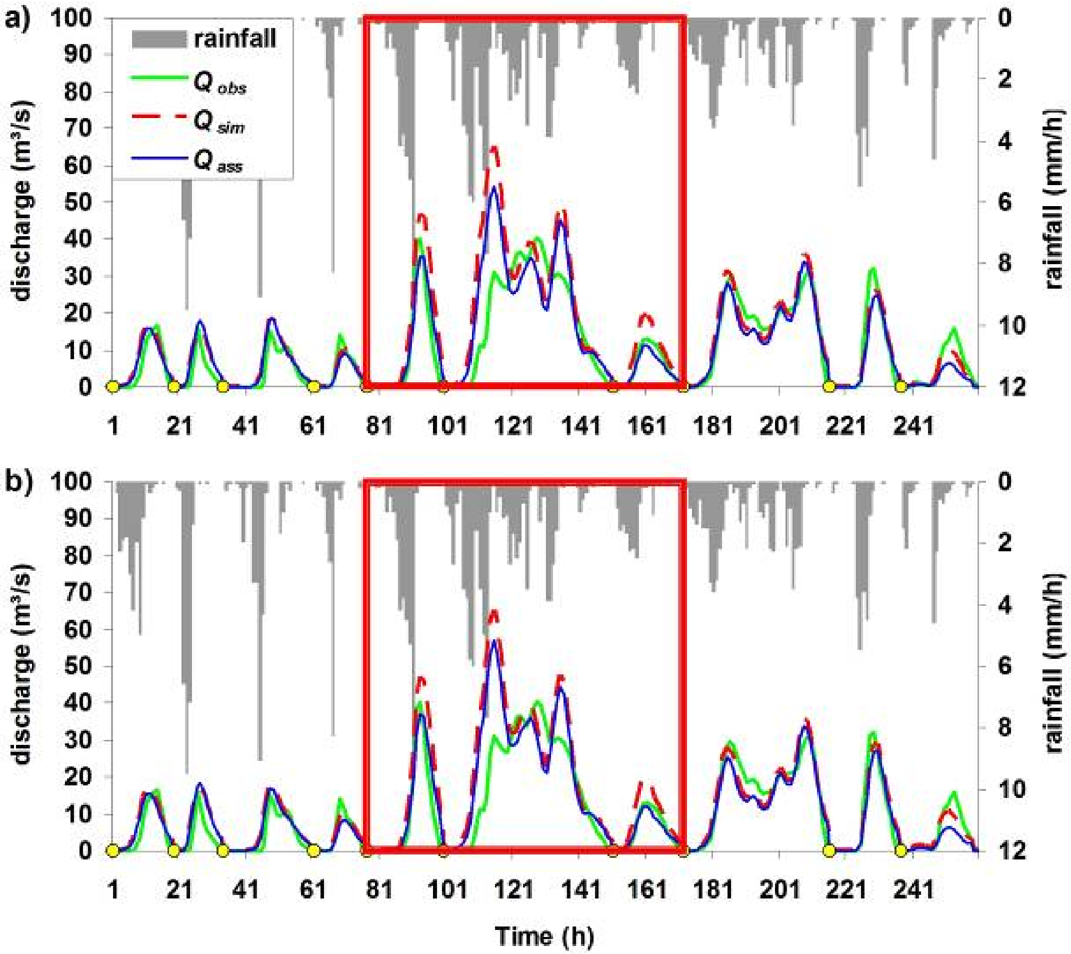
$$Q = \frac{(P - 0.2S)^2}{P + 0.8S} \quad \text{with} \quad S = c + d \cdot SWI$$

Q … runoff
P … precipitation
S … retention
SWI … Soil Water Index



Brocca L, Melone F, Moramarco T, et al. (2009) Antecedent wetness conditions based on ERS scatterometer data, Journal of Hydrology, 364(1-2), 73-87.

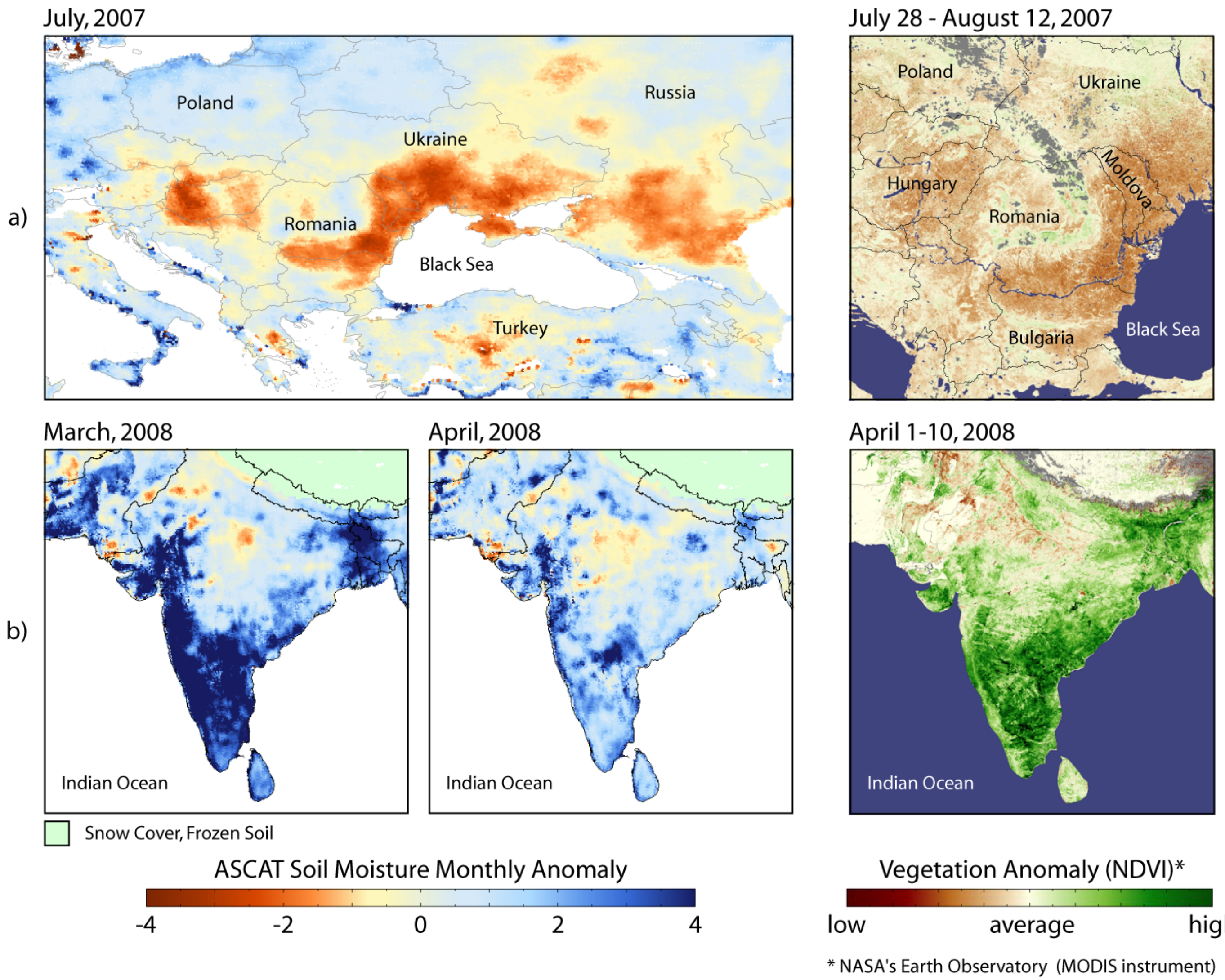
Runoff Prediction using ASCAT Soil Moisture



Sequence of the simulated flood events with and without ASCAT soil moisture assimilation for the CHI catchment in the period Jan 2008-June 2009 and considering an unbiased error on: a) rainfall, and b) model parameter. The simulated and assimilated discharge represents the average of 50 model runs.

Brocca, L., F. Melone, T. Moramarco, W. Wagner, V. Naeimi, Z. Bartalis, S. Hasenauer (2010) Potential of ASCAT soil moisture product to improve runoff prediction, ESA Special Publication, SP-674, in press.

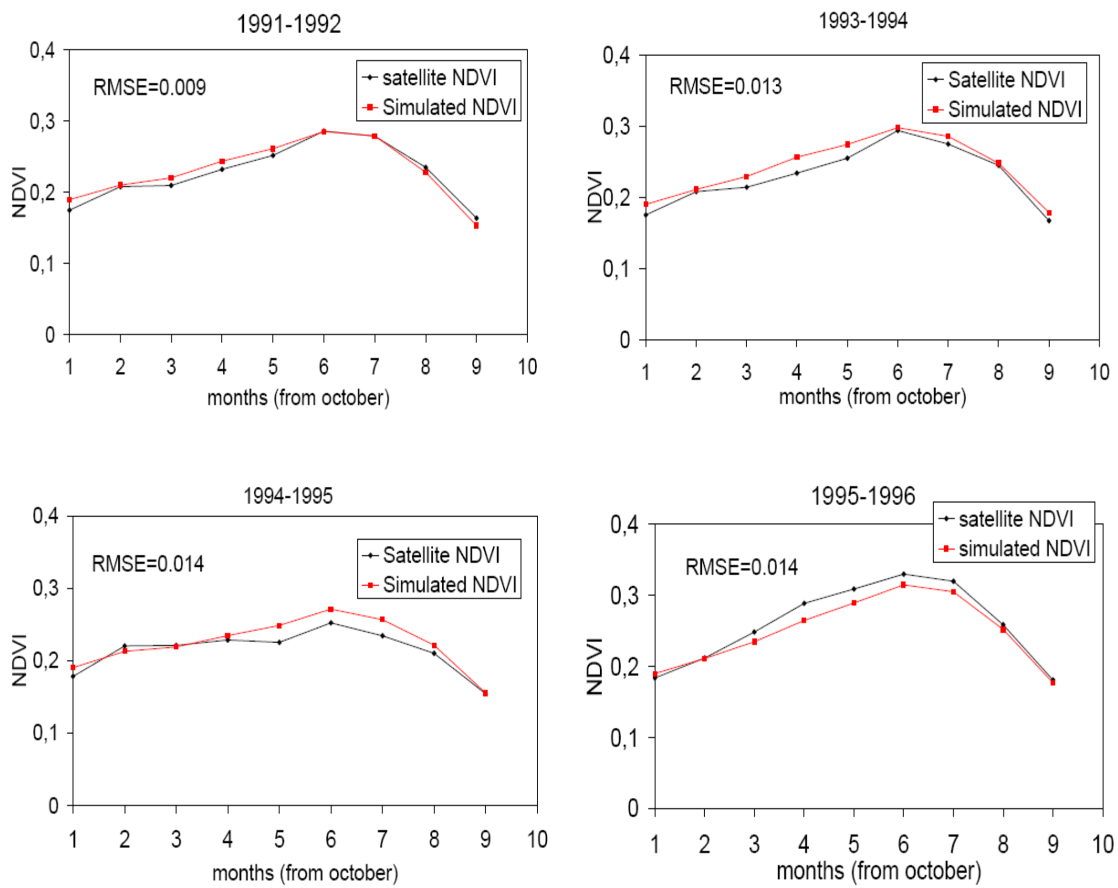
Soil Moisture and Vegetation



Naeimi, V., W. Wagner (2010). C-band Scatterometers and their Applications, Chapter 13 of "Geoscience and Remote Sensing New Achievements", Pasquale Imperatore and Daniele Riccio (Ed.), INTECH, Vukovar, Croatia, 230-246.

Prediction of NDVI using SWI

- Modelling next month's NDVI using SWI



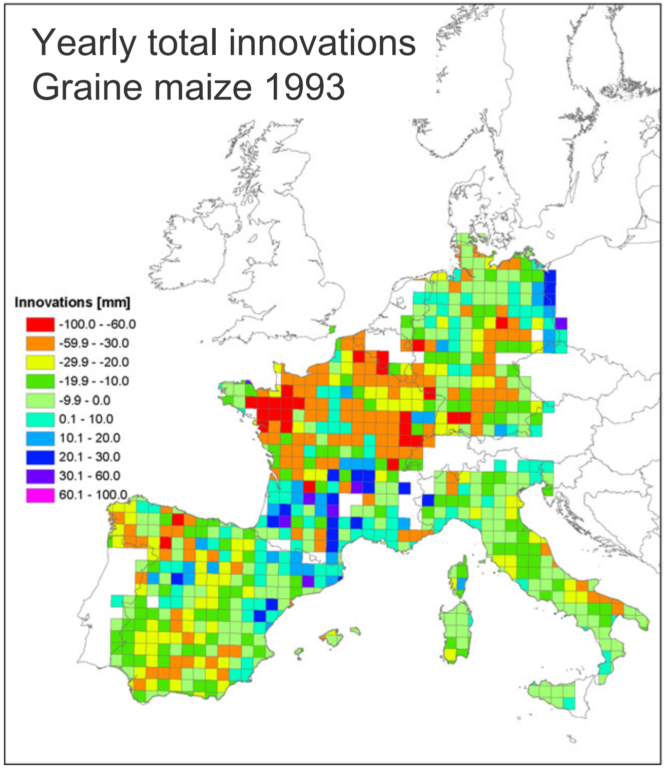
Zribi, M., T. Paris Anguela, B. Duchemin, Z. Lili, W. Wagner, S. Hasenauer, A. Chehbouni (2010) Relationship between soil moisture and vegetation in the Kairouan plain region of Tunisia using low spatial resolution satellite data, Water Resources Research, 46, W06508, 13 p.

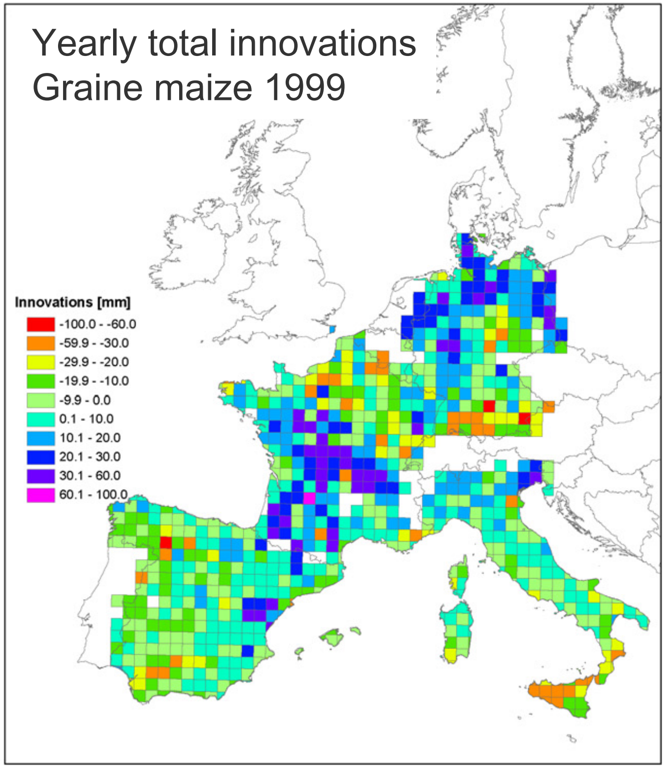
Yield Modelling

- Assimilation of SWI in crop model WOFOST
  - Crop model data assimilation with the Ensemble Kalman filter for improving regional crop yield forecasts

Model was wetter than SWI

Model was drier than SWI





de Wit, A. J. W., C. A. van Diepen (2007) Crop model data assimilation with the Ensemble Kalman filter for improving regional crop yield forecasts, Agricultural and Forest Meteorology, 146(1-2), 38-56.

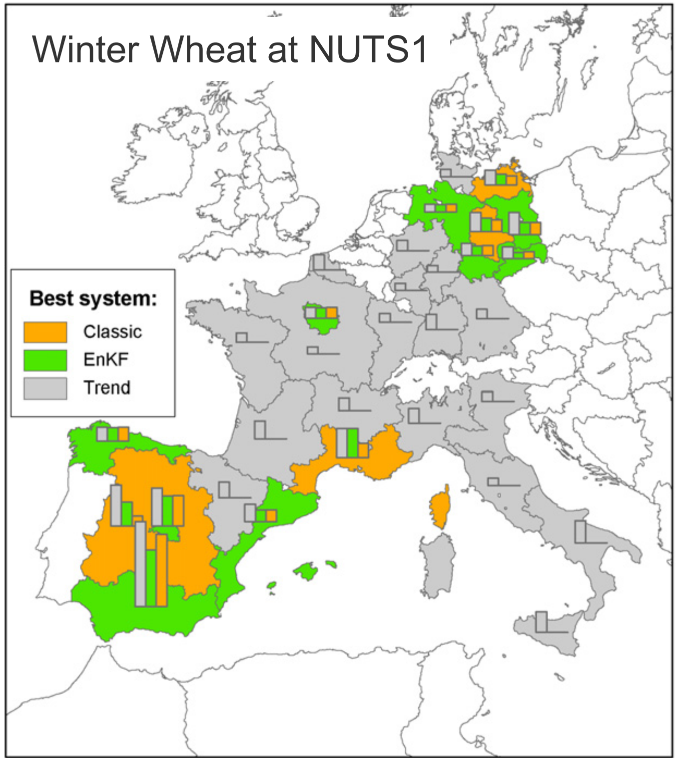
TU WIEN

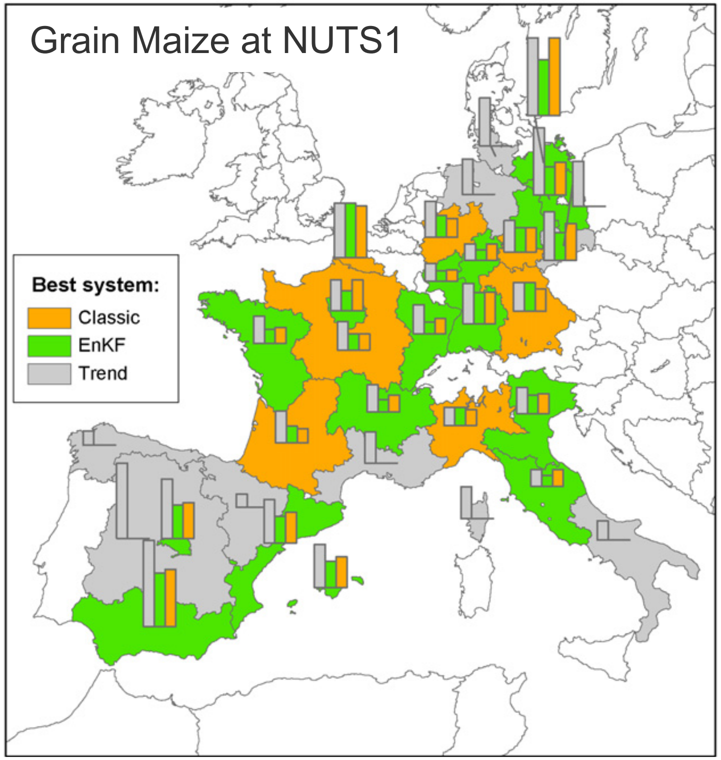
Results of Assimilation Experiment

- Assimilation of SWI improved relationship with crop yield statistics for winter wheat for 66 % of the regions
- For grain maize in only 56 % of the cases (effect of irrigation?)

Best crop forecast achieved using

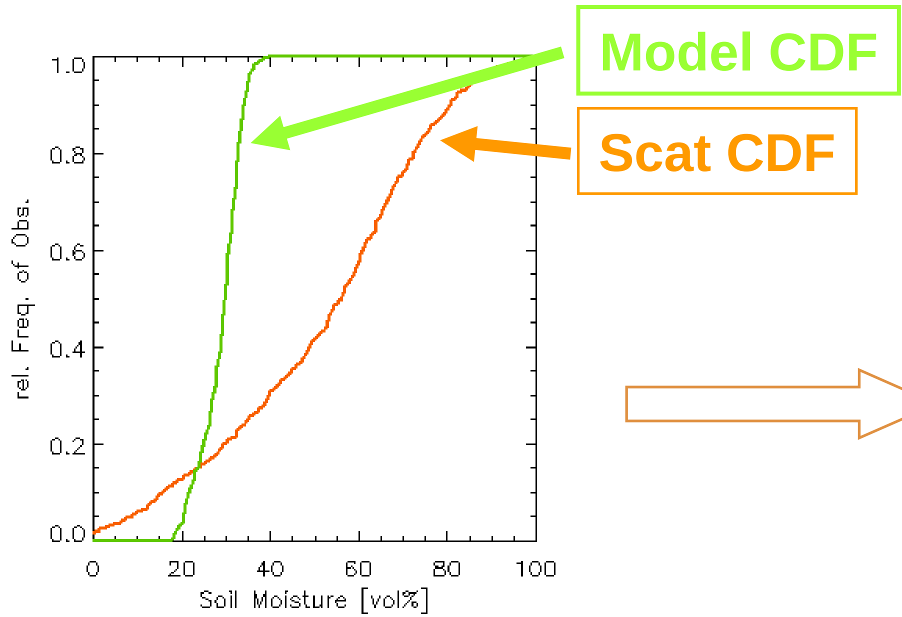
Classic
EnKF
Trend

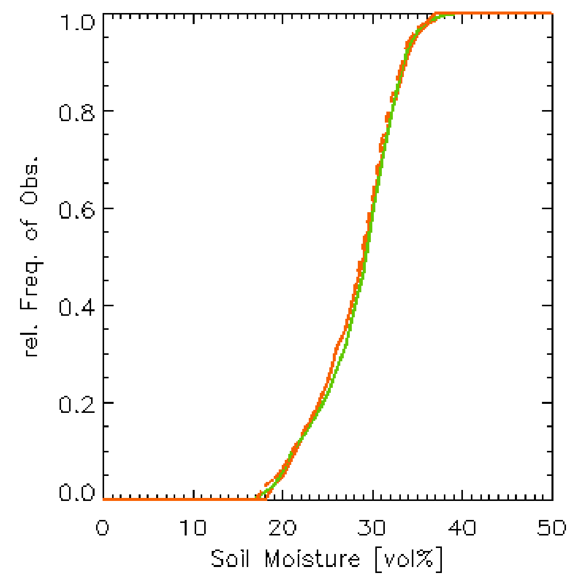




NWP Assimilation Experiment with ASCAT data

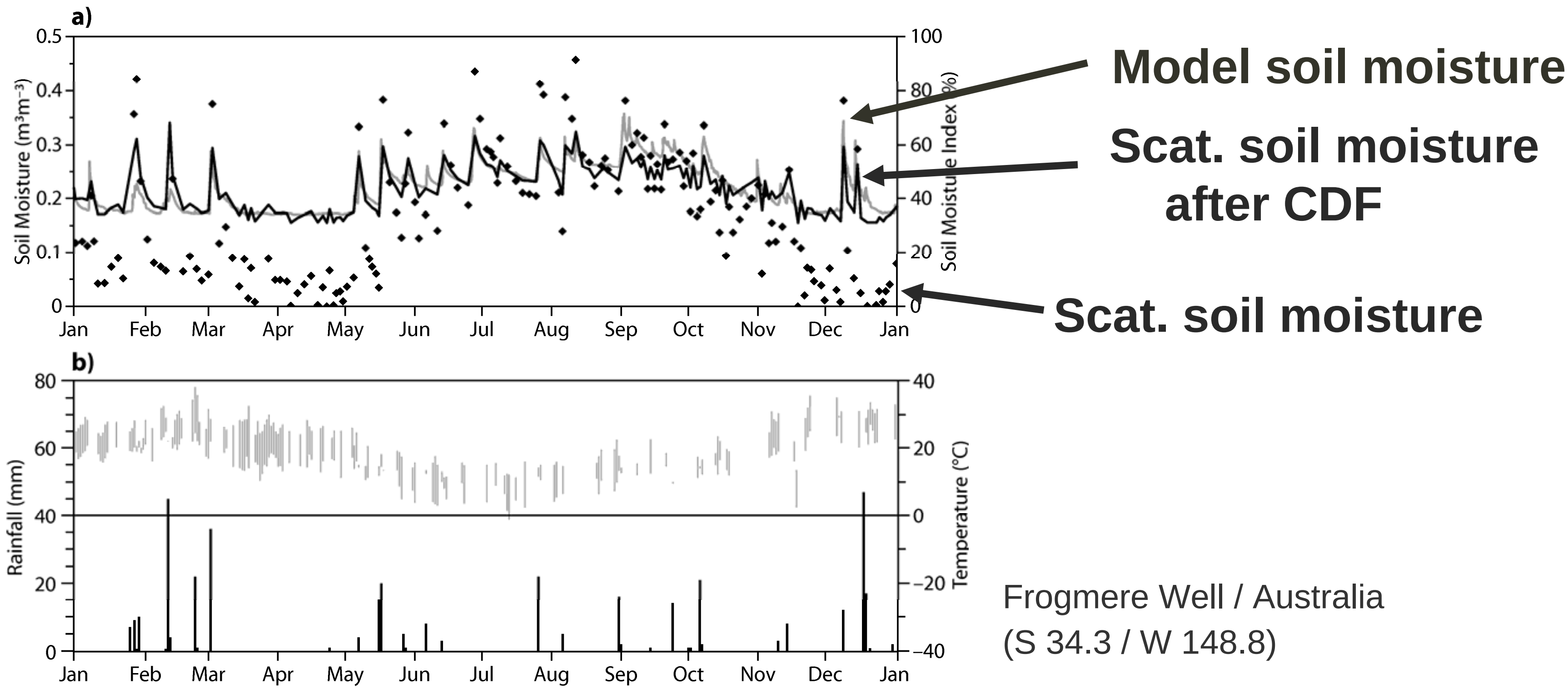
- Experiments
  - #1: Operational OI system
  - #2: EKF using 2m temperature and relative Humidity
  - #3: EKF using ASCAT observations
- Cumulative Distribution Function (CDF) matching





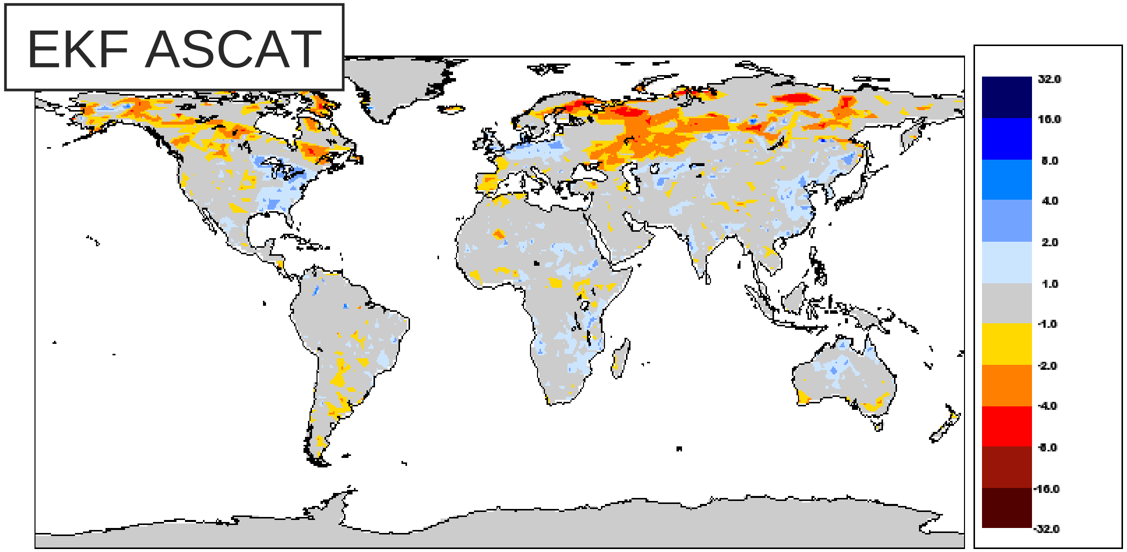
Scipal, K., Drusch, M., W. Wagner (2008) Assimilation of a ERS scatterometer derived soil moisture index in the ECMWF numerical weather prediction system, Advances in Water Resources, 31, 1101-1112.

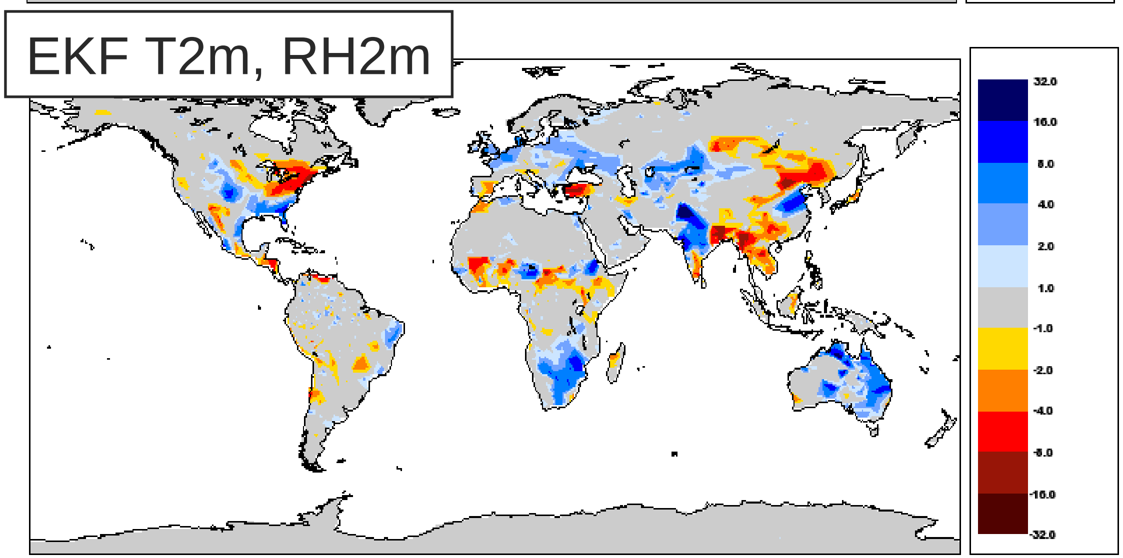
Example CDL Matching



Frogmere Well / Australia
(S 34.3 / W 148.8)

Accumulated Increments

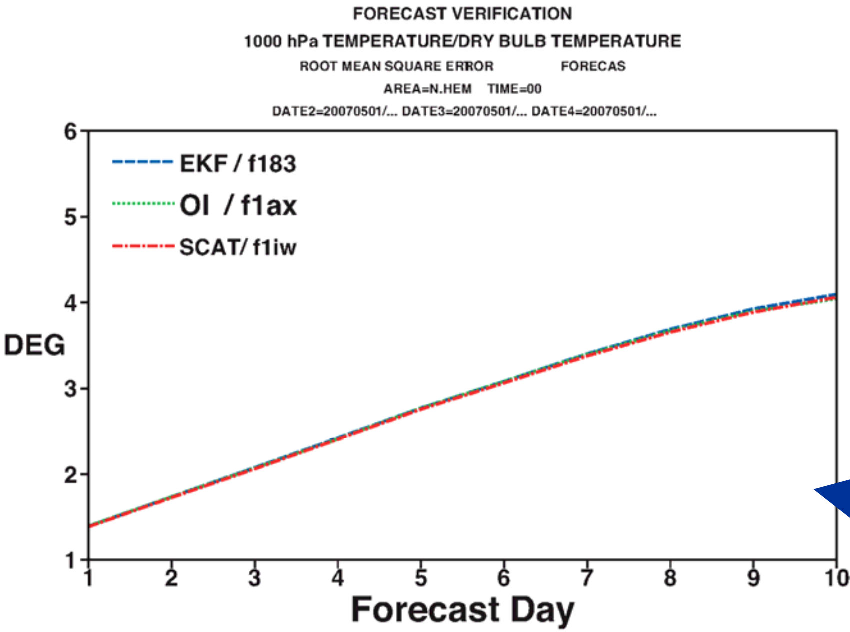


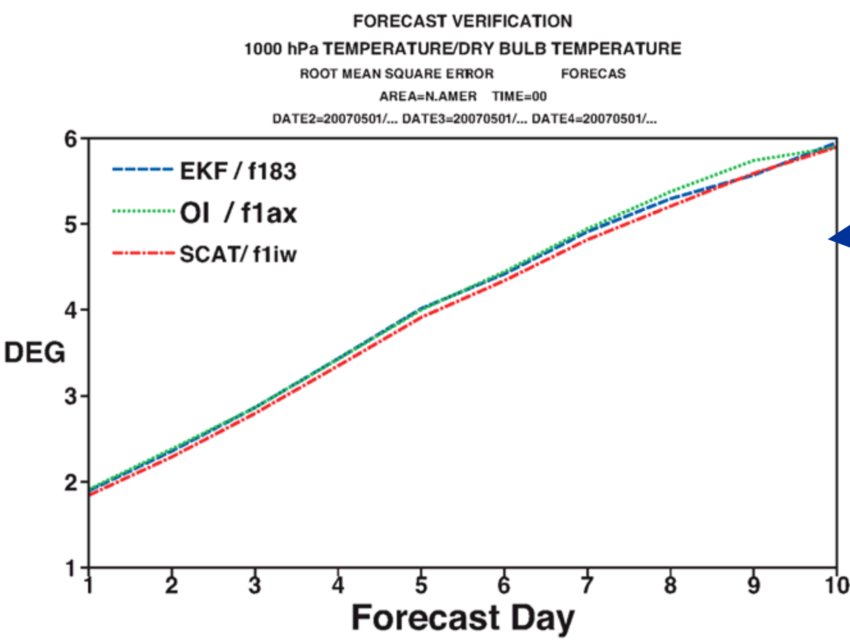


- Increments accumulated for
  - 3 layers
  - 1-10th May analyses steps

  = total water added through the analysis
- Increments generally small
  - Land-surface model and ASCAT in good agreement?
  - Large increments only in high latitudes
- Compared to T2m, Rh2m
  - Different patterns
  - Different magnitudes

Forecast Verification

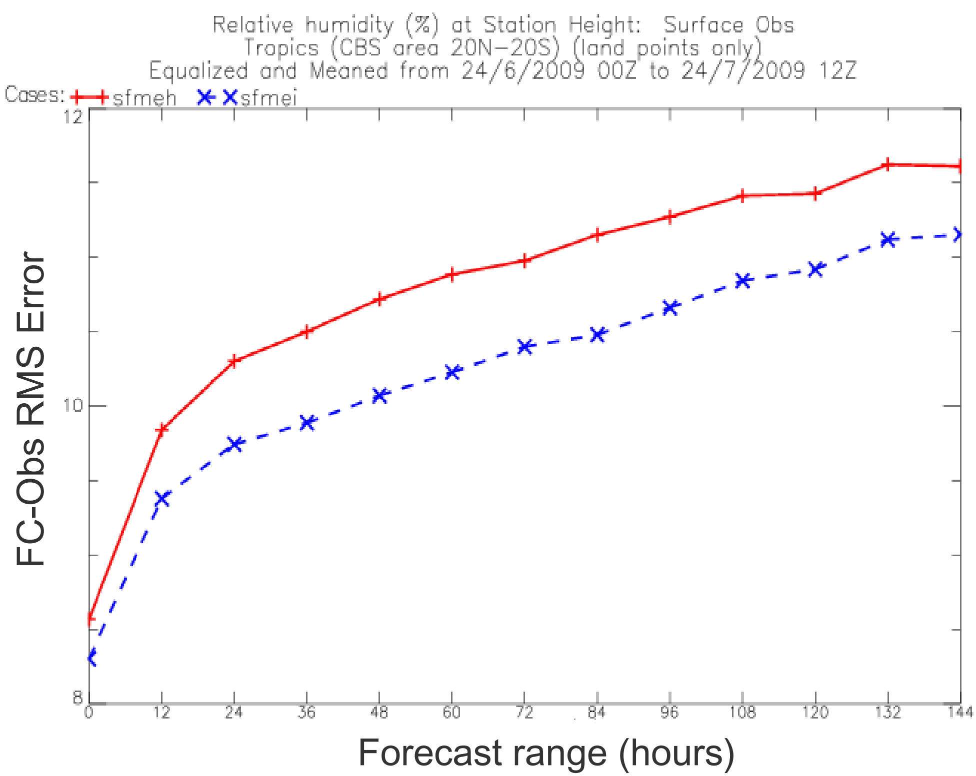




- Score plots
  - Based on a 1 month run (May 2007).
  - RMSE of 1000 hPa Temp.
- Global
  - Impact is neutral for the ASCAT ass. using the EKF compared to the operational OI and the EKF
- Local
  - significant differences
  - ASCAT ass. for example outperforms OI and EKF over North America
  - Negative impact for example over Europe

Assimilation of ASCAT in NWP

- First significant positive impact on forecast demonstrated by Met Office
  - Imtiaz Dharssi, Keir Bovis, Bruce Macpherson and Clive Jones
  - Their first trial experiments in 2009 showed that ASCAT soil wetness assimilation improves forecasts of screen temperature and humidity for the tropics. Impact in other regions was slightly positive or neutral.



Control experiment

Assimilation of ASCAT soil moisture

Conclusions

- Soil moisture is an important parameter in a large number of applications

- So far results from different validation studies are difficult to compare, but first standards arise
  - CEOS Land Product Validation Team on Soil Moisture
    - Established in 2009
    - Will develop Best Practice Guidelines

- First pilot studies are available that demonstrate the usefulness of satellite based soil moisture data in applications, yet, much more work is still required
  - Improve data assimilation
  - Adapt models
  - Better defined interfaces between satellite data and models