Predicting root zone soil moisture with satellite near-surface moisture data in semiarid environments

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Motivations

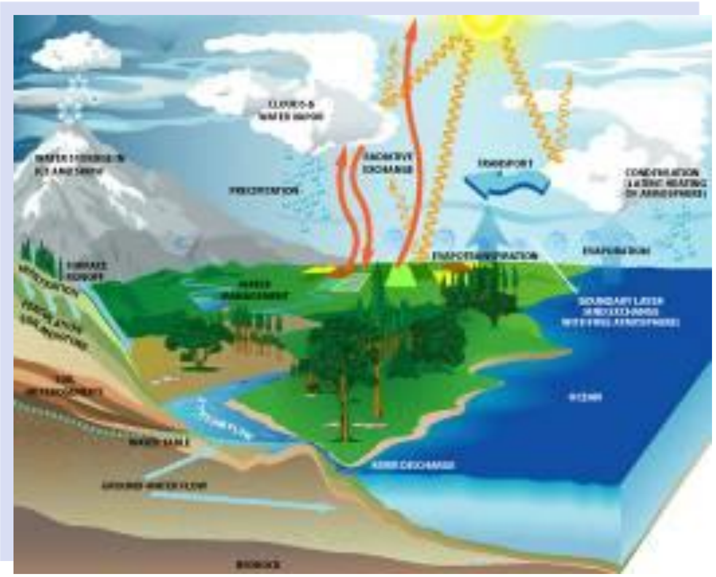
- New remote sensing missions will provide soil moisture measurements at high temporal and spatial resolution (SMAP);
- Explore the potential relationship existing between surface and root-zone soil moisture;
- Identify the controlling physical parameters for this relationship;
- Estimate root-zone soil moisture at regionally or globally distributed locations, using well-known soil physical properties as predictors.

Role of Soil Moisture

Soil moisture availability represents a critical control on plant growth dynamics and ecological patterns in semiarid ecosystems and its space-time variability is crucial to formulate accurate predictions on the behavior of hydrologic systems.

Soil moisture represents a key variable in several fields:

- Ecological patterns
- Agriculture and Plant Production
- Numerical Weather Forecasting
- Climate Prediction
- Shallow Landslide Forecasting
- Flood Prediction and Forecasting

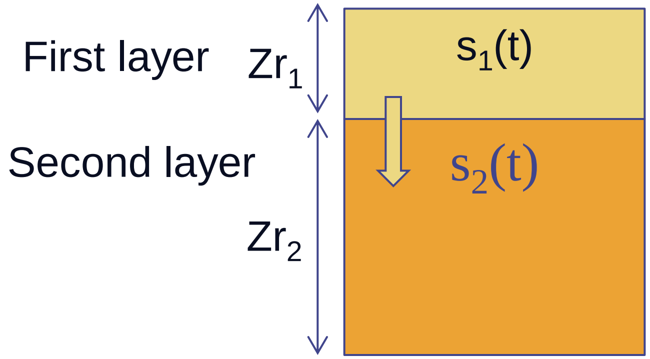


Soil Moisture Analytical Relationship (SMAR)

The schematization proposed assumes the soil composed of two layers, the first one at the surface of a few centimeters and the second one below with a depth that may be assumed coincident with the rooting depth of vegetation (of the order of 60–150 cm).

The challenge is to define a soil water balance equation where the infiltration term is not expressed as a function of rainfall, but of the soil moisture content in the surface soil layer.

This may allow the derivation of a function of the soil moisture in one layer as a function of the other one.



Manfreda et al. (HESS - 2014)

Soil water balance

Defining $x=(s-s_w)/(1-s_w)$ as the "effective" relative soil saturation and $w_0=(1-s_w)nZ_r$ the soil water storage, the soil water balance can be described by the following expression:

Infiltration Losses

$$(1-s_w)n_2 Z_{r2}\frac{dx_2(t)}{dt} = n_1 Z_{r1} y(t) - V_2 x_2(t) \qquad \textbf{(1)}$$

where:

s [–] represents the relative saturation of the soil,
s_w [–] is the relative saturation at the wilting point,
n [–] is the soil porosity,
Z_r [L] is the soil depth,
V_2 [LT^{-1}] is the soil water loss coefficient accounting for both evapotranspiration and percolation losses,
x_2 [–] is the "effective" relative soil saturation of the second soil layer.

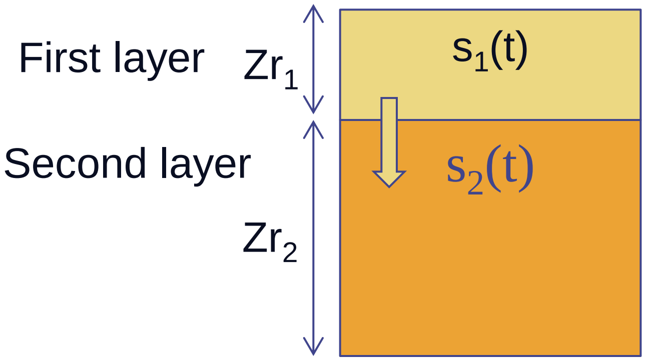
Water flux exchange between the surface and the lower layer

The water flux from the top layer can be considered significant only when the soil moisture exceeds field capacity (Laio, WRR 2006). Assuming that

$$n_1 Zr_1 y(t) = n_1 Zr_1 y[s_1(t), t] = n_1 Zr_1 \begin{cases} (s_1(t) - s_{c1}) & if s_1(t) \geq s_{c1} \\ 0 & if s_1(t) < s_{c1} \end{cases} \quad \textbf{(2)}$$

where $\mathbf{n}_1$ [-] is the soil porosity of the first layer;
$\mathbf{Zr}_1$ [L] is the depth of the first layer;
$\mathbf{s}_1$ ($\theta_1/\mathbf{n}_1$) [-] is the relative saturation of the first layer;

$\mathbf{s}_{c1}$ [-] is the value of relative saturation at field capacity.



Simplifying the soil water balance equation

The equation above can be simplified using normalized coefficients *a* and *b* defined as:

$$a = \frac{V_2}{(1-s_w)n_2 Z_{r2}}, \quad \text{dimensionless soil water coefficient} \qquad (4)$$

$$b = \frac{n_1 Z_{r1}}{(1-s_w)n_2 Z_{r2}}. \quad \text{ratio of the depths of the two layers} \qquad (5)$$

As a consequence, the soil water balance equation becomes:

$$\frac{dx_2(t)}{dt} = b\, y(t) - a\, x_2(t). \qquad (6)$$

Soil Moisture Analytical Relationship (SMAR) beetween surface and root zone soil moisture

Assuming an initial condition for the relative saturation $\mathbf{s_2(t)}$ equal to zero, one may derive an analytical solution to this linear differential equation that is

$$s_2(t) = \int_0^t b e^{a(w-t)} y(w) dw \tag{7}$$

For practical applications, one may need the discrete form as well:

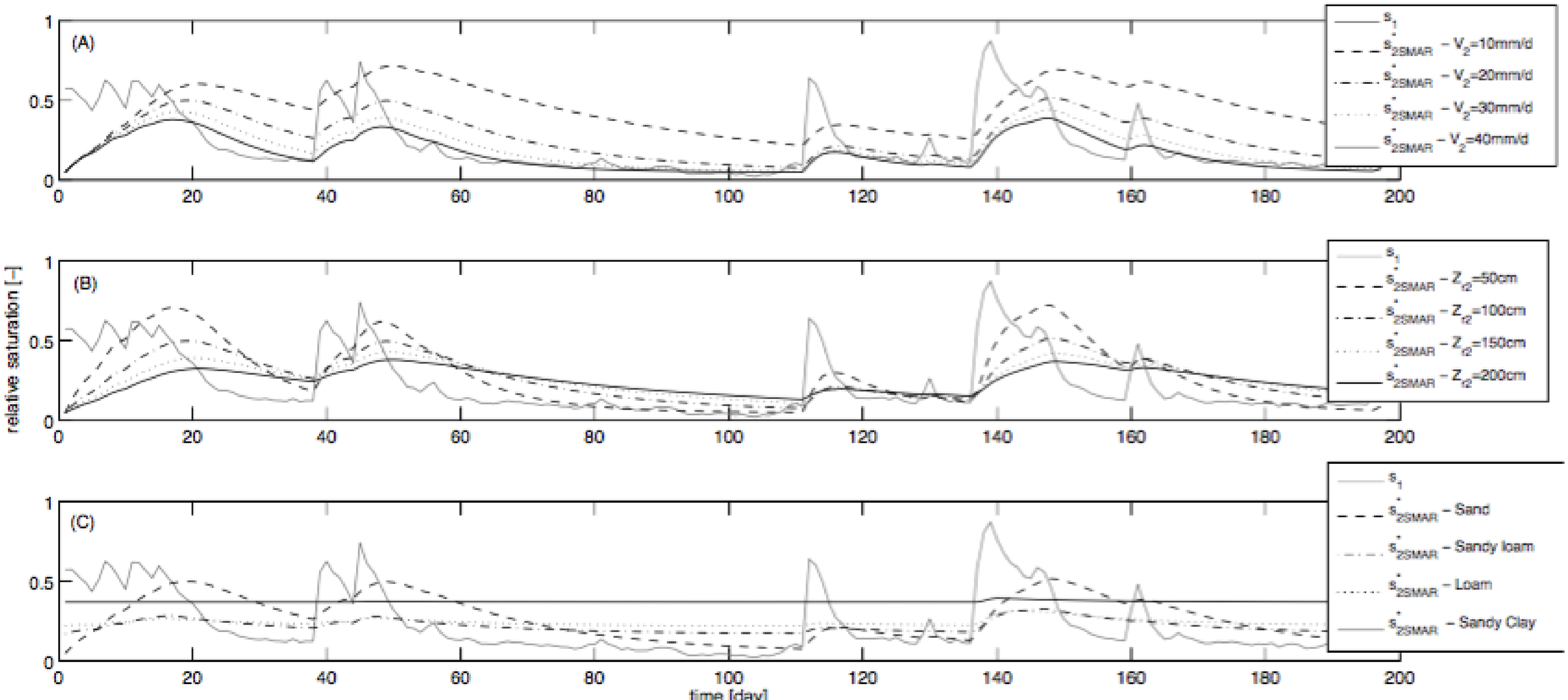
$$x_2(t_j) = \sum_{i=0}^{j} b \, e^{a(t_i - t_j)} y(t_i) \Delta t \tag{8}$$

Expanding Eq. 8 and assuming $\Delta t = (t_j - t_i)$, one may derive the following expression for the soil moisture in the second layer based on the time series of surface soil moisture:

$$s_2(t_j) = s_w + (s_2(t_{j-1}) - s_w) \, e^{-a(t_j - t_{j-1})} + (1 - s_w) b \, y(t_j)(t_j - t_{j-1}) \tag{9}$$

Sensitivity of SMAR's parameters

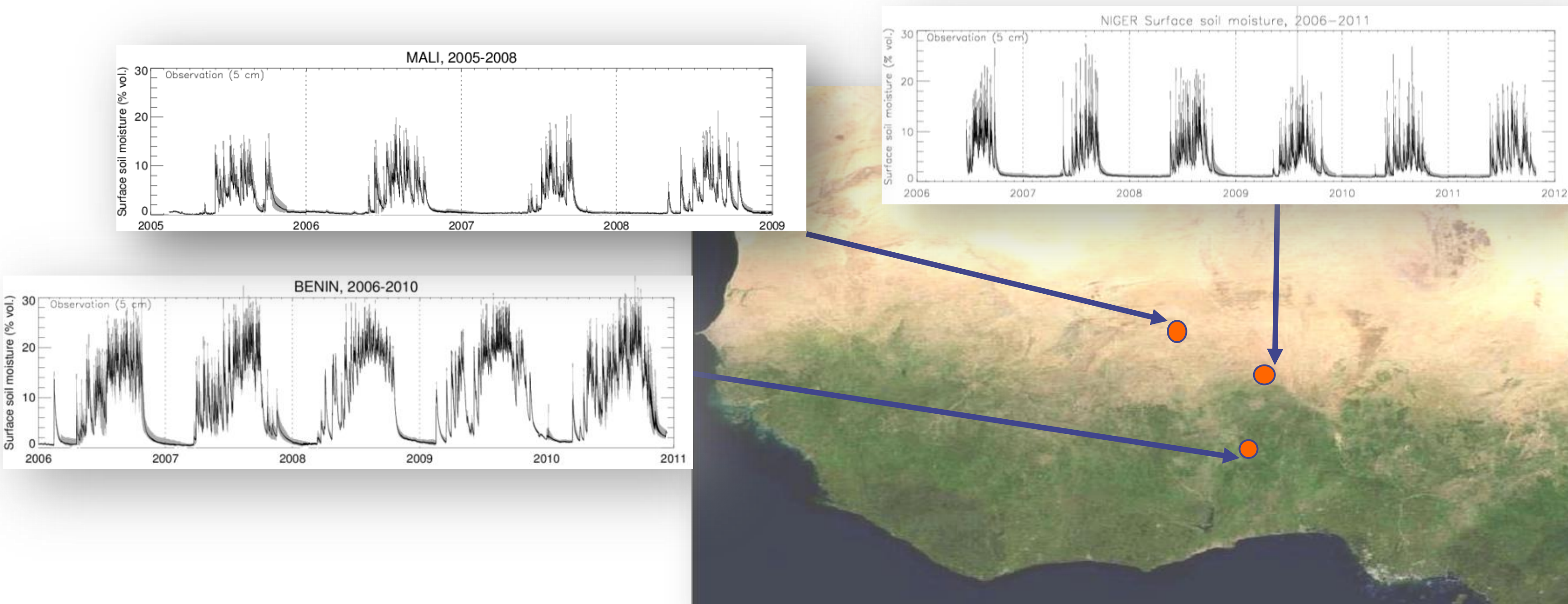
The derived root zone soil moisture (S_{RZ}) is plotted changing the soil water loss coefficient (**A**), the depth of the second soil layer (**B**), and the soil textures (**C**).



Manfreda et al. (HESS - 2014)

African Monsoon Multidisciplinary Analysis (AMMA) database

The SMAR approach was applied to soil measurements available in West Africa. These soil moisture measurements form an excellent database that well describes the soil moisture along the root-zone profile.



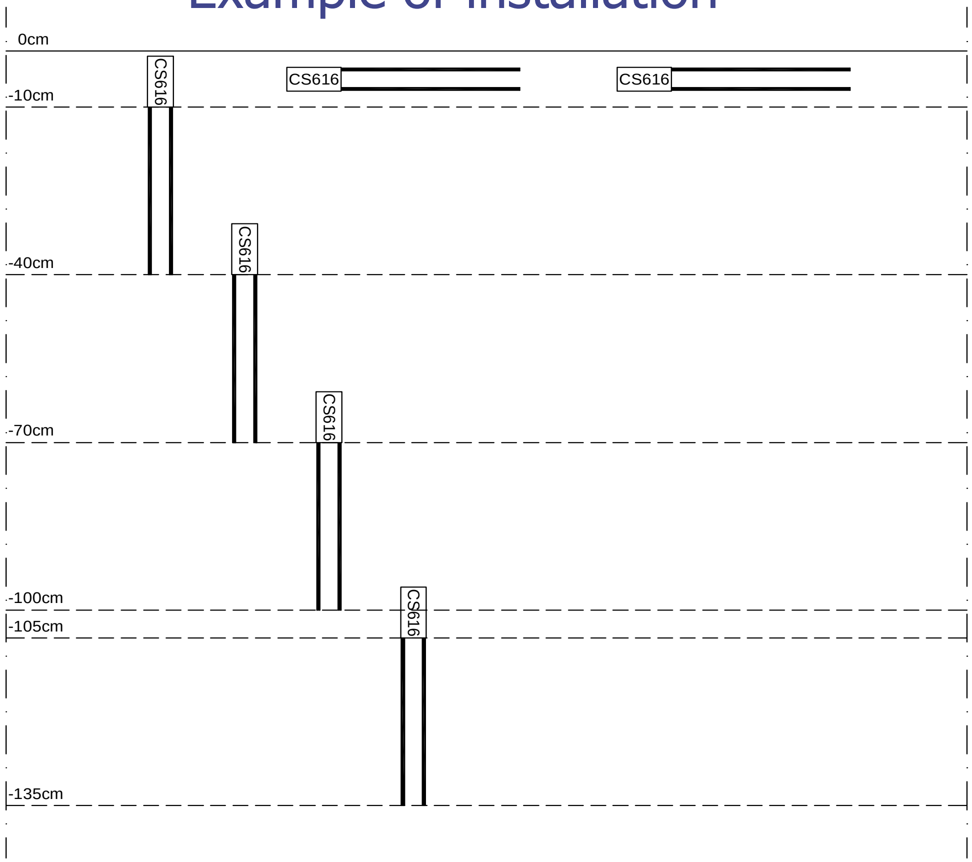
The entire dataset is available on http://www.ipf.tuwien.ac.at/insitu/

African Monsoon Multidisciplinary Analysis (AMMA) database

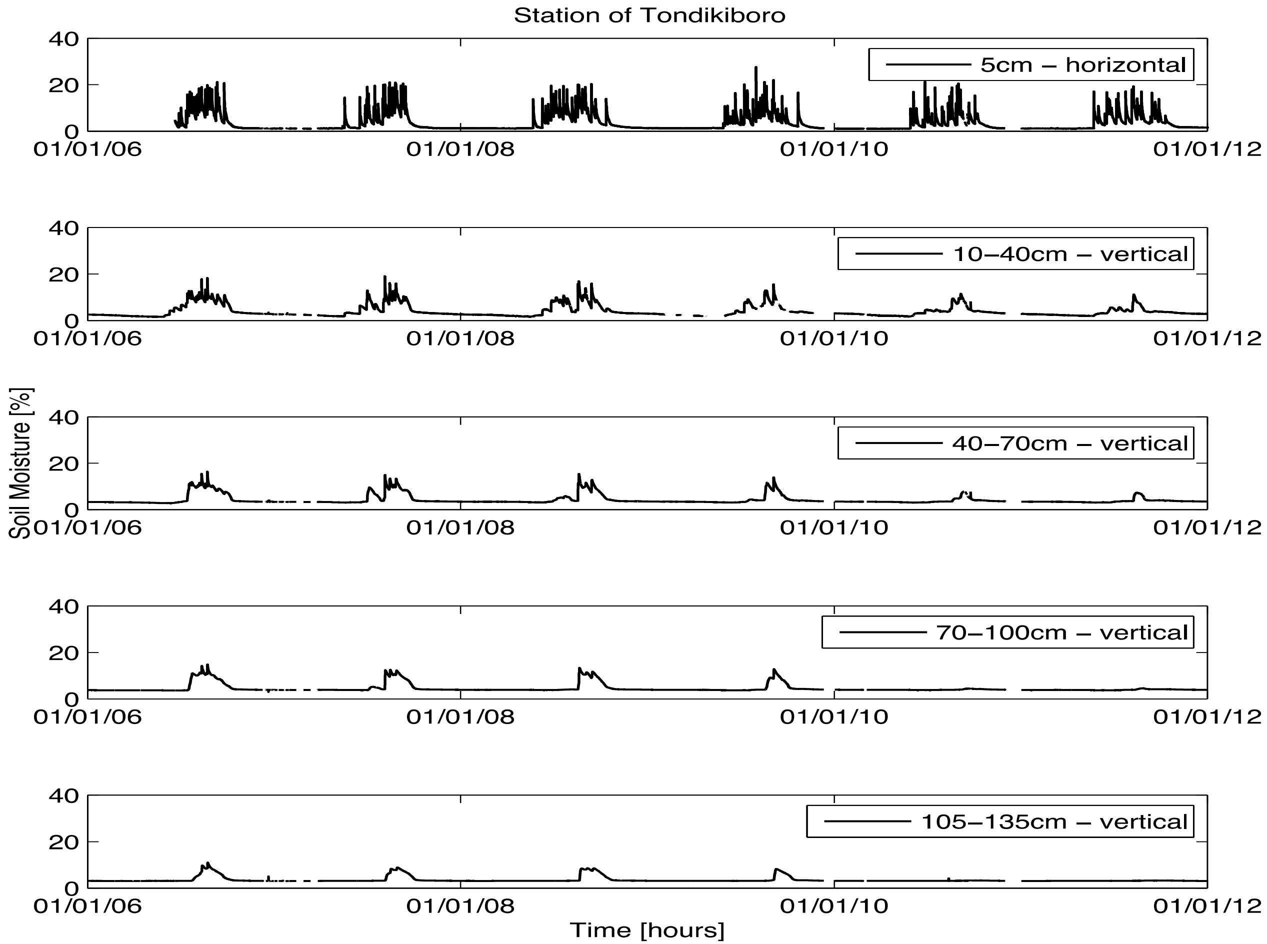
Tondikiboro station provides six soil moisture measurements over the soil profile starting from 5 cm of depth down to 135 cm.

The installation is composed by two horizontal probes at the depth of 5 cm and 4 vertical probes that provide a measure over a layer comparable to the probe length (about 30 cm).

Example of installation



Hourly soil moisture at different depths at the station of Tondikiboro in Niger

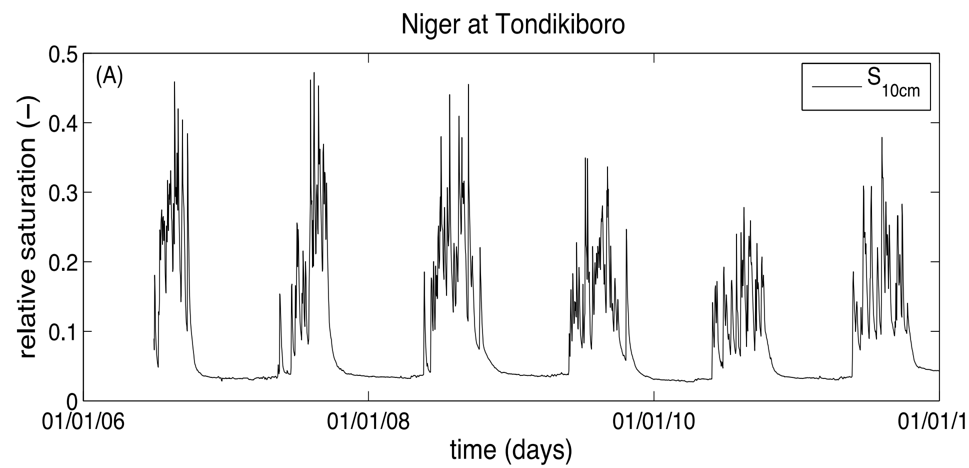


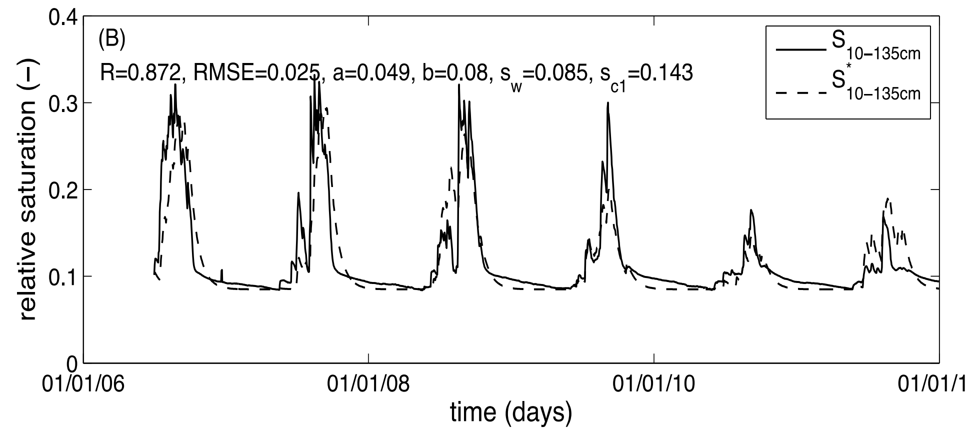
Data refers to the period 1 January 2006–31 December 2011

SMAR's results obtained with parameter assigned based on physical information

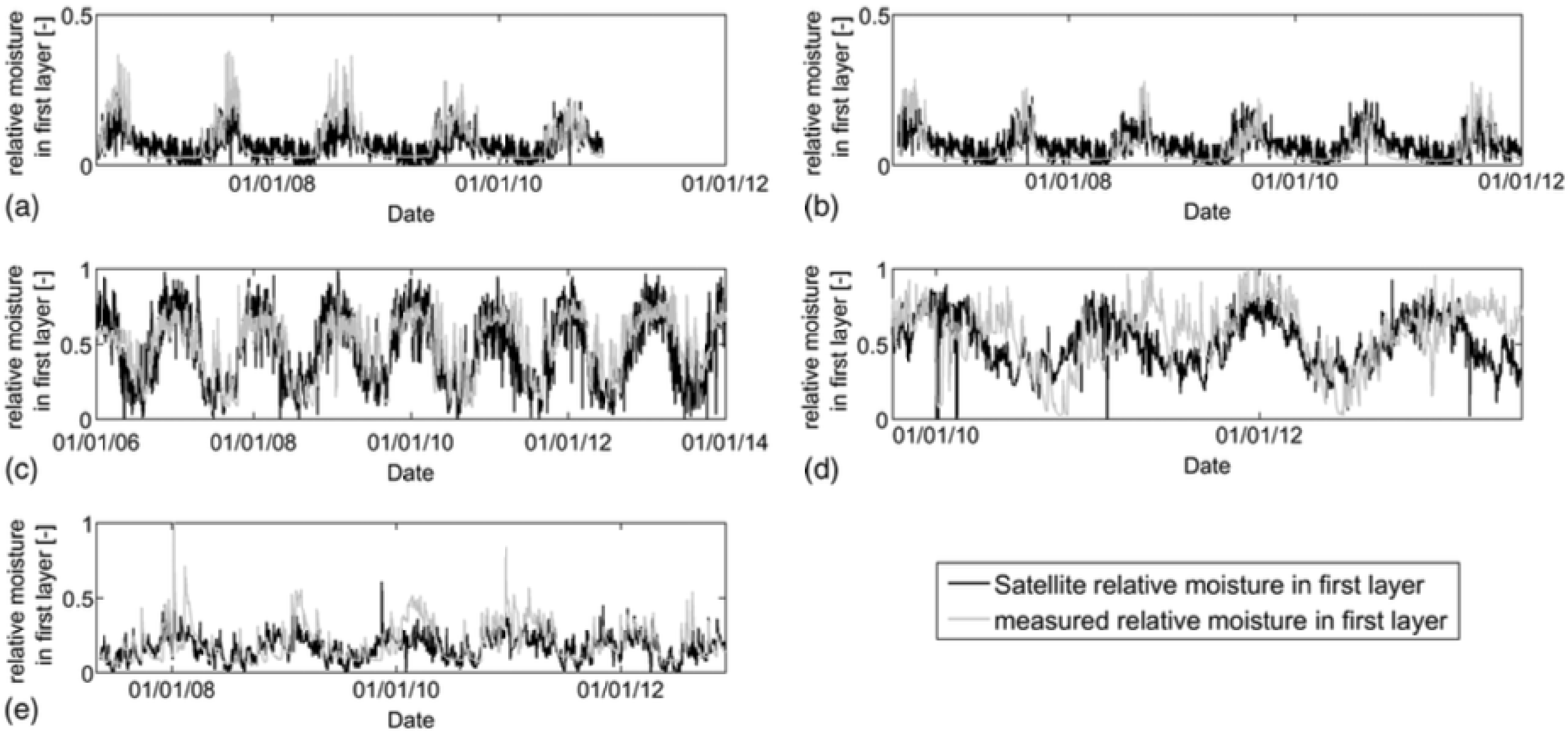
A) Time series of relative saturation, at the daily time-scale, in the first layer of soil measured at the station of Tondikiboro in Niger.

B) Averaged relative saturation in the lower layer of soil measured (continuous line) and filtered (dashed line) at the station of Tondikiboro. Parameters values used in the present application are a=0.049, b=0.08, s_w=0.085, and s_{c1}=0.143, respectively.





Remote sensed data vs field mesurements



(Faridani et al., J. Irr. Drain., 2016)

Use with satellite data: coupling the SMAR with EnKF

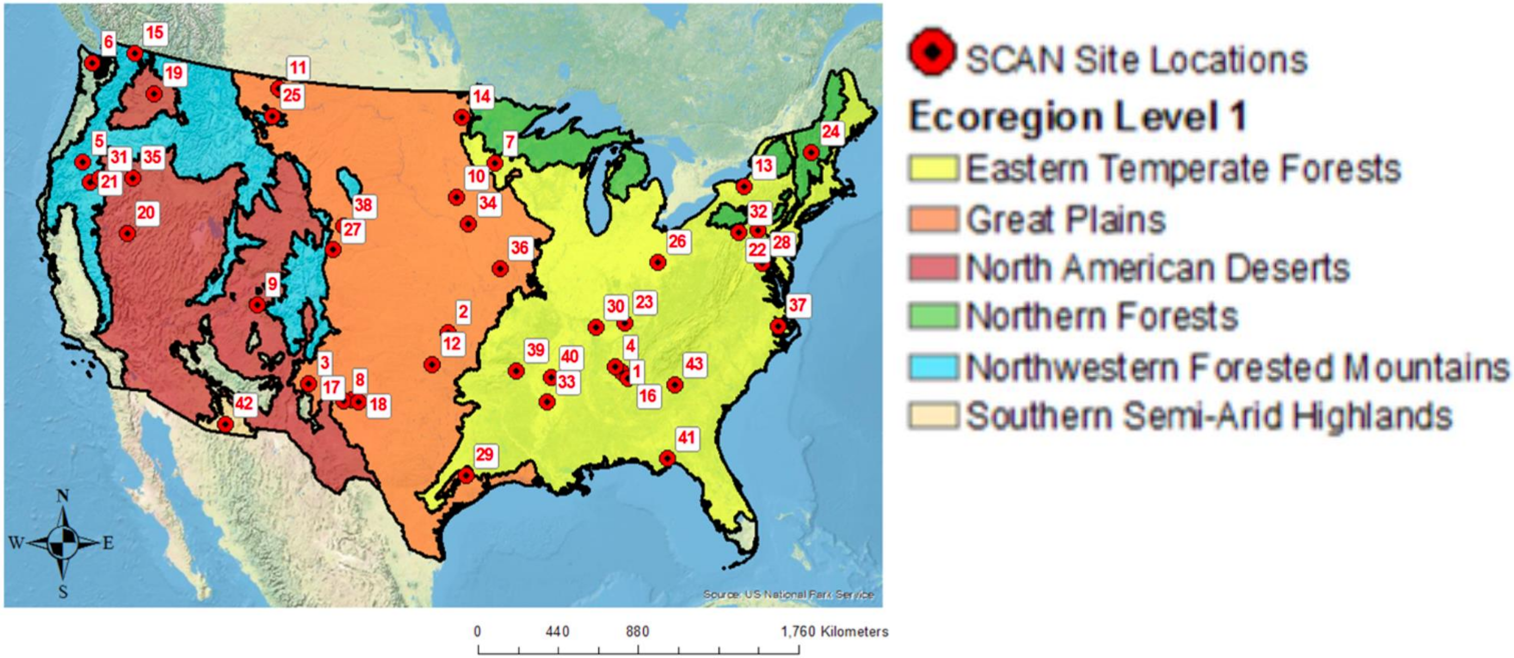
Ridler et al (2014) showed how a satellite correction bias could be calculated within the EnKF to correct the discrepancy between satellite and *in situ* near-surface measurements.

Integrating a simple hydrologic model with an EnKF algorithm can provide RZSM estimates as accurately as those made by complex process models (Bolten et al, 2010; Crow et al, 2012).

Since the SMAR model's four parameters (surface field capacity, root zone wilting level, diffusivity coefficient and water loss coefficients) are related theoretically to soil properties that are available globally, it would be possible to effectively run SMAR across space after uncovering relationships between soil physical variables and SMAR model parameters (Reichle et al, 2001).

(Baldwin et al., J. Hydr., 2016)

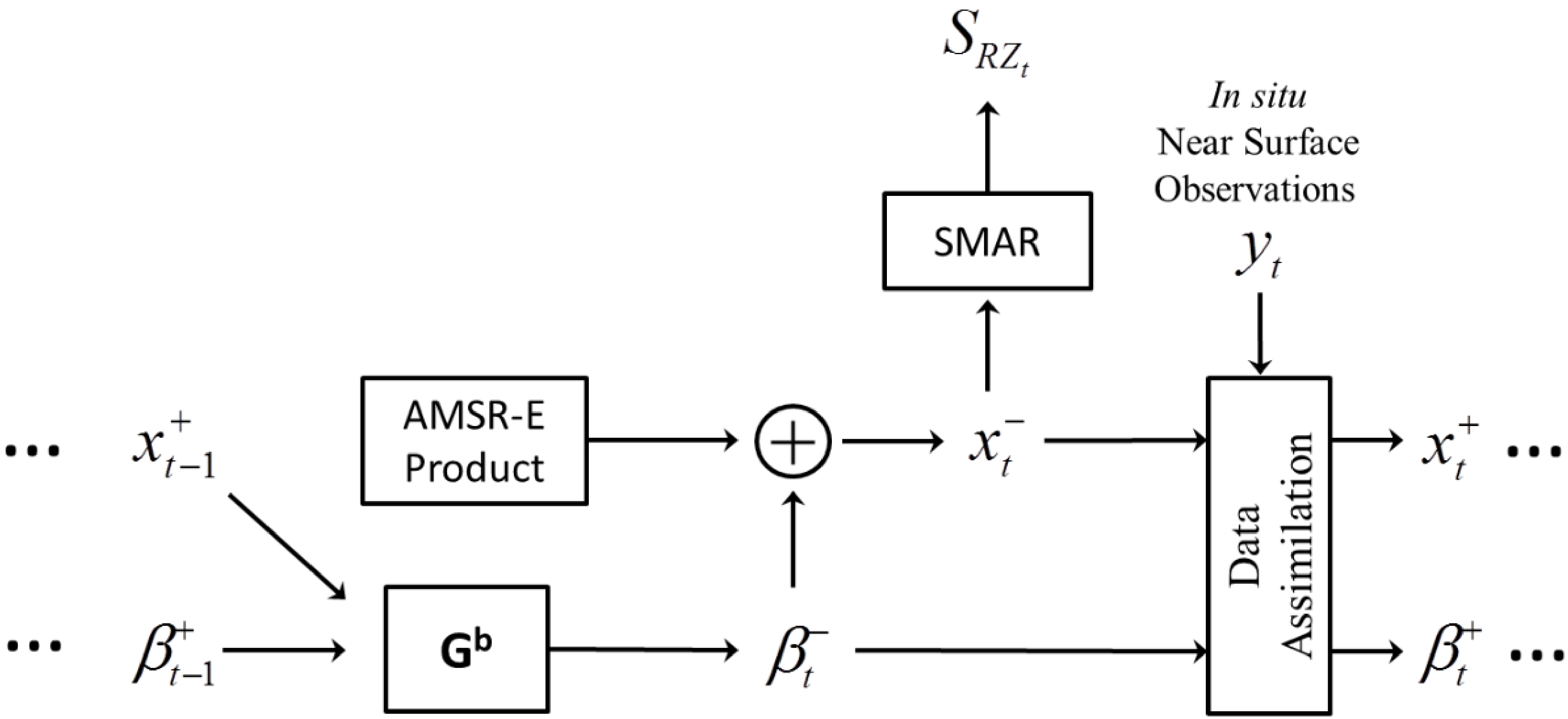
US soil moisture network: SCAN



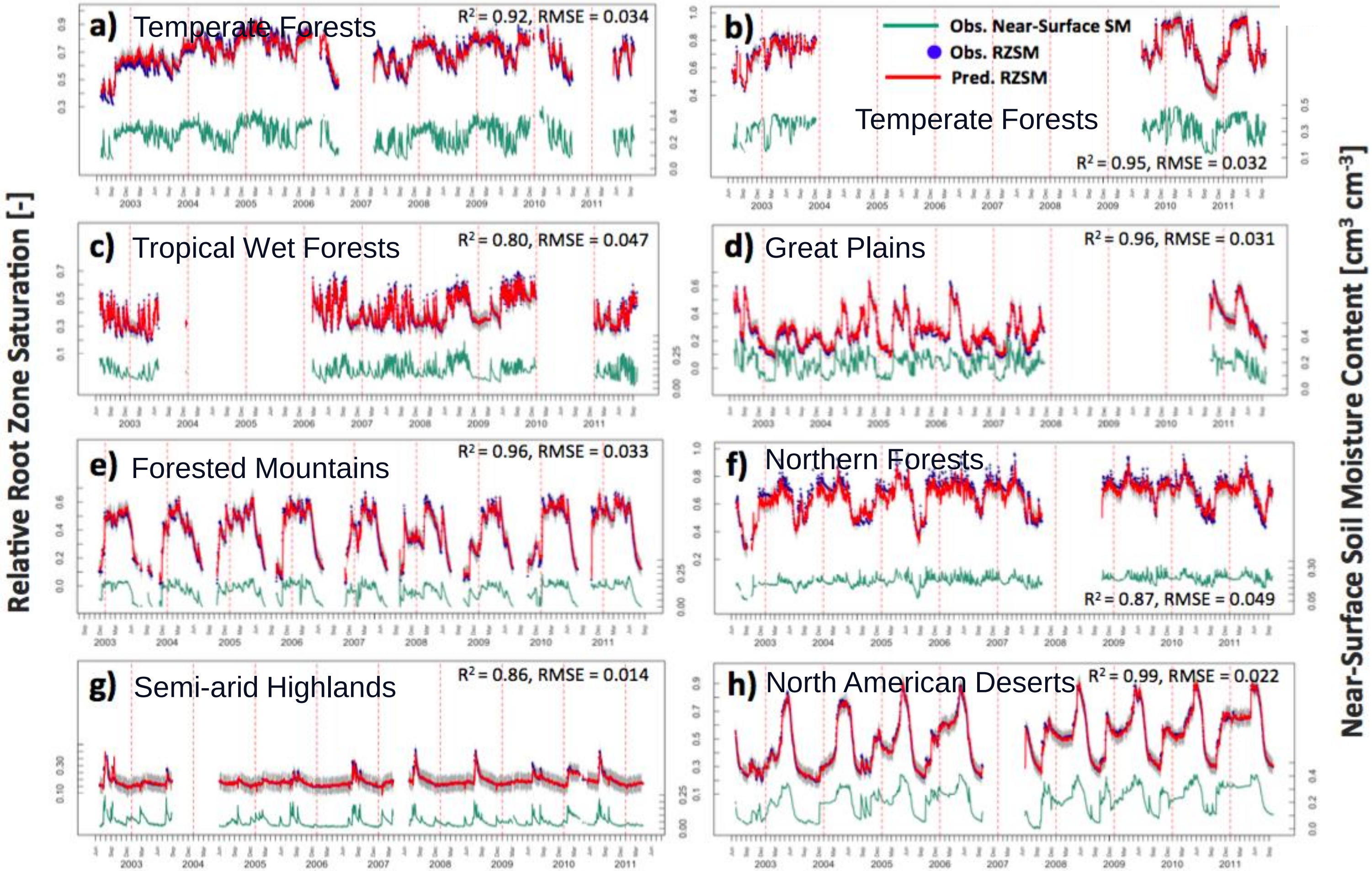
Criteria for choosing 51 locations are:

1) Availability of at least 2 years of data that match the AMSR-E measurement record (2002-2011);
2) laboratory measured soil texture information is available for each horizon to estimate total porosity;
3) represent a wide spatial spread of locations representative of U.S. ecoregions.

Schematic of the bias estimation procedure for SMAR-EnKF



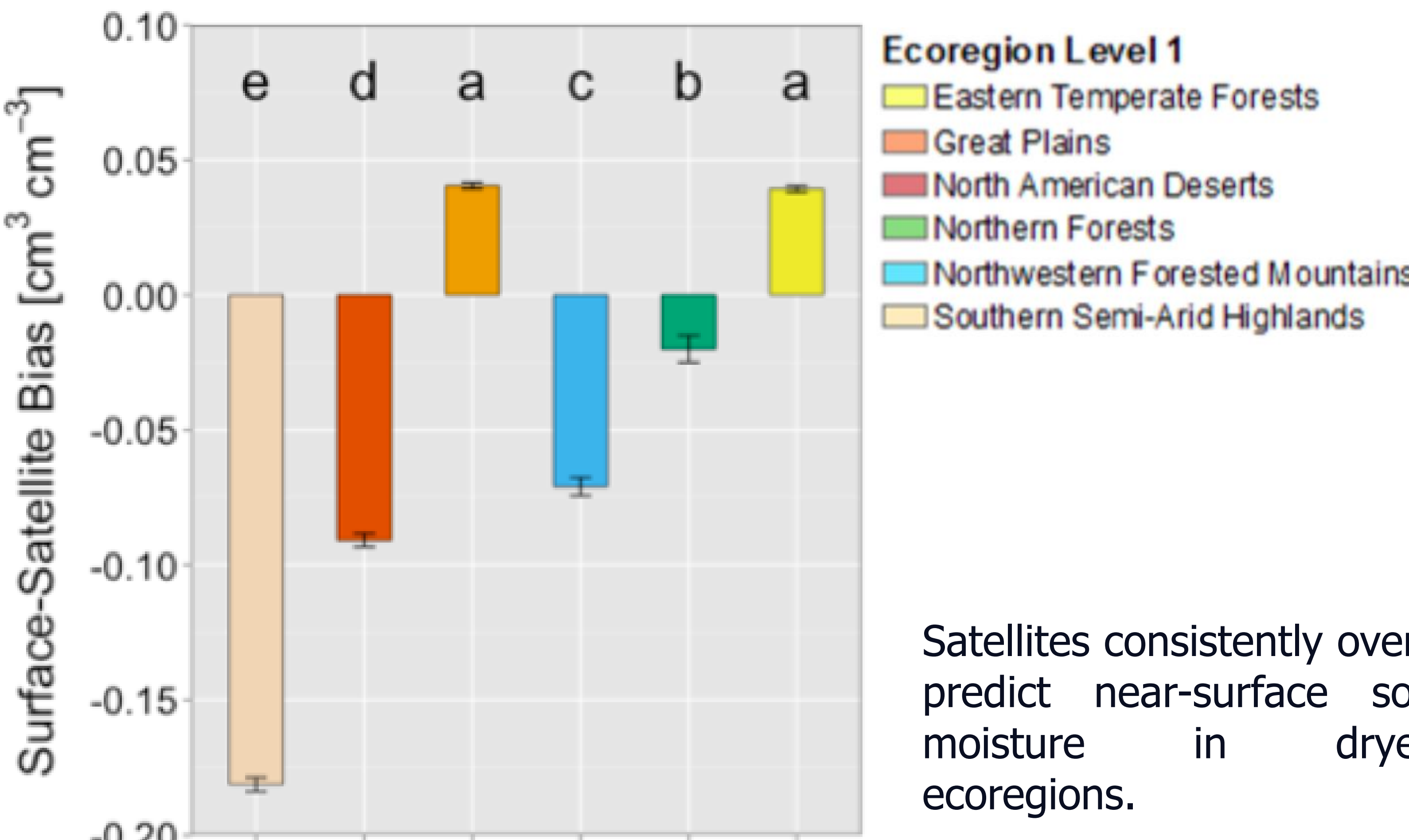
SMAR-EnKF optimization and prediction



Root mean square errors ranging from 0.014 - 0.049 [cm^3 cm^{-3}].

Predictive 95% confidence intervals captures no less than 86% of observations.

Results of SMAR-EnKF with AMSR-E



Satellites consistently over-predict near-surface soil moisture in dryer ecoregions.

(Baldwin et al., J. Hydr., 2016)

Multiple regression equations used for each SMAR model parameter

Multivariate regression models to estimate SMAR parameters at 11 other sites using STATSGO-derived soil properties and EPA Level 1 ecoregion type as covariates.

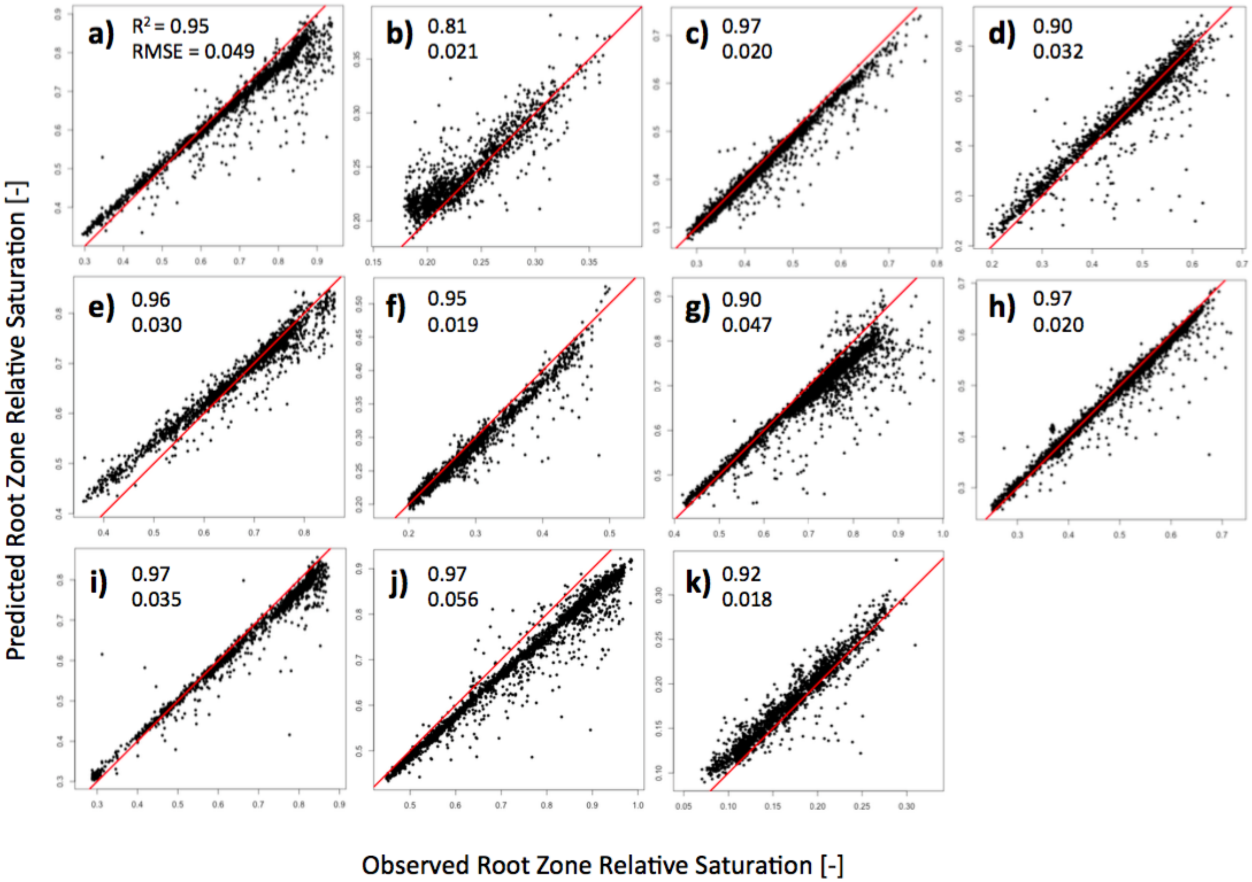
	Multivariate Linear Regression Function	R^2	p-v
S_{FC}	$1.40^{***} + Clay_{SL}\,(0.573)^{*} - \ln(AET)(0.203)^{***}$	0.36	<0.001
a	$0.42^{***} - \ln(DtB)\,(0.427)^{***} - Clay_{RZ}\,(0.066)$	0.32	<0.001
b	$-0.25 - \ln(DtB)\,(0.158)^{**} + \ln(AET)(0.078)^{*}$	0.30	<0.001
S_{WL}	$0.494^{***} + Clay_{RZ}\,(0.167) - Sand_{RZ}\,(0.454)^{***}$	0.54	<0.001

Significance levels of coefficients: *** = p < 0.001, ** p < 0.01, * p < 0.05;
AET = Average annual evapotranspiration;

Cross validation of SMAR-EnKF

The SMAR-EnKF has been validated using parameters based upon the STATSGO-based regression relationships.

The SMAR-EnKF system predicts S_{RZ} with R^2 between observed and predicted ranging from 0.81-0.97 (average: 0.93) and RMSE ranging from 0.018-0.056 [-] (average: 0.032 [-])



Conclusions

SMAR represents a feasible mathematical characterization of the relationship between the surface and the root zone soil moisture.

The SMAR model showed high reliability when applied over the AMMA and the SCAN dataset that has been improved with SMAR-EnKF.

The coupled model allows to estimate root zone soil moisture at regionally or globally distributed locations, using well-known soil physical properties as predictors.

This approach is a numerically effective strategy for estimating root zone soil moisture from satellite near-surface observations (e.g., the SMAP remote sensing platform) and in unmeasured locations, given basic soil texture information, providing a critical resource for estimating drought risk at regional to continental scales.

Papers related to this research line…

Baldwin, D., S. Manfreda, K. Keller, and E.A.H. Smithwick, Predicting root zone soil moisture with soil properties and satellite near-surface moisture data at locations across the United States, Journal of Hydrology, (under review) 2016.

Faridani, F., A. Farid, H. Ansari, and S. Manfreda, Estimation of the root-zone soil moisture using passive microwave remote sensing and SMAR model, Journal of Irrigation and Drainage Engineering, 04016070, 1-9, 2016.

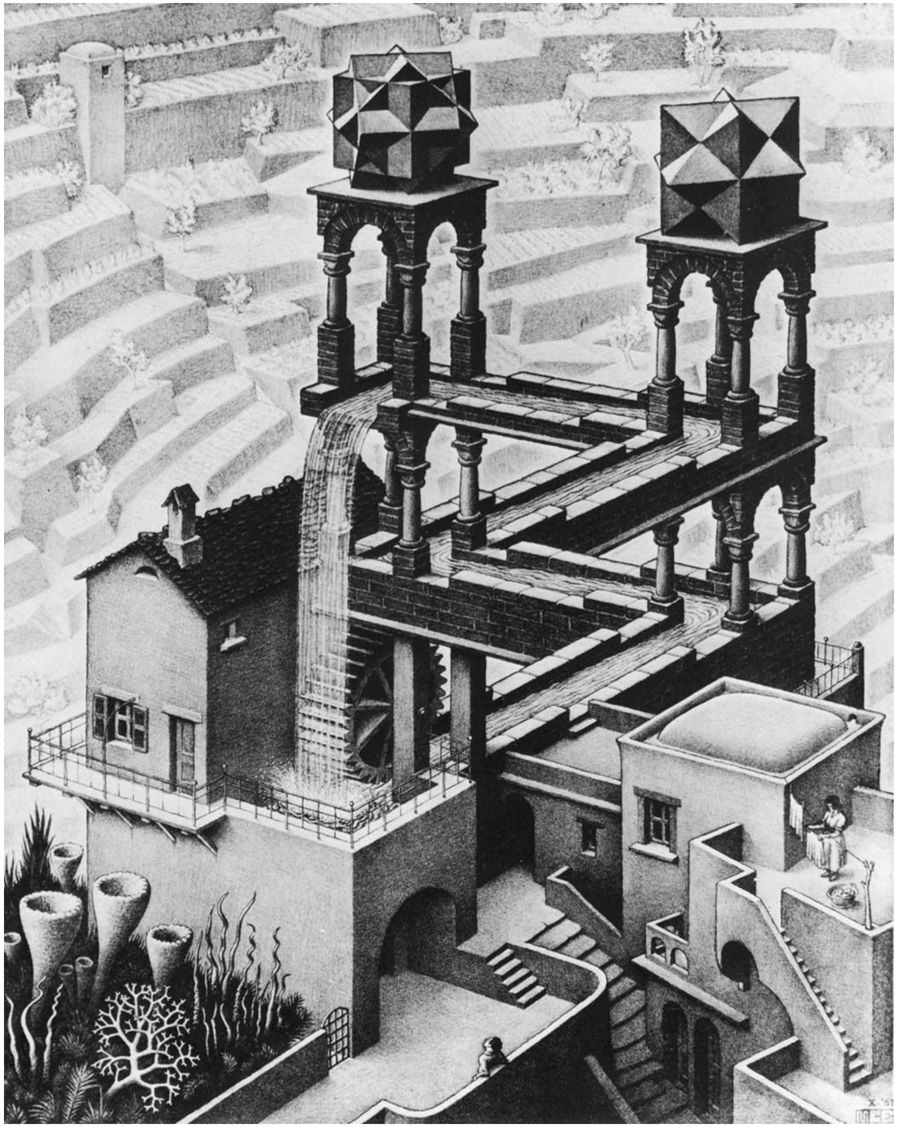
Faridani, F., A. Farid, H. Ansari, S. Manfreda, A modified version of the SMAR model for estimating root-zone soil moisture from time series of surface soil moisture, Water SA (under review), 2016

Manfreda, S., L. Brocca, T. Moramarco, F. Melone, and J. Sheffield, A physically based approach for the estimation of root-zone soil moisture from surface measurements, Hydrology and Earth System Sciences, 18, 1199-1212, 2014.

Manfreda, S., M. Fiorentino, C. Samela, M. R. Margiotta, L. Brocca, T. Moramarco, A physically based approach for the estimation of root-zone soil moisture from surface measurements: application on the AMMA database, Hydrology Days, pp. 47-56, 2013.

Manfreda, S., T. Lacava, B. Onorati, N. Pergola, M. Di Leo, M. R. Margiotta, and V. Tramutoli, *On the use of AMSU-based products for the description of soil water content at basin scale*, Hydrology and Earth System Sciences, 15, 2839-2852, 2011.

HydroLAB



Many Thanks...