Vegetation Modelling in WARP 6.0

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Abstract

Scatterometers have traditionally been used for measuring sea winds. However, as shown by (Wagner et al, 1999) they are also well suited for measuring soil moisture. Due to a growing interest in an operational soil moisture service in the NWP community, EUMETSAT decided to implement such a service for the ASCAT scatterometer onboard METOP-A. This service, which is known as WARP-NRT (Water Retrieval Package - Near Real Time), was developed in cooperation with TU Wien and put into operations in 2008. WARP-NRT processes and distributes soil moisture data within 135 minutes after acquisition. For its operation, it depends on several model parameters, which describe, among other things, noise characteristics and the effects of vegetation on the measured backscatter. Estimation of these parameters requires the availability long time backscatter time-series; the model parameters – and, conjointly, long-term soil-moisture time-series - are derived using the (offline) WARP processor, which was developed by and runs at TU Wien.

This paper discusses a novel approach to estimating the particularly important vegetation parameters, as well as the potential benefits from deriving this parameters annually (instead of only at the seasonal scale), which will be implemented in the next version of the WARP processor, WARP 6.0.

1 WARP

WARP was originally developed for deriving soil moisture time-series from ERS-AMISCAT scatterometer data. With the launch of METOP-A, support for the newer ASCAT scatterometer was added. Both scatterometers illuminate each point in its swath with 3 beams, resulting in 3 measurements taken under 3 different azimuth and 2 different incidence angles (fore- and aft-beam have the same incidence angle). This multi-beam capability plays an important role in the TU Wien algorithm, as will be seen below. For a recent in-depth review of WARP, see (Wagner et al., 2013).

WARP forgoes extensive geophysical modelling; instead, it is based on a semi-empirical change detection approach, which assumes the availability of long-term backscatter time-series. The key idea is to express soil moisture as a percentage, relative to the historically lowest and highest backscatter measurements in a given location (the dry and wet reference). It rests on several assumptions, the most important of which are

- Backscatter expressed in dB is linearly related to soil moisture, and
- Backscatter depends strongly on the incidence angle. This dependency can be modelled by a 2^{nd} order polynomial f. The 1^{st} and 2^{nd} derivative of f depend on the vegetation state, while its 0^{th} moment (intercept) depends on the soil moisture (i.e., an increase in soil moisture shifts the curve upwards, a decrease in soil moisture shifts it downwards).

The parameters governing the shape of the incidence angle – backscatter dependency are needed for incidence angle normalisation, for computing the dry and wet reference and in the derivation of noise estimates, so they are of central importance to the TU Wien method.

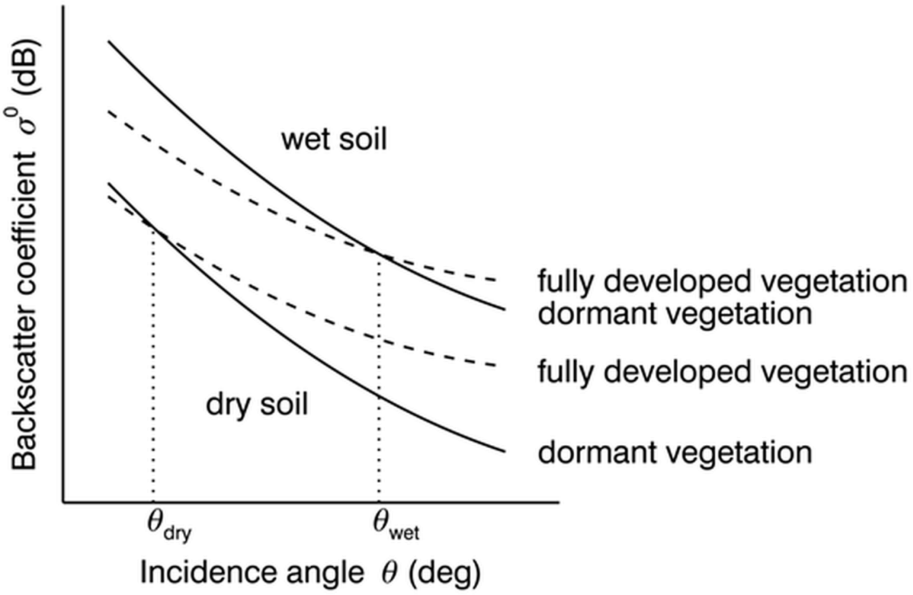

Figure 1: Assumed dependency between incidence angle and backscatter coefficient in the WARP model. The vegetation state effects the 1st and 2nd derivatives of the curve, while a change in soil moisture simply shifts it. From (Wagner et al., 2013).

Vegetation Modelling in WARP

The key equation of the WARP model expresses the observed backscatter $\sigma^0(\theta, t)$ as a function of the incidence angle θ at day d, more precisely as a second order polynomial about the reference angle $\theta_{ref} = 40^o$:

$$\sigma^0(\theta, d) \ = \ \sigma^0(\theta_{ref}, d) + \sigma' \ (\theta_{ref}, d)(\theta - \theta_{ref}) + \frac{1}{2}\sigma''(\theta_{ref}, d)(\theta - \theta_{ref})^2 \qquad (1)$$

whereby the 0th-order coefficient $\sigma^0(\theta_{ref}, d)$ is the normalised backscatter at the 40^o reference incidence angle, and the 1st and 2nd order coefficients $\sigma' \ (\theta_{ref}, d)$ and $\sigma''(\theta_{ref}, d)$ are referred to as slope and curvature parameters. Slope and curvature mediate the effect of vegetation on the functional relationship between σ^0 and θ: for sparse vegetation, the curve tends to drop off rapidly, while for fully grown vegetation, it becomes less steep, almost horizontal in the case of rain forest. In the WARP 5.5 model, it was assumed that the vegetation state is always the same at the same day of the year, i.e. it does not change inter-annually, and is thus a function of the day-of-year doy. Hence, for each DGG location, there would be 366 such curves, each determined by a slope/curvature pair $\sigma' \ (\theta_{ref}, doy)$, $\sigma''(\theta_{ref}, doy)$ $1 \leq doy \leq 366$.This assumption was introduced when WARP still used ERS-AMISCAT data as input. In WARP 6.0, which uses ASCAT data – which have a much better temporal resolution - we will drop the above assumption and compute a vegetation curve for each single day $2007.01.01 \leq d \leq 2012.12.31$.

Slope and curvature are determined as the coefficients of a straight line fitted to the so called local slopes. Local slopes are estimates of the first derivative of the backscatter - incidence angle dependency, and are computed as difference quotients between fore-and mid-beam, and aft- and mid-beam, respectively. To be more specific, each backscatter beam-triple $[\sigma_{i,f}, \sigma_{i,m}, \sigma_{i,a}]$ (fore-, mid-, and aft-beam measurements) taken at incidence angles $[\theta_{i,f}, \theta_{i,m}, \theta_{i,a}]$ yields two local slope estimates at day d_i:

$$\sigma'_{i,f}\left(\frac{\theta_{i,m}+\theta_{i,f}}{2},d_i\right)=\frac{\sigma_{i,m}-\sigma_{i,f}}{\theta_{i,m}-\theta_{i,f}}$$

$$\sigma'_{i,a}\left(\frac{\theta_{i,m}+\theta_{i,a}}{2},d_i\right)=\frac{\sigma_{i,m}-\sigma_{i,a}}{\theta_{i,m}-\theta_{i,a}}$$

These local slopes are taken as instances of the first derivative of Eq. 1

$$\sigma'(\theta,d) = \sigma'\left(\theta_{ref},d\right)+\sigma''\left(\theta_{ref},d\right)\left(\theta-\theta_{ref}\right)$$

Thus, the slope and curvature parameters can be retrieved as the intercept and slope of a linear function (note that the normalized backscatter $\sigma^0(\theta_{\mathrm{ref}},d)$, which depends on the unknown soil moisture, has vanished in the first derivative), by fitting a line to the local slopes.

In order to increase the precision of the estimates, the fit for a given day d is computed from the local slopes not only for day d, but from a time window with half-width λ centred at d. The width of the window is crucial for the quality of the estimates, since a window that is too short will lead to poor precision of the estimates, while a time window that is too long will tend to smooth local details or even average measurements taken from different vegetation periods.

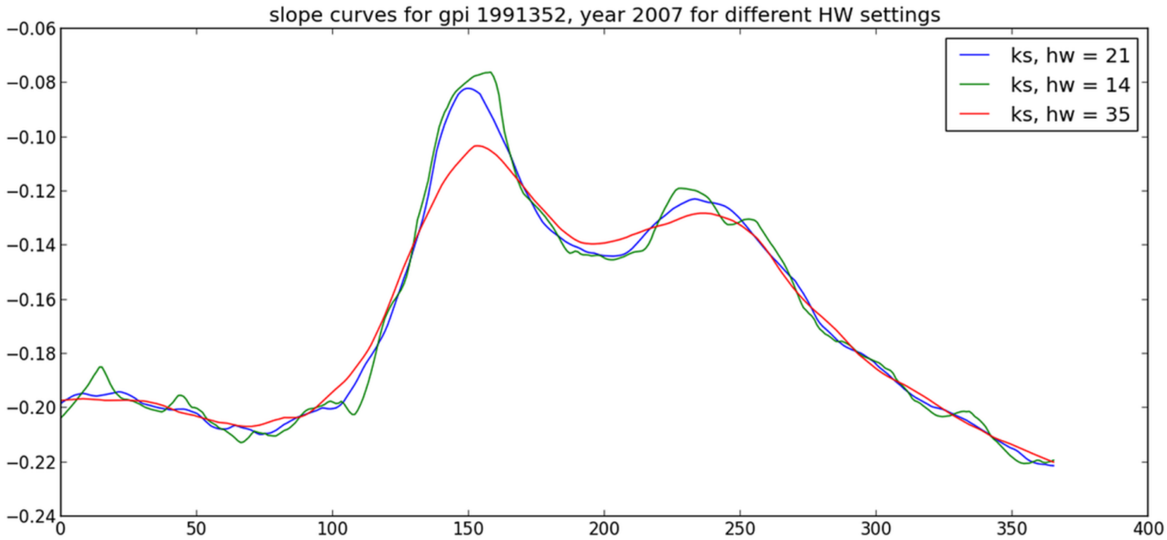

Figure 2: The WARP **slope parameter shown as function of the day of the year (vegetation curve). An increase in the window width (here shown for the kernel smoother ks) "trims the hills and fills the valleys", i.e., it increases estimation bias. hw=21 seems to best strike the balance between bias and variance of the estimates**

2 DERIVATION OF VEGETATION PARAMETERS IN WARP 6.0

Starting with WARP 5.2, in order to a) address the issue of time window length and b) to compute noise estimates for the parameters (which are difficult to obtain by error propagation in this case), a Monte Carlo approach was implemented (Naeimi, 2009). One of the drawbacks of this approach is its high computational burden, so estimates could be made only for a subset of 27 days and had to be extrapolated to the remaining days of the year.

One of the goals for the new implementation of vegetation modelling in WARP 6.0 was to replace the Monte Carlo approach with a faster one. The first step was to remove the costly averaging (marginalisation) over different values for the half width parameter. Experiments at our test site indicate that a fixed time window of 42 days ($\lambda = 21$) strikes a good balance between bias and variance of the estimates, and this value was used in the experiments reported (though, ultimately, λ should be determined in an adaptive, data-driven fashion, but this is made difficult by the relatively high noise variance of the local slopes).

Second, error estimates (noise variances) for the slope and curvature parameters are now derived using standard linear estimation theory. These error estimates will only be meaningful if the assumed model is correct, which in particular implies that all observations must come from the same distribution and hence λ must not be chosen too large.

Third, three different line estimators were evaluated. For a given day d, let the index $1 \leq j \leq N$ refer to all measurements within the time window $[d + \lambda, d - \lambda]$. The goal is to infer the optimal parameter vector $\boldsymbol{w}_d = [\sigma'(\theta_{ref}, d), \sigma''(\theta_{ref}, d)]$ for the (incidence angle, local slope) pairs $(\theta_j, \hat{\sigma}_j')$ with $d_j \in [d + \lambda, d - \lambda]$. The vegetation curves derived from the 3 estimators for a region in Kansas are shown in Fig. 3.

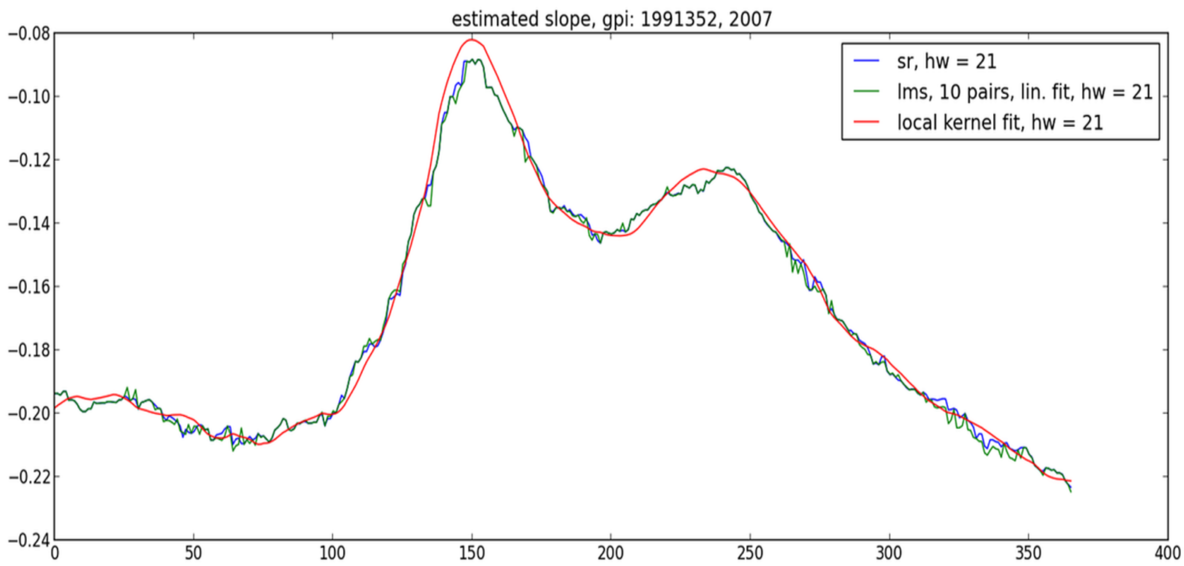

Figure 3: Test set: agricultural area in Kansas, USA, year: 2007. For this set, the 3 estimators give quite similar results, although sr and in particular lms are distinctly more rugged. The kernel smoother was chosen for WARP 6.0.

Simple Robust Fit (SR)

Repeatedly computes a standard linear least squares fit. After each iteration, points with their residuals outside a +/- 2*(est. standard deviation) interval are identified as outliers and removed. The algorithm terminates when the magnitude of change of the parameter vector falls below a given threshold. This method is also used in WARP 5.5. It is reasonably fast and has no immediate shortcomings. However, the estimates seen as function of d - i.e., as vegetation curve - are not smooth, so some smoothing has to be applied to the estimated parameters in a post-processing step.

Least Median of Squares (LMS)

This is a very powerful, robust regression paradigm that can also deal with extreme outliers (Rousseeuw, 1987). The idea is to select the parameters that minimize the median of the residuals r_j. Since there is no simple closed-form solution to this problem, in practice, this task is solved approximately by resampling: a number of hypotheses is generated by fitting the function to a „minimal subset“ (just sufficiently large to determine its parameters, e.g., 2 in case of a line) from the training set, and the hypothesis yielding the lowest median of the residuals is retained.

A main disadvantage is the high computational cost, due to the many tentative linear fits and computations of the median required. Also, the LMS estimates tend to be more rugged when seen as a function of time than the other estimates. This is a consequence of the higher variance of the robust estimator, which in turn is due to the less efficient – in the statistical sense – use it makes of the data. For these reasons, the LMS estimator was discarded (or kept in reserve for locations that produce a large percentage of outliers in the local slope estimates).

Kernel Smoother (KS)
Computes a weighted linear fit (Hastie, 2001). Normally, the weights are a monotonically decreasing function of the distance from the evaluation point θ_0. In our case, we perform the fit over the whole incidence angle range, and weigh the contributions according to their distance in time from the evaluation day d. The main advantage of this approach is that the estimated parameters seen as function of d are already smooth, and the smoothing is performed on the original data (not the estimated parameters). This estimator will be used in WARP 6.0 was used in the reported experiments unless stated otherwise.

3 RESULTS AND DISCUSSION

Due to the speed-up attained relative to the Monte Carlo-based approach, it became possible to calculate yearly slope curves in addition to the single aggregated (mean) curve computed in WARP 5.5. This is shown for the test site in Kansas in Fig. 4.

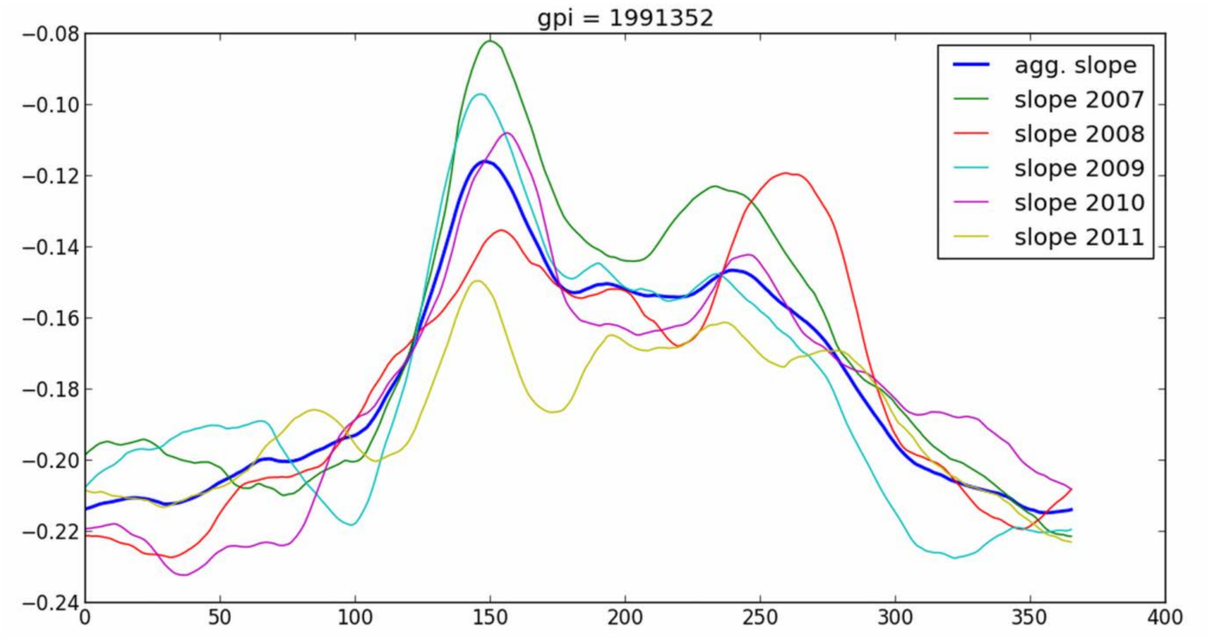

__Figure 4: Yearly and aggregated (mean) vegetation curves for the test site in Kansas.__

Although all yearly slope curves share the same basic bi-modal structure seen most clearly in the aggregated curve (blue line), they also show distinct differences. Indeed, the difference between the aggregated curve and the yearly curves is often significant at the 5% level, as shown in Fig. 5 for the year 2007. Provided these differences between the yearly slope curves are in fact due to different vegetation dynamics for the different years, the quality of the WARP soil moisture time-series could be improved by computing it using yearly slopes. Fig. 6, which compares a yearly slope curve against two vegetation indices, gives some evidence to the assumption that yearly curves do indeed reflect vegetation dynamics.

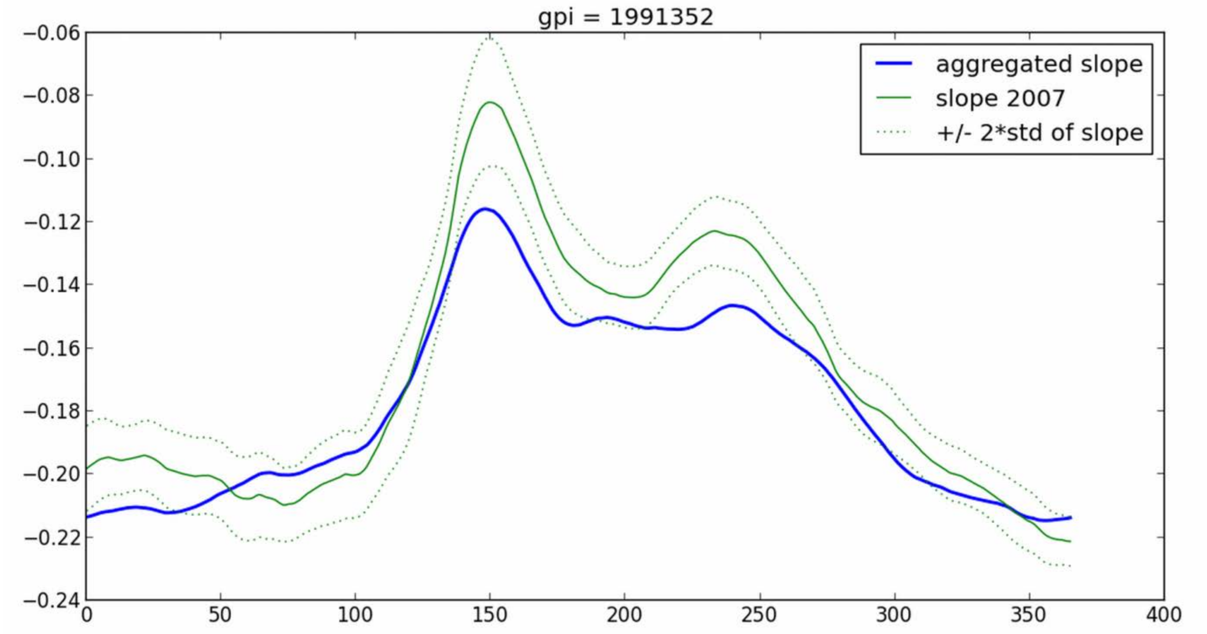

Figure 5: Yearly slope + confidence bounds vs. mean slope. The slopes are significantly different over wide periods, particularly around the local extrema during the mid and end of the year.

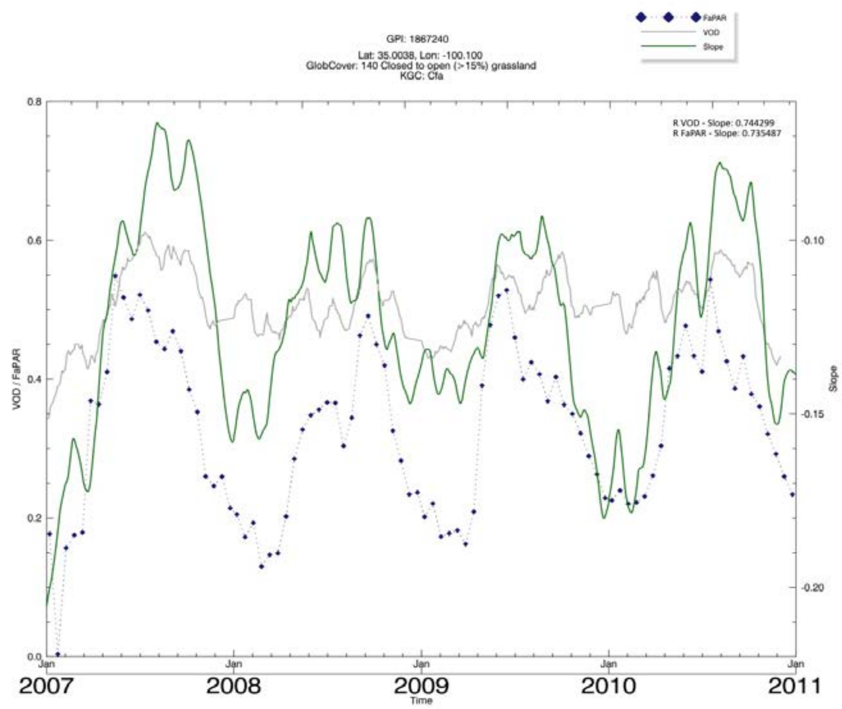

Figure 6: Comparison of a yearly WARP slope (green) with two other "vegetation indices", the Visual Optical Depth VOD (grey) and the Fraction of Absorbed Photosynthetically Active Radiation, FAPAR (blue diamonds), for a point in the Texas panhandle, USA. The correlation coefficient between the yearly WARP slope and the other curves is about 0.75.

Although WARP NRT will not directly benefit from the use of yearly slopes, the quality of the aggregated curve, which is used by WARP NRT, could well be improved by identifying and removing outlier years, before the aggregated curve is computed. This is, however, subject to future research.

ACKNOWLEDGMENTS

We gratefully acknowledge EUMETSAT through the “Satellite Application Facility on Support to Operational Hydrology and Water Management (H-SAF)” and ESA’s "Climate Change Initiative Phase 1 Soil Moisture Project".

REFERENCES

Hastie, T.; Tibshirani, R. & Friedman, J. (2001) *The Elements of Statistical Learning*, Springer.

Naeimi, V. (2009) 'Model Improvements and Error Characterization forGlobal ERS and METOP Scatterometer Soil Moisture Data'. PhD thesis, TU Vienna

Rousseeuw, P. J. & Leroy, A. M. (1987) *Robust regression and outlier detection*. John Wiley & Sons, Inc., New York, NY, USA.

Wagner, W.; Lemoine, G. & Rott, H. (1999) 'A Method for Estimating Soil Moisture from ERS Scatterometer and Soil Data'. *Remote Sensing of Environment* **70**(2), 191 --207.

Wagner, W.; Hahn, S.; Kidd, R.; Melzer, T.; Bartalis, Z.; Hasenauer, S.; Figa-Saldaca, J.; de Rosnay, P.; Jann, A.; Schneider, S.; Komma, J.; Kubu, G.; Brugger, K.; Aubrecht, C.; Züger, J.; Gangkofner, U.; Kienberger, S.; Brocca, L.; Wang, Y.; Blöschl, G.; Eitzinger, J.; Steinnocher, K.; Zeil, P. & Rubel, F. (2013) 'The ASCAT soil moisture product: A review of its specifications, validation results, and emerging applications'. *Meteorologische Zeitschrift* **22**(1), 5--33.